Design Software Failure Mode and Effect Analysis using Fuzzy TOPSIS Based on Fuzzy Entropy

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Abstract: *One of the key pillars of any operating system is its proper software performance. Software failure can have dangerous effects and consequences and can lead to adverse and undesirable events in the design or use phases. The goal of this study is to identify and evaluate the most significant software risks based on the FMEA indices with respect to reduce the risk level by means of experts' opinions. To this end, TOPSIS as one of the most applicable methods of prioritizing and ordering the significance of events has been used. Since uncertainty in the data is inevitable, the entropy principle has been applied with the help of fuzzy theory to overcome this problem to weigh the specified indices. The applicability and effectiveness of the proposed approach is validated through a real case study risk analysis of an Air/Space software system. The results show that the proposed approach is valid and can provide valuable and effective information in assisting risk management decision making of our software system that is in the early stages of software life cycle. After obtaining the events and assessing their risk using the existing method, finally, suggestions are given to reduce the risk of the event with a higher risk rating.*

Keywords: *Expert Opinion; Fuzzy TOPSIS; Fuzzy Entropy; Risk Assessment; Software FMEA.*

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I. INTRODUCTION

Design and produce a reliable and safe system is one of the essential characters in the aerospace industry and other advanced systems[1]. System engineers define reliability and safety requirements to achieve a system at a world-class level[2]. This system should work in various conditions and keeps its performance at an acceptable level. With the ever-increased high requirement of reliability and safety for critical and essential systems, accurately assessing the pending failure of a system has become an active research area over the past decades. Several techniques and tools have been developed to achieve a reliable system[3]. Some techniques focus on design steps; some work on manufacturing, and many tools have been developed for maintenance management. A few techniques have been emerged to handle the system life cycle.

FMEA is a technique that can be used throughout the software life cycle is FMEA. Failure mode and effects analysis (FMEA) is an accessible and useful approach applied to Identify potential failure modes of system components means determining the causes of their impact assessment on system performance and eventually specifying the approaches reducing the chances of occurrence and outcomes as well as increasing the ability to detect failure modes[4, 5]. The FMEA widely used early in the design process of products is usually known as the Design-FMEA (DFMEA), which is implemented by using various approaches. Design-FMEA can help the designers to know the effects of the failure mode of product reliability and to determine the priority of design improvement [6].

FMEA is a risk assessment methodology that is not evaluated solely based on personal opinion. Therefore, it is difficult to extract the actual value of each of the risk factors according to group opinion [7]. To overcome the above limitations, various evaluation methods are used, including prioritization based on similarity to ideal solution (TOPSIS), analytic hierarchy process (AHP), data envelopment analysis (DEA), decision making trial and evaluation laboratory (DEMATEL), and hybrid methods.

FMEA applies the Risk Priority Number (RPN) to calculate the risk of different system failure modes. RPN is the multiplication product of three risk factors: occurrence probability (O), the severity of outcome (S), and detection capability (D). Evidently, the higher the RPN value, the higher the risk associated with relevant failure mode. Despite its widespread use, the FMEA method has significant flaws that restrict the use of this technique, mainly when it is used for criticality in the calculation of RPNs. Traditional FMEA restrictions can be summarized as follows:

The relative importance of S, O, and D parameters is not considered in RPN calculation, and they are assumed to have equal weights. However, this can cause limitations in real applications. While the nature of developed risks is different, combining different risk factors can lead to the same RPNs. Correct determination of risk factors (D, O, S) is often a problem. FMEA team members may have different assessments for similar risk factors, some of which could be inaccurate, insecure, and incomplete and be caused by time constraints, lack of experience, and inadequate data. The RPN calculation formula is uncertain and lacks a strong scientific foundation. In other words, there is no particular logic explaining the multiplication of O, S, and D for calculating RPN. S, D, and O risk factors are evaluated based on hybrid discrete scales. This is while using multiplication operations for sequential scales is meaningless. Therefore, the results are not only meaningless but also misleading [8].

This article provides a way to assess software risk in the early stages of software development (the conceptual phase and requirements analysis phase). For this purpose, The paper presents a multi-factor decision-making approach for prioritizing failure modes as an alternative to the traditional approach of failure mode and effect analysis (FMEA) [9]. The fuzzy approach based on the technique for order performance by similarity to ideal solution (TOPSIS) to choose an optimal information system in a fuzzy environment where the data are often incomplete or not so deterministic. The priority ranking is formulated based on six parameters (failure occurrence, non-detection, maintainability, spare parts, economical safety, and economic cost). The Shannon's entropy concept has been used for assigning actual weights to maintenance parameters [10-14].

To evaluate the proposed method, it was applied to the Launch Abort System (LAS). A space vehicle LAS with functional dependencies among the elements. This system consists of two main subsystems which include the Emergency Detection System (EDS) as a module of the air/space vehicle system and the Launch Escape System (LES). EDS is used for detecting the abnormal and emergency conditions in a flying vehicle that designed to treat mechanical and electrical failures in each of the propulsion, electrical, and a control portion.

In this paper, after identifying the software failure modes using DFMEA and system hierarchy, the risk priority Number (RPN) of these scenarios was calculated by Fuzzy TOPSIS based Fuzzy Entropy. The rest of this paper is organized as follows. After the introduction, research background is presented in section 2, the proposed approach in the part 3 is explained in detail and step by step. In section 4, the proposed fuzzy approach, which includes fuzzy RPN, fuzzy entropy, and the TOPSIS fuzzy method, is examined in detail. In the section 5, the proposed method is applied step by step on a real case study of the air/space system and the results are shown. Finally, the conclusion is made in the section 6.

II. Research Background

FMEA goes back to the late 1940s. A US military manual entitled ‘Procedure for performing a failure mode, effects, and analysis’ was first published in 1949. Then, it was adopted by NASA, especially during the Apollo mission project in the early 1960s. In 1974, the US DoD (Department of Defense) extensively promoted the use of FMEA and formalized the technique under the MIL-STD 1629. After that, the Ford Motor Company promoted the use of FMEA in 1977 [15].

In the past years, various methods have been used to handle the uncertainty of assessment information given by FMEA team members. For example, Ilangkumaran et al. An FMEA framework for group evaluation have been developed using fuzzy analytic hierarchy process (AHP) to assess the risk of recovering a boiler in a paper- manufacturing unit [10, 16, 17]. Liu et al. presented a fuzzy risk assessment model for deciding the risk orders of failure modes using the VIKOR method to address some of the traditional FMEA flaws[18]. Liu et al. use a hybrid risk assessment model that takes advantage of a mean weighted fuzzy DEMETEL to prioritize failure modes [19, 20].

Liu et al. developed a comprehensive, prioritized risk approach using fuzzy Mooltimorato decide how to rank the risk scenarios [19]. On the other hand, Braglia et al. suggested a new rational model based on fuzzy TOPSIS to offer correct prioritization of detected failure modes [21].

