Heliyon 9 (2023) e16606

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Failure mode and Effect Analysis of personal fall arrest system under the intuitionistic fuzzy environment

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ARTICLE INFO

Keywords:
Fuzzy sets
Safety analysis
Risk assessment
Accident prevention

ABSTRACT

Background and aims: Intuitionistic fuzzy sets (IFS) theory is more powerful than classic fuzzy sets theory in handling uncertainty. A new approach for Failure Mode and Effect Analysis (FMEA) was developed based on IFS and group decision-making (known as IF-FMEA) for investigating Personal Fall Arrest System (PFAS).
Method: FMEA parameters, including occurrence, consequence, and detection, were re-defined based on a seven-point linguistic scale. Each linguistic term was associated with an intuitionistic triangular fuzzy set. Opinions on the parameters were gathered from a panel of experts, integrated using the similarity aggregation method, and defuzzified utilizing the center of gravity approach.
Results: Nine failure modes were identified and analyzed using both FMEA and IF-FMEA. The risk priority numbers (RPNs) and prioritization obtained from the two approaches were different, highlighting the importance of using IFS. The highest RPN was associated with the lanyard web failure, while the failure of the anchor D-ring had the least RPN. Detection score was higher for metal parts of the PFAS, suggesting that failures in these parts are harder to detect.
Conclusion: In addition to being economical in terms of calculations, the proposed method was efficient in handling uncertainty. Different parts of a PFAS create different levels of risk.

1. Introduction

Many techniques and methods have been developed for risk analysis of engineering systems and industrial operations, such as Fault Tree Analysis (FTA), Hazard and Operability (HAZOP) analysis, Event Tree Analysis (ETA), Job Safety Analysis (JSA), and so on [1,2]. Failure Modes and Effects Analysis (FMEA) is one of the most popular techniques for risk analysis of engineering systems [1]. The technique first explores the failure modes of a system and then assesses the potential effects of such failures. The output of the technique is a number known as Risk Priority Number or simply RPN, which is computed by multiplying three parameters: Severity (S), Detection (D), and Occurrence (O). Severity denotes the consequence magnitude of the failure when it occurs and starts an accident, detection determines how easy a failure mode is to detect by the user or the system itself before the accident, and occurrence is the likelihood or the frequency of the failure mode occurrence [3,4]. FMEA has been extensively and successfully used in many domains, such as wind turbines [5], the aircraft landing system [6], aircraft turbine rotor blades [7], compressor houses [8], and so on. The main

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https://doi.org/10.1016/j.heliyon.2023.e16606
Received 2 December 2022; Received in revised form 21 May 2023; Accepted 22 May 2023
Available online 1 June 2023

challenge in applying this technique is its reliance on expert judgment when data for estimating parameters are scarce [6,9]. In such a situation, the parameters are subjectively estimated by the assessor or a panel of experts, however, such subjective judgments contain a vast amount of uncertainty and subjectivity, reducing the reliability of the results. Uncertainty in the risk assessment process can be aleatory or epistemic. The former is due to the randomness of system behavior over time and has a natural origin, while the latter is due to the incompleteness of knowledge of the domain experts [10]. Fuzzy sets theory has been recognized as a potent tool for handling both uncertainties, notably the epistemic one [10].

Zadeh first conceived Fuzzy sets theory in 1965 for dealing with uncertain and ambiguous data and knowledge [11]. Since its conceptualization, Fuzzy sets theory has found many applications in a diversity of domains, such as risk assessment [12,13], accident investigation [14,15], human reliability analysis [16,17], and decision-making [18,19]. All these domains rely on experts' subjective judgment and evaluation, which contain considerable epistemic uncertainty because experts' knowledge can never be complete. Fuzzy sets theory is a strong tool for dealing with both problems [10]. Therefore, many researchers have attempted to integrate FMEA with Fuzzy sets theory. Lian et al. [20] integrated FMEA and Fuzzy PROMETHEE II to handle various types of biases and uncertainty in the risk assessment process. Zandi et al. [21] developed a method based on FMEA and Fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and Fuzzy (Analytical Hierarchy Process) AHP to manage agricultural risks. They broke down FMEA parameters into a number of sub-factors to take into account all variables affecting the final risk score in a more detailed manner. Fuzzy AHP was used to weigh FMEA parameters, and Fuzzy TOPSIS was exploited to rank failure modes. Gul and Ak [22] proposed a new algorithm to calculate RPN based on an interval-valued spherical fuzzy extension of TOPSIS (IVSF-TOPSIS). They also added several parameters to the original version of FMEA, including cost, effectiveness, and prevention. An interval-valued spherical weighted arithmetic mean operator (IVSWAM) was also applied for weighing the parameters. Boral et al. [9] employed Fuzzy AHP and the modified Fuzzy Multi-Attribute Ideal Real Comparative Analysis (modified FMAIRCA) to cover the downsides of the traditional FMEA. The Fuzzy AHP was applied to weigh the parameters, and the revised version of FMAIRCA was utilized to compute RPN. Akula et al. [23] developed a Fuzzy Inference System (FIS) based on FMEA and compared its results with the traditional FMEA. In contrast to the original version, the FIS-based FMEA produced different RPNs for the same parameter sets. The two FMEA versions tested in this study yielded different results. Zhu et al. [24] defined a methodology based on a novel Fuzzy rough number to deal with uncertainty and subjectivity inherited in the traditional FMEA. Similar to many other studies, Fuzzy AHP was used to weigh FMEA parameters. The authors also employed Fuzzy VIKOR to rank failure modes. Wang et al. [25] integrated the probabilistic hesitant fuzzy linguistic term sets (PHFLTSs), social network analysis (SNA), the best-worst method (BWM), and TOPSIS to tackle uncertainties at all steps of FMEA. PHFLTSs and SNA were used to handle uncertainties and subjectivities in the parameter evaluation step, the weight of parameters was calculated using BWM, and the rank of each failure mode was determined using TOPSIS. Li and Yazdi [10] developed an improved version of FMEA using probabilistic linguistic preference relations (PLPRs) and BWM to assess offshore wind turbines. PLPRs were used to explain risk factors (FMEA parameters), and the failure modes were ranked using BWM. Moreover, some studies have used non-Fuzzy approaches to tackle uncertainty in FMEA. These methods are commonly based on the Dempster-Shafer evidence theory and entropy [26,27].

