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Marine and Offshore Safety Assessment by Incorporative Risk Modeling in a Fuzzy-Bayesian Network of an Induced Mass Assignment Paradigm

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The incorporation of the human element into a probabilistic risk-based model is one that requires a possibilistic integration of appropriate techniques and/or that of vital inputs of linguistic nature. While fuzzy logic is an excellent tool for such integration, it tends not to cross its boundaries of possibility theory, except via an evidential reasoning supposition. Therefore, a fuzzy-Bayesian network (FBN) is proposed to enable a bridge to be made into a probabilistic setting of the domain. This bridge is formalized by way of the mass assignment theory. A framework is also proposed for its use in maritime safety assessment. Its implementation has been demonstrated in a maritime human performance case study that utilizes performance-shaping factors as the input variables of this groundbreaking FBN risk model.

KEY WORDS: Bayesian network; fuzzy logic; marine and offshore systems; safety assessment

1. INTRODUCTION

In risk analysis, cause-effect relationships are vital for achieving the modeling process. Thus, modeling in a network format becomes useful as it also gives an intuitive vital representation that mimics the domain of the real world. The most useful form of such a model is a causal diagram or network usually termed a directed acyclic graph, which uses nodes for representing distribution knowledge of variables and arcs for representing casual influences between nodes. If the data for a nodal variable are sufficient enough to enable the quantitative reasoning, then the form of the data (e.g., given as frequency of occurrence of the event) can be converted into a probability distribution for the analysis. The inherent uncertainty due to randomness then makes this a random node that can typically be applied in a Bayesian network (BN) (Pearl, 1988). On the other hand, if information associated with a node exhibits uncertainty that is, vague, ambiguous, or fuzzy, then it cannot be represented precisely by a probability distribution. Thus, fuzzy logic (FL) (Zadeh, 1975) may have to be utilized to achieve a possibility distribution via a rule-base inference engine that permits the subjective reasoning (Eleye-Datubo *et al.*, 2004).

When, for example, two nodes are both defined by possibilistic values, they exhibit conditional possibility and fuzzy set theory features. If they are both defined by probabilistic values, they exhibit conditional probability and Bayes's theory features. The obvious problem within the casual network arises when a fuzzy event node has a casual influence connection with that of a random event node. In this case, Bayes's theorem cannot be applied for the casual influence due to the fuzzy event present in the conditional connection. Therefore, a method of converting from possibility to probability distributions is most desirable. If such a method can

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provide bidirectional characteristics, then the fuzzy nature of a variable can always be recouped. The theory of mass assignment (MA) (Baldwin *et al.*, 1996) has been proven to offer one such feature. Hence, the causal formalism of using a combined fuzzy and Bayesian approach can be made possible. The resulting proposed route is given by the model name—"fuzzy Bayesian network." In recent research, developments, and applications, FL and BN have both emerged as powerful and effective tools for reasoning under conditions of uncertainty (Eleye-Datubo *et al.*, 2004, 2006; Sii *et al.*, 2004, 2005; Wang, 2006). Thus, it is certainly quite appropriate to investigate the amalgamation of both techniques.

The amalgamation of FL and BN may well prove to provide the indispensable means of incorporating human factors/elements in a probabilistic risk analysis model domain. Obviously, such an accomplishment is bound to be a key improvement to safety achievements in the marine and offshore industry, especially as human error has a substantial impact on the reliability of complex systems. For example, the safety of people on board a ship in distress is very much dependent on an effective emergency *escape, evacuation, and rescue (EER)* operational system (final barrier to avoid fatalities) being in place and being enabled in due time (Eleye-Datubo *et al.*, 2006). While much attention has been placed on improving design, construction, and operations of the EER system or other maritime operating equipment based on casualties, the human factor element remains the predominate contributing cause of accidents (The Nautical Institute, 2003) within each phase. Certainly, the marine and offshore industry cannot afford to simply accept that this situation is inevitable.

This article proposes a novel and flexible risk modeling approach making use of the advantages of both FL and BN. Through this approach, interactive risk scenarios in situations of high uncertainty in data can be facilitated.

2. A FUZZY-BAYESIAN LITERATURE

Viertl (1987) explains the necessity of developing a fuzzy-Bayesian inference and this paved the way for the first works on this inference, which come from safety project studies in structural reliability research (Chou & Yuan, 1993; Frühwirth-Schnatter, 1993; Itoh & Itagaki, 1989). The research results based on two examples, a reinforced concrete beam and a structural frame, showed that the fuzzy-Bayesian approach is a viable enhancement to the safety assessment of existing structures (Chou & Yuan, 1993). Nonetheless, that inference suffered from numeric stability problems in trying to achieve a justified fuzzy-probability transformation and further overlooked the conditional cases that can arise between fuzzy/possibility distribution events. The developed theory of MA by Baldwin *et al.* (1996) provides a bidirectional transformation platform between Bayesian probability theory and possibility/fuzzy set theory, and Dubois and Prade (1997) introduce a Bayesian conditioning operation in possibility theory, adapted to the idea of focusing on a body of knowledge for a reference class described by available evidence.

The work carried out so far on FBN cannot suitably be applied in the maritime domain, since the renowned leap in possibility-probability distribution inference process, as brought about by the theory of MA, is worthy of appropriate modifications to previous methodologies. With such modifications in place, the innovative FBN can now rightly be based on a more realistic inference process and may well offer a stable practical solution for those domains containing continuous and discrete variables and also those of random and vague uncertainties.

3. FUZZINESS AND PROBABILITY

Probability and fuzziness are related but different concepts. Fuzziness is a type of deterministic uncertainty that describes the event class ambiguity. Fuzziness measures the degree to which an event occurs, not whether it occurs. An issue is whether the event class can be unambiguously distinguished from its opposite. Probability arises from the question of whether or not an event occurs. Moreover, it assumes that the event class is crisply defined and that the law of noncontradiction (i.e., $A \cap \bar{A} = \emptyset$, where A is a set in the finite space) holds. Kosko (1990) shows that fuzziness occurs when the law of noncontradiction (and equivalently the law of excluded middle, that is, $A \cup \bar{A} = X$, where X is the universe of discourse) is violated. However, it seems more appropriate to investigate the fuzzy probability for the latter case (Dubois & Prade, 1993), than to completely dismiss probability as a special case of fuzziness (Kosko, 1990).

A fuzzy probability extends the traditional notion of a probability when there are outcomes that belong to several event classes at the same time but to different degrees. It is important to note that neither fuzziness nor probability governs the physical processes in nature, though they are orthogonal concepts that characterize different aspects of human experience (Dubois & Prade, 1993).

4. COMPARISON OF AXIOMS OF PROBABILISTIC AND POSSIBILITY-BASED METHODS

The objective of this section is to identify the differences in the axioms of probability and possibility and the impact of these differences on how probabilistic and fuzzy set methods model uncertainties and assess the reliability of a system.

Fuzzy set methods use possibility, which measures the degree to which an event is feasible, to quantify the likelihood this event will occur. One can think of possibility as complementary to the degree of surprise if an event occurs (Chen *et al.*, 1999). Possibility ranges from zero to one, like probability.

A key axiomatic difference between possibility and probability is that the possibility of a union of events (disjoint or overlapping) is equal to the maximum of the possibilities of the individual events, whereas the probability of a union of disjoint events is equal to the sum of the probabilities of these events. This leads to the following observations (Chen *et al.*, 1999).

1. The possibilities of an event and its complement may add up to more than one, whereas the probabilities of an event and its complement must add up to one.
2. The possibility of failure of a system, consisting of identical, independent components connected in series, is equal to the possibility of failure of one component, whereas the probability of failure of the system increases with the number of components.
3. The possibility of failure of a system, consisting of identical, independent components connected in parallel, is equal to the possibility of failure of a single component.
4. From Observation 2, it is concluded that the possibility of an event can be smaller than its probability. For example, even if the possibility of failure of each component is greater than the corresponding probability, a system with enough components will have a possibility of failure smaller than its probability of failure. This result is counterintuitive—since one may reason that the possibility of an event should be greater or equal to its probability because if an event is probable it should also be possible.

According to Observation 2, a fuzzy set method is likely to underestimate the chance of failure of a system with a large number of independent failure modes. On the other hand, it can be too conservative in systems for which the failure region is very small compared to the range of the uncertain variables. Therefore, compared to fuzzy set methods, probabilistic methods may provide a more accurate estimate of the chance of failure if there are enough data to model random uncertainties accurately and modeling errors are small.