Kai et al. [6] proposed a perceptual computing model based on interval type-2 fuzzy group decision-making for FMEA. Wang et al. [23] proposed a hybrid interval-valued intuitionistic fuzzy (IVIF) MCDM approach that combines COPRAS (Complex Proportional Assessment) and ANP for FMEA.

EA. Zhao et al. [26] developed an integrated method based on IVIF continuous weighted entropy and IVIF MULTIMOORA (Multi-Objective Optimization by Ratio Analysis plus the full multiplicative) for FMEA. Moreover, Liu et al. [24] combined the IVIF MABAC (Multi Attributive Border Approximation area Comparison) and mathematical programming model to derive the risk priorities of failure modes with incomplete weight information of risk factors. Huang et al.[5]proposed a novel FMEA model based on linguistic distribution assessments and TODIM (an acronym in Portuguese of interactive and MCDM), in which a combination structure was established to consider the subjective and objective weights of risk factors. Tian et al.[29]developed a comprehensive fuzzy MCDM approach for FMEA by combining fuzzy best-worst method (BWM) and relative entropy (RE) to formulate a feasible and effective risk priority ranking of failure modes. Fattahi and Khalilzadeh[30] proposed a novel fuzzy hybrid method based on fuzzy FMEA, extended fuzzy MULTIMOORA, and fuzzy AHP methods, the weights of the three factors and the weight of each failure mode are computed by the extended fuzzy AHP and fuzzy MULTIMOORA methods, respectively. Deng and Jiang[31]studied the fuzzy risk evaluation in FMEA from a perspective of multi-sensor information fusion. By considering the non-exclusiveness between the evaluations of fuzzy linguistic variables to failure modes, a novel model called D numbers is used to model the non-exclusive fuzzy evaluations. A D numbers based multi-sensor information fusion method is proposed to establish a new model for fuzzy risk evaluation in FMEA. Selim et al[32]developed a fuzzy TOPSIS and FMEA-based dynamic maintenance planning framework. Barukab et al[33]described a novel enhanced TOPSIS-based procedure for tackling multi attribute group decision making (MAGDM) issues under spherical fuzzy setting, in which the weights of both decision-makers (DMs) and criteria are totally unknown.Mangeli et al. [34] utilized a hybrid approach based on support vector machine and fuzzy inference system to decrease the effect of personal's opinions in determining the factors of the severity and occurrence. In Table1, contributions of this papers, are reviewed.

Based on the above literature review, the current methods for dealing with risk assessment information in FMEA can be mainly classified into three types, i.e., the methods based on membership functions, the linguistic, symbolic methods based on ordinal scales, and those based on linguistic 2-tuples. However, the membership function method can describe fuzziness but not randomness; the latter two methods cannot produce a clear description of either fuzziness or randomness of qualitative information. Moreover, in these articles, the vacancy of software risk assessment is felt using these decision-making methods. For this reason, this article examines this topic.

Table 1
Review Of Related Works

Authors	*Contributions*
Kai et al.	A perceptual computing model based on interval type-2 fuzzy group decision-making for FMEA.
Wang et al.	A hybrid interval-valued intuitionistic fuzzy (IVIF) MCDM approach that combines COPRAS (Complex Proportional Assessment) and ANP for FMEA.
EA. Zhao et al.	Developing an integrated method based on IVIF continuous weighted entropy and IVIF MULTIMOORA (Multi-Objective Optimization by Ratio Analysis plus the full multiplicative) for FMEA.
Moreover, Liu et al.	Combining the IVIF MABAC (Multi Attributive Border Approximation area Comparison) and mathematical programming model to derive the risk priorities of failure modes with incomplete weight information of risk factors.
Huang et al.	Proposing a novel FMEA model based on linguistic distribution assessments and TODIM (an acronym in Portuguese of interactive and MCDM), in which a combination structure was established to consider the subjective and objective weights of risk factors.
Tian et al.	developing a comprehensive fuzzy MCDM approach for FMEA by combining fuzzy best-worst method (BWM) and relative entropy (RE) to formulate a feasible and effective risk priority ranking of failure modes.
Fattahi and Khalilzadeh	proposinga novel fuzzy hybrid method based on fuzzy FMEA, extended fuzzy MULTIMOORA, and fuzzy AHP methods, the weights of the three factors and the weight of each failure mode are computed by the extended fuzzy AHP and fuzzy MULTIMOORA methods, respectively.
Deng and Jiang	The fuzzy risk evaluation in FMEA from a perspective of multi-sensor information fusion. By considering the non-exclusiveness between the evaluations of fuzzy linguistic variables to failure modes, a novel model called D numbers is used to model the non-exclusive fuzzy evaluations. A D numbers based multi-sensor information fusion method is proposed to establish a new model for fuzzy risk evaluation in FMEA.
Selim et al.	A fuzzy TOPSIS and FMEA-based dynamic maintenance planning framework.
Barukab et al.	A novel enhanced TOPSIS-based procedure for tackling multi attribute group decision making (MAGDM) issues under spherical fuzzy setting, in which the weights of both decision-makers (DMs) and criteria are totally unknown.
Mangeli et al.	Utilizing a hybrid approach based on support vector machine and fuzzy inference system to decrease the effect of personal's opinions in determining the factors of the severity and occurrence.
Ilangkumaran et al.	An FMEA framework for group evaluation have been developed using fuzzy analytic hierarchy process (AHP) to assess the risk of recovering a boiler in a paper- manufacturing unit
Liu et al.	A fuzzy risk assessment model for deciding the risk orders of failure modes using the VIKOR method to address some of the traditional FMEA flaws
Liu et al.	using a hybrid risk assessment model that takes advantage of a mean weighted fuzzy DEMETEL to prioritize failure modes
Liu et al.	developing a comprehensive, prioritized risk approach using fuzzy Mooltimorato decide how to rank the risk scenarios

III. BASED ON PROPOSED APPROACH

The present study is concerned with software risks in a space vehicle Launch Abort System (LAS). Design FMEA has been used to identify failures that may occur in this system through software. Afterward, to perform TOPSIS and develop the decision matrix, the indicators used in the FMEA method were ranked by experts, and the decision matrix was presented based on them for identified risks. The entropy method was used to weigh indicators in this research. Finally, after performing the TOPSIS steps, the risks were prioritized, and the most important and most effective ones were identified. The workflow is shown in **Fig. 1.**

DFMEA is a methodical approach used for identifying potential risks introduced in a new or changed design of a product/service. The Design FMEA initially identifies design functions, failure modes, and their effects with corresponding severity ranking/danger of the effect. Then, causes and their mechanisms of the failure mode are identified.