Since 1965, several extensions of Fuzzy sets theory have been developed [28]. The fourth extension is known as Intuitionistic Fuzzy Sets (IFS) and was introduced in 1983 by Atanassov [29,30]. IFS differs from the classical Fuzzy sets theory in several important ways. In classical Fuzzy sets theory, a membership degree, a value between 0 and 1, is assigned to each object in the universe of discourse, and the non-membership degree is automatically calculated as one minus the membership degree because membership and non-membership degrees are the complements of each other. The main drawback of this approach is the ignorance of hesitation stemming from the lack of knowledge or errors in judgment. IFS attempts to cover this disadvantage by taking into account such hesitation. In IFS, the sum of membership and non-membership degrees can be lower than one, and the remaining gap is called the hesitancy degree. In recent years, there has been a tendency to use this approach instead of classical Fuzzy sets theory because it is more powerful than classical Fuzzy sets theory in handling uncertainty and vagueness [31,32].

Fall from height is the leading cause of occupational fatality on construction sites [33]. There have been recommended many protection systems for preventing such accidents. Guardrail systems, safety nets, personal fall arrest systems (PFAS), fall restraint systems, and a variety of administrative measures are among the most popular methods employed for protecting workers against hazards of working at the height [34]. Occupational Health and Safety Administration (OSHA) requires employers to provide employees PFAS if other passive systems, such as guardrails, are impossible to apply. Guardrail systems prevent a fall, while PFAS reduces the fall height, so the priority always belongs to guardrails. However, sometimes the use of guardrails is not feasible, and PFAS is inevitably the only choice. The main parts of a PFAS are (1) a full-body harness, (2) a lanyard, and (3) an anchor. Various types of connectors, such as carbines and snap hooks, are also used to connect these parts. Moreover, the lanyard may be equipped with an energy absorber to promote its ability to absorb fall shocks. Although very effective in fall protection, PFAS sometimes fails to provide the required protection [35]. In other words, the forces resulting from the falling person cause various parts of PFAS to fail, resulting in the falling and death of the user. Failures can occur in any part of an FPAS. Prolonged exposure to sunlight, direct contact with corrosive compounds, excessive use, and so on can weaken various parts of a PFAS [36]. A small cut can reduce the strength of webbing material significantly, and any discoloration, regardless of its size, is indicative of a serious problem [36]. OSHA requires employees to inspect their PFAS before each usage, while American National Standard Institute (ANSI) mandates that a competent person must regularly inspect PFASs. Any defective PFAS should be completely dismantled and removed from the workplace.

Despite all precautions and inspections, PFASs still fail, and to the best of our knowledge, no study has yet investigated failure modes and associated risks of a PFAS. Therefore, such a study seems to be necessary. Among available techniques, FMEA appears to be the most appropriate for the risk analysis of PFASs because of its unique focus on the failure modes of a system. As there is no reliable data for estimating FMEA parameters in this case study, the use of experts' opinions is inevitable. However, such opinions contain a considerable amount of uncertainty and subjectivity that needs to be appropriately addressed in an accurate, effective, and computationally inexpensive manner. Moreover, it is much easier and more accurate for experts to express their opinions in terms of linguistic variables. Fuzzy logic can well handle both situations. Additionally, IFS is superior to classic fuzzy sets theory by taking into account the hesitancy degree. Therefore, in this study, we used the IFS theory to handle mentioned uncertainties and sources of uncertainties. Furthermore, some of the previous studies have developed methodologies that are somewhat complex and time-consuming to use. For example, they require the use of an array of MCDMs. There is no doubt that the use of MCDMs, such as AHP, BWM, or TOPSIS, is very beneficial for weighting parameters and ranking failure modes, but the interpretation of final results may be confusing. For example, the cut point above which the risk should be regarded as unacceptable, similar to RPNs higher than 125, has yet to be well-defined when such techniques are used to calculate RPN or to rank failure modes based on their criticality and risk.

This study aims to assess risks associated with PFAS using a methodology that is not only strong in handling uncertainties but also computationally inexpensive while remaining loyal to the basic concepts of FMEA, i.e., the same relative importance of parameters and the equation used to calculate RPN. Accordingly, the present study aimed at failure analysis and risk assessment of PFAS using FMEA in the intuitionistic Fuzzy environment in which all numbers are intuitionistic fuzzy sets and all computations are based on the principles of intuitionistic fuzzy sets.

2. Material and methods

2.1. Intuitionistic fuzzy sets (IFS)

A classic fuzzy set developed by Zadeh [11] has the following characteristics:

Considering B as a classic Fuzzy set and y as an object in the universe of discourse Y, then B can be expressed using Equation (1):

$$B = \{\langle y, \mu_B(y)\rangle | y \in Y\} \tag{1}$$

Where, $\mu_B(y)$ is the membership function y in B with a value between zero and one.

