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ORIGINAL ARTICLE

Creating proactive behavior for the risk assessment by considering expert evaluation: a case of textile manufacturing plant

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Abstract

Applying risk assessment approaches to improve quality in enterprises is of great importance especially for sectors that are labor-intensive and thus frequently encountered failures. One of the methods frequently used to take precautions against failures caused by high variability in this type of sector is failure mode and effects analysis (FMEA). In this study, a hybrid FMEA approach is proposed so as to take measures against failures in the textile sector where there are high-quality differences due to its structure and failures frequently occurred. Since the different combinations of risk parameters' scores may produce the same risk degree based on the function of the FMEA's basis, misleading results for the risk analysis in the practical risk management can be occurred. Moreover, the risk priority number (RPN) function has a limitation in the weight determining process, since it assigns the equal weight for each risk parameter in the classical FMEA. To overcome these shortcomings in the RPN calculation for the risks in the FMEA approach, a multi-criteria decision-making (MCDM) approach is applied under the framework of fuzzy logic. Through that, in this study, we aimed to prove an expert system based on the rules that specifically focusing on the risk sources of the woven fabric industry. To create such a rule-based system, inputs are generated using fuzzy AHP and modified fuzzy TOPSIS. A case study is carried out with the method proposed in a textile mill, and it is determined which risks arising from failures are higher. For the validation of the results, a comparative analysis is conducted. Moreover, for the robustness of the decisions, one-at-a-time sensitivity analysis with respect to different scenarios are applied. As a result of the analyses, it is shown that our proposed model can be used as an efficient proactive risk calculator for the managers or researchers to make useful inferences, judgments, and decisions of the production processes for eliminating the shortcomings of the traditional FMEA.

Keywords FMEA · Fuzzy sets · AHP · TOPSIS · Fuzzy inference system · Textile industry

Introduction

Risk assessment is a comprehensive process to evaluate the possible impact of an event or outcome [1]. Applying to risk assessment applications to prevent poor quality within the enterprises is a crucial step to prevent losses in the market. High variability in quality characteristics, especially in labor-intensive sectors, has adverse consequences for the purpose of producing defect-free products of businesses and obliges preventive actions to be taken to prevent failures. Textile is among the sectors where quality variations are intensive due to its structure and where failures are also frequently encountered. Despite increasing automation, the textile industry performs a labor-intensive production, so variability caused by human or process can cause production failures [2]. In addition, textile companies have long production lines, from raw material to complex, which are effective on many external factors, and due to this complex structure, it is natural to encounter errors [3]. Therefore, risk analysis studies to prevent errors are very important in textile sector where errors are frequently encountered.

Failure Modes and Effects Analysis (FMEA), which is frequently used in risk analysis studies, is a powerful method that can prohibit failures by estimating the risks of avoiding failures [4]. FMEA is an approach that provides great convenience to businesses to predict the error and its possible effects in different processes of production [2]. FMEA

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analyzes the system or process to determine potential failure modes and their causation and effects on system or process performance [5]. The primary purpose of FMEA is to fix the most critical failure modes before they reach the customer, instead of solving them after the failures are occurred [6]. FMEA method can be applied to many different areas to analyze the causes and effects of risks, increase the reliability and security of the systems, and take appropriate proactive measures [7]. FMEA was originally developed by the USA in the 1960s for the aerospace industry and then applied by Ford Motor for the quality and safety improvements in design and manufacturing [8]. In FMEA, failure modes are assessed based on risk factors which are probability of occurrence (O), severity of effects (S), and chance of detection (D). Risk prioritization of failure modes is computed by calculating the risk priority numbers (RPNs) obtained by multiplying the O, S, and D risk factors [6]. While determining the risk priority number in the traditional FMEA, these factors are determined as crisp numbers between 1 and 10. At this point, fuzzy logic is used to overcome this weakness of traditional FMEA [7]. Experts identify three risk factors O, S, and D in fuzzy linguistic terms in fuzzy FMEA [9].