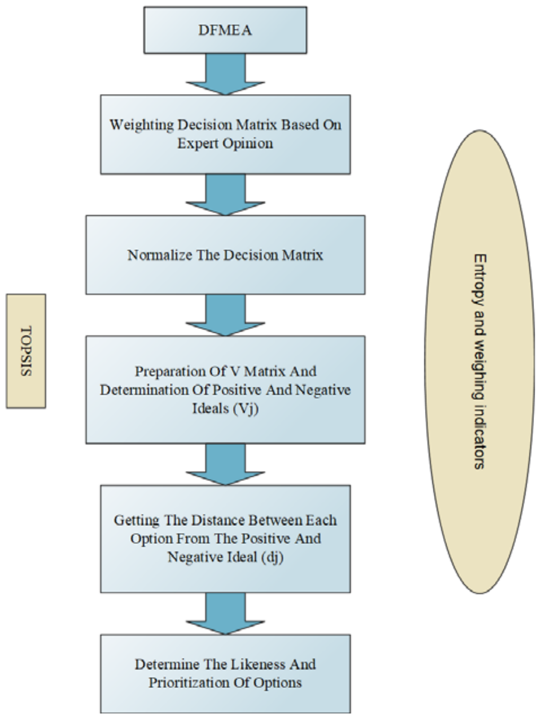

Fig. 1. Proposed Fuzzy TOPSIS-Entropy Workflow

1. Software Design FMEA

High probability causes, indicated by the occurrence ranking, may drive action to prevent or reduce the cause's impact on the failure mode. The detection ranking highlights the ability of specific tests to confirm the failure mode/ causes are eliminated. The DFMEA also tracks improvements through Risk Priority Number (RPN) reductions. By comparing the before and after RPN, a history of improvement and risk mitigation can be chronicled [22]. SFMEA Design and SFMEA procedures are shown in **Fig.2** and **Fig. 3.**

2. FMEA Block Diagram

An FMEA Block Diagram is a graphical representation of the whole system or design that represents the limits of FMEA analysis. User interfaces between items and other information can help display the FMEA domain. FMEA Block Diagram identifies a representation of relationships and dependencies between components, including physical connection, material exchange, energy transfer, and data exchange. In systemic FMEA mode, FMEA Block Diagram should clearly show the interfaces between the system and users among various subsystems. For a sub-system FMEA, the FMEA Block Diagram should indicate the interfaces between several components [23].

3. FMEA Interface Matrix

FMEA Interface Matrix is a table representing subsystems or components on both dimensions of the graph. The table shows that user interfaces should be assessed in terms of interface type and analysis. There are four types of user interfaces: physical communication, material exchange, energy transfer, and data exchange. When failures comprise 50% or more of failure scenarios, it is imperative that each FMEA accurately examines the user interfaces between subsystems and components [6].

4. Gathering Information of FMEA

Gathering all the documentation and event information is one of the essential steps in preparing FMEA. If this step is not appropriately performed, FMEA encounters a series of duties related to a lack of information and will cause a loss of time. Several essential measures taken at this step are as follows: Bill of material (BOM), Legal and regulatory, Past FMEA, Field history, etc. BOM is known as the system history, which should be available to the FMEA team. Legal and regulatory cases related to all applicable laws as well as issues and documentation, should be accessible to the FMEA team. Field history also involves an attempt to prevent past failures [6].

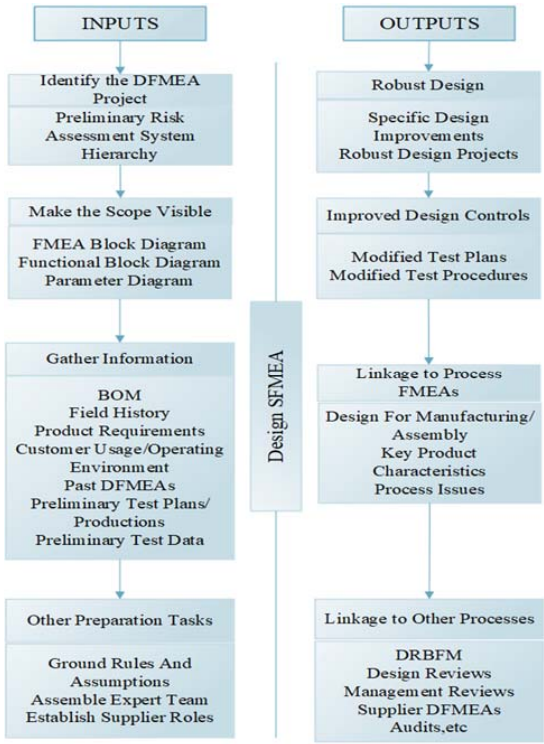

Fig. 2. Design SFMEA Overview

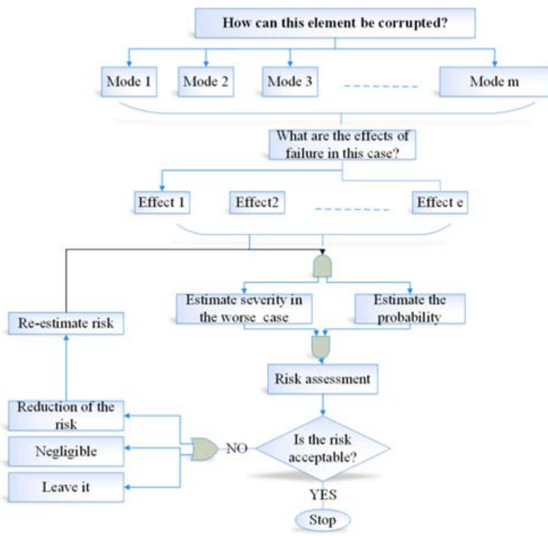

Fig. 3. SFMEA Process

5. Risk Priority Number (RPN)

RPN calculation is required after identifying failure modes in a system and the need for their prioritization. RPN is a risk assessment method in FMEA. In this method, three factors of Occurrence (O), Severity (S), and Detection (D) are used, the product of which is equal to RPN given the independence of these factors. These three factors are traditionally divided into ten levels, which are detailed in some works, such as [24]. In this regard, the RPN value can be evaluated as:

$$RPN = D \times S \times O \quad (1)$$

II. PROPOSED FUZZY APPROACH

In order to express the fuzzy representation of the proposed method, the following subsections have been prepared.

1. Fuzzy RPN

Failure Mode and Effects Analysis (FMEA) is an analysis method of potential failure in products or processes, which is used in many quality management systems. FMEA is a crucial issue in determining the risk priorities of failure scenarios. In the classical FMEA method, the risk priorities of failure modes are determined by risk priority numbers (RPNs) through multiplying risk factors such as severity (S), occurrence (O), and the probability of detection (D). However, definite RPNs have been criticized by many scholars and experts because of their shortcomings and disadvantages, so that significant efforts have been made in FMEA literature to address these shortcomings [20, 25]. In this paper, we used FMEA, which is a powerful tool for risk evaluation. In traditional FMEA, risk priority number (RPN), has been calculated by multiplication of three criteria, the severities of the traditional FMEA, in this paper, instead of calculating RPN-prioritizes risk factors with fuzzy TOPSIS.