Several decades later, Atanassov [29,30] developed the concept of IFS as an extension of classic fuzzy sets with the following characteristics:

Considering A as an IFS and x as an object in the universe of discourse X, A is expressed using Equation (2):

$$A = \{\langle x, \mu_A(x), v_A(x)\rangle | x \in X\} \tag{2}$$

Where, $\mu_A(x)$ is the membership function and $v_A(x)$ is the non-membership function of x in A [31,37]. The following relationships (Equations (3)–(5)) must also be satisfied:

$$0 \le \mu_A(x) \le 1 \tag{3}$$

$$0 \le v_A(x) \le 1 \tag{4}$$

$$0 \le \mu_A(x) + v_A(x) \le 1 \tag{5}$$

Moreover, for each x, a hesitancy function is defined using Equation (6):

$$\pi_A(x) = 1 - \mu_A(x) - v_A(x) \tag{6}$$

Where $\pi_A(x)$ is the hesitancy or indeterminacy of x to A. It has also been defined as an intuitionistic index of x in A [38].

Fig. 1 is the graphical representation of a general intuitionistic fuzzy set.

A triangular IFS (TIFS) is an IFS with the following membership and non-membership functions (Equations (7) and (8)):

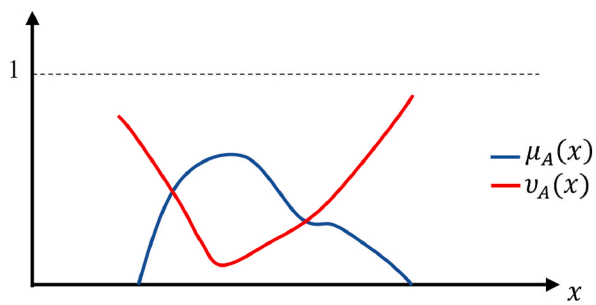

Fig. 1. Graphical representation of intuitionistic Fuzzy set A.

$$\mu_A(x) = \begin{cases} \frac{x-a}{b-a}, a \le x \le b \\ \frac{c-x}{c-b}, b \le x \le c \\ 0, otherwise \end{cases} \tag{7}$$

$$\upsilon_A(x) = \begin{cases} \frac{x-a'}{b-a'}, a' \le x \le b \\ \frac{c'-x}{c'-b}, b \le x \le c' \\ 0, otherwise \end{cases} \tag{8}$$

Where, $a' \le a \le b \le c \le c'$. A triangular IFS is demonstrated as A = $(a, b, c; a', b, c')$. A typical triangular IFS is depicted in Fig. 2 [37].

2.2. The proposed methodology

The steps of the present study are demonstrated in Fig. 3. The methodology comprises four main steps that will be explained in this section. It should be mentioned that the study protocol was approved by the ethic committee of Abadan University of Medical Sciences (Ethic Code: IR.ABADANUMS.REC.1400.098).

Step 1. Creating a framework for rating FMEA parameters using intuitionistic fuzzy numbers

Performing FMEA using the intuitionistic fuzzy numbers requires a framework for rating its parameters, i.e., S, C, and D. Accordingly, a 7-point scale of linguistic terms (very low, low, relatively low, medium, relatively high, high, very high) was defined for measuring FMEA parameters. Linguistic terms, their definitions, and corresponding triangular intuitionistic fuzzy sets associated with these parameters are presented in Table 1, Table 2, and Table 3. The linguistic scale has been previously utilized by Mirazaei Aliabadi [37], and the definitions are based on previous studies, including Yazdi et al. [6], Jiang et al. [7], and Arabian-Hoseynabadi et al. [5]. These tables would help experts and practitioners to assign linguistic terms in a more objective manner.

Step 2. Identification of failure modes

For doing this step, first a typical PFAS was decomposed into its components. Then, the various failure modes of each components were identified by interviewing with experienced employees and also manufacturers and importers of PFAS.

Step 3. Rating of FMEA parameters using the developed framework

Step 3.1. Gathering opinions from an expert panel: For rating FMEA parameters, six experts were invited to the study. All experts had more than seven years of practical experience regarding PFAS. Opinions from six experts were gathered in this step through the following questions:

- Question 1 (occurrence): how often does this part of PFAS is failed?
- Question 2 (detection): how probable is it to find this failure during a routine inspection?
- Question 3 (severity): how severe is the consequence if this failure realizes?

Step 3.2. Calculating the similarity degree between experts' opinions: Considering R_u and R_v two TIFS from experts E_u and E_v, the similarity degree, $S_{uv}(R_u, R_v)$, is calculated using Equation (9) [37,39].

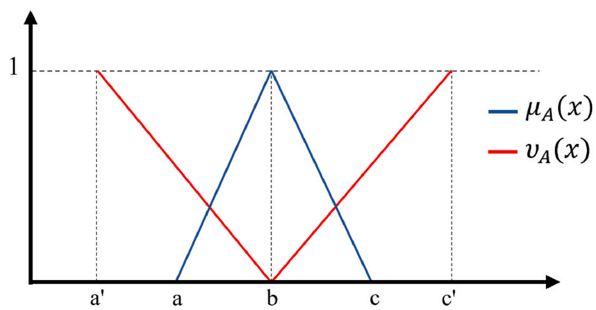

Fig. 2. A typical triangular IFS.