It has been clearly seen that MCDM approaches are frequently used in risk analysis methods. Due to the flexibility of decision-makers to overcome some of the traditional risk prioritization methods' shortcomings, MCDM approaches have been used extended with fuzzy logic, especially in risk analysis and assessment studies [9–11]. In the classical FMEA, the different combinations of risk parameters' scores may produce the same risk degree, which will lead to a misleading result of risk analysis in practical risk management. Also, classical FMEA has a limitation in the weight determining process, since it assigns the equal weight for each risk parameter. Therefore, a more sophisticated approach is essential for a more valid results.

In this study, an integrated fuzzy decision-making methodology consists of Buckley's fuzzy AHP, fuzzy TOPSIS, and Fuzzy Inference System (FIS) is introduced to prioritize the risk sources of the woven fabrics industry. Buckley's fuzzy AHP is applied to determine weights of the experts. Fuzzy TOPSIS is conducted to calculate the risk parameter scores of risk sources based on the each FMEA parameter. After, FIS is constructed based on the decision-makers' knowledge and evaluations. Therefore, calculated risk parameter scores are used as input of the system and the final risk magnitudes of risk sources are obtained.

Rest of the paper is organized as follows: In section "Literature Review", it reviews the studies, which related with MCDM methods and risk analysis applications are discussed. In section "Methodology", applied methodology and its basic preliminary definitions are presented. In section "Application", the application and its basic steps are given. In section "Discussion", sensitivity analyses and interpretation of the results are presented. The paper ends with conclusions and for further study suggestions.

Literature review

One of the most commonly used approaches in risk analysis studies is MCDM approaches. Fuzzy logic is also applied in studies where uncertainty exists and linguistic evaluations are needed. Therefore, fuzzy logic and MCDM methods are frequently used together. The highlights of these studies can be summarized as follows. Bao et al. suggested a model that includes the concept of knowledge to the risk calculation in addition to the consequence and probability [1]. In this context, fuzzy multi-criteria decision-making method was used to evaluate the effectiveness of knowledge. Yłlmaz et al. integrated fuzzy logic and MCDM methods into the risk analysis process, thus increasing the effectiveness of traditional risk analysis approach [12]. In the first step, cost factor was included to risk analysis, and then, hazards were prioritized with Fuzzy–AHP. In the second stage, the priority order of the measures was determined using Fuzzy–TOPSIS. Wang presented a fuzzy multi-criteria decision-based framework including fuzzy entropy and fuzzy TOPSIS to improve traditional FMEA and applied the proposed methodology for the printed circuit board manufacturing process [8]. Ilbahar et al. proposed an integrated approach including Fine Kinney, Pythagorean fuzzy AHP, and fuzzy inference system for analyzing risks of an excavation process in a construction yard [13]. Tian et al. proposed an integrated fuzzy MCDM approach to improve the performance of the classic FMEA [5]. For this purpose, fuzzy best method was used to obtain the weights of risk factors, a fuzzy proximity, and fuzzy similarity entropy weight-based model developed to obtain the weight of FMEA team members, and eventually, a fuzzy VIKOR approach is used to acquire the risk priorities of failure modes. Jozi et al. determined the environmental and human health risks caused during the construction period of Balarood Dam [14]. First, all risks were identified using a Delphi Survey, and then, criteria were prioritized using AHP and TOPSIS methods. AHP and TOPSIS results revealed a mismatch in priorities, so an integrated method which hybridizes Mean-Rank, Borda, and Copeland methods was applied. Wang et al. evaluated the risk of failure modes by hybridizing COPRAS and ANP methods under interval-valued intuitionistic fuzzy environment [6]. Ilangkumaran et al. suggested fuzzy ANP (Analytic Network Process) method for assessing occupational safety in hot environments [15]. Ouédraogo et al. introduced a new methodology for Risk analysis named as Laboratory Assessment and Risk Analysis—LARA—to assess risks in the research/academia environment with using AHP method [16]. Shariat et al. analyzed risk in urban rainwater systems with using Multiple

Criteria Decision-Making (MCDM), geographic information systems (GIS), and fuzzy sets [17]. Tesfamariam and Sadiq assessed the decision-maker's risk attitude and related confidence in the choice of drilling fluid/sludge for offshore oil and gas operations using fuzzy-based AHP method with a hypothetical example [18]. Yan et al. applied the cost-benefit ratio and fuzzy TOPSIS methods to identify the congestion risks of the Yangtze River to make flexible decisions based on the dynamics of congestion risks and to make temporary risk analysis to prioritize congestion risk control options [19].