On the other hand, it is easier to determine the most conservative fuzzy set model than to determine the most conservative probabilistic model that is consistent with given information about a problem. A primary reason is that, although the area below the probability density function of a random variable must be equal to one, there is no such constraint on the possibility density function.

5. PROPOSED SEMANTICS FOR A FUZZY-BAYESIAN NETWORK

The key feature of the proposed *fuzzy-Bayesian networks (FBNs)* is that they enable modeling and reasoning about uncertainty that can be due to a combination of inherent vagueness and randomness. Hence, essential to their formalism is the idea of relating, combining, and converting possibilitistic values into their probabilistic counterpart for use within the same model framework. As such, it is quite possible that the proposed FBN modeling may realize anything FL can do and also inherit the entire rigor, flexibility, and other superior properties of probabilistic approaches.

5.1. Possibility-Probability Directed Acyclic Graph

A FBN provides factorized representation of a possibility-probability model that explicitly captures both a logical and network structure typical in human-engineered models. More generally, a FBN is a DAG of a *BN* nature that allows for the encoded *probability distribution* of a node to be derived from its *fuzzy* derivation. The fuzzy-to-probability distribution conversion is normally induced via a suitable algorithm, for example, by *mass assignment (MA)* formalism.

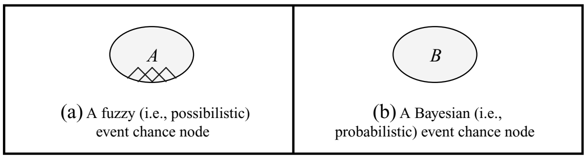

Fig. 1. Proposed nodal representation for fuzzy and Bayesian chance events.

Fig. 1(a) gives a proposed nodal representation for a fuzzy event, A. Such a node basically obtains its prior probability input from a fuzzy set output. In order to enable this conversion of probability distribution, a conversion inference via MA is utilized. The typical representation of a random event, B, in a BN is as shown in Fig. 1(b).

To understand how they are utilized in a FBN, it is worth having the most basic formats of their representation within the network. These are as given in Fig. 2(a)–(d).

As expected, from a Bayesian viewpoint, a direct probabilistic inference linking from Event G to Event F is represented by a line of its terminating arrowhead resting on the later. An optional direct possibilistic inference (not shown in Fig. 2) may be represented as a dashed terminating arrowhead line between fuzzy events. Such an optional possibilistic inference can enable a means by which a comparison study can be effected between conditional possibility and conditional probability of the fuzzy events.

5.2. Conditional Probability of Fuzzy Events

For a probability distribution $P(.)$ on a finite universe X, the conditional probability of f (a state of Event F) given g (a state of Event G) can now be defined as the expected value of the conditional probability of the focal elements for mass assignment of f, m_f, given the focal elements for mass assignment of g, m_g, relative to $P(.)$ and assuming that the joint MA generated by f and g is given by $m_f \times m_g$ (Baldwin *et al.*, 1996). Basically, every set for $A \in P(X)$ for which $m(\phi) > 0$ is usually called a focal element of m. As the name suggests, focal elements are subsets of X on which the available evidence focuses. The idea behind this is that since the definitions for f and g are uncertain there is also uncertainty regarding to which (classical) conditional probability $P(f \mid g)$ refers. If the assumption is made that the two definitions come from different and independent sources, then $m_f \times m_g$ gives us a probability distribution across possible conditional probability values. In this case a natural estimate for $P(f \mid g)$ is to take the expected value of this distribution.

For $P(.)$, a probability distribution on a finite universe X, and f and g fuzzy subsets of X such that g is normalized, the conditional probability of f given g is defined by:

$$P(f \mid g) = \sum_{F_i} \sum_{G_j} \frac{P(F_i \cap G_j)}{P(G_j)} m_f(F_i) m_g(G_j), \quad (1)$$

where m_f, $\{F_i\}_i$, and m_g, $\{G_j\}_j$ are the MAs and focal elements for f and g, respectively.

Now for any normalized fuzzy set g, a posterior distribution result from conditioning on g can be clearly defined, according to Equation (1). This is referred to as the least prejudiced distribution (*lpd*) of g with respect to the prior $P(x)$.

More formally:

$$\forall \mathrm{x} \in X;\ lpd_g(x) = P(x|g) = P(x) \sum_{G_{j:x \in G_j}} \frac{m_g(G_j)}{P(G_j)}. \quad (2)$$

Indeed, it can be shown (Baldwin *et al.*, 1996) that the probability of f given g as defined in Equation (1) is equivalent to the probability of f

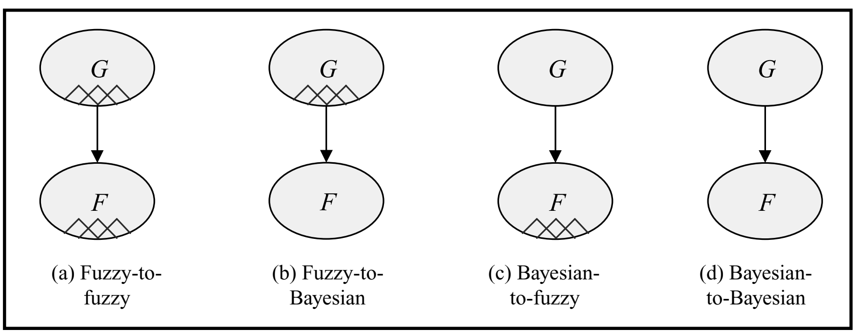

Fig. 2. Proposed FBN semantic representations between two random nature event nodes.

relative to the distribution lpd_g on X (Zadeh, 1968), that is:

$$P(f \mid g) = \sum_{x \in \Omega} \mu_f(x) lpd_g(x), \tag{3}$$

where $\mu_f(x)$ is the membership function of the fuzzy subset f on X.

The notion of *lpd* provides a mechanism by which a fuzzy set can be converted into a probability distribution. In the absence of any prior knowledge, the *lpd* might be relative to the uniform prior on knowing that g naturally infers the distribution lpd_g. If, however, fuzzy sets are to serve as descriptions of probability distributions, the converse must also hold. In other words, given a probability distribution, it will be required to hold that there is a unique fuzzy set conditioning on which this distribution yields.

6. MECHANISM FOR FUZZY-BAYESIAN CONVERSION

Fuzzy-Bayesian inference is not quite as direct as one would like to imagine. Instead, it relies on the use of the *theory of MAs* to play the central role. Therefore, the inferential pattern goes from a fuzzy set into MAs, and then from MAs into the prior probabilities. With Bayesian inference being enabled, the likelihood probabilities must be provided by the likes of this similar means. Similarly, the concept of conditional independence is applied to simplify the joint probability distribution of the modeling domain.

6.1. Basics of Mass Assignment

MA unifies probability, possibility, and fuzzy sets into a single theory termed mass assignment theory (MAT). If two or more groups of MAs are necessary to provide a single MA, then operations of MAT would have to be applied.

6.1.1. Mass Assignment Theory

The theory of MAs has been developed by Baldwin (Baldwin, 1992; Baldwin *et al.*, 1995) to provide a formal framework for manipulating both probabilistic and fuzzy uncertainties. Without such a theory, the construction of systems capable of handling uncertainty in a unified manner may be difficult.

The motivation for considering MAs (Baldwin, 1991, 1992; Baldwin *et al.*, 1995) is to provide semantics for membership functions of fuzzy sets. Essentially, the idea is that a fuzzy (or vague) concept is simply a concept for which the definition is uncertain or variable (across, say, a population of voters (Williamson, 1994)). Each possible definition corresponds to a subset of the universe of discourse and a probability distribution MA across these definitions can then be defined. Given such a distribution, the focal sets are taken to be those with nonzero mass. In fact, for the above definition the added assumption is made that the uncertainty is only regarding the degree of generality or specificity of the definition so that the focal sets form a nested hierarchy. The membership value of an element is then defined as the sum of the masses for the focal sets containing that element. Given these constraints, there is a unique MA corresponding to any fuzzy set. Note that a slightly different perspective on the above is to view the definition of a vague concept as a random set into the power set of the universe and the MA as its distribution (Goodman & Nguyen, 1985; Kreinovich, 1997).

