

Use of Fuzzy Rule-Based Evidential Reasoning Approach in the Navigational Risk Assessment of Inland Waterway Transportation Systems

D. Zhang^{1,2}, X.P. Yan^{1,2}, J.F. Zhang³, Z.L. Yang^{4*}, J. Wang⁴

1. National Engineering Research Center for Water Transport Safety, Wuhan, 430063, China.
2. Intelligent Transport Systems Research Center, Wuhan University of Technology, Wuhan, 430063, China.
3. Centre for Marine Technology and Engineering (CENTEC), Instituto Superior Técnico, University of Lisbon, Lisbon, 1049-001, Portugal
4. Liverpool Logistics, Offshore and Marine (LOOM) Research Institute, Liverpool John Moores University, L3 3AF, UK.

ABSTRACT

A novel approach incorporating a fuzzy rule base technique and an Evidential Reasoning (ER) algorithm is applied to conduct the navigational risk assessment of an Inland Waterway Transportation System (IWTS). A hierarchical structure for modeling IWTS hazards (hazard identification model) is first constructed taking into account both qualitative and quantitative criteria. The quantitative criteria are converted to qualitative ones by applying a fuzzy rule base technique, which enables the use of ER to synthesize the risk estimates from the bottom to the top along the hierarchy. Intelligent Decision System (IDS) Software is used for facilitating risk synthesis and estimation. The proposed method is tested in a case study to compare the navigational safety levels of three different regions in the Yangtze River.

1 INTRODUCTION

An Inland Waterway Transportation System (IWTS) is a complex and dynamic system in which various factors influencing each other increase the difficulty to assess its navigational risk (Zhang *et al.*, 2014; Zhang *et al.*, 2013; Qu & Meng, 2012; Qu *et al.*, 2011; Dobbins & Jenkins, 2011). Furthermore, uncertainties are involved when evaluating the navigational risk of an IWTS because objective data is sometimes incomplete and its collection is costly and time consuming, especially in the situation of taking into account the factors involving human and management aspects (Pedersen, 2010; Li *et al.*, 2012). Thus, a novel method utilizing Fuzzy Rule-Based Evidential Reasoning (FRBER) is adopted and further applied in the case study of the Yangtze River in this paper.

FRBER is implemented because it well describes the “riskiness” of the system for each combination of input variables (Bowles & Pelaez, 1995). Fuzzy rules are usually more conveniently formulated in linguistic terms than in numerical terms. They are often expressed as “If-Then” rules, which can be implemented by fuzzy conditional statements. The Evidential Reasoning (ER) approach is suitable for modeling subjective credibility induced by partial evidence (Yang & Xu, 2002). The kernel of this approach is an ER

* Corresponding author: z.yang@ljmu.ac.uk

algorithm produced on the basis of the Dempster-Shafer (D-S) theory. The algorithm can be used to aggregate criteria of a multilevel structure. The ER has been widely used in industries such as engineering and management for decision making purposes (Liu *et al.*, 2013; Chin *et al.*, 2009; Liu *et al.*, 2008; Ren *et al.*, 2008; Lam *et al.*, 2007).

The main aim of this paper is to conduct the quantitative navigational risk estimation of an IWTS via evaluating each Safety Critical Element (SCE) in the system and aggregating the estimations to obtain the overall risk estimate using the ER approach. In a preliminary study (Zhang *et al.*, 2012), a risk hierarchical structure of an IWTS was established and the SCEs were identified through an Analytic Hierarchy Process (AHP) approach. This paper further investigates assessment grades for each criterion, converts quantitative criteria to qualitative ones by employing a rule-based technique and applies the ER approach to synthesize the risk estimates. A case study of the Yangtze River is used based on the hierarchical structure to demonstrate the applicability of the proposed approach in the navigational risk estimation of an IWTS.

2 BACKGROUND

2.1 Evidential Reasoning Approach

ER was developed in the 1990s to deal with Multiple Criteria Decision Making (MCDM) problems under uncertainty. The ER algorithm is based on the decision theory and the D-S theory of evidence, which is well suited for handling incomplete assessment of uncertainty (Yang, 2001; Yang & Singh, 1994). The algorithm can be used to aggregate criteria of a multilevel structure.

ER is widely used in many applications such as engineering design, system safety, risk assessment, organizational self-assessment and supplier assessment (Chin *et al.*, 2009; Liu *et al.*, 2008; Ren *et al.*, 2008; Lam *et al.*, 2007). ER has the following useful properties (Yang & Xu, 2002; Sönmez *et al.*, 2001):

- It is difficult to deal with both quantitative and qualitative criteria under uncertainty, however ER provides an alternative way of handling such information systematically and consistently.
- The uncertainty and risk surrounding the problem can be represented through the concept of Degree of Belief (DoB).
- Both complete and incomplete information can be aggregated and modeled using a belief structure.
- The ER algorithm is integrated into a software package called Intelligent Decision System, IDS (Xu & Yang, 2005). It is a graphically designed decision support tool. The IDS allows decision makers to build their own models and input their own data.

2.2 Fuzzy Rule Base Technique

An important point of dealing with uncertainty came in 1965 with the publication of a fuzzy logic-based paper by Zadeh (Zadeh, 1965). Fuzzy logic is an extension of classical Boolean logic from crisp sets to fuzzy sets. Fuzzy logic is the first new method of dealing with uncertainty since the development of probability. Fuzzy logic has various fuzzy

techniques which can be used in uncertainty treatment, notably fuzzy sets and fuzzy rule base. The application of these fuzzy logic techniques depends on the contexts to be modeled. They are widely used in many applications (Yang, *et al.*, 2012; Zadeh, 1987).