Literature review studies have also been revealed by researching and compiling MCDM methods used in risk analysis. For example, Almeida et al. reviewed the literature to identify the state-of-the-art research guidelines for multi-criteria models applied in risk management [20]. Gul organized a review about the risk assessment studies applied in Occupational Health & Safety (OHS) using MCDM-based approaches [21]. Liu et al. reviewed the papers which examine the FMEA studies using MCDM approaches to evaluate and prioritize failure modes [22].

FMEA analysis is one of the techniques frequently used in studies where the risks related to failures are analyzed. In addition, studies using FMEA in the textile industry are examined and summarized as follows. Nguyen et al. suggested an extension of FMEA taking into account the associated quality cost and additional determinants to indicate the priority level of the fault detection system for each fault mode [23]. An empirical analysis was applied at the non-woven fabric manufacturer to measure the performance of extended version of FMEA. Erdil and Tacgin applied the FMEA approach to take into account the risks in providing a higher quality in meeting the clothing needs of the household while reducing the environmental, economic, and social problems of the clothing industry's sustainable supply chain and extending the life of the clothing [24]. Lingam et al. implemented various lean tools such as value stream mapping, kaizen, failure mode effect analysis, time, and motion study to reduce the cycle time of T-shirt production [25]. Mutlu and Altuntas proposed an approach that combines the benefits of the fault tree analysis and the fuzzy probability estimates of the time algorithm to advance the performance of the FMEA method [26]. Dedimas and Gebeyehu tried to demonstrate the economic increment of decreasing high downtime in the case company using the benefits of FMEA, and identified and prioritized failure modes, causes, and effects in a particular segment of the company using RPNs [27]. Ozyazgan determined the failure probabilities, weight values, and detectability values of failures arising in a factory producing fabric using process FMEA and presented suggestions for detection according to the current failures types [28]. Esmaeilian et al. suggested a new model to decrease RPNs by increasing overall equipment efficiency using the heuristic math model based on the total productive maintenance index and a company producing products for the seat cover was used for the case study [29]. Sivakumar received data from various experts, field experts, and engineers, and analyzed fuzzy RPNs for efficiency and quality dimensions was determined using an Experimental analysis in the textile industry [30]. Efe et al. aimed to handle the disadvantages of traditional FMEA using an integrated intuitionistic fuzzy MCDM method and linear programming in creating an occupational health and safety policy [31]. Yucel determined the factors that produce errors within the factory by applying the FMEA method with a team established in a garment company and systematic FMEA approach applied to eliminate sewing errors [2]. Sabir applied to FMEA technique in textile dyeing finishing business and three types of errors/defects that have priority in the enterprise identified and preventive actions are suggested [3]. Ozyazgan and Engin presented a process FMEA approach to obtain the error probabilities, severity values, and detectability values of the errors encountered in a knitting business [4]. Correction measures were specified according to the types of errors based on the RPNs determined. Pazireh implemented the FMEA approach to design and implement a quality control system on apparel production lines, identify and sort out possible challenges, and then issue correct commands to quality control stations [32]. Tekez carried out fuzzy TOPSIS application in the knitting process as failure type and effects to detect, eliminate, or minimize errors to ensure customer satisfaction [33].

Risk analysis studies that have attracted attention recently in the textile field can also be summarized in the following. Mutlu and Altuntas developed an approach based on FMEA and Fault Tree Analysis (FTA) to analyze the ring yarn manufacturing process in the textile industry [34]. Fithri et al. proposed an approach to reduce defects at PT Unitex using FMEA, Pareto analysis, and fishbone diagrams in a textile company [35]. Grundmann et al. applied FMEA in the fully automatic thermoplastic tape laying process and aimed to obtain high-quality products [36]. Thawkar et al. adopted the FMEA approach to the analysis of machine failures in developing a reliability centered maintenance methodology to improve card usability in the textile industry [37]. Shafira and Mansur used the FMEA AHP hybrid method in the production quality improvement analysis of gray cambric using the six sigma approach and determined the most critical failures based on RPNs [38]. Similar to the previous study, Purnama et al. carried out a risk analysis study by applying fuzzy AHP and FMEA methods within the scope of the six sigma project [39]. Ghoushchi et al. developed an integrated BWM and MOORA method under uncertain environment for the consideration of risk sources' magnitudes with respect to FMEA parameters [40].