A MA on a finite set X is a function $m : P(X) \to [0, 1]$ such that $\Sigma_{S \subseteq X}\ m(S) = 1$. Note that m_f has the property that it is nonzero only on some sequence of subsets of $X\{S_i\}$ such that $S_i \subseteq S_{i+1}$. Such MAs are strongly related to consonant basic probability assignments, which, in actual fact, represent a family of probability distributions. Furthermore, m_f satisfies $\Sigma_{S \subseteq X}\ m(S) = \mu_f(x)$. This is a fundamental requirement of any MA corresponding to f.

6.1.2. Operations of Mass Assignment

One of the most attractive features of MA theory is that operations of MA are defined in a way compatible to set operations (Baldwin *et al.*, 1995). They include the complement ($^-$), meet ($\cap$), and join ($\cup$). Given two MAs, $m(A) = \{M_i : m_i\}$ and $m(B) = \{M_j : m_j\}$, on universal set X, the general definitions of these operations are stated as follows.

- *Meet* of $m(A)$ and $m(B)$ is the intersection: $m(A) \cap m(B) = \{x_k : y_k\}$, where the new focal elements are given by $x_k = M_i \cap M_j$ and $y_k = \sum_{i,j; x_{ij} = x_k} y_{ij}$, respectively.
- *Join* of $m(A)$ and $m(B)$ is the union: $m(A) \cup m(B) = \{x_k : y_k\}$, where the new focal elements are given by $x_k = M_i \cup M_j$ and $y_k = \sum_{i,j; x_{ij} = x_k} y_{ij}$, respectively.
- *Complement* of $m(A)$ is the complementation: $\overline{m}(A) = m(\bar{A} = X - A)$, $\forall A \in P(X)$. Also, the

focal elements of $\overline{m}(A)$ are the complements of the focal elements of $m(A)$.

$\sum_j y_{ij} = m_i \; \forall i$ and $\sum_i y_{ij} = m_j \; \forall j$ are referred to as the *row* and *column* constraints, respectively. It can be noted that the complement is determined uniquely. However, the meet and the join operations are not determined uniquely because of possible combinations of redistribution of mass over new focal elements as determined by taking either intersection (meet) or union (join) of original focal elements.

6.2. Inferential Relationship

In order to enable inference via MA from a fuzzy set (FS) weights have to be assigned by a population of voters or a panel of experts to every fuzzy subset, $\mu_1, \mu_2, \ldots, \mu_n$, on the universe of discourse. In this layer, each weight, w_i, by members can be either 0 or 1. This can then be transformed to the corresponding MA, that is, $m_1, m_2, \ldots, m_n$, at the MA layer on each focal element, x_i. In contrast to the basic probability assignment in Dempster-Shafer (DS) theory, $\emptyset$ can be a focal element. At the probability distribution (PD) level, $w_i \to [0, 1]$ and $\Sigma w_i = 1$.

Fig. 3 gives a mapping overview of the FS-MA-PD inferential relationship. Sections 6.2.1 to 6.2.3 provide the breakdown of this inferential process. Note that the entire inferential process is bidirectional. The key advantage offered by the bidirectional nature is that the originally normalized output fuzzy set values can be obtained from the achieved probability distribution values and vice-versa.

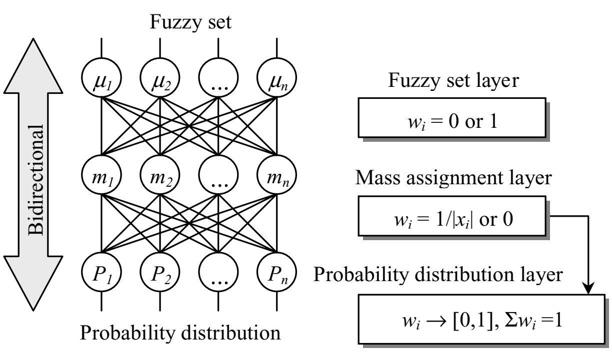

Fig. 3. Illustrative overview of a FS-MA-PD inferential relationship.

6.2.1. *Fuzzy Set-Mass Assignment Relation*

Let S be a sample space. Then, a mass assignment m_S associated with S is a function from the power set, $P(X)$, to an interval of real numbers such that $m_S : P(X) \to [0, 1]$ and $\Sigma_{A \subseteq S}\, m_S(A) = 1$. A subset $A \subseteq S$ is referred to the focal element for mass assignment m_S if $m_S(A) > 0$. Given a normalized discrete fuzzy subset $F = x_1/\mu_1 + \ldots + x_n/\mu_n$ over S, it can be denoted that $\mu_i = \mu_F(x_i)$. Without loss of generality for the normalized fuzzy subset, one can assume that:

$1 = \mu_1 \geq \ldots \geq \mu_n \geq \mu_{n+1} = 0.$

Then a MA with nested focal elements $\{x_1, \ldots, x_i\}$ for $i = 1, \ldots, n$ can be derived as:

$$m_S(A) = \mu_i - \mu_{i+1}, \quad \text{if } A = \{x_1, \ldots, x_i\}. \quad (4)$$

In effect, then, the definition of MA is a weakening of the definition of DS basic probability assignments to allow for the possibility of allocating nonzero mass to the empty set. Besides the fact that the calculus beyond the verification role is enhanced, the MA theory furnishes the calculus to handle imprecision, whereas the theory, due to DS, deals mainly with uncertainty caused by lack of information from the probability point of view.

6.2.2. *Mass Assignment-Probabilities Relation*

In MA theory, there exists the relation between a discrete probability distribution, for example, a normalized histogram, associated with elements of a sample space, S, on the power set, $P(X)$, and a least prejudiced probability distribution, lpd_A, (i.e., a selection rule) for each $A \in P(X)$. Basically, lpd_A is the case for which the assumption is made that mass assigned to a set A is equally likely to belong to any element in A. As a result mass assigned to A is distributed equally across all elements in A. More formally, given a mass $m(A)$:

$$m_s(\{x\}) = \frac{m_s(A)}{|A|}, \; \forall x \in A, \quad (5)$$

where 1/|A| is the *lpd* of A. |A| denotes the magnitude (modulus) of A, which refers to its size.

Masses assigned to singletons $\{x\}$ are now summed and assigned as probabilities for X.

A probability $P_s(x)$ is therefore defined as:

$$P_s(x) = \sum_{A \subseteq S, x \in A} \frac{m_s(A)}{|A|} = \sum_{A \subseteq S, x \in A} lpd_A(x) m_s(A). \quad (6)$$

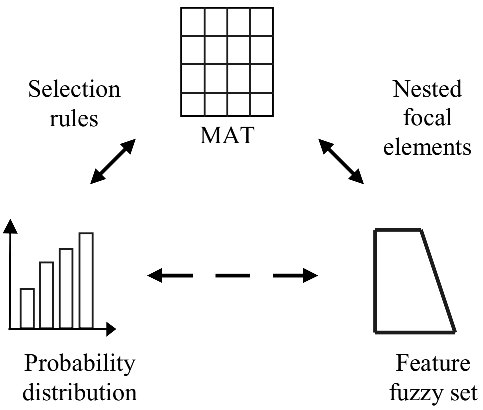

Fig. 4. Mapping consistency between a fuzzy set and a probability distribution.

The main role of the selection rules is in maintaining consistency between a fuzzy set and different probability distributions that satisfy Equation (6).

6.2.3. *Mapping Between Fuzzy Set and Probability*

Using the relation of fuzzy set-MA and MA-probability, one can now obtain the mapping between a fuzzy set and a probability distribution as shown in Fig. 4. Let $P_s(x_k)$ be a probability of a sample space S, and $lpd_{Ai}(x_k)$ be a selection rule for x_k from the focal element $A_i = x_1, \ldots, x_i$, $i = 1, \ldots, k$ of a MA. Then:

$$P_s(x_k) = \sum_{i=k}^{n} lpd_{Ai}(x_k).(\mu_i - \mu_{i+1}). \qquad (7)$$

It is noted that all focal elements are nested as they correspond to the level sets (α-cuts) for $\mu_i \forall i = 1, \ldots, n$.

The selection rules lpd_{Ai} can be tuned if the fuzzy set (i.e., the membership values μ_i's) is always manually changed in order for P_s to remain the same. This feature is important to determine the valid range of data for a given fuzzy set. Inconsistency in the data set is detected by obtaining some invalid probability in Equation (7). Such results are obtained when the order of membership values is not maintained. From a different angle, this can be used to determine what is lacking in order to keep the consistency.