2.3 Research Origin

The navigational safety of an IWTS has attracted great concern from academics and industrialists. Despite the use of fuzzy rule base and ER in the shipping industry, it has not been applied in the area of IWTS risk management. A feasible methodology is proposed in the following sections in order to demonstrate the applicability of ER and fuzzy rule base for the navigational IWTS risk assessment. Furthermore, the navigational risk of the Yangtze River is evaluated using the method for the very first time which enables risk assessment under uncertainties.

3 MODELING OF IWTS

Various factors may influence the navigational safety of IWTS. In a preliminary study (Zhang *et al.*, 2012), a hierarchical structure for IWTS modeling was developed using both AHP and discrete fuzzy sets which identifies the SCEs in terms of navigational risk. The proposed method was further demonstrated and validated in a case study that the SCEs of the Yangtze River in terms of navigational risk are studied. Specifically, the IWTS safety is set as the goal of assessment. The elements in Level 1 are set to be Human, Vessel, Environment and Management. Each element in Level 1 is investigated based on its associated elements given in Level 2 and Level 3. These elements are chosen because they are regarded as the most significant ones associated with major causes which lead to marine accidents of the IWTS. The selection of such elements is conducted based on extensive discussions with experts in the area in which the accident records are also taken into account. The pairwise comparisons in each level of the hierarchical structure in terms of relative importance to navigational risk were carried out via the AHP method. The weighting vectors of the elements in each level showing their relative importance in terms of IWTS safety were obtained and presented as the numerical values in Table 1 accordingly.

TABLE 1 The Hierarchical Model of IWTS Safety (Zhang *et al.*, 2012)

Goal	Level 1	Level 2	Level 3
IWTS Safety (1.00)	Human (0.43)	Qualification (0.37)	
		Experience (0.15)	
		Safety Awareness (0.48)	
	Vessel (0.21)	Seaworthiness (0.41)	
		Vessel Age (0.30) Tonnage (0.29)	
Environment (0.24)	Natural (0.31)	Visibility (0.45)	
		Wind (0.34) Current (0.21)	
Management		Navigational (0.69)	Channel Dimension (0.65) Traffic Volume (0.09) Navaid (0.26)
		MSA (0.48)	

In Table 1, qualification, experience and safety awareness are considered as the most critical elements in the Human aspect. In the Vessel aspect, seaworthiness, vessel age as well as tonnage of ship are taken into account. In the Environment aspect, visibility, wind and current are considered from the natural perspective while channel dimension, traffic volume and aid to navigation (Naviaid) are regarded as SCEs in terms of navigational environment. Moreover, Maritime Safety Administration (MSA) and shipping company (Shipowner) are both taken into account in the Management aspect referring to IWTS safety.

Three domain experts were interviewed to identify the factors and to evaluate their weights. They represented the major personnel who were involved in the navigational risk analysis in the Yangtze River. Simultaneously, they also possessed diversified interests and perception about how the navigational safety of the river can be evaluated and managed. The three experts' details are shown as follows:

- Expert No.1: An experienced seafarer with experience of more than 5 years as a master onboard.
- Expert No.2: A professor engaged in maritime research for more than 15 years.
- Expert No.3: A senior officer from Chang Jiang Maritime Safety Administration (MSA).

4 METHODOLOGY

The following steps are developed in order to carry out the navigational risk estimation of IWTS.

Step 1: All the criteria (elements) in the hierarchical structure (Table 1) are assigned assessment grades. These assessment grades could be either qualitative or quantitative based on the available data.

Step 2: The quantitative criteria in the hierarchy are represented by a fuzzy rule base. All of them are transformed into qualitative ones using a rule-based information transformation technique (Liu et al., 2005).

Step 3: The lower level qualitative criteria are converted into the upper level criteria and subsequent quantification of the belief degrees associated with each qualitative criterion is conducted by formulating “a mapping process” (Godaliyadde, 2010). A fuzzy rule base is developed to conduct the mapping process.

Step 4: The ER algorithm is used to carry out the assessment. In this case the IDS software (Yang and Xu, 2002) is used for the synthesis of basic criteria in the hierarchical structure and to produce the results graphically.

Step 5: The results are prioritized and compared by using utility values for obtaining the navigational risk ranking of different regions.

4.1 Fuzzy Rule Base

The “If-Then” rules (fuzzy rule base) have two parts, namely, an antecedent that is the inputs and a consequent part which is the results (Pillay & Wang, 2003; Bowles & Pelaez,

1995). A single “If-Then” rule is illustrated by an example as follows:

Rule # 1: If Channel Dimension = “Very Good”, Then Navigational Environment = (Good 0.5, Very Good 0.5).

The above rule can be interpreted as “If Channel Dimension is *Very Good* then Navigational Environment is *Good with a belief degree of 50%*, and *Very Good with a belief degree of 50%*”. The belief degrees can be assigned by averaging domain experts’ judgments. The rule is developed to convert the lower level qualitative criteria into the upper level criteria with subsequent quantification of the belief degrees so that the following mapping and aggregating process can be achieved (Liu et al., 2005; Yang et al., 2009).

