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FUZZY METHODS IN RISK ESTIMATION OF THE SHIP SYSTEM FAILURES BASED ON THE EXPERT JUDGMENTS

ROZMYTE METODY ESTYMACJI RYZYKA USZKODZEŃ SYSTEMÓW OKRĘTOWYCH NA PODSTAWIE OPINII EKSPERTÓW

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***Abstract**: The paper presents the fuzzy methods in failure modes and effects analysis (FMEA) for estimating the risk of the ship system failures based on the expert judgments. It provides an appropriate representation of the uncertain and ambiguous notions expressed in the natural language. An example of fuzzy intuitionistic FMEA analysis is illustrated in estimating the risk of tanker system failures. The results show that the proposed method in comparison with the traditional FMEA is more effective and useful in estimating the risk of ship system failures based on the expert opinions, available in such cases.*

***Keywords:** Intuitionistic fuzzy set, risk estimation, expert judgment, ship system failure.*

***Streszczenie:** Praca przedstawia rozmyte metody w analizy rodzajów i skutków uszkodzeń (FMEA) do estimacji ryzyka uszkodzeń systemów okrętowych. Zapewnia ona odpowiednią reprezentację niepewnych i niejasnych pojęć wyrażonych w języku naturalnym. Przykład zastosowania rozmytej, intuicjonistycznej analizy FMEA został zilustrowany w estymacji ryzyka uszkodzeń systemów tankowca. Uzyskane wyniki wskazują, że proponowana metoda w porównaniu z tradycyjną analizą FMEA, jest bardziej skuteczna w estymacji ryzyka uszkodzeń systemów okrętowych, na podstawie opinii ekspertów.*

***Słowa kluczowe:** Intuicjonistyczne zbiory rozmyte, estymacja ryzyka, opinia ekspertów, uszkodzenie systemu okrętowego.*

1. Introduction

Risk is an evaluation (often subjective) of the hazard resulting from the possible adverse consequences after making certain decisions. It is important to note that risk is inherent in every human activity. In many cases, however, it is so small that it does not have any implications. However, in some situations such conduct can lead to unpleasant consequences that could easily be avoided. In maritime transport, the risk assessment of damage to some, especially key sea-going ship systems, is important, as their consequences can be serious accidents or even marine disasters. For example, loss of propulsion function by a ship is one of the most dangerous categories of hazard events. Under certain external conditions, this can lead to loss of the ship and environmental pollution. The consequences of loss of propulsion by the ship are events classified by the International Maritime Organization as accidents or incidents. Consequently, estimating the risk of damage to ship systems based on failure modes and effects analysis (FMEA) is necessary to make appropriate inspection and maintenance decisions, which in turn will increase system reliability and shipping safety.

Estimating the risk of such a system encounters difficulties due to system complexity and negligible historical data. In such cases, subjective evaluations prove to be useful on the basis of expert opinion. However, such assessments to some extent are subject to imprecision or uncertainty due to the level of education, experience and knowledge of the considered field.

Among the risk assessment methods, FMEA is the most widely used engineering technique in many industries that can be used to identify and eliminate known or potential failures to improve the reliability and safety of complex systems. It is also intended to provide information for risk management decisions. Traditional FMEA defines the risk priorities of failures using the so-called Risk Priority Number (RPN), which is defined as the simple product of probabilities of failure occurrence (O), severity (S), and difficulty of detecting (D) failure. Determining these probabilities in practice encounters the difficulty of missing data. In such cases, we must rely on subjective assessments made by persons with practical knowledge in the area under consideration, i.e. experts. However, their practical knowledge can to some extent contain ambiguity and uncertainty. On the other hand, experts prefer to formulate their opinions in linguistic terms.

Traditional FMEA analysis seems insufficient to extract important information from subjective evaluations in these situations. Consequently, fuzzy theory was introduced into the traditional FMEA, which makes it more flexible in describing them. Wang et al. [14] proposed a new, fuzzy FMEA that assesses risk factors and their relative weight in linguistic form.

Abdelgawad and Fayek [1] used a combination of fuzzy FMEA and fuzzy analytical hierarchical process (AHP) to develop a risk management method in construction. Brandowski et al. [3] developed a fuzzy-neuron model of the seagoing ship risk estimation. Laarhoven and Pedrycz [8] introduced the fuzzy AHP (FAHP), where each evaluation of pairwise comparison is represented by the fuzzy triangular membership function to a given set.