Fuzzy inference system is a frequently used approach to risk assessment in different areas. For example, Elsayed applied the FIS approach in the risk assessment of liquefied natural gas carriers during loading/unloading at the terminals [41]. Carreño et al. proposed an approach to assess physical risks using a fuzzy inference system called an MuHRA in an urban area [42]. Kim et al. provided a model that hybridizes the AHP and FIS approaches to risk assessment of overseas steel mill projects and to mitigate these risks [43]. Ramkumar et al. integrated SWOT analysis with ANP-based fuzzy inference system in risk assessment of outsourcing e-procurement services [44]. Elsayed et al. applied to the qualitative risk matrix method in the fire and explosion risk assessment of the floating storage and unloading vessel, and then applied to the fuzzy inference system [45]. As a result of the study, it was seen that the FIS approach provides a more robust framework for more output information than the qualitative matrix approach. Azimi et al. proposed a comprehensive model based on the FIS approach to determine the landslide risk more reliably and accurately [46]. Tsai and Yeh used a mixed model of FMEA and FIS to identify the sources of critical soldering failures and evaluate their risks in surface mounting assembly [47]. Jamshidi et al. presented an FIS-based approach on relative risk score methodology in risk assessment for the pipeline [48]. Rezaee et al. offered a hybrid approach based on the linguistic FMEA, FIS, and Fuzzy Data Envelopment Analysis model to overcome the shortcomings in calculating the traditional risk priority number and prioritize health, safety, and environmental risks [49]. When the studies conducted by applying the FIS approach in different fields for risk assessment are examined, no studies using the hybrid approach adopted for the textile industry have been found. At this point, it can be said that this study fills an important gap in the literature and will be a study guiding researchers and practitioners.

When the application-based studies and literature studies are examined, it can be revealed that this study has the following aspects unlike the others.

- The proposed study consists of an integrated methodology, which collects the data from a group decision in form of linguistic information.
- Since the data consist of linguistic information, fuzzy sets are used to represent them in the mathematical calculations.
- In comparison with the classical FMEA, constructed rule-based system is sensitive to the changes in the inputs. For example, let be P = 7, F = 3, D = 8 for a risk, and P = 3, F = 8, D = 7 for the other one. Since the results of them are equal, classical FMEA cannot provide an accurate solution. In our model, each input is evaluated with respect to the determined rules by a consensus.

In the traditional FMEA, neither the lack in calculations steps nor the results scale cannot respond the all-risk areas. Moreover, outcome of a risk in heavy industry differs from the outcome of the textile industry with respect to risk magnitudes. Through that, in this study, we aimed to prove an expert system based on the rules that specifically focusing on the accident environment. To create such a rule-based system, inputs are generated using F-AHP and F-TOPSIS. Utilization of these methods may not be novel for the FMEA technique, but different from the other case studies, a modified TOPSIS method is conducted with respect to the each FMEA parameter. F-AHP is conducted to determine the experts' weights. The experts act as the evaluation criteria during the TOPSIS calculations. Based on their weights, most ideal solutions both for negative and positive are determined. Moreover, the risk sources act as alternatives. Through the results of the TOPSIS method, we obtained 3 scores with respect to each risk sources based on the each FMEA parameter. Instead of scalar multiplication, construction of a rule-based system based on the stated reasons above is more reliable for the risk environment.In addition to all these, for the first time in this study, an FIS-based FMEA study was carried out in the analysis of failures for the textile industry.