2. Fuzzy Entropy

Shannon entropy is a measure of uncertainty in information formulated in terms of probability theory. It is well suited for measuring the relative contrast intensities of criteria to represent the average intrinsic information transmitted to the decision-maker. Therefore, this concept has been highlighted by many researchers for deciding the actual weights of criteria [20].In this study, the weight of criteria was determined based on Shannon entropy method following formulas (2) and (3):

$$E_j = -\sum_{i=1}^{m} Pij \ln(Pij) \quad (2)$$

$$Pij = \frac{aij}{\sum_{i=1}^{m} aij} \quad (3)$$

By determining entropy in each index, the dispersion of values in each *j* index was obtained by:

$$dj = 1 - E \quad (4)$$

Finally, the weights of indices were calculated using Eq. (5).

$$Wj = \frac{dj}{\sum_{j=1}^{n} dj} \quad (5)$$

In this research, the weights of criteria were calculated based on the Shannon entropy method.

3. Fuzzy TOPSIS Method

TOPSIS is one of the developed classic multi-criteria decision-making methods[26, 27]. It is based on the concept that the chosen alternative should have the shortest distance from the positive ideal solution (PIS) and the farthest from the negative ideal solution (NIS). In the traditional formulation of the TOP¬SIS method, personal judges are represented with crisp values. Nevertheless, in reality, it is not always possible. A real lift Measurement by using crisp values is not always possible. A better approach may be to use linguistic value rather than a crisp value. Fuzzy Set theory can be used to present linguistic values for this reason; the fuzzy TOPSIS method is very suitable for salving real-life application problems under a fuzzy environment [10].

Step 1: Choose the linguistic rating values for the alternative concerning criteria.

Let us assume there are m possible alternatives called A= $\{A_1, A_2, \ldots, A_m\}$ which are to be evaluated against the criteria, C=$\{C_1, C_2, \ldots, C_n)$ the criteria weights are denoted by wj (j=1,2,…,n). The performance ratings of each expert D_k(k=1,2,...,K) for each alternative A_i(i=1,2,...,m) concerning criteria, C_j(j=1,2....,n) is denoted by

$\tilde{R}_K = \tilde{X}_{ijk}(i = 1.2 \dots m; j = 1.2 \dots . n; C_j(j = 1.2 \dots n)$ membership function $\mu\tilde{R}k(x)$.The scale used for solutions rating is given in **Table 2**.

Table 2
Linguistic variables for solutions ratings

Linguistic variables	Corresponding TFN
Very poor	(1,1,3)
Poor	(1,3,5)
Medium	(3, 5,7)
Good	(5,7,9)
Very good	(7,9,11)

Step2: Calculate fuzzy aggregate ratings for the alternatives

If the fuzzy ratings of all experts are described as TFN $\tilde{R}_K = (ak, bk, ck)\ k = 1.2 \dots K)$ then the aggregated fuzzy rating is given by $\tilde{R} = (a, b, c)k = 1,2, \dots$ where

$$a=min_k\ \{a_k\},b=\frac{1}{k}\sum_{k=1}^{k} b_k, c = max_k\ \{c_k\} \quad (6)$$

If the fuzzy rating or the k_{th} decision-maker are $\tilde{X}_{IJK}=(a_{ijk}, b_{ijk}, c_{ijk})$, i=1,2,…,m , j=1,2,…,n then the aggregated fuzzy rating $\tilde{X}_{ij}$ of alternatives concerning each criterion are given by $\tilde{X}_{ij}\ (a_{ij}, b_{ij}, c_{ij})$, where

$$a_{ij}=min_k\{a_k\}; \text{b}=\frac{1}{k}\sum_{k=1}^{k} b_{ijk};\ c = max_k\ \{c_k\} \quad (7)$$

Step 3: Construct the fuzzy decision matrix. The fuzzy decision matrix for the alternative$\langle\tilde{D}\rangle$ is constructed as follows: $C_1C_2C_n$

$$\tilde{D} = \begin{array}{c} A_1 \\ A_2 \\ \\ \\ A_3 \end{array} \begin{bmatrix} \tilde{X}_{11} & \tilde{X}_{12} & '' & '' & \tilde{X}_{11} \\ \tilde{X}_{21} & \tilde{X}_{22} & '' & '' & \tilde{X}_{2n} \\ '' & '' & '' & '' & '' \\ '' & '' & '' & '' & '' \\ \tilde{X}_{m1} & \tilde{X}_{m2} & '' & '' & \tilde{X}_{mn} \end{bmatrix} \quad i = 1,2, \dots, m; j = 1,2, \dots, n \quad (8)$$

Step 4: Construct the Normalize fuzzy decision matrix

The raw data are normalized using linear scale transformation to bring the various criteria scales into a comparable scale. The normalized fuzzy decision matrix R ˜ is given by:

$$\tilde{R} = [\text{r}_{\text{ij}}]m_\times n, i = 1,2, \dots m;\ j = 1,2, \dots . n, \quad (9)$$

Where

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{C^*{}_j}, \frac{b_{ij}}{C^*{}_j}, \frac{c_{ij}}{C^*{}_j}\right) and\ c_j^* = max_i c_{ij}(\text{benefit criteria})$$
$$\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right) and\ a_j^- = max_i a_{ij}(\text{benefit criteria}) \quad (10)$$

Step 5: Construct the weighted normalized matrix

The weighted normalized matrix $\tilde{v}$ for criteria is computed by multiplying the weights (w_j) of evaluation criteria with the normalized fuzzy decision matrix $\tilde{r}_{ij}$

$$\tilde{V} = [\tilde{\text{v}}_{\text{ij}}]m_\times n, i = 1,2, \dots, m;\ j = 1,2, \dots n \quad (11)$$

Where, $\tilde{v}_{ij} = w_j$. Note that $\tilde{v}_{ij} isaTFN$ represented by $(\tilde{a}_{ijk,}\tilde{b}_{ijk,}\tilde{c}_{ijk})$

Step 6: Determine the fuzzy ideal solution (FPIS) and fuzzy negative ideal solution (FNIS)

The FPIS and FNIS of the alternatives are computed as follow:

$$A^* = \{\tilde{V}_1^*, \tilde{V}_2^*, \dots . \tilde{V}_n^*\} where \tilde{V}_j^* = \{\tilde{c}_j^*, \tilde{c}_j^*, \dots . c_j^*) and \tilde{c}_1 = max_i\{\tilde{c}_{ij}\} \quad (12)$$

$$A^- = \{\tilde{V}_1^-, \tilde{V}_2^-, \dots . \tilde{V}_n^-\} where \tilde{V}_j^- = \{\tilde{a}_j^-, \tilde{a}_j^-, \dots . \tilde{a}_j^-) and \tilde{a}_1 = min_i\{\tilde{a}_{ij}\};\ \forall \text{i=1,2,…,m; j=1,2,…n} \quad (13)$$

Step7: Calculate the distance of each alternative from FPIS and FNIS, The distance (d_i^+, d_i^-) ofeach weighted alterative i=1,2,..,m

from the FPIS and the FNIS is computed as follows:

$$d_i^+ = \sum_{j=1}^{n} dv(\tilde{v}_{ij}, \tilde{v}_j), i = 1,2, \dots, m \tag{14}$$

$$d_i^- = \sum_{j=1}^{n} dv(\tilde{v}_{ij}, \tilde{v}_j), i = 1,2, \dots, m \tag{15}$$

STEP 8: Calculate the closeness coefficient (CCi) of each alternative. The closeness coefficient CCi represents the distances to the fuzzy positive ideal solution (A*) and the fuzzy negative ideal solution (A-) simultaneously. The closeness coefficient of each alternative is calculated as:

$$CC_i = \frac{d_i^-}{d_i^- + d_i^+} \tag{16}$$

Step 9: Rank the alternatives

In step 9, the different alternatives are ranked according to the closeness coefficient (CCi) in decreasing order.