The selection rules can also be used to establish a many-to-many relationship between probability distributions of data and its fuzzy set definition. Selection rules can also be one way of implementing experts' perception. In this case, selection rules are given arbitrarily. Then either a fuzzy set for a given data set or an ideal data set biased by experts' perception (i.e., a selection rules) for a fuzzy set representing a concept can be obtained by Equation (7).

7. PROPOSED FUZZY-BAYESIAN NETWORK METHODOLOGY

A FBN reasoning process has been developed to provide a natural framework for maritime risk assessment and decision support. A flow chart of the approach is shown in Fig. 5, and this format ensures that the FBN analyses are conducted in a disciplined, well-managed, and consistent manner that promotes the delivery of quality maritime decision-making results. The depth or extent of application of the methodology should be commensurate with the nature and significance of the problem. Nonetheless, the entire methodology is made up of three key modules:

- Module 1: Normalized Fuzzy Set from Output Values of FL Module.
- Module 2: MA Module.
- Module 3: Input Values as Prior Probabilities of BN Module.

In building a FBN model, one can first focus on specifying the qualitative structure of the domain and then focus on quantifying the influences. When finished, one is guaranteed to have a complete specification of the possibility and probability distributions. Then following evidence propagation, an intuitive evaluation for decision making can be enabled through added nodes of decisions and utilities as in a BN. *Hugin* (Jensen, 1993) can thus be is used as the robust BN programming environment for the risk

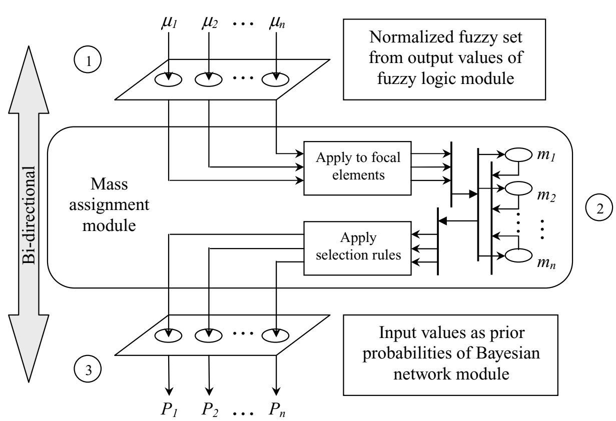

Fig. 5. Flow chart of a proposed FBN framework of analysis.

modeling and its probability calculations. Explanations for each of the underlying modules are given as follows.

Module 1: *Normalized fuzzy set from output values of FL module*. The aggregation procedure acting on fuzzy sets means that fuzzy sets are generated from data sets, and aggregated by fuzzy set operations.

Module 2: *MA module*. The aggregation procedure acting on MAs means applying MA theory operations such as meet and join on MAs generated least prejudiced distributions. Only then can the aggregated MA (as in Equation (5)) be suited for its transformation into the probability distributions of its essential focal elements.

Considering the original motivation of MA theory as a treatment of evidence, it is natural to treat each data set as evidence and, thus, to treat features extracted from a single text as a focal element and sizes of features are aggregated directly as selected rules of aggregated MA's using MA theory.

Module 3: *Input values as prior probabilities of BN module*. The aggregation procedure acting on least prejudiced distributions means that it can be generated from the MAs, and transformed into a probability distributions using Equation (6).

8. HUMAN ELEMENT ISSUE IN MARINE AND OFFSHORE SAFETY-CRITICAL APPLICATIONS

Wherever there is a human interacting with a system there is a human element issue. Modern technology has revolutionized the way in which a ship is operated, but lack of attention to the human-system interface, in terms of the design, layout, and integration of systems, and training in their use, is a major root cause of many accidents today. The maritime industry recognizes that such accidents are the direct consequence of human failings and that in reality many of the disregarded incidents and errors have a strong element of human involvement.

8.1. Human Errors in Maritime Operations

Human errors include (HSE, 2002):

- Slips—making an unintended action through lack of attention or skill.
- Lapses—unintended action through memory failures.
- Mistakes—an intended but incorrect action.
- Violations—a deliberate deviation from standard practice.

Human errors in marine operations, such as towing or ballast system operation, tend to have immediate effects. They may be recovered with no harm done, or they may have some direct harmful impact. This may then require some form of emergency response to mitigate the impacts. Similarly, errors may occur during evacuation, with a direct effect, for example, incorrect release of a lifeboat.

Errors can also occur during maintenance, and may then remain undiscovered (latent) until the equipment is required. These errors in effect cause equipment unavailability, and the significance of this depends on the system design. For example, this type of error may result in a ballast pump being unavailable when required. In fact, human error is human misery: careers blighted, lives lost, seafarers injured, and the environment despoiled. As continually stressed by the UK P&I Club, equipment, mechanical, and structural failure together are far outstripped by human error as the sole or major cause of incidents giving rise to claims. In looking at major claims, a current report (The Nautical Institute, 2003) finds that more than 62% are directly attributable to error by one or more individuals.

8.2. Human Factors in Maritime Risk Assessments

Since it is rightly the crew and the shipboard management that will always be working in an increasingly demanding, technically complex system, the maritime industry needs to grasp human element issues at a higher, more integrated level to make a real difference to safety. A FBN may well prove to be adequate in an integrated task of reducing the risk due to human factor. Obviously, the key to improvement is in the close involvement of all stakeholders to ensure that a ship is "fit for purpose," and that the master and the crew are provided with the proper tools and adequately training to be able to conduct their business in a safe and efficient manner.

9. FUZZY-BAYESIAN ANALYSIS MODEL IN A MARITIME DOMAIN

The fuzzy-Bayesian approach possesses great potential across many domains of marine and offshore applications. To provide a brief insight into some potential areas that could quite easily use fuzzy-Bayesian modeling, the following case is sited:

- Incorporation of human element in a risk analysis

To illustrate the universal applicability of FBNs to a modeling domain, it is best to imagine a situation in which causality plays a role but where an understanding of what is actually going on exhibits both vague and random features. Thus, things need to be described possibilistically, probabilistically, and by inference.

Human reliability analysis (HRA) endeavors to predict the probability of human error (typically uncorrected error) against a specified base rate. While it is concerned with causal analysis, it relies heavily on factors (in the operator, the environment, the equipment or the task) that affect the likelihood of error. These factors, which are termed "*performance-shaping factors,*" are not models in their own right, but, rather, they are input attributes that have an effect on the output of human performance. In the maritime industry, the quantification of such attributes exhibits a vast amount of vagueness for which their direct input into a probabilistic model needs to allow for this uncertainty. Hence, FBN is offered as the assessment platform.

9.1. Performance-Shaping Factors as Model Variables

Performance-shaping factors (PSFs) are those factors that can have positive or negative influence/effect on the effectiveness of human performance and the likelihood of errors (HSE, 1999). It is essential that the proper PSFs be identified to determine the effect external influences have on the basic human error probabilities (HEPs). Examples of PSFs in the marine and offshore industry, as well as in most industries, include (Boring & Gertman, 2004; Brown & Amrozowicz, 1996):

- Available time.
- Stress and stressors.
- Experience and training.
- Complexity and workload.
- Ergonomics (including human-machine interaction).
- Environmental effects.
- The quality of operating procedures.
- Language and culture.
- Morale and motivation.
- Operator fitness for duty.
- Work processes.

These factors, which are "human process variables" in the operator, the environment, the equipment, or the task, may be linked directly to human error through quantification. Despite their clear importance in human error likely situations, they have been hard to implement in quantitative risk assessment. The reason for this is more or less obvious: How is it possible to estimate, for example, culture or self-confidence that actually does influence the safety of a system? PSFs are therefore important to take into account, but the integrating strategy is more indistinct (Kjestveit *et al*., 2003). Seaver and Stillwell (1983) addressed the need for approaches that explicates paired comparisons, ranking and rating, direct numerical estimation, and indirect numerical estimation techniques applied to error estimation, with a particular emphasis on aggregating the estimates from multiple experts to arrive at error probabilities. Thus, due to the qualitative characteristics of PSFs, a FL approach can be utilized to allow for their input via expert judgment process.

PSFs work to increase or decrease the error rate due to situational characteristics. If, for example, the person is experiencing considerable stress, his or her task performance will decrease proportionate to the level of stress. Conversely, if a person has extensive training and practice doing a task, that person's proficiency may mitigate the chance of human error.