This technique is utilized in the quantitative criteria transformation (Step 2) and the mapping process (Step 3).

4.2 Quantitative Data Transformation Technique

In general there are two types of basic criteria, namely, qualitative and quantitative. Qualitative criteria are always represented by linguistic terms such as Very Good, Good, Bad, etc., while quantitative ones represented by numerical values instead of qualitative grades need to be converted into qualitative criteria for rational synthesis where the transformation technique needs to be used.

If quantitative criteria are available in the hierarchical structure, it is necessary to use a transformation technique to convert them into qualitative criteria. This is achieved through a rule-based technique (Yang, 2001):

Suppose a value $h_{n,i}$ for a criterion e_i is judged to be similar to a grade H_n (a grade used to define e_i) or:

$$h_{n,i} \Rightarrow H_n \quad (n = 1, \dots, N) \quad (1)$$

Without loss of generality, suppose e_i is a “profit” criterion, that is, a larger value $h_{n+1,i}$ is preferred to a smaller value $h_{n,i}$. Let $h_{N,i}$ be the largest feasible value and $h_{1,i}$ be the smallest. Then a value h_j on e_i can be denoted by using the following equation:

$$S^i(h_j) = \{(h_{n,i}, \gamma_{n,j}), n = 1, \dots, N\} \quad (2)$$

$$\text{where, } \gamma_{n,j} = \frac{h_{n+1,i} - h_j}{h_{n+1,i} - h_{n,i}} \quad \text{and} \quad \gamma_{n+1,j} = 1 - \gamma_{n,j}, \text{ if } h_{n,i} \leq h_j \leq h_{n+1,i} \quad (3)$$

$$\gamma_{k,j} = 0 \quad \text{for} \quad k = 1, \dots, n-1, n+2, \dots, N \quad (4)$$

For the rules described in Eq. (1), a value of h_j can be represented by using the following equation:

$$S(h_j) = \{(H_n, \beta_{n,j}), n = 1, \dots, N\} \quad (5)$$

$$\text{where, } \beta_{n,j} = \gamma_{n,j}, n = 1, \dots, N \quad (6)$$

On the contrary, if e_i is a “cost” criterion, a smaller value is then preferred instead. Thus, Eq. (3) can be changed as the following equation:

$$\gamma_{n,j} = \frac{h_j - h_{n+1,i}}{h_{n,i} - h_{n+1,i}} \quad \text{and} \quad \gamma_{n+1,j} = 1 - \gamma_{n,j}, \text{ if } h_{n+1,i} \leq h_j \leq h_{n,i} \quad (7)$$

Therefore, $S(h_j)$ needs to be obtained via Eq. (4) to Eq. (6) in a similar way.

In a real-world situation, if it is difficult to determine the value $h_{n,i}$ for each criterion, the two extreme values, $h_{min,i}$ and $h_{max,i}$ can be obtained with respect to the historical data. If this is the case, the value $h_{n,i}$ for each criterion can be calculated as:

$$h_{n,i} = h_{min,i} + \frac{h_{max,i} - h_{min,i}}{N-1} \times (n-1) \quad n = 1, 2, \dots, N \quad (8)$$

4.3 Mapping Process

In nature there are situations where different amounts and types of linguistic terms are used to describe both lower level criteria and their associated upper level criteria. To apply the ER approach, it is necessary to have all data and information on the basis of the same universe (common utility space). Therefore, the information and data need to be transformed before being aggregated. The fuzzy rule base can be used to transform fuzzy input (lower level criterion) to fuzzy output (upper level criterion). This method can function very well in dealing with risk estimation problems. However, it requires the development of multiple fuzzy rules in a hierarchical structure which has a general criterion (top level) and many basic criteria (lower levels). The transformation, which has been previously mentioned, is called “Mapping Process” (Yang et al., 2009; Godaliyadde, 2010). By taking the lower level criterion “Channel Dimension” in the hierarchical structure as an example, the mapping process to its upper level criterion “Navigational Environment” can be introduced as follows.

Prior to the mapping process, the following rules need to be obtained with respect to expert judgments:

If Channel Dimension is Very Good, Then Navigational Environment is “Very Good 50%, Good 50%”.

If Channel Dimension is Good, Then Navigational Environment is “Good 100%”.

If Channel Dimension is Average, Then Navigational Environment is “Average 70%, Poor 30%”.

If Channel Dimension is Poor, Then Navigational Environment is “Poor 100%”.

If Channel Dimension is Very Poor, Then Navigational Environment is “Very Poor 100%”.

Suppose the fuzzy input of Channel Dimension is “Very Good 0.2, Good 0.3, Average 0.2, Poor 0.3, and Very Poor 0”. According to the mapping rules introduced, the following belief degrees in terms of each grade of Navigational Environment can be obtained:

$$P(\text{Navigational Environment} = \text{“Very Good”}) = 0.2 \times 0.5 = 0.1;$$

$$P(\text{Navigational Environment} = \text{“Good”}) = 0.2 \times 0.5 + 0.3 \times 1 = 0.4;$$

$$P(\text{Navigational Environment} = \text{“Average”}) = 0.2 \times 0.7 = 0.14;$$

$$P(\text{Navigational Environment} = \text{“Poor”}) = 0.2 \times 0.3 + 0.3 \times 1 = 0.36;$$

$$P(\text{Navigational Environment} = \text{“Very Poor”}) = 0 \times 1 = 0.$$

Thus, according to the fuzzy output of this mapping process, Navigational Environment is “Very Good 0.1, Good 0.4, Average 0.14, Poor 0.36, and Very Poor 0”, as shown in Figure 1.