Because this feature describes only the membership degree of an item to a fuzzy set, it cannot be used to express support and opposition opinions that occur simultaneously in many practical situations. Decision makers also may not be able to accurately assess their ratings or preferences because of insufficient knowledge of the domain under consideration or cannot clearly distinguish the extent to which one alternative is better than the other. In other words, there is some degree of hesitation in expert opinions. Atanassov [2] extended Zadeh's fuzzy set to an intuitionistic fuzzy set (IFS), characterized by degree of membership, degree of non-membership and degree of hesitation, to describe such situations and to understand more about human perception and cognition. IFSs have been attracting rapidly increasing attention from researchers and have been used in many areas such as decision making [6], [12], fuzzy cognitive maps [10], medical diagnosis [5], fault diagnosis and pattern recognition [9, 13]. Xu and Liao [15] have extended the classic AHP and FAHP to intuitionistic fuzzy IFAHPs to solve comprehensive decision-making criteria.

In this article, a methodology for estimating the risk of ship system failures is proposed. Estimation is fully based on expert opinion. It is adapted to their knowledge gained from long-term professional work in the operation of ship systems and their ability to express this knowledge. The presented method has been developed for use in decision-making procedures for predicting risks during ship operation.

2. Theoretical background

In 1983 Atanassov generalized the concept of fuzzy sets given by Zadeh [16] by using membership function and non-membership function for any elements of the universe of discourse. An Atanassov's Intuitionistic Fuzzy Set (IFS) is described by [2]:

$$A = \{(x, \mu_A(x), \nu_A(x)) | x \in X\}, \tag{1}$$

where $\mu_A(x)$ denotes a degree of membership and $\nu_A(x)$ denotes a degree of non-membership of x to A, $\mu_A: X \to [0,1]$ and $\nu_A: X \to [0,1]$ such that

$$0 \leq \mu_A(x) + \nu_A(x) \leq 1, \forall x \in X. \tag{2}$$

The intuitionistic fuzzy index or the hesitation margin of an element x to the intuitionistic fuzzy set A was introduced as:

$$\pi_A(x) = 1 - \mu_A(x) - \nu_A(x). \tag{3}$$

It is obvious, that $0 \le \pi_A(x) \le 1, \forall x \in X$.

If $\pi_A(x) = 0, \forall x \in X$, then $\mu_A(x) + \nu_A(x) = 1$ and the intuitionistic fuzzy set A reduces to an ordinary fuzzy set, which is defined as: $A = \{(x, \mu_A(x)) | x \in X\}$. The trapezoidal and triangular fuzzy numbers are the most popular fuzzy sets used in various applications.

The concept of a complement of an IFS A, denoted by A^c is defined as:

$$A^c = \{(x, \nu_A(x), \mu_A(x), \pi_A(x)) | x \in X\}. \tag{4}$$

The operations of addition $\oplus$ and multiplication $\otimes$ on intuitionistic fuzzy values (IFVs) were defined by Atanassov [2] as follows. Let $A = \langle \mu_A, \nu_A \rangle$ and $B = \langle \mu_B, \nu_B \rangle$ be IFVs, then the following operators were defined:

$$A \oplus B = (\mu_A + \mu_B - \mu_A\mu_B, \nu_A\nu_B), \tag{5}$$

$$A \otimes B = (\mu_A\mu_B, \nu_A + \nu_B - \nu_A\nu_B), \tag{6}$$

$$\lambda A = \left(1 - (1 - \mu_A)^\lambda, \nu_A{}^\lambda\right), (\lambda > 0), \tag{7}$$

$$A^\lambda = \left(\mu_A{}^\lambda, 1 - (1 - \upsilon_A)^\lambda\right), (\lambda > 0). \tag{8}$$

The operations (5) – (8) are used to aggregate local criteria for solving MCDM problems in the intuitionistic fuzzy setting. Let $A_1, \ldots, A_m$ be IFVs representing the values of local criteria and $w_1, \ldots, w_m$; $\sum_{j=1}^{m} w_j = 1$ be their weights. Then intuitionistic fuzzy weighted arithmetic mean (IFWA) can be obtained using operations (5) and (7) as follows:

$$\begin{aligned} \mathrm{IFWA}_w(A_1, \ldots, A_m) &= w_1A_1 \oplus \ldots \oplus w_mA_m \\ &= \langle 1 - \textstyle\prod_{j=1}^{m}(1 - \mu_A)^{w_j}, \ \prod_{j=1}^{m}(\nu_A)^{w_j} \rangle \end{aligned} \tag{9}$$

Intuitionistic fuzzy weighted geometric mean (IFWG) can be obtained using operations (6) and (8) as follows:

$$\begin{aligned} \mathrm{IFWG}_w(A_1, \ldots, A_m) &= w_1A_1 \otimes \ldots \otimes w_mA_m \\ &= \langle \textstyle\prod_{j=1}^{m}(\mu_A)^{w_j}, 1 - \prod_{j=1}^{m}(1 - \nu_A)^{w_j} \rangle \end{aligned} \tag{10}$$