III. IMPLEMENTATION ON AIR/SPACE APPLICATION EXAMPLE

We applied the results of our approach to a part of a real CPS known as Launch Abort System (LAS), the architecture of which is shown in **Fig. 4.** As shown, the tree construction of a space vehicle Launch Abort System (LAS) with functional dependencies among the elements. This system consists of two main subsystems which include the Emergency Detection System (EDS) as a module of the air/space vehicle system and the Launch Escape System (LES). EDS is used for detecting the abnormal and emergency conditions in flying vehicle that designed to treat mechanical and electrical failures in each of the propulsion, electrical and control portion. While the EDS system detects an unusual and faulty condition in one of the main parts of the LES system (i.e., electrical power failure, structural failure, guidance, and control faulty, etc.), it sensed and transmitted through a signal to trigger the FDEP gate of LES system. Generally, the launch escape system consists of: launch escape motor, pitch control motor, tower jettison motor, landing parachute, and the Master Event Sequencing Controller Subsystems (MESC). According to the launch and flight regimes and based on the flight altitude, the operation time of each motor-based subsystem is varied. A master event sequence controller on LES is an intelligent standalone microprocessor-based system, which monitors external inputs and controls the time and sequence of the event's changes. MESCs are therefore utilized as a prioritizing tool to dictate the occurrence events. Fig. 5 is a demonstration of system hierarchy for the all-terrain LAS (showing three of the subsystems down to components). Accordingly, Fig. 6 is the example of system FMEA Block Diagrams from the all-space launch abort system FMEAs. In this kind of system FMEA demonstration, there are missing elements to the FMEA Block Diagram at the system level in comparison with the system hierarchy components. As shown, the system parts or subsystems can take various forms of interface. In the LAS system, there are four primary types of interfaces: a mechanical connection, a data exchange, energy transfer, and material exchange. Since the interface scan contains up to 50% or more of the total failure modes, it is essential that any FMEA carefully consider the interfaces between subsystems and components in addition to the content of the subsystems and components themselves. The interface matrix of the launch abort system FMEA block diagram based on the extracted system FMEA block diagram in **Fig. 5** is tabulated.

After displaying the system hierarchy, the system FMEA block diagram, the LAS Interface Matrix, which was used to obtain Software DFMEA. Based on the type of connections between the elements of the system, we see the failure of our data study case study, which was obtained as a result of the FMEA design analysis (Table3).

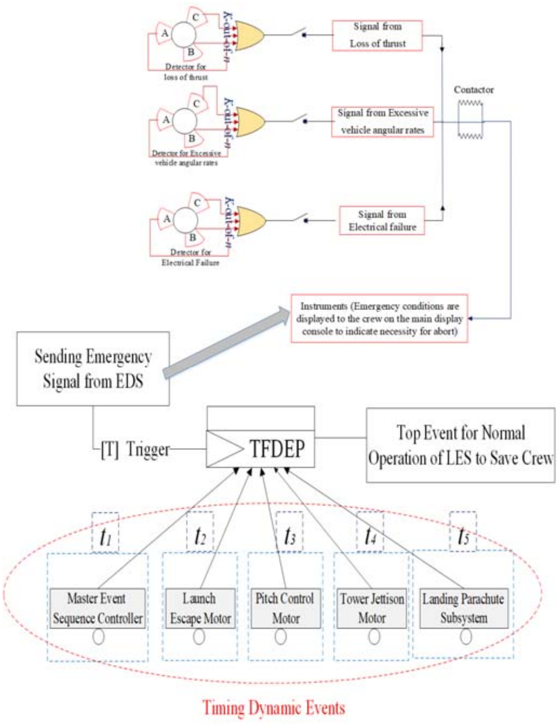

Fig. 4. Tree Construction With The Dependency Of LAS

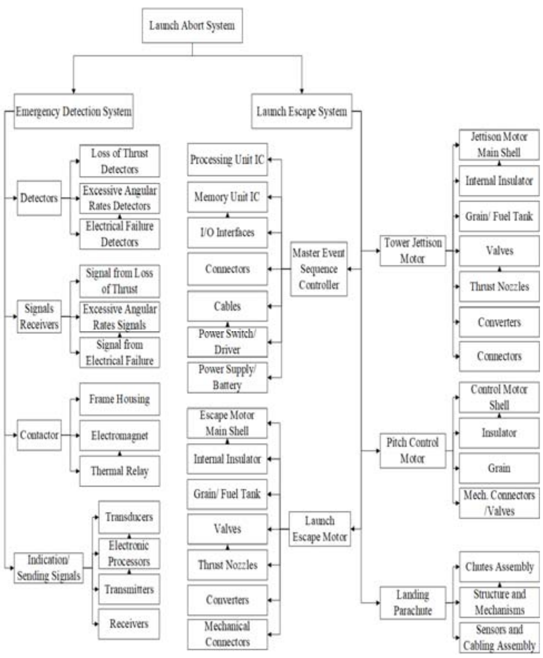

Fig. 5. Demonstration Of System Hierarchy For Launch Abort System

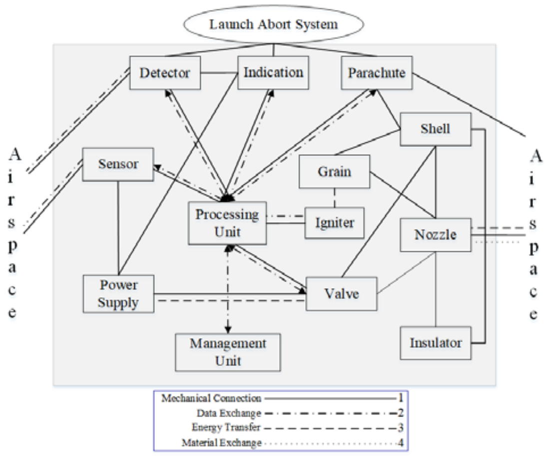

Fig. 6. System FMEA Block Diagram All-Space Of LAS

The linguistic variables which are assigned for severity, occurrence, and detection by experts should be converted to a fuzzy format. Also, the weights of the criteria should change to the fuzzy format. The resulting fuzzy numbers act as data for entering the fuzzy TOPSIS technique.