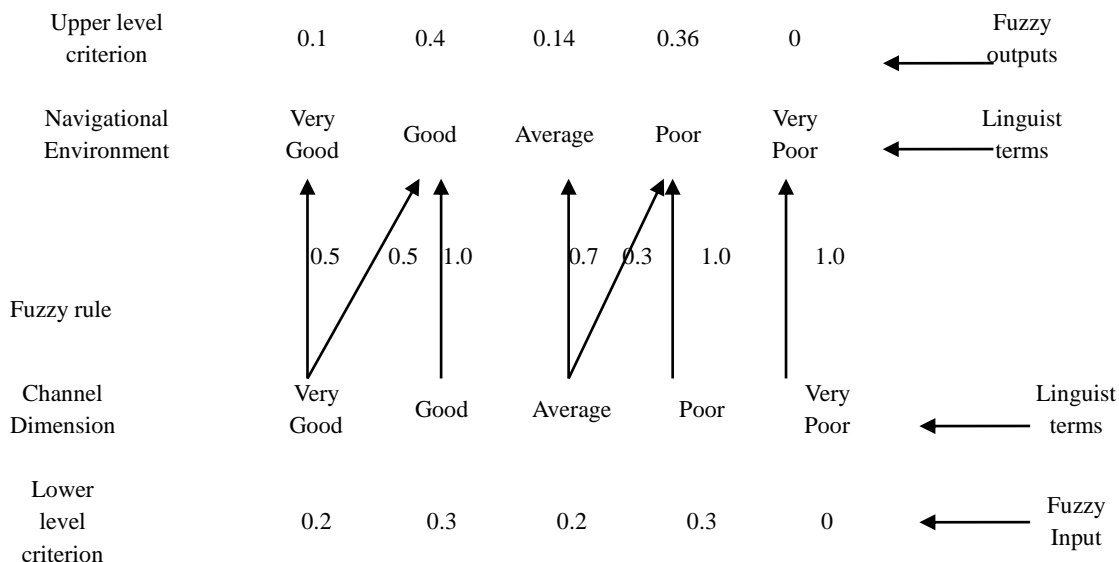


FIGURE 1 An Example of Mapping Process

Through the above process, all assessment results of the lower level criteria can be mapped to the target so as to facilitate the overall integration based on the ER algorithm introduced in the next section.

4.4 ER Algorithm

The set $S(E) = \{(H_n, \beta_n), n = 1, \dots, N\}$ represents a criterion E which is assessed to grade H_n with degree of belief $\beta_n, n = 1, \dots, N$. Let $m_{n,i}$ be a basic probability mass representing the degree to which the i th basic criterion e_i supports the hypothesis that the criterion y is assessed to the n th grade H_n . Therefore $m_{n,i}$ can be represented as follows (Xie *et al.*, 2006; Yang & Xu, 2002; Yang, 2001):

$$m_{n,i} = \omega_i \beta_{n,i} \quad n = 1, 2, \dots, N; \quad i = 1, 2, \dots, L \quad (9)$$

$m_{H,i}$ is the remaining probability mass, that can be stated as:

$$m_{H,i} = 1 - \sum_{n=1}^N m_{n,i} \quad i = 1, 2, \dots, L \quad (10)$$

The remaining probability mass $m_{H,i}$ can be split into two parts $\bar{m}_{H,i}$ and $\tilde{m}_{H,i}$, which can be calculated by using the following formulas:

$$\bar{m}_{H,i} = 1 - \omega_i \quad i = 1, 2, \dots, L \quad (11)$$

$$\tilde{m}_{H,i} = \omega_i \left(1 - \sum_{n=1}^N \beta_{n,i} \right) \quad i = 1, 2, \dots, L \quad (12)$$

$\bar{m}_{H,i}$ is the first part of the remaining probability mass that is not yet assigned to individual grades due to the fact that criterion i (denoted by e_i) only plays one part in the assessment relative to its weight. $\tilde{m}_{H,i}$ is the second part of the remaining probability mass unassigned to individual grades, which is caused due to the incompleteness in the assessment $S(e_i)$.

To obtain the combined degrees of belief of all the basic criteria, $E_{I(i)}$ is firstly defined as the subset of the first i basic criteria as follows:

$$E_{I(i)} = \{e_1, e_2, \dots, e_i\} \quad (13)$$

Let $m_{n,I(i)}$ be a probability mass defined as the degree to which all the i criteria in $E_{I(i)}$ support the hypothesis that E is assessed to the grade H_n and let $m_{H,I(i)}$ be the remaining probability mass unassigned to individual grades after all the basic criteria in $E_{I(i)}$ have been assessed. Eq. (14) and Eq. (15) are obviously correct when $i = 1$.

$$m_{n,I(1)} = m_{n,1}, \quad n = 1, 2, \dots, N \quad (14)$$

$$m_{H,I(1)} = m_{H,1} \quad (15)$$

By using Eq. (14) and Eq. (15), Eq. (16) can be constructed for $i = 1, 2, \dots, L-1$ to obtain the coefficients $m_{n,I(L)}$, $\bar{m}_{H,I(L)}$ and $\tilde{m}_{H,I(L)}$ (Yang & Xu, 2002):

$$K_{I(i+1)} = \left[1 - \sum_{t=1}^N \sum_{\substack{j=1 \\ j \neq t}}^N m_{t,I(i)} m_{j,i+1} \right]^{-1} \quad (16)$$

$K_{I(i+1)}$ is a normalizing factor.