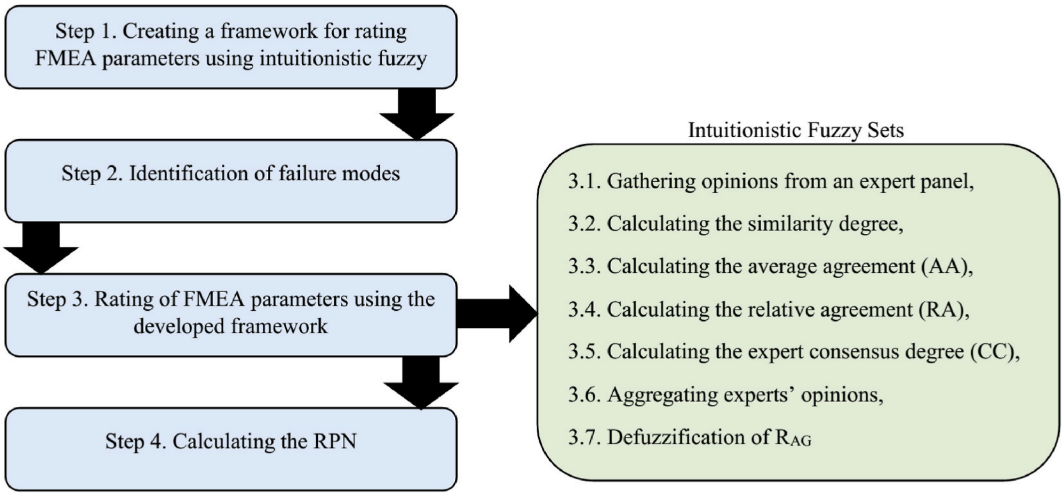

Fig. 3. Overview of the methodology used in this study.

Table 1
Linguistic terms, their definitions, and corresponding triangular intuitionistic fuzzy sets associated with severity.

Rank	Linguistic term (effect)	Description (severity)	Triangular Intuitionistic Fuzzy Set (TIFS)
1	Very Low (VL)	Very low or no health effect and injury, The system can sustain its optimal performance,	(0.00, 0.04, 0.08; 0.00, 0.04, 0.08)
2	Low (L)	Minor effects and injuries required only first aids, The system performance may be affected,	(0.07, 0.13, 0.19; 0.06, 0.13, 0.20)
3,4	Mildly Low (ML)	Injuries and health effects resulted in less than three lost working days, The system is operable but loses some of its functions for a short time,	(0.17, 0.27, 0.37; 0.15, 0.27, 0.39)
5,6	Medium (M)	Reversible injuries and health effects resulted in more than three lost working days, The system is operable but a slight decrease in its performance may occurred.	(0.35, 0.50, 0.65; 0.32, 0.50, 0.68)
7,8	Mildly High (MH)	Severe irreversible injuries and health effect is possible, The system is operable but a huge decrease in its performance may occurred.	(0.62, 0.73, 0.82; 0.61, 0.73, 0.85)
9	High (H)	The failure can result in a death, The system is inoperable and loses its primary function,	(0.81, 0.87, 0.93; 0.79, 0.87, 0.95)
10	Very High (VH)	The failure definitely results in at least one death, The system is inoperable and negatively affects downstream equipment,	(0.92, 0.96, 1.00; 0.92, 0.96, 1.00)

Table 2
Linguistic terms, their definitions, and corresponding triangular intuitionistic fuzzy sets associated with occurrence.

Rank	Linguistic term (likelihood)	Description (occurrence)	Failure frequency	Triangular Intuitionistic Fuzzy Set (TIFS)
1	Very Low (VL)	Failure is unlikely,	$\leq$1 in 10^6	(0.00, 0.04, 0.08; 0.00, 0.04, 0.08)
2	Low (L)	The failure rate is low,	<1 in 20000	(0.07, 0.13, 0.19; 0.06, 0.13, 0.20)
3,4	Mildly Low (ML)	The failure rate is relatively low,	<1 in 1000	(0.17, 0.27, 0.37; 0.15, 0.27, 0.39)
5,6	Medium (M)	Occasional failures are possible,	<1 in 80	(0.35, 0.50, 0.65; 0.32, 0.50, 0.68)
7,8	Mildly High (MH)	The failure rate is relatively high,	<1 in 20	(0.62, 0.73, 0.82; 0.61, 0.73, 0.85)
9	High (H)	The failure rate is high,	<1 in 8	(0.81, 0.87, 0.93; 0.79, 0.87, 0.95)
10	Very High (VH)	Failure is almost certain and inevitable,	>1 in 2	(0.92, 0.96, 1.00; 0.92, 0.96, 1.00)

Table 3
Linguistic terms, their definitions, and corresponding triangular intuitionistic fuzzy sets associated with detection.

Rank	Linguistic term (detectability)	Description (Detection)	Triangular Intuitionistic Fuzzy Set (TIFS)
1	Very High (VH)	The failure is certainly detected by any user,	(0.00, 0.04, 0.08; 0.00, 0.04, 0.08)
2	High (H)	The failure is likely to be detected by any user,	(0.07, 0.13, 0.19; 0.06, 0.13, 0.20)
3,4	Mildly High (MH)	The failure can be detected only by an experienced user,	(0.17, 0.27, 0.37; 0.15, 0.27, 0.39)
5,6	Medium (M)	It is not easy to detect the failure, but an experienced user still has a chance to detect it,	(0.35, 0.50, 0.65; 0.32, 0.50, 0.68)
7,8	Mildly Low (ML)	The failure is unlikely to be detected by a normal user,	(0.62, 0.73, 0.82; 0.61, 0.73, 0.85)
9	Low (L)	The failure is unlikely to be detected even by an experienced user,	(0.81, 0.87, 0.93; 0.79, 0.87, 0.95)
10	Very Low (VL)	There is no way for detecting the failure,	(0.92, 0.96, 1.00; 0.92, 0.96, 1.00)

$$S_{uv}(R_u, R_v) = \begin{cases} \dfrac{EV_u}{EV_v}, \text{if } EV_u \leq EV_v \\ \dfrac{EV_v}{EV_u}, \text{if } EV_u \geq EV_v \end{cases} \tag{9}$$

Where, EV is the expectancy value and for a TIFS R (a, b, c; a', b, c') is calculated by Equation (10) [37,39]:

$$EV(R) = \frac{(a + a') + 4 \times b + (c + c')}{8} \tag{10}$$

Step 3.3. Calculating the average agreement (AA) for each expert: In this step, AA was calculated for each expert using Equation (11) [37,39]:

$$AA(E_u) = \frac{1}{m-1} \sum_{u \neq v}^{m} S_{uv}(R_u, R_v) \tag{11}$$

Where, m is the total number of experts participated in the study.