9.2. Developing Degree of Relationship Rule Base

Individual performance is degraded when the body's circadian rhythms are disrupted. For example, when loading and unloading cargo is coupled with scheduling pressures, time stress can occur. In addition to the stress that can be induced from long work hours, fatigue/nonfitness for duty becomes a critical factor. Studies have shown that as fatigue increases, the detection of visual signals deteriorates and individuals exhibit more errors (Swain & Guttmann, 1983). Table I (Boring & Gertman, 2004) gives the relationship on how available time as a PSF (PSF_1) is influenced by the other PSFs (PSF_i) and, as well, how it affects them.

The parametric relationship between one PSF and another for a marine vessel or an offshore installation is determined by simulation and expert opinion.

Note that PSFs can be combined for specific rules in a FL rule base. In the case where more than one PSF is being considered, absolute HEP values can be

Table I. Influence of and Effects on Other PSFs on Time Availability

	Available Time, PSF_1	
PSF_i	Influence	Effect
Stress and stressors, PSF_2	Amount of stress does not change the available time.	Less time may increase stress.
Experience and training, PSF_3	Greater experience means that less time is required for actions and decisions.	Available time has little or no effect on experience and training.
Task complexity, PSF_4	Too much complexity and workload can make the time available insufficient.	Little time makes the task more complex, for which the workload may require more hands on.
Ergonomics (including human-machine interaction), PSF_5	Poor layout can result in increased reaction time, lessening the available time to respond.	Available time has little or no effect on ergonomics and human-machine interaction.
Environmental effects, PSF_6	The likes of room temperature, vibration, and sea motion can make the time available insufficient.	Available time has no effect on environmental state/condition.
The quality of operating procedures, PSF_7	Complex or poorly conceived procedures increase how much time one needs to act.	Available time has little or no effect on the quality of operating procedures.
Language and culture, PSF_8	Misunderstanding can result in increased reaction time, lessening the available time to respond.	In some cases, time may lead to misunderstanding in language and culture.
Moral and motivation, PSF_9	Greater motivation means that less time is required for actions and decisions.	In some cases, time may have a significant effect on moral and motivation.
Operator fitness for duty, PSF_{10}	Illness or drug abuse may require increased time to decide or act.	Available time has little or no effect on the operator's fitness for duty.
Work processes, PSF_{11}	Poor shift turnover of information can reduce time available.	In some cases, time may enhance or compromise work processes.

computed by adding individual PSF multipliers. This would be the case, for example, if available time and stress contributed to a human error (Boring & Gertman, 2004).

In the event of multiple concurrent tasks, as is common in most real-world scenarios, Boring and Gertman (2004) state that the HEP values may also be combined. If two events must occur together for an error to occur, the HEP values are multiplied together to create a logical "AND" relationship. For example, losing a fresh program file that is important to the shipboard system requires the user both to fail to save the program file *and* to quit the program. If, however, errors are not in any way related to one another, the two task HEP values are added together to create a logical "OR" relationship. For example, a person may not be able to log in to an authorizing computer either by forgetting his or her computer password *or* by failing to type the password in the correct CapsLock case. Thus, using the generic PSFs as fuzzy linguistic variables, specific IF-THEN rules can be created via such logical "OR" and "AND" operators for a FL rule base.

9.3. Categorization of Performance-Shaping Factors

PSFs are characterized according to whether the task is cognitively engaging (i.e., a diagnosis task) or routinized (i.e., an action task). Operational research suggests that for cognitively engaging tasks such as diagnosis, people tend to exhibit a base human error rate equal to 1.0×10^{-2} (Boring & Gertman, 2004). This means that people have about a 1 in 100 chance of making a diagnosis error. For tasks that are more action oriented, the base human error rate is equal to about 1.0×10^{-3}, suggesting about a 1 in 1,000 chance

Table II. Available Time in a Fault-Intolerant Condition

Available Time Variable, $PSF_{1,i}$	Diagnosis	HEP	Action	HEP
Inadequate time, $PSF_{1,1}$	If the operator cannot perform the task in the amount of time available, no matter what s/he does, then failure is certain.	1.0	If the operator cannot execute the appropriate action in the amount of time available, no matter what s/he does, then failure is certain.	1.0
Barely adequate time, $PSF_{1,2}$	Two-thirds of the average time required to complete the task is available.	0.1	There is just enough time to execute the appropriate action.	0.01
Nominal time, $PSF_{1,3}$	On average, there is sufficient time to diagnose the problem.	0.01	There is some extra time above what is minimally required to execute the appropriate action.	0.001
Extra time, $PSF_{1,4}$	The time available is between one to two times greater than the nominal time required.	0.001	There is an extra amount of time to execute the appropriate action (i.e., the approximate ratio of 5:1).	0.0001
Expansive time, $PSF_{1,5}$	The time available is greater than two times the nominal time required.	0.0001	There is an expansive amount of time to execute the appropriate action (i.e., the approximate ratio of 50:1).	0.00001
Insufficient information, $PSF_{1,6}$	If you do not have sufficient information to choose among the other alternatives, assign this PSF level.	0.01	If you do not have sufficient information to choose among the other alternatives, assign this PSF level.	0.001

of making an error (Boring & Gertman, 2004). Base error rates for the two task types associated with the Standardized Plant Analysis Risk Human Reliability Analysis (SPAR-H) method were calibrated against other HRA methods. The calibration revealed that the SPAR-H human error rates fall within the range of rates predicted by other methods (Gertman *et al.*, 2004).

The PSFs are further classified according to whether they occur in a fault-tolerant situation or a fault-intolerant condition (Boring & Gertman, 2004). Table II (Boring & Gertman, 2004) exhibits how PSFs shape human error by using available time in a fault-intolerant condition, which is the condition of occurrence during critical operation.

Now, given PSF_i as a fuzzy input of an ith PSF having subset $PSF_{i,j}$ as its jth category, the rule base for a fuzzy output of human performance, H_p, with subset $H_{p,k}$ for its kth category, can be represented for the lth rule as:

$$R_l \text{ rule} = \text{IF } PSF_1 \text{ is } PSF_{1,j} \text{ AND/OR } PSF_2 \text{ is } PSF_{2j,} \text{ AND/OR}, \ldots, \text{ AND/OR } PSF_{11} \text{ is } PSF_{11,j}, \quad \text{THEN } H_p \text{ is } H_{p,k}. \tag{8}$$

In this study, only the "AND" operation is applied. A complete example of fuzzy rule from the rule base of human performance is:

IF "available time" is "extra" AND "stress and stressors" is "minimal" AND "experience and training" is "very good" AND "task complexity" is "slight" AND "ergonomics" is "fantastic" AND "environmental effects" is "inconsequential" AND "quality of operating procedures" is "high" AND "language and culture" is "fair" AND "moral and motivation" is "acceptable" AND "operator fitness for duty" is "certified very healthy" AND "work processes" is "normal,"

THEN "human performance" is "excellent."

Owing to the number of input PSFs in rule, R_l, a software program, such as Fuzzy Logic Toolbox 2.2.1 of Matlab 6.5 (The MathWorks, 2005), may be most essential to minimize complexity of the fuzzy mathematics.

9.4. Determination of Human Performance Output

PSFs determine whether individual performance will be very poor, excellent, or at some level in between. For this performance output, the assessment team assigns numeric values based on a 0–100% fuzzy scale (Fig. 6) as anchored by linguistic variables and descriptors provided in the evaluation layer of instrument.

This process of measuring the output attribute is in a similar fashion as those undertaken for all 11 PSFs in the antecedent of the FL rule base. The typical fuzzy set definition for the output attribute (i.e., human performance, H_p), which is represented by membership functions in which each fuzzy set overlaps to a certain degree with its neighbors

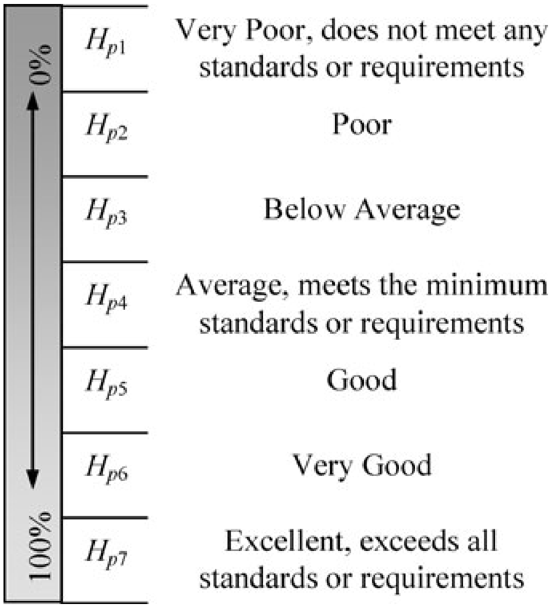

Fig. 6. Human performance grading scale for fuzzy set definition.