$\{H_n\}$:

$$m_{n,I(i+1)} = K_{I(i+1)} [m_{n,I(i)} m_{n,i+1} + m_{H,I(i)} m_{n,i+1} + m_{n,I(i)} m_{H,i+1}] \quad n = 1, 2, \dots, N \quad (17)$$

$$\tilde{m}_{H,I(i+1)} = K_{I(i+1)} [\tilde{m}_{H,I(i)} \tilde{m}_{H,i+1} + \bar{m}_{H,I(i)} \tilde{m}_{H,i+1} + \tilde{m}_{H,I(i)} \bar{m}_{H,i+1}] \quad (18)$$

$$\bar{m}_{H,I(i+1)} = K_{I(i+1)} \bar{m}_{H,I(i)} \bar{m}_{H,i+1} \quad (19)$$

$\{H\}$:

$$m_{H,I(i)} = \tilde{m}_{H,I(i)} + \bar{m}_{H,I(i)} \quad i = 1, 2, \dots, L-1 \quad (20)$$

At last, the combined degrees of belief of all the basic criteria for the assessment to criterion E are calculated by:

$$\{H_n\}: \beta_n = \frac{m_{n,I(L)}}{1 - \bar{m}_{H,I(L)}} \quad n = 1, 2, \dots, N \quad (21)$$

$$\{H\}: \beta_H = \frac{\tilde{m}_{H,I(L)}}{1 - \bar{m}_{H,I(L)}} \quad (22)$$

The ER approach is used in Step 4 of the proposed methodology for synthesizing the evaluations of the basic criteria in the hierarchical structure.

4.5 Utility Value

It is difficult to prioritize the navigational risk levels when using belief degrees associated with linguistic terms. Numerical values (crisp values) are normally required for such a task. The concept of expected utility is used to obtain crisp risk values for the investigated regions in order to rank them in terms of their navigational safety levels.

Suppose the utility of an evaluation grade H_n is denoted by $u(H_n)$ and $u(H_{n+1}) > u(H_n)$ if H_{n+1} is more preferable than H_n (Yang, 2001). The expected utility is calculated for the top level or general criterion (i.e. IWTS Safety) in Figure 1. Therefore, the utility of the general criterion can be calculated using an even distribution as Eq. (23) and Eq. (24):

$$u(H_n) = \frac{n-1}{N-1} \quad n = 1, 2, \dots, N \quad (23)$$

where, $u(H_n)$ denotes the utility value of an evaluation grade H_n and N denotes the number of the linguist terms.

$$u(E) = \sum_{n=1}^N \beta_n u(H_n) \quad (24)$$

where, $u(E)$ denotes the overall utility value of criterion E .

Thus, a crisp value can be calculated based on the distribution generated via the ER technique (Eq. (21) and Eq. (22)) so that a comparison between alternatives can therefore be carried out.

5 CASE STUDY

This section demonstrates how the proposed methodology can be applied to evaluate the navigational risk of IWTS with respect to three different regions of the Yangtze River, namely, Regions A, B and C representing the upstream, midstream and downstream of the Yangtze River, respectively. Subjective data is obtained from the three mentioned experts to complement the historical objective data. Since the knowledge and experience of all three experts involved are considered as equivalent, the normalized relative weight of every expert is equally assigned when combining their judgments.

5.1 IWTS Criteria Modeling (Step 1)

The hierarchical model presented in Table 1 is utilized in this study and five qualitative grades are assigned to each criterion for further evaluation. The grades shown in Table 2 are generated with respect to a consensus from the three domain experts.

TABLE 2 Assessment Grades for Each Criterion

Level	Criterion	Grades				
Goal	IWTS Safety	Very Poor	Poor	Average	Good	Very Good
1	Human	Very Poor	Poor	Average	Good	Very Good
	Vessel	Very Poor	Poor	Average	Good	Very Good
	Environment	Very Poor	Poor	Average	Good	Very Good
	Management	Very Poor	Poor	Average	Good	Very Good
2	Qualification	Least Eligible	Slightly Eligible	Moderately Eligible	Fairly Eligible	Very Eligible
	Experience	Least Experienced	Slightly Experienced	Moderately Experienced	Fairly Experienced	Very Experienced
	Safety Awareness	Very Poor	Poor	Average	Good	Very Good
	Seaworthiness	Very Poor	Poor	Average	Good	Very Good
		Seaworthiness	Seaworthiness	Seaworthiness	Seaworthiness	Seaworthiness
	Vessel Age	Very Aged	Moderately Aged	Averagely Aged	Slightly Aged	Least Aged
	Tonnage	Very Large	Large	Average	Small	Very Small
	Natural	Very Poor	Poor	Average	Good	Very Good
	Navigational	Very Poor	Poor	Average	Good	Very Good
	MSA	Very Poor	Poor	Average	Good	Very Good
Shipowner	Very Poor	Poor	Average	Good	Very Good	
3	Visibility	Very Poor	Poor	Average	Good	Very Good
	Wind	Very Poor	Poor	Average	Good	Very Good
	Current	Very Poor	Poor	Average	Good	Very Good
	Channel Dimension	Very Poor	Poor	Average	Good	Very Good
	Traffic Volume	Huge	Large	Moderate	Small	Very Small
	Navaid	Least Complete	Slightly Complete	Moderately Complete	Fairly Complete	Very Complete

The grades can be defined either quantitatively or qualitatively. For instance, Traffic Volume is a typical quantitative criterion; its daily average numerical values range from 171 vessels to 1,645 vessels with respect to different regions of the Yangtze River according to the historical data collected. Thus Table 3 for transformation can be obtained via Eq. (8).