Step 3.4. Calculating the relative agreement (RA) for each expert: In this step, RA is calculated for each expert using Equation (12) [37,39].

$$RA(E_u) = \frac{AA(E_u)}{\sum_{u=1}^{m} AA(E_u)} \tag{12}$$

Step 3.5. Calculating the expert consensus degree (CC): CC is calculated for each expert using Equation (13) [37,39]:

$$CC(E_u) = \beta.W(E_u) + (1 - \beta).RA(E_u) \tag{13}$$

Where, W is the weight of expert E_u calculated based on her/his experience, field of study, and education level and β is a relaxation factor ranging from 0 to 1 and demonstrates the relative importance of $W(E_u)$ over RA (E_u).

Step 3.6. Aggregating experts' opinions: In this step, the experts' opinions is aggregated using Equation (14) [37,39]:

$$R_{AG} = \sum_{i=1}^{m} CC(E_i).R_i \tag{14}$$

Where, R_i is a TIFS expressed by expert E_i.

Step 3.7. Defuzzification of R_{AG}: The output of previous is a TIFS which should be transformed into a crisp value. There are several ways for the defuzzification of a TFFS. In this study, Equation (15) was used for this purpose [37,39]:

$$X^* = \frac{1}{3}\left(\frac{(c' - a')(b - 2c' - 2a') + (c - a)(a + b + c) + 3(c'^2 - a'^2)}{c' - a' + c - a}\right) \tag{15}$$

Step 4. calculating the RPN

In the final step of the study, RPN was computed for each identified failure mode. Crisp values obtained from Equation (7) are within a range from 0 to 1, but the parameters of FMEA, i.e. severity, occurrence, and detection, are within the 1 to 10 range. To solve this problem, values obtained from Equation (15) were multiplied by 10 [6]. Then, RPN was calculated by multiplying S, D, and O, as demonstrated in Equation (16):

$$RPN = \left(X_S^* \times 10\right).\left(X_D^* \times 10\right).\left(X_O^* \times 10\right) \tag{16}$$

3. Results

3.1. Failure modes of PFAS

In the first part of the study, failure modes of the PFAS were identified. Five experienced safety practitioners were interviewed, and nine failure modes were singled out. The failure modes, their potential causes, and consequences are presented in Table 4. Misuse and overuse, improper maintenance, and using low-quality equipment are the leading causes of PFAS failure. Furthermore, failure in various parts of a PFAS can lead to the fall and death of the user.

3.2. Rating of FMEA parameter

The opinions of six domain experts were gathered in this step. All experts had at least seven years of experience and a master's degree in a safety-related field, so they all weighed equally. The linguistic terms reported by each expert for the nine failure modes are presented in Table 5. These data were processed using the procedure explained in section 2.3.

For more clarity, an example are presented here. The opinions of experts on the occurrence of failure mode 1 were: E_1: VL, E_2: M, E_3: H, E_4: H, E_5: M, and E_6: M.

The expectancy value of these opinions according to Equation (10) are:

$$\mathrm{EV}(\mathrm{E}_1) = 0.04, \mathrm{EV}(\mathrm{E}_2) = 0.5, \mathrm{EV}(\mathrm{E}_3) = 0.87, \mathrm{EV}(\mathrm{E}_4) = 0.87, \mathrm{EV}(\mathrm{E}_5) = 0.5, \mathrm{EV}(\mathrm{E}_6) = 0.5$$

Then, the similarity degree between each pair of experts was calculated using Equation (9):

$$\mathrm{S}(\mathrm{E}_1, \mathrm{E}_2) = 0.08, \mathrm{S}(\mathrm{E}_1, \mathrm{E}_3) = 0.046, \mathrm{S}(\mathrm{E}_1, \mathrm{E}_4) = 0.046, \mathrm{S}(\mathrm{E}_1, \mathrm{E}_5) = 0.08, \text{and } \mathrm{S}(\mathrm{E}_1, \mathrm{E}_6) = 0.08.$$

$$\mathrm{S}(\mathrm{E}_2, \mathrm{E}_1) = 0.08, \mathrm{S}(\mathrm{E}_2, \mathrm{E}_3) = 0.575, \mathrm{S}(\mathrm{E}_2, \mathrm{E}_4) = 0.575, \mathrm{S}(\mathrm{E}_2, \mathrm{E}_5) = 1.00, \text{and } \mathrm{S}(\mathrm{E}_2, \mathrm{E}_6) = 1.00.$$

$$\mathrm{S}(\mathrm{E}_3, \mathrm{E}_1) = 0.046, \mathrm{S}(\mathrm{E}_3, \mathrm{E}_2) = 0.575, \mathrm{S}(\mathrm{E}_3, \mathrm{E}_4) = 1.00, \mathrm{S}(\mathrm{E}_3, \mathrm{E}_5) = 0.575, \text{and } \mathrm{S}(\mathrm{E}_3, \mathrm{E}_6) = 0.575.$$

$$\mathrm{S}(\mathrm{E}_4, \mathrm{E}_1) = 0.046, \mathrm{S}(\mathrm{E}_4, \mathrm{E}_2) = 0.575, \mathrm{S}(\mathrm{E}_4, \mathrm{E}_3) = 1.00, \mathrm{S}(\mathrm{E}_4, \mathrm{E}_5) = 0.575, \text{and } \mathrm{S}(\mathrm{E}_4, \mathrm{E}_6) = 0.575.$$