These aggregation operators provide IFVs, are idempotent and currently are most popular in the solution of decision-making problems in the intuitionistic fuzzy setting. An important problem is the comparison of IFVs to choose the best alternative when the final scores of alternatives are presented by IFVs. The specific methods were developed to compare IFVs. Chen and Tan [4] proposed to use the so-called score function S (or net membership). In addition to the above score function, Hong and Choi [7] introduced the so-called accuracy function H and showed that the relation between functions S and H is similar to the relation between mean and variance in statistics. In [11] Szmidt et al. proposed a knowledge measure of IFV, taking into account all its parameters, i.e. membership, non-membership and hesitancy degrees. Since these methods are rather of heuristic nature, there have been different other definitions of the score function proposed in the literature.

In order to rank the IFVs, we utilize the membership knowledge measure $K_F(\alpha)$ proposed in [9], which is well interpreted and simply in computation. Let $\alpha = \langle \mu_\alpha, \nu_\alpha \rangle$ be an IFV in finite universe of discourse X. The score function of $\alpha \in X$ is defined as:

$$S(\alpha) = \begin{cases} K_F(\alpha) \ \text{ for } \mu_\alpha \geq \nu_\alpha \\ -K_F(\alpha) \ \text{ for } \mu_\alpha < \nu_\alpha \end{cases}, \qquad (11)$$

where

$$K_F(\alpha) = \frac{1}{\sqrt{2}}\sqrt{{\mu_\alpha}^2 + {\nu_\alpha}^2 + (\mu_\alpha + \nu_\alpha)^2}. \qquad (12)$$

The score function $S(\alpha)$, $-1 \geq S(\alpha) \geq 1$ measures amount of knowledge conveyed by linguistic evaluation presented in form of IFVs. In the case, when the positive information is bigger than negative one, i.e. for $\mu_\alpha \geq \nu_\alpha$ (the supporting evidence is larger than the against one), the score function sets the plus sign to the knowledge measure. In the contrary, the minus one is assigned to the score function for $\mu_\alpha < \nu_\alpha$. Naturally, that the positive information is preferred to than negative one, so the larger value of score function $S(\alpha)$, the higher rank of IFV α.

3. Methodology of the intuitionistic fuzzy FMEA

Usually, the risk factors O, S and D are evaluated by experts in linguistic terms. The linguistic terms and their related intuitionistic fuzzy numbers are shown in Tables 1–3. For example, experts revealed their opinions on the occurrence probability of the ship system failures in the form of linguistic values chosen from the given linguistic set (Table 1): very high (VH), high (H), moderate (M), low (L) and very low (VL). We take into account period of practical experience of experts as a factor of their hesitancy degree in judgments as follows:

$$\pi_j = 1/2^{p_j} \qquad (13)$$

where p_j denotes the expert's professional experience in years. The more experience, the less uncertainty he/she has. The rating of failure mode F_i made by the expert E_j on the risk factor O is represented by $R_{ij}^o = \langle \mu_{ij}^o, \nu_{ij}^o \rangle$, where μ_{ij}^o is the membership degree of the failure mode to the risk factor O, related to the linguistic rating. The non-membership degree is determined as:

$$\nu_{ij}^o = 1 - \mu_{ij}^o - \pi_{ij}^o, 0 \le \nu_{ij}^o \le 1. \quad (14)$$

Hence, the intuitionistic fuzzy numbers related to the linguistic values of the given set should be suitable to hesitancy degree (knowledge level) of the experts.

Suppose there are n failure modes $F_i, (i = 1, \dots, n)$ of the seagoing ship systems, and m experts $E_j, (j = 1, \dots, m)$ evaluating the failure modes on the risk factors in the linguistic values.

Let $R_{ij}^o = \langle \mu_{ij}^o, \nu_{ij}^o \rangle$, $R_{ij}^s = \langle \mu_{ij}^s, \nu_{ij}^s \rangle$ and $R_{ij}^d = \langle \mu_{ij}^d, \nu_{ij}^d \rangle$ be the IF ratings of F_i on the risk factors O, S and D corresponding to the linguistic values; ω_o, ω_s and ω_d be the weights of the three risk factors, $\lambda_j, (j = 1, \dots, m)$ be the relative importance weights of the experts, $\sum_{j=1}^{m} \lambda_j = 1$.