Table 3
Failures Of Data Exchange (Software) In The Launch Abort System

Event name	Event
X1	Failure in sending data from the sensor to the processing unit
X2	Failure in receiving data from the processing unit to sensor
X3	Failure in sending data from the detector to processing unit
X4	Failure in receiving data from processing unit to detector
X5	Failure in sending data from Indication to processing unit
X6	Failure in receiving data from processing unit to indication
X7	Failure in sending data from parachute to processing unit
X8	Failure in receiving data from processing unit to parachute
X9	Failure in sending data from valve to processing unit
X10	Failure in receiving data from processing unit to valve
X11	Failure in sending data from management to processing unit
X12	Failure in receiving data from processing to management unit
X13	Failure in receiving data from the detector
X14	Failure in receiving data from Airspace (sensor)
X15	Failure in sending data from processing unit to Igniter
X16	Failure in receiving data from Igniter to processing unit

Experts used ten-scale linguistic variables for evaluating the risk factors and their relative importance significances. They chose one linguistic variable based on their experience and insight; then, linguistic variables were converted into fuzzy triangular numbers, which are shown in **Table 4**.

According to the **Table 4**, linguistic terms converted and aggregated to the triangular fuzzy number and the decision matrix (Based on the evaluations of five FMEA team members about the importance of fuzzy aggregate ratings of 16 risk Factors) was constructed as **Table 5**. To obtain the weights of Occurrence, Severity, and Detection criteria, the entropy method described previously, and the results are presented in the following tables.

Table 4
Relation Between Linguistic Variables And Fuzzy Triangular Numbers

Triangular fuzzy numbers		Linguistic variables
(0,0,1)	NI	Nearly impossible
(0,1,2)	R	Remote
(1,2,3)	L	Low
(2,3,4)	RL	Relatively low
(3,4,5)	M	Moderate
(4,5,6)	MH	Moderate high
(5,6,7)	H	High
(6,7,8)	MJ	Major
(7,8,9)	VH	Very high
(8,9,10)	EH	Extremely high

`Table 5
Assessment Information On Four Risk Factor In Three Criteria By Five Experts

Risk factor	Occurrence	Severity	Detection
X1	(1.4 2.4 3.4)	(6 7 8)	(7 8 9)
X2	(1.2 2.2 3.2)	(5.4 6.4 7.4)	(3.4 4.4 5.4)
X3	(1.6 2.6 3.6)	(5.8 6.8 7.8)	(3.4 4.4 5.4)
X4	(0.4 1.2 2.2)	(5 6 7)	(2.6 3.6 4.6)
X5	(2.6 3.6 4.6)	(3.2 4.2 5.2)	(5.8 6.8 7.8)
X6	(0.6 1.6 2.6)	(5.6 6.6 7.6)	(6.4 7.4 8.4)
X7	(1.8 2.8 3.8)	(6.6 7.6 8.6)	(3 4 5)
X8	(0.6 1.6 2.6)	(5.8 6.8 7.8)	(6.8 7.8 8.8)
X9	(1.4 2.4 3.4)	(5.46.47.4)	(7 8 9)
X10	(2.6 3.6 4.6)	(4 5 6)	(5 6 7)
X11	(1.6 2.6 3.6)	(4.6 5.6 6.6)	(5.2 6.2 7.2)
X12	(0.8 1.8 2.8)	(4.2 5.2 6.2)	(4.2 5.2 6.2)
X13	(3.6 4.6 5.6)	(5.4 6.4 7.4)	(3.6 4.6 5.6)
X14	(1.2 2.2 3.2)	(4.8 5.8 6.8)	(7 8 9)
X15	(0.6 1.6 2.6)	(3.8 4.8 5.8)	(4.2 5.2 6.2)
X16	(1.8 2.8 3.8)	(5.4 6.4 7.4)	(3 4 5)

Weights of Occurrence, Severity, and Detection were calculated using entropy, which is presented in **Table 6**.

Table 6
Weights Of The Criteria

Criteria	Fuzzy weights
Occurrence	(0.397, 0.397, 0.397)
Severity	(0.33 ,0.33 ,0.33)
Detection	(0.253, 0.253, 0.253)

TOPSIS fuzzy based on the Expert's values was performed, as shown in Tables 7-10, and the rankings are presented in Table 10.

Table 9
Idele+ And Idele-

Idele+	0.397	0.33	0.253
Idele-	0.028357	0.122791	0.073089

Table10
Closeness Coefficient (CCi) And final Ranking

Risk factor	d_i^+	d_i^-	(CC_i)	Rank
X1	0.670867	0.103079	0.033792	16
X2	0.580332	0.203197	0.065799	4
X3	0.60555	0.172686	0.056299	9
X4	0.469936	0.412482	0.1186	1
X5	0.592083	0.19727	0.063408	6
X6	0.60223	0.207959	0.065125	5
X7	0.614281	0.167537	0.05437	10
X8	0.611636	0.198538	0.062176	8
X9	0.656592	0.117852	0.03861	15
X10	0.611302	0.163836	0.053627	11
X11	0.615614	0.159268	0.052149	12
X12	0.540184	0.257493	0.081902	3
X13	0.633724	0.138999	0.04564	14
X14	0.630987	0.147814	0.048155	13
X15	0.505791	0.315106	0.097392	2
X16	0.587936	0.194025	0.062955	7

As can be seen in **Table 10**, failure in receiving data from the processing unit to the detector (x4) and failure in sending data from sensor to processing unit (x1) are the most and least risky events, respectively. To reduce the risk, the following measures are recommended:

1. Risk Reduction

In **Fig. 7**, a simple presentation of the procedure of software that is applied to send data from the sensor and receive data, as well as the communication path between them, have been presented. All of our software failures have occurred in the type of data exchange and the receipt and transmission of information, in order to improve the performance and promote the reliability of data paths, the data transfer paths have increased to two paths, and to prevent

Table 7
Normalized Fuzzy Decision Matrix

Criterion															
Risk factor	**Expert#1**			**Expert#2**			**Expert#3**			**Expert#4**			**Expert#5**		
	Occur.	Severity	Detect	Occur.	Severity	Detect	Occur.	Severity	Detect	Occur.	Severity	Detect	Occur.	Severity	Detect
X1	RL	H	VH	RL	MJ	VH	L	MJ	VH	L	EH	VH	L	H	VH
X2	R	H	MH	L	MJ	M	RL	H	MH	L	H	MH	R	MJ	RL
X3	L	EH	VH	RL	H	MJ	RL	H	H	L	MJ	MH	RL	H	VH
X4	R	H	RL	L	MJ	MH	L	H	RL	NI	H	M	R	MH	RL
X5	M	M	MJ	RL	MH	VH	M	M	H	RL	M	MJ	M	M	H
X6	R	H	MJ	L	H	MJ	R	MJ	MJ	L	MJ	VH	L	MJ	VH
X7	M	VH	M	L	MJ	M	RL	VH	M	RL	MJ	M	L	VH	M
X8	R	H	VH	R	MJ	VH	L	VH	MJ	L	MJ	VH	L	H	VH
X9	L	H	VH	L	EH	VH	L	M	VH	RL	M	VH	RL	H	VH
X_{10}	RL	H	VH	L	L	H	VH	L	M	RL	H	M	L	EH	VH
X_{11}	RL	H	VH	L	M	MH	RL	H	H	RL	H	M	L	H	VH
X_{12}	R	M	RL	RL	H	MH	L	H	MH	L	M	MH	R	H	RL
X_{13}	H	H	M	M	VH	MH	MH	H	MH	M	M	M	M	VH	MH
X_{14}	L	H	VH	RL	M	VH	L	H	VH	L	EH	VH	L	M	VH
X_{15}	L	M	MH	L	H	M	R	H	MH	L	M	VH	R	M	M
X_{16}	M	VH	M	L	VH	M	RL	M	M	RL	VH	M	L	M	M