$$\mathrm{S}(\mathrm{E}_5, \mathrm{E}_1) = 0.08, \mathrm{S}(\mathrm{E}_5, \mathrm{E}_2) = 1.00, \mathrm{S}(\mathrm{E}_5, \mathrm{E}_3) = 0.575, \mathrm{S}(\mathrm{E}_5, \mathrm{E}_4) = 0.575, \text{and } \mathrm{S}(\mathrm{E}_5, \mathrm{E}_6) = 1.00.$$

$$\mathrm{S}(\mathrm{E}_6, \mathrm{E}_1) = 0.08, \mathrm{S}(\mathrm{E}_6, \mathrm{E}_2) = 1.00, \mathrm{S}(\mathrm{E}_6, \mathrm{E}_3) = 0.575, \mathrm{S}(\mathrm{E}_6, \mathrm{E}_4) = 0.575, \text{and } \mathrm{S}(\mathrm{E}_6, \mathrm{E}_5) = 1.00.$$

- Next, the average agreement of each expert was calculated using Equation (11):

$$\mathrm{AA}(\mathrm{E}_1) = \frac{0.08 + 0.046 + 0.046 + 0.08 + 0.08}{5} = \frac{0.332}{5} = 0.0664$$

Table 4
Failure modes of PFAS.

Failure mode	Potential causes	Potential consequences
FM1: failure of anchor point.	Using weak structures as the anchor point,	User death
FM2: failure of the D-ring of anchor.	Improper maintenance, using low quality D-rings,	User death
FM3: failure of the snaphook of lanyard.	Improper maintenance, using low quality snaphook,	User death
FM4: failure of the lanyard web	Misuse and overuse, improper maintenance, purchasing inexpensive low quality equipment,	User death
FM5: failure of the sewing parts of lanyard.	Misuse and overuse, improper maintenance, purchasing inexpensive low quality equipment,	User death
FM6: failure of the harness web	Misuse and overuse, improper maintenance, purchasing inexpensive low quality equipment,	Severe injury, death is possible,
FM7: failure of the sewing parts of harness.	Misuse and overuse, improper maintenance, purchasing inexpensive low quality equipment,	Severe injury, death is possible,
FM8: failure of the harness buckles.	Misuse and overuse, improper maintenance, purchasing inexpensive low quality equipment,	Severe injury, death is possible,
FM9: failure of the harness D-ring.	Improper maintenance, using low quality D-ring,	User death

Table 5
Expert opinions on the rating of occurrence (O), detection (D), and consequence (C).

Failure mode	E1			E2			E3			E4			E5			E6		
Parameters	O	D	C	O	D	C	O	D	C	O	D	C	O	D	C	O	D	C
FM1	VL	MH	VH	M	VH	VH	H	H	VH	H	H	VH	M	H	VH	M	ML	VH
FM2	VL	MH	VH	M	H	VH	M	H	VH	M	H	VH	M	H	VH	ML	MH	VH
FM3	L	MH	VH	ML	H	VH	H	H	VH	VH	H	VH	VH	VH	VH	L	MH	VH
FM4	VH	ML	VH	MH	MH	VH	M	M	VH	H	H	VH	VH	VH	VH	VL	VH	VH
FM5	VH	H	VH	H	VH	VH	VH	H	VH	M	H	VH	M	H	VH	M	H	VH
FM6	VH	ML	H	M	MH	H	M	H	H	L	VH	H	H	M	H	VL	VH	H
FM7	VH	H	H	H	VH	H	H	M	H	L	H	H	L	H	H	M	H	H
FM8	VL	MH	H	MH	ML	H	M	M	H	M	M	H	VL	MH	H	VL	H	H
FM9	VL	MH	VH	M	M	VH	L	MH	VH	M	H	VH	H	H	VH	L	M	VH

$$\mathrm{AA(E_2)} = \frac{3.23}{5} = 0.6460, \mathrm{AA(E_3)} = \frac{2.771}{5} = 0.5542, \mathrm{AA(E_4)} = \frac{2.771}{5} = 0.5542,$$

$$\mathrm{AA(E_5)} = \frac{3.23}{5} = 0.6460, \mathrm{AA(E_6)} = \frac{3.23}{5} = 0.6460,$$

- Then, the relative agreement of each expert was calculated using Equation (12):

$$RA(E_1) = \frac{0.0664}{0.0664 + 0.6460 + 0.5542 + 0.5542 + 0.6460 + 0.6460} = \frac{0.0664}{3.1128} = 0.0213$$

$$RA(E_2) = 0.2075, RA(E_3) = 0.1780, RA(E_4) = 0.1780, RA(E_5) = 0.2075, RA(E_2) = 0.2075$$

- Based on the relative agreement and $\beta = 0.5$, the consensus degree of each expert was computed using Equation (13):

$$CC(E_1) = 0.5 \times 0.167 + (1 - 0.5) \times 0.0213 = 0.0942$$

, similarly;

$$\mathrm{CC(E_2)} = 0.1873, \mathrm{CC(E_3)} = 0.1725, \mathrm{CC(E_4)} = 0.1725, \mathrm{CC(E_5)} = 0.1873, \mathrm{CC(E_6)} = 0.1873$$

- In the next step, the opinions of experts were aggregated using Equation (14):

$$\begin{aligned} R_{AG} = {} & 0.0942 \otimes (0.00, 0.04, 0.08; 0.00, 0.04, 0.08) \oplus 0.1873 \otimes (0.35, 0.5, 0.65; 0.32, 0.5, 0.68) \oplus 0.1725 \otimes (0.81, 0.87, 0.93; 0.79, 0.87, 0.95) \\ & \oplus 0.1725 \otimes (0.81, 0.87, 0.93; 0.79, 0.87, 0.95) \oplus 0.1873 \otimes (0.35, 0.5, 0.65; 0.32, 0.5, 0.68) \oplus 0.1873 \otimes (0.35, 0.5, 0.65; 0.32, 0.5, 0.68) \\ & = (0.476, 0.585, 0.694; 0.452, 0.585, 0.717) \end{aligned}$$