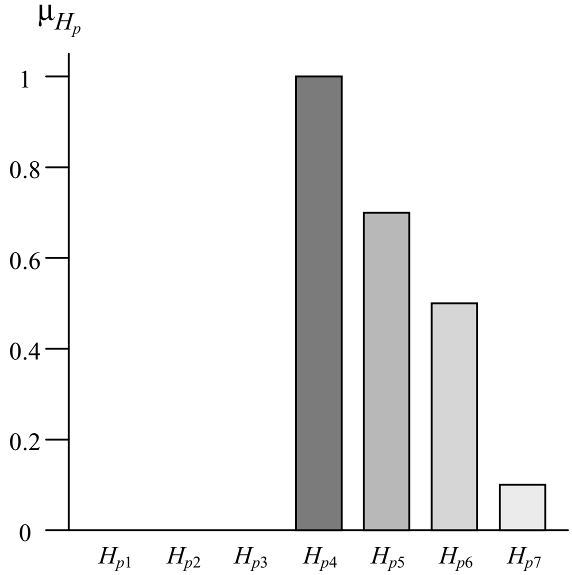

Fig. 8. An example of a normalized fuzzy set utilized as human performance output, H_p.

(Eleye-Datubo *et al.*, 2004; Sii *et al.*, 2004, 2005), can be expressed as shown in Fig. 7.

In utilizing expert judgment while executing the rule base of the generic PSF via the FL module of the FBN methodology that has been presented in Section 7, the fuzzy H_p set is obtained as the fuzzy output result of the study. A hypothetical example of a normalized fuzzy set, as shown in Fig. 8, is employed herein as the yielded discrete result for H_p to demonstrate the applicability of the FBN framework.

Membership values for each element in the H_p fuzzy set are $\mu H_{p1} = 0$, $\mu H_{p2} = 0$, $\mu H_{p3} = 0$, $\mu H_{p4} = 1$, $\mu H_{p5} = 0.7$, $\mu H_{p6} = 0.5$, and $\mu H_{p7} = 0.1$. Since focal elements of H_p have to be only those elements of $P(H_p)$ that have nonzero probability assignment, then clearly μH_{p1}, μH_{p2}, and μH_{p3} are not required for further analysis into their probability conversion.

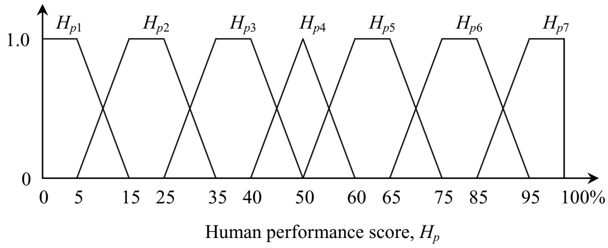

Fig. 7. Fuzzy set definition for human performance output.

Therefore, the normalized fuzzy set of H_p may be represented as:

$$H_p = \{H_{p5}/1 + H_{p5}/0.7 + H_{p5}/0.5 + H_{p5}/0.1\}.$$

The mass assignment, $m(H_p)$, is derived from H_p by *weighting* the combined mass of each element in H_p. As assigned in Fig. 9, the weighting of 10, 9, and 8 is attributable to only H_{p4}, the weighting of 7 and 6 is attributable to only H_{p4} or H_{p5}, the weighting of 5, 4, 3, and 2 is attributable to only H_{p4} or H_{p5} or H_{p6}, and the weighting of 1 is attributable to any of H_{p4}, H_{p5}, H_{p6}, or H_{p7}. Normalizing the number of weighting attributable to any one proposition then generates the mass assignment $m(H_p)$ for fuzzy set H_p as based on the use of Equation (4), which is given as:

$$\begin{aligned} m(H_p) &= \{H_{p4}\} : \mu_{H_{p4}} - \mu_{H_{p5}}, \{H_{p4}, H_{p5}\} : \\ &\quad \mu_{H_{p5}} - \mu_{H_{p6}}, \{H_{p4}, H_{p5}, H_{p6}\} : \\ &\quad \mu_{H_{p6}} - \mu_{H_{p7}}, \{H_{p4}, H_{p5}, H_{p6}, H_{p7}\} : \mu_{H_{p7}} \\ &= \{H_{p4}\} : 0.3, \{H_{p4}, H_{p5}\} : \\ &\quad 0.2, \{H_{p4}, H_{p5}, H_{p6}\} : \\ &\quad 0.4, \{H_{p4}, H_{p5}, H_{p6}, H_{p7}\} : 0.1. \end{aligned}$$

This obtained MA can be restricted using the least prejudiced distribution to give a single probability distribution. This probability distribution is defined across the human performance set H_p as is the corresponding fuzzy set. First, the magnitude of masses in

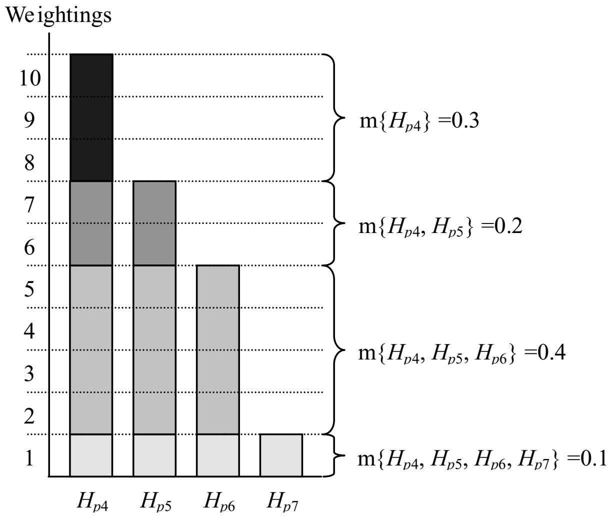

Fig. 9. A weighting interpretation of mass assignment of human performance output, H_p.

H_p is:

$$|\{H_p\}| = |\{H_{p4}\}| : 1, |\{H_{p4}, H_{p5}\}| : 2, |\{H_{p4}, H_{p5}, H_{p6}\}| : 3, |\{H_{p4}, H_{p5}, H_{p6}, H_{p7}\}| : 4.$$

Having converted a fuzzy set into a MA, the calculus of MA can now be used to reason with fuzzy sets at the mass level. The advantage of this representation is the close relationship between MAs and their corresponding families of probability distributions. MA therefore provides the crucial link between probability and fuzzy sets. This is a great enabler in developing maritime human element solutions based on a more unified theory than those that may be enacted by just an individual BN or FL approach.

By distributing mass across singleton subsets of the four focal elements, this now provides the probabilities from using Equation (6) as follows:

$$P(H_{p4}) = \frac{\{H_{p4}\}}{|\{H_{p4}\}|} + \frac{\{H_{p4}, H_{p5}\}}{|\{H_{p4}, H_{p5}\}|} + \frac{\{H_{p4}, H_{p5}, H_{p6}\}}{|\{H_{p4}, H_{p5}, H_{p6}\}|} + \frac{\{H_{p4}, H_{p5}, H_{p6}, H_{p7}\}}{|\{H_{p4}, H_{p5}, H_{p6}, H_{p7}\}|}$$

$$= 0.3 + 0.2\left(\frac{1}{2}\right) + 0.4\left(\frac{1}{3}\right) + 0.1\left(\frac{1}{4}\right) \approx 0.5583',$$

$$P(H_{p5}) = \frac{\{H_{p4}, H_{p5}\}}{|\{H_{p4}, H_{p5}\}|} + \frac{\{H_{p4}, H_{p5}, H_{p6}\}}{|\{H_{p4}, H_{p5}, H_{p6}\}|} + \frac{\{H_{p4}, H_{p5}, H_{p6}, H_{p7}\}}{|\{H_{p4}, H_{p5}, H_{p6}, H_{p7}\}|}$$

$$= 0.2\left(\frac{1}{2}\right) + 0.4\left(\frac{1}{3}\right) + 0.1\left(\frac{1}{4}\right) \approx 0.2583^{s}xs',$$

$$P(H_{p6}) = \frac{\{H_{p4}, H_{p5}, H_{p6}\}}{|\{H_{p4}, H_{p5}, H_{p6}\}|} + \frac{\{H_{p4}, H_{p5}, H_{p6}, H_{p7}\}}{|\{H_{p4}, H_{p5}, H_{p6}, H_{p7}\}|}$$

$$= 0.4\left(\frac{1}{3}\right) + 0.1\left(\frac{1}{4}\right) \approx 0.1583',$$

$$P(H_{p7}) = \frac{\{H_{p4}, H_{p5}, H_{p6}, H_{p7}\}}{|\{H_{p4}, H_{p5}, H_{p6}, H_{p7}\}|} = 0.1\left(\frac{1}{4}\right) \approx 0.0250.$$