Table 8
Weighted Normalized Fuzzy Decision Matrix

Risk factor	Occurrence	Occurrence	Occurrence	Severity	Severity	Severity	Detection	Detection	Detection
X1	0.046706	0.066167	0.113429	0.132	0.150857	0.176	0.073089	0.082225	0.093971
X2	0.049625	0.072182	0.132333	0.142703	0.165	0.195556	0.121815	0.1495	0.193471
X3	0.044111	0.061077	0.09925	0.135385	0.155294	0.182069	0.121815	0.1495	0.193471
X4	0.072182	0.132333	0.397	0.150857	0.176	0.2112	0.143	0.182722	0.253
X5	0.034522	0.044111	0.061077	0.203077	0.251429	0.33	0.084333	0.096735	0.113414
X6	0.061077	0.09925	0.264667	0.138947	0.16	0.188571	0.07831	0.088892	0.102781
X7	0.041789	0.056714	0.088222	0.122791	0.138947	0.16	0.13156	0.16445	0.219267
X8	0.061077	0.09925	0.264667	0.135385	0.155294	0.182069	0.07475	0.084333	0.096735
X9	0.046706	0.066167	0.113429	0.142703	0.165	0.195556	0.073089	0.082225	0.093971
X10	0.034522	0.044111	0.061077	0.176	0.2112	0.264	0.093971	0.109633	0.13156
X11	0.044111	0.061077	0.09925	0.16	0.188571	0.229565	0.091361	0.106097	0.1265
X12	0.056714	0.088222	0.1985	0.170323	0.203077	0.251429	0.106097	0.1265	0.156619
X13	0.028357	0.034522	0.044111	0.142703	0.165	0.195556	0.117464	0.143	0.182722
X14	0.049625	0.072182	0.132333	0.155294	0.182069	0.22	0.073089	0.082225	0.093971
X15	0.061077	0.09925	0.264667	0.182069	0.22	0.277895	0.106097	0.1265	0.156619
X16	0.041789	0.056714	0.088222	0.142703	0.165	0.195556	0.13156	0.16445	0.219267

CCF occurrence, the method of sending and communicating from two different mechanisms has been used as a redundant [28]. In later sections, the cause of the failure of all the items as mentioned above has been investigated.

To improve performance and promote reliability, data transfer paths have increased to two paths, and to prevent CCF, the method of sending and communicating from two different mechanisms is used as a redundant. In later sections, the cause of failure in all of the items, as mentioned above, has been investigated.

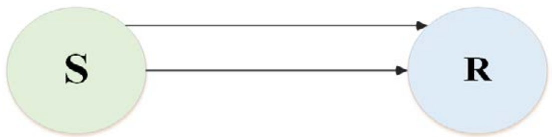

Fig. 7. General Working Procedure Of The Software

Systems that are used to reduce the error rate, when more than one of them is used in the system, are called redundant. Redundant systems fail due to two types of failures: independent and dependent. One of the most critical dependent failures in redundant systems is a common cause of failure. This type of failure leads to concomitant failure in components of the redundant system. In other words, the failure of more than two components in a redundant system, which occurs over a short period of time, is the common cause of failure. There are some factors in redundant systems that multiply the failure among the components. This widespread failure causes simultaneous failure of system components and causes problems in the whole system during the mission period. Consideration of the common cause of failure begins from the design phase and should minimize the factors causing the common failure, calculate the incidence rate of common failure cause, and include it in the assessment of reliability.

IV. CONCLUSIONS

Software plays a crucial role in critical industries so that a software failure can cause irreparable damage. DFMEA is a method for identifying potential risks introduced in a new or modified design of a product/service, and the risks can be assessed based on three criteria of severity, occurrence, and detection. In this article, first the events that caused the failure of the software system (Risk factors) of the existing case study (Launch Abort System), which is in the early stages of software development identified using the DFMEA method and the steps of extracting these events step by step We analyzed. To obtain the prioritization factors, instead of using the traditional RPN, the extracted risks prioritization factors calculated using the Fuzzy TOPSIS method. Moreover, we obtained the weights based on the Shannon entropy fuzzy method. Finally, these risk factors ranked using the existing proposed method, and high-risk events identified and strategies proposed to reduce the risk. For further research, we suggest analysis and noise detection in software systems and safety in multi-thread programming methods. Also, the maintenance policy based on risk and safety criteria can be considered in another study.

REFERENCES

1. Farsi, M. A., & Zio, E. (2019). Industry 4.0: Some challenges and opportunities for Reliability Engineering. International Journal of Reliability, Risk and Safety: Theory and Application, 2(1), 23-34.

2. Zio, E. (2016). Some challenges and opportunities in reliability engineering. IEEE Transactions on Reliability, 65(4), 1769-1782.

3. Oveisi, S., & Ravanmehr, R. (2017). Analysis of software safety and reliability methods in cyber physical systems. International journal of critical infrastructures, 13(1), 1-15.

4. Oveisi, S., Farsi, M. A., Nadjafi, M., & Moeini, A., 2019. A New Approach to Promote Safety in the Software Life Cycle. Journal of Computer & Robotics, 12(1), 77-91.

5. Narayanagounder, S., & Gurusami, K.,2009. A new approach for prioritization of failure modes in design FMEA using ANOVA. World Academy of Science, Engineering and Technology, 49(524-31).

6. Stamatis, D. H. (2003). Failure mode and effect analysis: FMEA from theory to execution. Quality Press.

7. Patil, S. K., & Kant, R. (2014). A fuzzy AHP-TOPSIS framework for ranking the solutions of Knowledge Management adoption in Supply Chain to overcome its barriers. Expert systems with applications, 41(2), 679-693.

8. Liu, H. C., Liu, L., Liu, N., & Mao, L. X. (2012). Risk evaluation in failure mode and effects analysis with extended VIKOR method under fuzzy environment. Expert Systems with Applications, 39(17), 12926-12934.

9. Bowles, J. B., & Peláez, C. E. (1995). Fuzzy logic prioritization of failures in a system failure mode, effects and criticality analysis. Reliability Engineering & System Safety, 50(2), 203-213.