As a result of the literature research, studies that deal with hybrid multi-criteria decision-making methods with uncertainty in risk analysis approach have been focused in more detail. In this step, in which it was investigated whether the proposed method was adopted by another study before, the originality of the method was examined. For this reason, a literature table has been created as in Table 1, focusing on the characteristics of the studies closest to the proposed approach

In the studies that are the subject of the literature table, especially the methods of determining the weights of the risk factors, the methods adopted when listing the failure modes, and the approaches to handling uncertainty were emphasized in columns. No similar studies were found among the examined studies in terms of both method and application area. Moreover, since the categorized risk sources are grouped into 3 main areas and the number of risk sources are 8, 4, and 20, respectively. In this kind of environment, making a consistent matrix for a 20 × 20 size for the weighting the risk sources is almost impossible without making manipulations in the evaluations. Besides, considering the FMEA environment, the lowest probability and the severity are the most desirable levels for the risk sources. On the other hand, the highest detectability for a risk source is the most desirable. Therefore, it is essential to find the risk sources' places between the minimum and maximum with respect to each parameter. BWM method can be a good alternative under the circumstance of a feasible number of risk sources in the main areas, which is lower than 10 risk sources. Therefore, instead of pairwise comparison evaluations such as AHP and BWM methods, we applied a distance-based method, which is fuzzy TOPSIS. It can be seen that the proposed study is the first and pioneering work in its field with the methodology and application area adopted.

Table 1 Characteristics of the reference studies

#	Authors	Adopted methodology		Level of uncertainty
		For determining weights of risk factors	For prioritizing failure modes	
1	Bao et al.	An entropy-based optimization	Weighted scored method	Crisp data
2	Yılmaz et al.	Fuzzy AHP	Fuzzy TOPSIS	One dimensional
3	Wang	Fuzzy entropy	Fuzzy TOPSIS	One dimensional
4	Tian et al.	Fuzzy best–worst method	Fuzzy VIKOR	One dimensional
5	Ilangkumaran et al.	Fuzzy ANP	Fuzzy ANP	One dimensional
6	Ouédraogo et al.	AHP	LARA	Crisp Data
7	Shariat et al.	Fuzzy SAW	Fuzzy TOPSIS	One dimensional
8	Yan et al.		Fuzzy TOPSIS	One dimensional
9	Purnama et al.	Fuzzy AHP	FMEA	One dimensional
10	Ghoushchi et al.	Fuzzy best–worst method	Z-MOORA	Two-dimensional

Through the advantages of our proposed model, it can be used as an efficient proactive risk calculator for the managers or researchers to make useful inferences, judgments, and decisions of the production processes. Moreover, since our model can handle uncertain information, which can be both represented as linguistic information or fuzzy numbers, it can be useful for the production plants, where have uncertain and vague data for decision-making processes.

Methodology

In this section, an integrated methodology consists of Buckley's Fuzzy AHP and Fuzzy TOPSIS, and fuzzy inference system (FIS) to calculate risk magnitudes based on FMEA is presented.

Ordinary fuzzy sets

Zadeh introduced fuzzy logic and fuzzy sets in 1965 [50]. The basic idea of it is to represent uncertain environments in mathematical formulations without loss of information. This idea is developed and extended in many types such as intuitionistic fuzzy sets [51], neutrosophic sets [52], hesitant fuzzy sets [53], Pythagorean fuzzy sets [54], and spherical fuzzy sets [55]. Based on the extensions, there is no superiority one to another, but some sophistic advantages based on the available data. Since there is no hesitancy among the experts for our data, usage of ordinary fuzzy sets for the uncertainty is a proper way of representing the data for our application.

Definition 1 If X is a collection of elements denoted by a, then a fuzzy set $\tilde{A}$ in X is a set of ordered pairs can be represented as in Eq. (1) [50]:

$$\tilde{A} = \left\{ \left(a, \mu_{\tilde{A}}(a) | a \in X \right) \right\}, \tag{1}$$

where $\mu_{\tilde{A}}$ is membership function of $A–X$.

In the real case applications, $\mu_{\tilde{A}}$ is extended with many forms such as interval-valued, triangular, and trapezoidal fuzzy numbers. Since we used triangular fuzzy forms, the basic arithmetical operations for the them are presented.