Thus, the probability distribution achieved from the fuzzy event of human performance, H_p, is given as

$$P(H_{p4}) = 0.5583',\ P(H_{p5}) = 0.2583',\ P(H_{p6}) = 0.1583',\ P(H_{p7}) = 0.0250.$$

Note that $'$is used after to show a recurring decimal digit, which in this case is the number 3. The reverse operation is also possible, that is, converting a probability distribution into a MA, and then into a fuzzy set. For this reverse operation some assumptions must be made to generate only one fuzzy set rather than a whole family of fuzzy sets. The problem arises since masses are assigned across members of the $P(H_p)$ while the H_p fuzzy set is defined on the universe of H_p itself.

Once again, the least prejudiced distribution approach of distributing mass across singleton subsets of the MA focal elements is favored. This least prejudiced distribution notion relies on an assumption of an equal-likelihood prior to generate a single fuzzy set.

For a normalized fuzzy set, the membership of an element with the largest frequency is always 1. This element is also that which gives the largest probability associated with the least prejudiced distribution assumption, since the order of frequencies in H_p is given for the probabilities as

$$P(H_{p4}) > P(H_{p5}) > P(H_{p6}) > P(H_{p7}).$$

Then, the order of frequencies in H_p is given for the elements in its fuzzy set can be given as:

$$\mu_{Hp4} > \mu_{Hp5} > \mu_{Hp6} > \mu_{Hp7}.$$

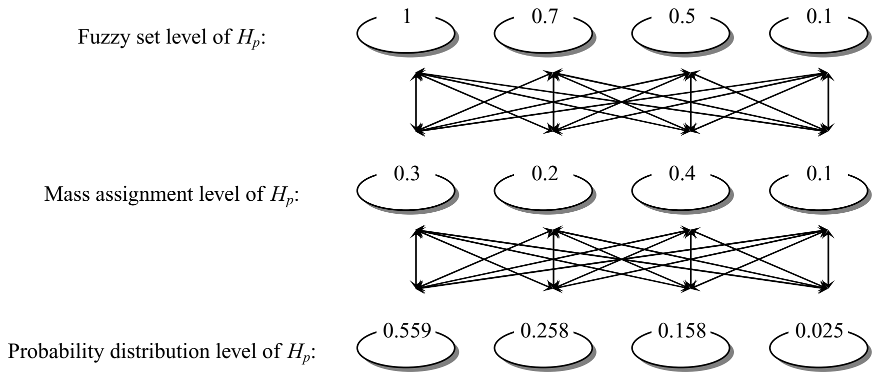

Fig. 10. Levels and values in the bidirectional processed human performance output, H_p.

Therefore, the MA for H_p is well generated, by applying Equation (4), as:

$$m(H_p) = \{H_{p4}\} : \mu_{H_{p4}} - \mu_{H_{p5}}, \{H_{p4}, H_{p5}\} : \mu_{H_{p5}} - \mu_{H_{p6}}, \{H_{p4}, H_{p5}, H_{p6}\} : \mu_{H_{p6}} - \mu_{H_{p7}}, \{H_{p4}, H_{p5}, H_{p6}, H_{p7}\} : \mu_{H_{p7}}.$$

Now, using the least prejudiced distribution assumption, a corresponding fuzzy set can be generated by assigning each element within each focal element. The probability distribution of the mass assigned to that focal element can be obtained via Equation (7) as follows:

$$P(H_{p4}) = \mu_{H_{p4}} - \mu_{H_{p5}} + \left(\frac{1}{2}\right)(\mu_{H_{p5}} - \mu_{H_{p6}}) + \left(\frac{1}{3}\right)(\mu_{H_{p6}} - \mu_{H_{p7}}) + \left(\frac{1}{4}\right)\mu_{H_{p7}} \approx 0.5583',$$

$$P(H_{p5}) = \left(\frac{1}{2}\right)(\mu_{H_{p5}} - \mu_{H_{p6}}) + \left(\frac{1}{3}\right)(\mu_{H_{p6}} - \mu_{H_{p7}}) + \left(\frac{1}{4}\right)\mu_{H_{p7}} \approx 0.2583',$$

$$P(H_{p6}) = \left(\frac{1}{3}\right)(\mu_{H_{p6}} - \mu_{H_{p7}}) + \left(\frac{1}{4}\right)\mu_{H_{p7}} \approx 0.1583',$$

$$P(H_{p7}) = \left(\frac{1}{4}\right)\mu_{H_{p7}} \approx 0.0250.$$

Thus, in working backward, the focal element's membership values are obtained as:

$$\mu_{H_{p7}} = 0.1, \mu_{H_{p6}} = 0.5, \mu_{H_{p5}} = 0.7 \text{ and } \mu_{H_{p4}} = 1.$$

Hence, this gives the discrete fuzzy set of H_p as:

$$H_p = \{1/_{H_{p4}} + 0.7/_{H_{p5}} + 0.5/_{H_{p6}} + 0.1/_{H_{p7}}\}.$$

The bidirectional processed values for the fuzzy, mass, and probability level of the H_p output set focal elements, are pictorially represented as shown in Fig. 10.

It has been well recognized that the element of human factor holds an all-essential input role into countless maritime risk investigation domains. For example, successful marine emergency *escape, evacuation, and rescue (EER)* are achieved through an effective and efficient interaction of the evacuees' human performance and the mechanical performance of the physical EER system (Bercha *et al.*, 2003). Nonetheless, without a fit for the function physical EER system, human performance becomes an act of brute survival—running, jumping, swimming, and fighting hypothermia. Clearly, the subject here is not on human performance alone, but rather on the modeling of the interaction between humans and EER physical systems.

A typical marine evacuation scenario for examining the reliability of an EER system, as based on performance aspects relating to both mechanical and human cause-effect relationships with free-fall lifeboats and rescue boats, may utilize the BN models of Fig. 11(a) and Fig. 11(b), respectively. Moreover,

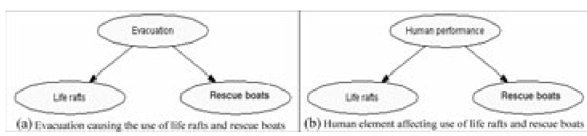

Fig. 11. Bayesian network of a cause-effect evacuation scenario. (a) Evacuation causing the use of life rafts and rescue boats. (b) Human element affecting use of life rafts and rescue boats.

such a BN can be constructed from the likes of other causal models such as fault trees, event trees, and risk contribution trees (Eleye-Datubo *et al.*, 2006) and still pave the way for inference processing that is based on the sound Bayes's theorem.

The state of evacuation being necessary is not typically dependent on evacuees. Rather, the state may be effected by some accident event such as fire, contact and collision, and/or loss of hull integrity (LOHI) (IMO, 1997). Evacuees normally exhibit fuzzy qualities that are dependent on the PSFs of the marine environment. In utilizing the hypothetical H_p output that has been analyzed earlier in this section, interactions of the evacuees with the physical EER system can thus give an intuitive evacuation domain FBN of the type presented in Fig. 12. The probabilistic cause-effect analysis of this underlying network can be achieved via the BN module of the FBN methodology that has been presented in Section 7.

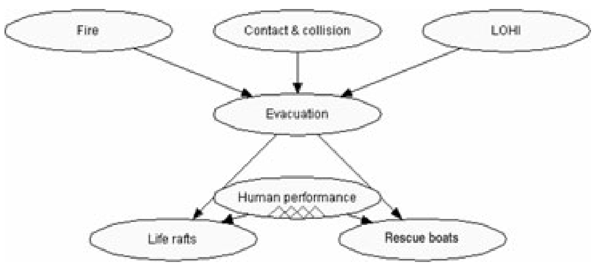

Fig. 12. A fuzzy-Bayesian network of a typical marine evacuation analysis domain.