Using the intuitionistic fuzzy weighted averaging (IFWA) operator (9) we aggregate the IF ratings of failure mode F_i on the risk factors O, S and D, respectively:

$$R_i^o = IFWA_\lambda(R_{i1}^o, R_{i2}^o, \dots, R_{im}^o) = \lambda_1 R_{i1}^o \oplus \dots \oplus \lambda_m R_{im}^o$$
$$= \langle 1 - \prod_{j=1}^{m} \left(1 - \mu_{ij}^o\right)^{\lambda_j}, \ \prod_{j=1}^{m} \left(\nu_{ij}^o\right)^{\lambda_j} \rangle = \langle \mu_i^o, \nu_i^o \rangle, \quad (15)$$

$$R_i^s = IFWA_\lambda(R_{i1}^s, R_{i2}^s, \dots, R_{im}^s) = \lambda_1 R_{i1}^s \oplus \dots \oplus \lambda_m R_{im}^s$$
$$= \langle 1 - \prod_{j=1}^{m} \left(1 - \mu_{ij}^s\right)^{\lambda_j}, \ \prod_{j=1}^{m} \left(\nu_{ij}^s\right)^{\lambda_j} \rangle = \langle \mu_i^s, \nu_i^s \rangle, \quad (16)$$

$$R_i^d = IFWA_\lambda(R_{i1}^d, R_{i2}^d, \dots, R_{im}^d) = \lambda_1 R_{i1}^d \oplus \dots \oplus \lambda_m R_{im}^d$$
$$= \langle 1 - \prod_{j=1}^{m} \left(1 - \mu_{ij}^d\right)^{\lambda_j}, \ \prod_{j=1}^{m} \left(\nu_{ij}^d\right)^{\lambda_j} \rangle = \langle \mu_i^d, \nu_i^d \rangle. \quad (17)$$

Table 1 Fuzzy ratings for probability of failure occurrence (with $\pi_j = 0.1$).

Rating	Probability of occurrence	Intuitionistic fuzzy number
Very high (VH)	Failure is almost inevitable	<0.8, 0.1>
High (H)	Repeated failures	<0.6, 0.3>
Moderate (M)	Occasional failures	<0.45, 0.45>
Low (L)	Relatively few failures	<0.3, 0.6>
Remote (R)	Failure is unlikely	<0.1, 0.8>

Table 2 Fuzzy ratings for probability of failure severity (with $\pi_j = 0.1$*).*

Rating	Severity of failure occurrence	Intuitionistic fuzzy number
Very serious casualty (C1)	Loss of the ship, loss of human life and/or heavy marine environment pollution.	<0.8, 0.1>
Serious casualty (C2)	Injuries or human health deterioration, ship grounding, touching a submarine object, contact with a solid object, lost seaworthiness due to defects, necessity of towing or assistance from the shore and/or marine environment pollution.	<0.6, 0.3>
Incident I (I1)	Prolonged hazard to the ship, people and environment which can cause a sea accident. After repair by the ship crew, the ship functionality is not fully restored (lower ship system operational parameters).	<0.45, 0.45>
Incident II (I2)	As in I1, but after repair the ship functionality is fully restored.	<0.3, 0.6>
Incident III (I3)	Temporary hazard to the ship, people and environment which can cause a sea accident. No repair needed.	<0.1, 0.8>

Table 3 Fuzzy ratings for probability of failure detection (with $\pi_j = 0.1$*).*

Rating	Probability of failure detection	Intuitionistic fuzzy number
Very remote (VR)	Very remote chance	<0.1, 0.8>
Very low (VL)	Very low chance	<0.2, 0.7>
Low (L)	Low chance	<0.3, 0.6>
Moderately low (ML)	Moderately low chance	<0.4, 0.5>
Moderate (M)	Moderate chance	<0.45, 0.45>
Moderately high (MH)	Moderately high chance	<0.5, 0.4>
High (H)	High chance	<0.6, 0.3>
Very high (VH)	Very high chance	<0.7, 0.2>
Almost certain (AC)	Almost certainty	<0.8, 0.1>

The traditional FMEA defines RPNs as the simple product of O, S and D without considering their relative importance weights, whereas the IFRPN is defined as the fuzzy weighted geometric mean of the three risk factors O, S and D. This overcomes the drawback that the three risk factors are treated equally. IFRPN of the failure mode F_i can be aggregated using the intuitionistic fuzzy weighted geometric (IFWG) operator (10) as follows:

$$\mathrm{IFRPN}_i = \omega_o R_i^o \otimes \omega_s R_i^s \otimes \omega_d R_i^d$$
$$= \langle (\mu_i^o)^{\omega_o} . (\mu_i^s)^{\omega_s} . (\mu_i^d)^{\omega_d}, 1-(1-\nu_i^o)^{\omega_o} . (1-\nu_i^s)^{\omega_s} . (1-\nu_i^d)^{\omega_d} \rangle = \langle \mu_i, \nu_i \rangle. \quad (18)$$

Using (11), the score functions of the IFRPNs of failure modes F_i can be calculated. The increasing order of the score functions represents the risk priority of potential causes. For the ship system failure analysis, failure mode with the biggest score function should be given the top priority.