Let $\tilde{C} = (c_L, c_M, c_R)$ and $\tilde{K} = (k_L, k_M, k_R)$ be positive triangular fuzzy numbers (TFNs). The arithmetic operations of these fuzzy numbers can be given as below:

Addition: $\tilde{C} \oplus \tilde{K} = (c_L + k_L, c_M + k_M, c_R + k_R)$.

Subtraction: $\tilde{C} \ominus \tilde{K} = (c_L - k_L, c_M - k_M, c_R - k_R)$.

Multiplication: $\tilde{C} \otimes \tilde{K} = (c_L k_{1L}, c_M k_M, c_R k_R)$.

Division: $\tilde{C} \oslash \tilde{K} = (c_L / k_L, c_M / k_M, c_R / k_R)$.

Definition 2 Let $\tilde{C} = (c_L, c_M, c_R)$ and $\tilde{K} = (k_L, k_M, k_R)$ be positive triangular fuzzy numbers (TFNs). Hamming Distance ($H_{(\tilde{C},\tilde{K})}$) between these two fuzzy numbers are defined as in Eq. (2):

$$H_{\left(\tilde{C},\tilde{K}\right)} = \frac{|c_L - k_L| + |c_M - k_M| + |c_R - k_R|}{3}. \tag{2}$$

Buckley's fuzzy AHP

AHP is introduced by Saaty to solve the complex hierarchies by considering both evaluation criteria and alternatives based on the qualitative and quantitative data [56]. Buckley's Fuzzy AHP is an extension of Saaty's AHP method to reflect the uncertainty while representing it in the mathematical model [57]. For our methodology, Buckley's fuzzy AHP is used to calculate experts' weights based on the judgments of the company's managerial consensus. During the evaluations, the scale given in Table 2 is used [58].

The pseudocode of the method is presented as in Algorithm 1:

Table 2 Linguistic scale for Buckley's fuzzy AHP

Linguistic term	Corresponded triangular fuzzy number
Absolutely low importance—ALI	(0.11, 0.11, 0.14)
Very low importance—VLI	(0.11, 0.14, 0.2)
Low importance—LI	(0.14, 0.2, 0.33)
Weakly low importance—WLI	(0.2, 0.33, 1)
Exactly equal—1	(1, 1, 1)
Weakly high importance—WHI	(1, 3, 5)
High importance—HI	(3, 5, 7)
Very high importance—VHI	(5, 7, 9)
Absolutely high importance—AHI	(7, 9, 9)

Algorithm 1: Pseudorepresentation of Buckley's Fuzzy AHP

Input : n: number of experts, $(n = 1, \cdots, i)$
Output: w_i: weights of the experts
Step 1: Construct linguistic pairwise comparison matrix $\left(\tilde{R} = (\tilde{r}_{ij})_{n \times n}\right) \Rightarrow$ Based on Table 2
Step 2: Convert linguistic terms into corresponded triangular fuzzy numbers where $\tilde{R} = (\tilde{r}_{ij})_{n \times n} \Rightarrow$ Based on Table 2
Step 3: Defuzzification Procedure
Apply the defuzzification formula where
$x = 0.5\left(\tau\left(\tilde{x}_l + \tilde{x}_m\right) + (1-\tau)\left(\tilde{x}_m + \tilde{x}_r\right)\right)$
τ is a trade off coefficient between lower and upper value of triangular fuzzy number and x is the defuzzified value of $\tilde{x}$.
Step 4: Normalization Procedure
for $n \leftarrow 1$ **to** i, j **do**
  $\frac{x_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{n} x_{ij}}$
end
Step 5: Calculate the arithmetic average of each row to obtain the weights
for $n \leftarrow 1$ **to** i, j **do**
  $\frac{\frac{x_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{n} x_{ij}}}{n}$
end
Step 6: Consistency Check Procedure
Apply the Saaty's consistency algorithm.
$CR = \frac{CI}{RI}$ where $CI = \frac{\lambda\max}{n-1}$
if $CR > 0.1$ **then**
  return Step 1;
else
  finish Algorithm;
end

Since the experts will be used as evaluation criteria in the fuzzy TOPSIS, the results of the fuzzy AHP are the inputs of the fuzzy TOPSIS as criteria weights.