In this setting, the human performance node will always remain as a fuzzy event/variable node since its probability cannot be directly ascertained unless via PSF interactions. In cases where sufficient data become available for a fuzzy event, then the node for such an event becomes a complete Bayesian chance variable node (as in the nodes for fire, contact and collision, LOHI, evacuation, life rafts, and rescue boat in the network).

Owing to the MA bidirectional transformation enabled earlier in the H_p output analysis, the human performance node can now utilize the probability distribution values in the normal way of a BN analysis. Fig. 13 shows the calculated probabilistic values for the FL-MA-BN human performance event. The figure gives further addition of new nodes that one may also wish to study in the evacuation analysis. These include a fire and a hull stress alarm as the effect of the fire and the LOHI event, respectively. These two nodes are also those of Bayesian chance variables for which reliable probability data could be obtained. Also, the life-saving node and the marine evacuation system (MES) optimal survival node, represent, the standard utility node and decision node, respectively, that aids in achieving the decision-making aspect of the model.

In this case study, the H_p output modeled into the evacuation FBN does designate evacuees to be normally meeting the requirements of their standard work practice. Therefore, the conditional probability of life rafts and rescue boats given these human

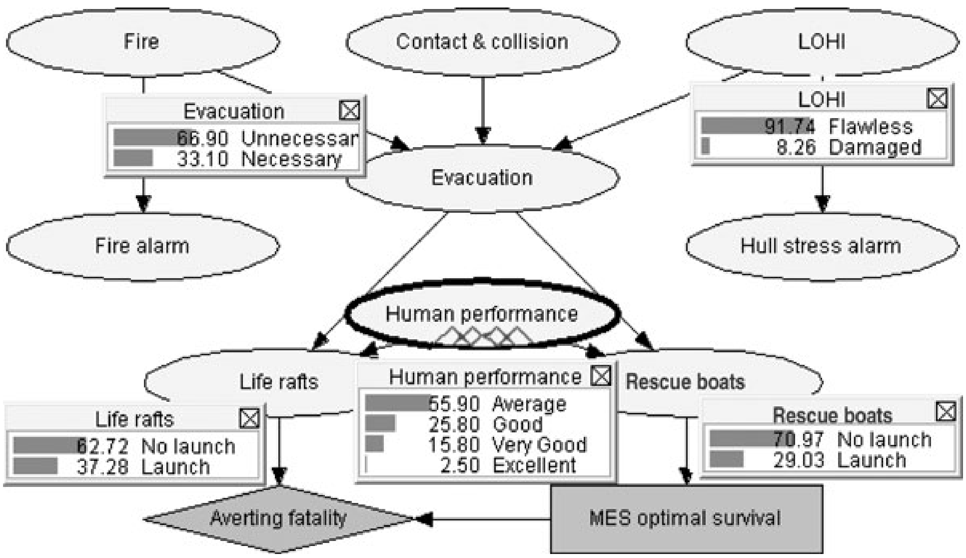

Fig. 13. A fuzzy-Bayesian decision model for a typical marine evacuation analysis domain.

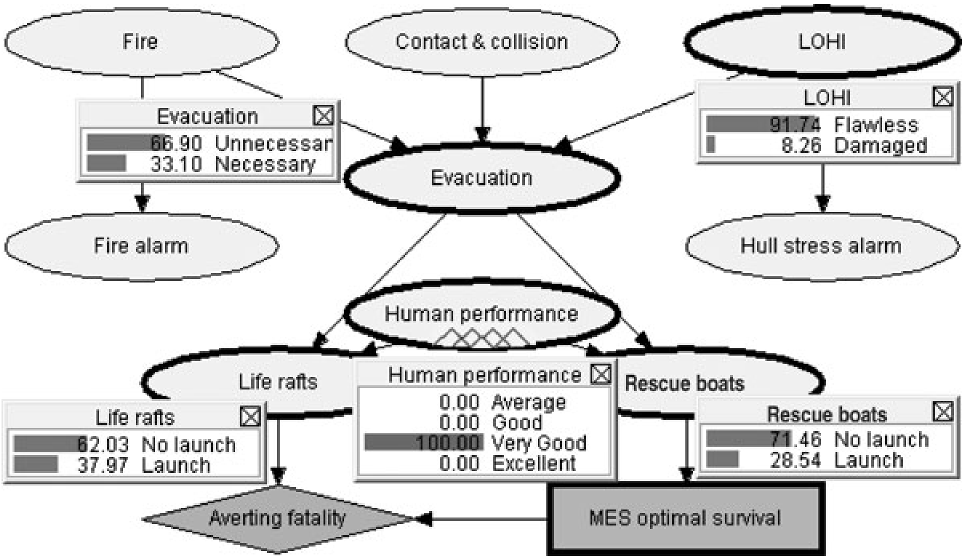

Fig. 14. Propagation of human performance in a typical marine evacuation fuzzy-Bayesian model.

performance values have been modeled to reflect a reliable EER operation. When "*human performance = very good*" is the entered evidence, this effect on the probability of life rafts being launched is that of a slight increase from 0.3728 to 0.3797 while its effect on the probability of rescue boats being launched becomes that of a slight decrease from 0.2903 to 0.2854 (See Figs. 13 and 14). As one would inevitably expect, values of such events as LOHI and that of a necessary evacuation have been unaffected by this human performance propagation.

If "*LOHI = damaged*" is additionally entered as new evidence, then the probability of evacuation being necessary shoots up from 0.3310 to 0.7176 (see Figs. 13 and 15), which in turn causes the probability of life rafts being launched to increase drastically to 0.7234. Similarly, the probability of rescue boats being launched increases to 0.5705.

10. CONCLUDING REMARKS

In the risk analysis of a safety-critical maritime system, each hazard event within the domain may be subject to prior insufficient and vague knowledge or that of an inherently random nature. To permit a combination of both such uncertainty characteristics,

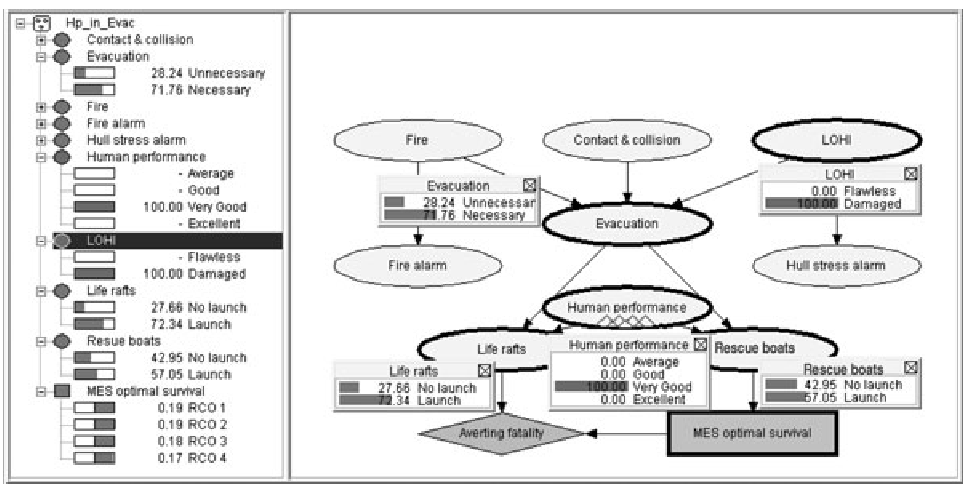

Fig. 15. Propagation of LOHI event and human performance in a typical marine evacuation fuzzy-Bayesian model.

the modeling of their cause-effect relationship will require some form of possibility-probability linked inference mechanism. As the theories of possibility and probability, which can be handled by FL and BN, respectively, are completely distinct but parallel, a link is made possible by way of their compatibility with MA theory. A framework for a proposed FBN permits the application of the inference algorithm while justifying data problem cases and, at the same time, aiding to provide a proficient graphical tool for risk-based decision making of the model. Following from the analysis outcome of the typical ship evacuation scenario case study, incorporation of the human element into maritime risk assessment is an area prone to benefit from the combined use of fuzzy and Bayesian principles as a causal network solution. The hypothetical human performance outcome in the case study has demonstrated how the fuzzy PSFs can be incorporated into any random processing risk-based model. The FBN is also able to handle the cause-effect relationship of FTs, ETs, and RCTs and still provide update reasoning that considers untreated uncertainty within the domain model. Therefore, the FBN modeling should offer a sound means for improving safety knowledge/assessments/practices in the marine and offshore industry.

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