TABLE 3 Assessment Grades for Traffic Volume

Grades	Huge	Large	Moderate	Small	Very Small
Daily Average Value	1645	1276.5	908	539.5	171

With reference to Table 3, the estimated value of a specific area's traffic volume

can be transformed into qualitative grades with belief degrees using the rule base method while this criterion is treated as a “cost” one.

5.2 Criteria Transformation (Step 2)

In this section a rule-based technique is used to convert quantitative input and describe it using the predefined qualitative criteria. Take Traffic Volume as a demonstrative example, the daily average traffic volume of Regions A, B and C were 194, 218 and 1023, respectively. Therefore, the transformation result of Traffic Volume can be calculated via Eq. (7), as shown in Table 4.

TABLE 4 Transformation Result of Traffic Volume

Region A	Region B	Region C
(Small 0.06),(Very Small 0.94)	(Small 0.13),(Very Small 0.87)	(Large 0.31),(Moderate 0.69)

When Region A is used as an example, its quantitative result can be transformed to qualitative terms with belief degrees based on the assessment grades introduced in Table 3 and Eq. (7):

$$\text{Belief degree for "Very Small"} = (192-171) / (539.5-171) = 0.06;$$

$$\text{Belief degree for "Small"} = 1 - 0.06 = 0.94.$$

In a similar way, all assessment results of bottom level criteria can be converted to qualitative inputs, as shown in Table 5.

TABLE 5 Qualitative Inputs of Bottom Level

Bottom Level Criterion	Qualitative Inputs		
	Region A	Region B	Region C
Qualification	Moderately Eligible 100%	Moderately Eligible 100%	Moderately Eligible 100%
Experience	Moderately Experienced 100%	Moderately Experienced 100%	Moderately Experienced 100%
Safety Awareness	Very Good 33%; Good 67%	Good 84%; Average 16%	Very Good 19%; Good 81%
Seaworthiness	Average Seaworthiness 100%	Average Seaworthiness 100%	Average Seaworthiness 100%
Vessel Age	Averagely Aged 100%	Averagely Aged 100%	Averagely Aged 100%
Tonnage	Small 50%; Average 50%	Average 100%	Average 50%; Large 50%
MSA	Average 100%	Average 50%; Poor 50%	Good 100%
Shipowner	Average 80%; Poor 20%	Average 80%; Poor 20%	Average 80%; Poor 20%
Visibility	Average 100%	Average 100%	Average 100%
Wind	Average 100%	Average 100%	Average 100%
Current	Average 100%	Average 100%	Average 100%
Channel Dimension	Very Poor 8%; Poor 92%	Very Poor 79%; Poor 21%	Good 46%; Average 54%

Traffic Volume	Very Small 94%; Small 6%	Very Small 87%; Small 13%	Moderate 69%; Large 31%
Navaid	Fairly Complete 80%; Moderately Complete 20%	Fairly Complete 50%; Moderately Complete 50%	Very Complete 30%; Fairly Complete 70%

5.3 Conduct Mapping Process (Step 3)

Following the process demonstrated in Figure 1, the fuzzy outputs of the lower level criteria in terms of their upper level criteria can be obtained.

Taking the criterion Safety Awareness as a demonstration, its associated fuzzy rules developed and verified by the three experts are shown in Table 6.

TABLE 6 Fuzzy Rules Associated with Safety Awareness

No	Fuzzy Rules
1	If Safety Awareness = Very Poor Then Human = Very Poor 100%
2	If Safety Awareness = Poor Then Human = Poor 100%
3	If Safety Awareness = Average Then Human = Average 100%
4	If Safety Awareness = Good Then Human = Good 100%
5	If Safety Awareness = Very Good Then Human = Very Good 80%, Good 20%
6	If Human = Very Poor Then IWTS Safety = Very Poor 100%
7	If Human = Poor Then IWTS Safety = Poor 100%
8	If Human = Average Then IWTS Safety = Average 100%
9	If Human = Good Then IWTS Safety = Good 100%
10	If Human = Very Good Then IWTS Safety = Very Good 80%, Good 20%

Thus, the fuzzy output of Safety Awareness in terms of Human can be mapped as:

- Region A

$$P(\text{Human} = \text{"Very Good"}) = 0.33 \times 0.8 = 0.264;$$

$$P(\text{Human} = \text{"Good"}) = 0.33 \times 0.2 + 0.67 \times 1 = 0.736.$$

- Region B

$$P(\text{Human} = \text{"Good"}) = 0.84 \times 1 = 0.84;$$

$$P(\text{Human} = \text{"Average"}) = 0.16 \times 1 = 0.16.$$

- Region C

$$P(\text{Human} = \text{"Very Good"}) = 0.19 \times 0.8 = 0.152;$$

$$P(\text{Human} = \text{"Good"}) = 0.19 \times 0.2 + 0.81 \times 1 = 0.848.$$

Finally, the fuzzy output of Safety Awareness in terms of IWTS Safety can be generated as:

- Region A

$$P(\text{IWTS Safety} = \text{"Very Good"}) = 0.264 \times 0.8 = 0.2112;$$

$$P(\text{IWTS Safety} = \text{“Good”}) = 0.264 \times 0.2 + 0.736 \times 1 = 0.7888.$$

- Region B

$$P(\text{IWTS Safety} = \text{“Good”}) = 0.84 \times 1 = 0.84;$$

$$P(\text{IWTS Safety} = \text{“Average”}) = 0.16 \times 1 = 0.16.$$

- Region C

$$P(\text{IWTS Safety} = \text{“Very Good”}) = 0.152 \times 0.8 = 0.1216;$$

$$P(\text{IWTS Safety} = \text{“Good”}) = 0.152 \times 0.2 + 0.848 \times 1 = 0.8784.$$

Similarly, the outputs of all bottom level criteria in terms of IWTS Safety are shown in Table 7. The weights assigned to the criteria are generated by a multiplication of all the associated weights of its upper levels criteria given in Table 1.

TABLE 7 Fuzzy Outputs in Terms of IWTS Safety

Bottom Level Criterion	Normalized Weight	Outputs in terms of IWTS Safety		
		Region A	Region B	Region C
Qualification	0.161	Average 100%	Average 100%	Average 100%
Experience	0.065	Average 100%	Average 100%	Average 100%
Safety Awareness	0.207	Very Good 21.12%	Good 84%	Very Good 12.16%
		Good 78.88%	Average 16%	Good 87.84%
		Average 100%	Average 100%	Average 100%
Seaworthiness	0.084	Average 100%	Average 100%	Average 100%
Vessel Age	0.061	Average 100%	Average 100%	Average 100%
Tonnage	0.060	Good 50%	Average 100%	Average 50%
		Average 50%	Average 50%	Poor 50%
MSA	0.060	Average 100%	Average 50%	Good 100%
		Average 80%	Poor 50%	Average 80%
Shipowner	0.065	Poor 20%	Average 80%	Poor 20%
		Average 100%	Poor 20%	Poor 20%
Visibility	0.033	Average 100%	Average 100%	Average 100%
Wind	0.025	Average 100%	Average 100%	Average 100%
Current	0.015	Average 100%	Average 100%	Average 100%
Channel Dimension	0.106	Very Poor 8%	Very Poor 79%	Good 46%
		Poor 92%	Poor 21%	Average 54%
Traffic Volume	0.014	Very Good 18.8%	Very Good 17.4%	Average 69%
		Good 81.2%	Good 82.6%	Poor 31%
Navaid	0.044	Good 80%	Good 50%	Very Good 6%
		Average 20%	Average 50%	Good 94%

5.4 Application of ER for Synthesis (Step 4)

In this section, the ER algorithm and its associated IDS software were used to compute the navigational risk of each of three areas. IDS incorporates the ER algorithm employed for synthesis of the criteria in the hierarchical structure into it. All the inputs with

weightings of the relevant lowest level criteria are combined to determine the risk estimation of each higher level criterion.

To demonstrate the application of the ER and IDS, the results of synthesizing the three regions in terms of level 1 criteria are shown in Table 8.

TABLE 8 Synthesis Results for Level 1

Area	Level 1			
	Human	Vessel	Environment	Management
Region A	Very Good 13.61%	Good 9.63%	Very Good 1.32%	Average 92.28%
	Good 37.94%		Average 20.22%	
	Average 48.45%	Average 90.37%	Poor 60.54%	
			Very Poor 5.26%	
Region B	Good 40.41%	Average 100%	Very Good 1.20%	Average 68.95%
	Average 59.59%		Good 8.73%	
			Average 25.22%	
			Poor 13.62%	
			Very Poor 51.23%	
Region C	Very Good 7.84%	Average 90.37%	Very Good 1.15%	Good 46.01%
	Good 43.72%		Good 38.61%	
	Average 48.44%	Poor 9.63%	Average 59.41%	Poor 10.80%
			Poor 0.83%	

Furthermore, the overall results for the three areas can be obtained by synthesizing the criteria in Level 1 via the ER algorithm, as shown in Figure 2.

- Region A = (Very Poor 0.96%, Poor 11.78%, Average 59.45%, Good 22.93%, Very Good 4.88%)
- Region B = (Very Poor 9.18%, Poor 4.95%, Average 56.27%, Good 19.49%, Very Good 0.11%)
- Region C = (Very Poor 0.00%, Poor 2.38%, Average 61.91%, Good 33.01%, Very Good 2.70%)