4. Intuitionistic fuzzy risk estimation of the ship system failures

To demonstrate the applicability of the proposed method, an example about tanker system failure from a global tanker ship management company is adopted from [17]. Assume that a FMEA team consisting of five experts identifies 17 potential system failure modes on tankers (Table 4) and needs to prioritize them in terms of their failure risks so that high risky failure modes can be corrected with top priorities. Experts evaluate the risk factors of failure modes as probability of their occurrence, severity and detect ability using the linguistic terms defined in Tables 1–3. The five experts are assigned with the following relative weights: 0.15, 0.25, 0.25, 0.20 and 0.15. The weights of the risk factors O, S and D are assumed to be 0.40, 0.35 and 0.25. The relative weights of risk factors can be decided by experts, considering both historical data and factors which are more concerned about. For example, if the consequence of a failure is more important, the weight of its severity may be assigned with a higher value than that of others. Based on the above information, intuitionistic fuzzy RPNs of the 17 failure modes can be calculated. The score functions of the obtained IFRPNs indicate the priority order of ship system failure modes.
Table 4 shows the results of comparing the proposed method with fuzzy method [17] for the given example. The rankings of the tanker system failure modes by both approaches are almost the same, i.e. the riskiest failure is F_{12} (main engine) and the least risky one is F_5 (Cargo system). The ranking of other failure modes is also consistent, e.g. the five most risky failures and three least risky ones. There are some differences in the middle rankings between approaches due to different used methods. For example, the rank of F_1 (Auxiliary engine) is seventh by the IFRPN method, while it is eighth by the fuzzy method.

Table 4 Results of comparing proposed IF method with fuzzy method [17].

No.	Failure mode (F_i)	Ranking by FRPN	Ranking by IFRPN	Ranking by IFRPN	Ranking by IFRPN
			$\pi_j = 0$	$\pi_j = 0.05$	$\pi_j = 0.1$
1	Auxiliary engine	8	7	9	4
2	Auxiliary machinery	6	9	7	9
3	Boiler	7	8	10	5
4	Cargo pump	14	14	13	11
5	Cargo system	**17**	**17**	**17**	17
6	Deck machinery	**3**	**3**	**3**	2
7	Electrical system	10	10	8	10
8	Emergency system	12	13	14	14
9	Hull part	**15**	**15**	**15**	15
10	Hydraulic system	13	12	12	13
11	Inert gas system	11	11	11	12
12	Main engine	**1**	**1**	**1**	1
13	Monitoring system	**4**	**4**	**4**	3
14	Mooring	9	6	6	7
15	Navigation system	**2**	**2**	**2**	8
16	Piping system	**5**	**5**	**5**	6
17	Steering Gear	**16**	**16**	**16**	16

Meanwhile, the rank of F_3 (Boiler) is eighth by the IFRPN method, while it is seventh by the fuzzy method. Additionally, the proposed method showed that with the increasing hesitation margin ($\pi_j = 0.1$ related to about 3 years of practical experience) the consistency of the obtained results is deteriorating.

As can be seen from Table 4, F_{12} (Main engine) is apparently the failure mode with the maximum overall risk and should be given the top priority, followed by F_{15} (Navigation system), F_6 (Deck Machinery), F_{13} (Monitoring system) and F_{16} (Piping system). The ranking can be used for the decision-making of managers, arranging the inspection and maintenance of the equipment properly, which can optimise the maintenance resources and avoid the risk.

5. Conclusions

In this paper, the IF method has been proposed for the risk estimation of the ship system failures, which is based exclusively on the judgments elicited by experts - experienced marine engineers. The obtained results show that the proposed method is powerful and useful in dealing with imprecise and uncertain data, which are available in the such cases.

Combining IFS and FMEA methods allows incorporating the hesitancy and limited knowledge of expert judgments. Compared with the traditional FMEA, the proposed method seems more effective for risk evaluation. Compared with the fuzzy FMEA, the proposed method shows more practical and flexible in describing the real-life problems. The proposed method is particularly useful in the expert investigations. It is worth noticing that subjective investigation results may (but not necessarily) be charged with greater error than objective results acquired in real operational process. Therefore, the further researches should be focused on validation of the proposed method by the objective results.

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