- Finally, the intuitionistic IFS obtained in the previous step was defuzzfied using Equation (15):

$$\begin{aligned} \mathrm{X}^* = {} & \frac{1}{3}\left(\frac{(0.717 - 0.452)(0.585 - 2 \times 0.717 - 2 \times 0.452) + (0.694 - 0.476)(0.476 + 0.585 + 0.694) + 3(0.717 \times 0.717 - 0.452 \times 0.452)}{0.717 - 0.452 + 0.694 - 0.476}\right) \\ & = 0.585 \end{aligned}$$

The values of FMEA parameters are between 0 and 10, while the output of the defuzzification is between zero and one. So, the crisp values obtained from the last step should be multiplied by 10.

$$0.585 \times 10 = 5.85$$

3.3. Calculating RPN

The RPNs of various failure modes based on both conventional FMEA and IF-FMEA are presented in Table 6. As evident, IF-FMEA can change the prioritization of failure modes. Accordingly, FM4, failure of the lanyard web, and FM6, failure of the harness web, had the highest RPNs. In contrast, FM8, failure of the harness buckles, and FM2, failure of the sewing parts of the lanyard, had the lowest RPNs. Moreover, lower RPN values were obtained by the IF-FMEA compared with those obtained from the conventional FMEA. Commonly, failure modes with RPNs higher than 125 are considered critical and need more attention. The conventional FMEA resulted in six RPNs higher than 125, while only two failure modes had an RPN higher than 125 in IF-FMEA.

Values of occurrence, detection, and consequence based on the IFS approach are demonstrated in Fig. 4. As evident, the highest scores in all failure modes are associated with the consequence, followed by occurrence and detection. FM4, failure of the lanyard web, and FM8, failure of the harness buckles, had the highest and lowest occurrence values, respectively. The detection values are typically low, emphasizing that any sign of failure in the PFAS is relatively easy to detect. However, the highest detection value was associated with FM8, failure of the harness buckles, followed by FM9, failure of the harness D-ring.

The sensitivity of the results to the experts' weights was assessed by calculating RPNs based on different values of β. The results are presented in Fig. 5. Although various RPNs are obtained for different values of β, the ranking of failure modes remains unchanged in each β category. When $\beta = 0.9$, the initial weights of experts are more prominent in calculating RPN, while the similarity degree of experts' opinions is more important when $\beta = 0.1$.

Table 6
The prioritization of failure modes based on RPNs obtained from the original FMEA and IF-FMEA.

Failure mode	Conventional FMEA		IF-FMEA (β = 0.5)	
	RPN	Priority	RPN	Priority
FM1	151	2	118.2	3
FM2	107	8	72.7	9
FM3	140	3	89.5	6
FM4	195	1	186.6	1
FM5	117	7	79.0	8
FM6	131	6	125.9	2
FM7	104	9	88.6	7
FM8	135	4	99.6	5
FM9	134	5	106.0	4

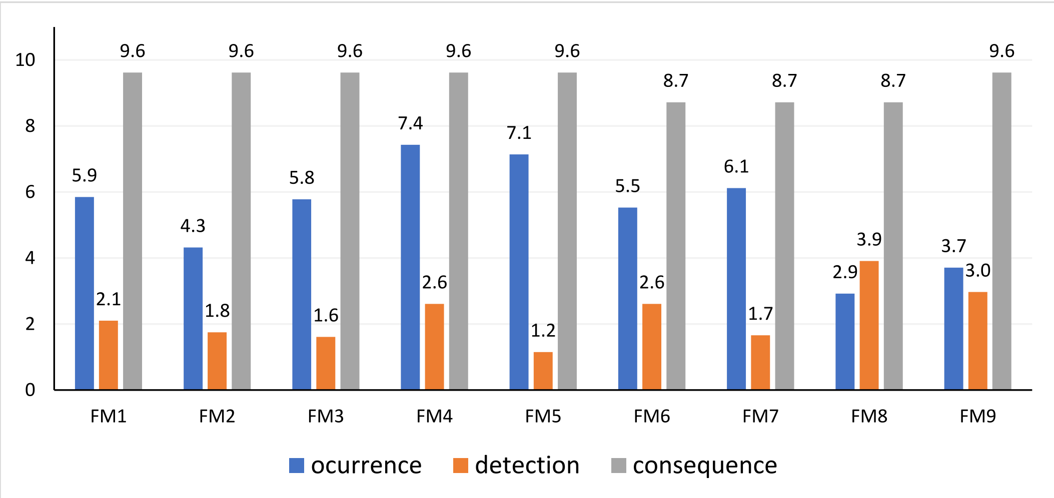

Fig. 4. Values of occurrence, detection, and consequence based on the IFS approach.