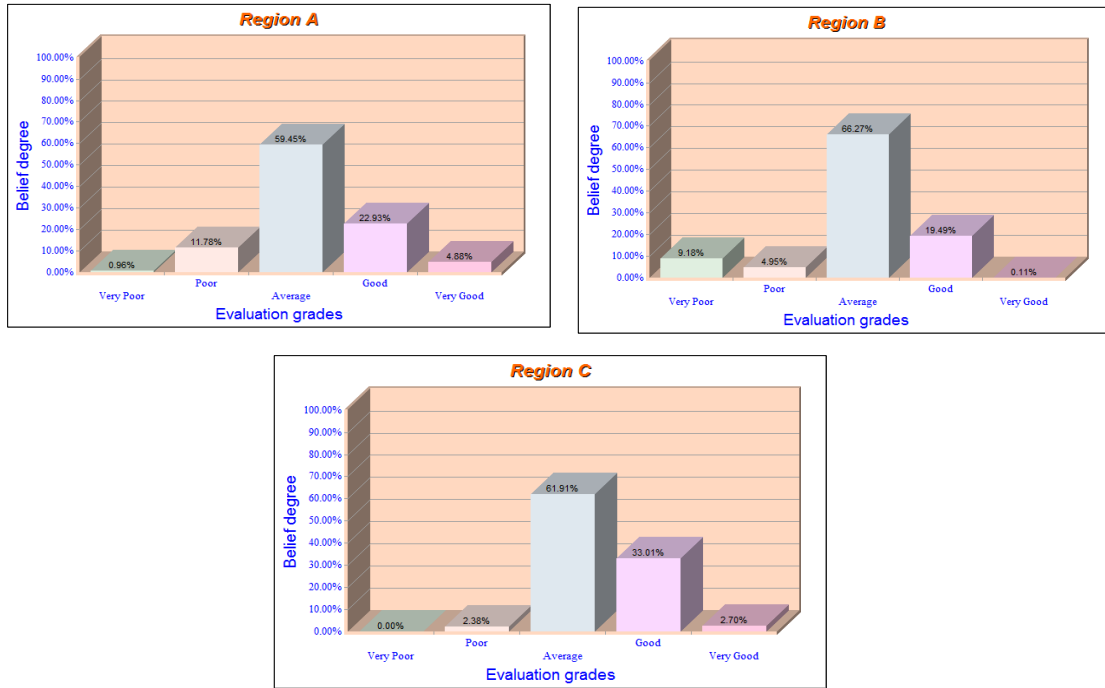


FIGURE 2 Risk Estimation Results

5.5 Overall Utility Value Ranking (Step 5)

In order to rank the navigational safety levels of the three regions, the proposed utility value technique in Section 4.5 is utilized as follows.

Through Eq. (21), the utility value of each grade of the top criterion can be calculated as shown in Table 9.

TABLE 9 Utility Values of Grades

Grades(H_n)	Very Poor	Poor	Moderate	Good	Very Good
Utility Value $u(H_n)$	0	0.25	0.5	0.75	1

The utility value distribution in Table 9 indicates that the higher the overall safety utility value is, the better the safety level it represents. Therefore, the risk estimation results obtained in the previous section can be applied in Eq. (22) in order to rank the navigational safety levels of different regions of the Yangtze River. The results are shown in Table 10.

TABLE 10 Overall Utility Value Ranking

Areas	Grades					Overall Utility Value	Rank
	Very Poor	Poor	Moderate	Good	Very Good		
	0	0.25	0.5	0.75	1		
Region A	0.010	0.118	0.595	0.229	0.049	0.548	2
Region B	0.092	0.050	0.663	0.195	0.001	0.491	3
Region C	0	0.024	0.619	0.330	0.027	0.590	1

The results reveal that Region C tends to be the safest area followed by Regions A

and B. This is in harmony with the phenomenon indicated by the historical data that marine accidents are more likely to happen in the midstream of the Yangtze River, especially during the dry season, thus partially validating the proposed method.

6 DISCUSSIONS

The ER can also be used to evaluate the safety level of different sub criteria levels. The utility values of the level-1 criteria in terms of each region are computed and shown in Table 11.

TABLE 11 Utility Values of Level 1

Area	Human		Vessel		Environment		Management	
	Utility Value	Rank	Utility Value	Rank	Utility Value	Rank	Utility Value	Rank
Region A	0.656	1	0.524	1	0.359	2	0.481	2
Region B	0.601	3	0.500	2	0.236	3	0.422	3
Region C	0.645	2	0.476	3	0.599	1	0.588	1

It can be seen that most ranking results in level 1 comply with the overall ranking order proposed in Table 10 as a whole. To be specific, Region C shows its obvious advantage compared to Regions A and B in terms of the elements of Environment and Management. Although Region C is ranked as the 2nd and the 3rd in the Human and Vessel aspects, its differences with the other two regions are insignificant. On the contrary, Region B is ranked poorly in all the three criteria in level 1, revealing its worrisome navigational safety conditions. Thus, the proposed methodology is further validated.

7 CONCLUSIONS

This paper applies the FRBER to the risk analysis of an IWTS based on a hierarchical model in which critical safety factors are identified and presented. The developed approach using both fuzzy rule base and ER highlights the relevant qualitative and quantitative criteria, describes the application of a rule-based transformation technique to convert quantitative criteria into qualitative criteria, and deals with synthesis so as to achieve the estimation of the top level goal. The proposed method is further demonstrated and validated in a case study of analyzing the navigational risks of the three different regions of the Yangtze River. This novel and flexible approach could be adapted to model IWTS behaviors in other areas such as America and Europe for improving inland waterway safety in general. The results of this study provide useful insights for enhancing the safety of the shipping industry and can be tailored to tackle risks in wider transportation scenarios.

ACKNOWLEDGEMENTS

The authors would like to thank the Nature Science Foundation of China (51209165) and the EU FP7 Marie Curie IRSES projects “REFERENCE” and “ENRICH” for their financial support, and also China Maritime Safety Administration (MSA) and Changjiang Waterway Bureau (CWB) for their assistance in data collection.

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