10. Kutlu, A. C., & Ekmekçioğlu, M. (2012). Fuzzy failure modes and effects analysis by using fuzzy TOPSIS-based fuzzy AHP. Expert Systems with Applications, 39(1), 61-67.

11. Liu, H. C., Liu, L., & Liu, N. (2013). Risk evaluation approaches in failure mode and effects analysis: A literature review. Expert systems with applications, 40(2), 828-838.

12. Yazdani, M., Alidoosti, A., & Zavadskas, E. K. (2011). Risk analysis of critical infrastructures using fuzzy COPRAS. Economic research-Ekonomska istraživanja, 24(4), 27-40.

13. Zhang, F., & Zhang, W. (2015, August). Failure modes and effects analysis based on fuzzy TOPSIS. In 2015 IEEE International Conference on Grey Systems and Intelligent Services (GSIS) (pp. 588-593). IEEE.

14. CAO, W., NIU, C., & FAN, Y. (2013). A Grey Relational Projection Method for Multi-attribute Decision Making Based on Interval-valued Intuitionistic Trapezoidal Fuzzy Number. Journal of Taiyuan University of Technology, 2(026), 3467-3477.

15. Oveisi, S., & Farsi, M. A. (2018). Software safety analysis with UML-Based SRBD and fuzzy VIKOR-Based FMEA. International Journal of Reliability, Risk and Safety: Theory and Application, 1(1), 35-44.

16. Abdelgawad, M., & Fayek, A. R. (2010). Risk management in the construction industry using combined fuzzy FMEA and fuzzy AHP. Journal of Construction Engineering and Management, 136(9), 1028-1036.

17. Ilangkumaran, M., Shanmugam, P., Sakthivel, G., & Visagavel, K. (2014). Failure mode and effect analysis using fuzzy analytic hierarchy process. International Journal of Productivity and Quality Management, 14(3), 296-313.

18. Liu, H. C., You, J. X., You, X. Y., & Shan, M. M. (2015). A novel approach for failure mode and effects analysis using combination weighting and fuzzy VIKOR method. Applied soft computing, 28, 579-588.

19. Liu, H. C., Fan, X. J., Li, P., & Chen, Y. Z. (2014). Evaluating the risk of failure modes with extended MULTIMOORA method under fuzzy environment. Engineering Applications of Artificial Intelligence, 34, 168-177.

20. Liu, H. C., You, J. X., Lin, Q. L., & Li, H. (2015). Risk assessment in system FMEA combining fuzzy weighted average with fuzzy decision-making trial and evaluation laboratory. International Journal of Computer Integrated Manufacturing, 28(7), 701-714.

21. Braglia, M., Frosolini, M., & Montanari, R. (2003). Fuzzy TOPSIS approach for failure mode, effects and criticality analysis. Quality and reliability engineering international, 19(5), 425-443.

22. Yang, J., Huang, H. Z., He, L. P., Zhu, S. P., & Wen, D. (2011). Risk evaluation in failure mode and effects analysis of aircraft turbine rotor blades using Dempster–Shafer evidence theory under uncertainty. Engineering Failure Analysis, 18(8), 2084-2092.

23. Oveisi, S., & Ravanmehr, R. (2017). SFTA-Based Approach for Safety/Reliability Analysis of Operational Use-Cases in Cyber-Physical Systems. Journal of Computing and Information Science in Engineering, 17(3).

24. Chang, C. L., Wei, C. C., & Lee, Y. H. (1999). Failure mode and effects analysis using fuzzy method and grey theory. Kybernetes.

25. Wang, Y. M., Chin, K. S., Poon, G. K. K., & Yang, J. B. (2009). Risk evaluation in failure mode and effects analysis using fuzzy weighted geometric mean. Expert systems with applications, 36(2), 1195-1207.

26. Chanamool, N., & Naenna, T. (2016). Fuzzy FMEA application to improve decision-making

process in an emergency department. Applied Soft Computing, 43, 441-453.

27. Opricovic, S., & Tzeng, G. H. (2004). Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. European journal of operational research, 156(2), 445-455.

28. Zhu, P., Han, J., Liu, L., & Lombardi, F. (2015). A stochastic approach for the analysis of dynamic fault trees with spare gates under probabilistic common cause failures. IEEE Transactions on Reliability, 64(3), 878-892.

29. Tian, Z. P., Wang, J. Q., & Zhang, H. Y. (2018). An integrated approach for failure mode and effects analysis based on fuzzy best-worst, relative entropy, and VIKOR methods. Applied Soft Computing, 72, 636-646.

30. Fattahi, R., & Khalilzadeh, M. (2018). Risk evaluation using a novel hybrid method based on FMEA, extended MULTIMOORA, and AHP methods under fuzzy environment. Safety science, 102, 290-300.

31. Deng, X., & Jiang, W. (2017). Fuzzy risk evaluation in failure mode and effects analysis using a D numbers based multi-sensor information fusion method. Sensors, 17(9), 2086.

32. Selim, H., Yunusoglu, M. G., & Yılmaz Balaman, Ş., "A dynamic maintenance planning framework based on fuzzy TOPSIS and FMEA: application in an international food company, " Quality and Reliability Engineering International, 32(3), 2016, pp. 795-804.

33. Barukab, O., Abdullah, S., Ashraf, S., Arif, M., & Khan, S. A. (2019). A New Approach to Fuzzy TOPSIS Method Based on Entropy Measure under Spherical Fuzzy Information. Entropy, 21(12), 1231.

34. Mangeli, M., Shahraki, A., & Saljooghi, F. H. (2019). Improvement of risk assessment in the FMEA using nonlinear model, revised fuzzy TOPSIS, and support vector machine. International Journal of Industrial Ergonomics, 69, 209-216.

35. Chai, K. C., Jong, C. H., Tay, K. M., & Lim, C. P. (2016). A perceptual computing-based method to prioritize failure modes in failure mode and effect analysis and its application to edible bird nest farming. Applied Soft Computing, 49, 734-747.

36. Wang, L. E., Liu, H. C., & Quan, M. Y. (2016). Evaluating the risk of failure modes with a hybrid MCDM model under interval-valued intuitionistic fuzzy environments. Computers & Industrial Engineering, 102, 175-185.

37. Zhao, H., You, J. X., & Liu, H. C. (2017). Failure mode and effect analysis using MULTIMOORA method with continuous weighted entropy under interval-valued intuitionistic fuzzy environment. Soft Computing, 21(18), 5355-5367.

38. Liu, H. C., You, J. X., & Duan, C. Y. (2019). An integrated approach for failure mode and effect analysis under interval-valued intuitionistic fuzzy environment. International Journal of Production Economics, 207, 163-172.

39. Huang, J., Li, Z. S., & Liu, H. C. (2017). New approach for failure mode and effect analysis using linguistic distribution assessments and TODIM method. Reliability Engineering & System Safety, 167, 302-309.