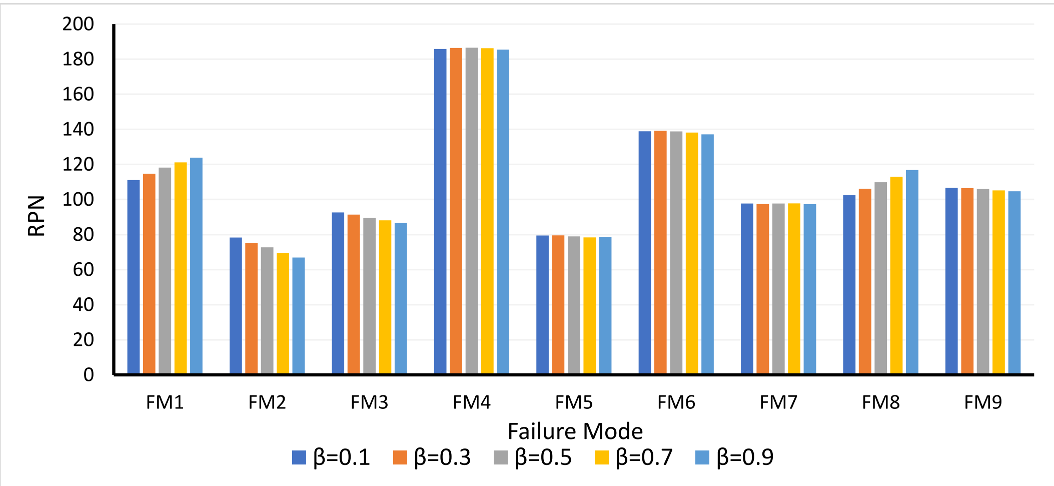

Fig. 5. The RPN of various failure modes based on different values of β

4. Discussion

FMEA is one of the most popular techniques for the risk assessment of engineering systems. However, the method is based on experts' judgment that generally contains considerable uncertainty. Fuzzy sets theory is a solution for reducing such uncertainty. So far, several studies have tried to improve FMEA using Fuzzy sets theory in different ways. For example, Kutlu and Ekmekçioglu [40] used fuzzy TOPSIS and fuzzy AHP, Boral et al. [9] employed fuzzy AHP and fuzzy MAIRCA, and Song et al. [41] handled the uncertainty using the integrated weight-based fuzzy TOPSIS. However, all these studies used the classic Fuzzy sets theory, while in the present study, IFS was utilized. IFS is shown to be stronger than the traditional Fuzzy sets theory in handling uncertainty and vagueness [39]. IFS seems to be a better option for solving problems that are based on human expertise and judgment because the concept of vagueness has a more remarkable similarity with IFS [42]. It considers not only membership and non-membership functions but also the hesitancy function, making it able to capture the lack of knowledge regarding the membership degree [43]. Most studies have employed a series of MCDM methods alongside other tools to capture uncertainties in the use and implementation of FMEA, making their methodology complex and somewhat hard to follow. This study utilized IFS to collect and quantify experts' opinions, so the methodology is able to tackle uncertainties in the risk assessment process. Moreover, previous studies have used a variety of methods, commonly TOPSIS or Fuzzy TOPSIS, to calculate RPN. In contrast to these studies, we used the original equation to calculate RPN to avoid making the methodology more complex and time-consuming.

PFAS is one of the essential protective systems for preventing falls from height. However, the failure of PFAS can lead to severe consequences. In this study, PFAS was investigated using both original FMEA and IF-FMEA. Nine different failure modes in various parts of PFAS were identified and analyzed. The results demonstrated that these two approaches result in different RPNs. Moreover, the prioritization of failure modes was different in these methods. In FMEA, six failure modes had RPNs higher than 125, while two failure modes had RPNs higher than 125 according to IF-FMEA. This finding demonstrates that FMEA tends to provide higher RPNs than IF-FMEA. Considering the benefits and advantages of IFS, the results of IF-FMEA are more reliable.

The results of this study can help safety practitioners in managing the safety of work at height. According to the results of IF-FMEA, the highest RPN was associated with the lanyard web, i.e., FM4. Moreover, it had the highest occurrence score, suggesting that this part of PFAS has the highest failure likelihood. Poor maintenance, such as exposure to sunlight, contact with corrosive materials, and brushing sharp edges, can be the reasons for lanyard web failure. Galecka and Smith [36] explained that even small cuts in the web and discoloration in the size of a pen point could result in the total breakage of the lanyard web. Olbina and Hinze [35] found three deadly accidents because of lanyard web failure in their study. Therefore, users should pay special attention to the inspection of this part. There are several international standards and guidelines for storing PFAS to prevent lanyards from becoming damaged. In contrast, metal parts such as D-ring and harness buckles, FM8 and FM9, were rated lower in terms of occurrence, emphasizing that the failure likelihood in these parts is lower than in others. FM8, failure of the harness buckles, and FM9, failure of the harness D-ring, had the highest detection scores, suggesting that detecting failures in these parts of a PFAS is more challenging than others. Small cracks, distortion, and damages are common signs of failure in these parts. Unfortunately, there is a misunderstanding among PFAS users that metal parts are solid and unlikely to fail; however, such overreliance can lead to fatal accidents. ANSI Z359 provides guidelines for inspecting various parts of PFAS, including buckles and D-rings. Exposure to corrosive materials and extreme environments may fasten the degradation of metal parts.

In this study, we used IFS to develop a new extension of FMEA for the risk assessment of PFASs. However, more recently-developed versions of Fuzzy sets such as the Pythagorean fuzzy set (PFS) can also be employed in this regard. Moreover, in this study, the opinions of only six experts were collected, and as there is no reliable data regarding the failure probability of PFAS components, including more safety experts from different sectors, such as construction, mining, process industries, offshore installations, and so on can result in more reliable outputs.

5. Conclusion

A four-step methodology was recommended to conduct FMEA under the intuitionistic Fuzzy environment. IFS was used to capture and quantify the experts' opinions. The methodology does not need complex calculations and is very efficient in handling uncertainty by simultaneously considering membership, non-membership, and hesitancy functions. The case study highlights that nine failure modes can occur while using a PFAS. Among them, the lanyard web failure has the highest RPN. However, experts believe that detecting a failure in metal parts of PFAS is more challenging, so more training and awareness are needed in this regard.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

The authors would like to thank Abadan University of Medical Sciences for financial support (Grant number: 1400U-1348).

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