Fuzzy TOPSIS

TOPSIS is introduced by Hwang & Yoon to rank alternatives with respect to evaluation criteria based on the available data [59]. Its fuzzy extension is introduced by Chen to make a more comprehensive evaluation by adding linguistic

Table 3 Linguistic scale of probability for fuzzy TOPSIS

Linguistic term	Corresponded triangular fuzzy number
Probability Parameter	
Practically impossible—PI	(0.05, 0.1, 0.15)
Extremely remote—ER	(0.4, 0.5, 0.6)
Remotely possible—RP	(0.8, 1, 1.2)
Unusual—UU	(2.5, 3, 3.5)
Quite possible—QP	(5, 6, 7)
Most likely—ML	(8, 9, 10)
Detectability parameter	
Almost impossible—AI	(0.05, 0.1, 0.15)
Very difficult—VD	(0.4, 0.5, 0.6)
Difficult to detect—DtD	(0.8, 1, 1.2)
Easy to detect—EtD	(2.5, 3, 3.5)
Very easy—VE	(5, 6, 7)
Almost certain—AC	(8, 9, 10)
Frequency parameter	
Very rarely—Vra	(0.05, 0.1, 0.15)
Rarely—Rae	(0.4, 0.5, 0.6)
Unusually—Unu	(0.8, 1, 1.2)
Occasionally—Occ	(2.5, 3, 3.5)
Frequently—Fre	(5, 6, 7)
Continuously—Con	(8, 9, 10)

information to solution process [60]. For our methodology, fuzzy TOPSIS is used to obtain risks' scores based on the each FMEA parameter. Experts are used as evaluation criteria and their weights are calculated in fuzzy AHP method. During the evaluations, three scales for each FMEA parameter are used during the evaluations and given as in Table 3.

The pseudocode of the method is presented as in Algorithm 2:[1]

[1] During the calculations in fuzzy inference system (FIS), it was noticed that using the scores of fuzzy TOPSIS method conducting the classical positive and negative ideal solutions makes interrelated results which are dispersed around the average risk magnitude value (in our case, it is 5). To eliminate this relationship, the equations presented in Step 4 and Step 5 are used. The values in the equations are taken from the linguistic scale given in Table 3.

Algorithm 2: Pseudo Representation of fuzzy TOPSIS

Input : n: number of evaluation criteria, $(n = 1, \cdots, i)$
m: number of risks, $(m = 1, \cdots, j)$
k: FMEA parameters $(k = 1, 2, 3)$ where 1: Probability, 2: Detectability, 3: Frequency
Output: s_j^k: score of the risk i based on the parameter k

for $k \leftarrow 1$ **to** 3 **do**
  Step 1: Construct linguistic decision matrix $(\tilde{L}) \Rightarrow$ Based on Table 3
  Step 2: Convert linguistic terms to their corresponded triangular fuzzy numbers to construct fuzzy decision matrix $(\tilde{F} = (\tilde{f}_{ij}^k)_{(n \times m)}) \Rightarrow$ Based on Table 3
  Step 3: Obtain the weighted fuzzy decision matrix using the following equation
  $\tilde{x}_{ij}^k = w_j \times \tilde{f}_{ij}^k$
  Step 4: Determine the Positive ideal solution $(PIS_i^k = (l_i^*, m_i^*, r_i^*)$ 2
  for $n \leftarrow 1$ **to** i **do**
    if *COST type parameter* **then**
      Left: $w_i \times \min(0.05, 0.4, 0.8, 2.5, 5, 8)$
      Mid: $w_i \times \min(0.1, 0.5, 1, 3, 6, 9)$
      Right: $w_i \times \min(0.15, 0.6, 1.2, 3.5, 7, 10)$
    else
      Left: $w_i \times \max(0.05, 0.4, 0.8, 2.5, 5, 8)$
      Mid: $w_i \times \max(0.1, 0.5, 1, 3, 6, 9)$
      Right: $w_i \times \max(0.15, 0.6, 1.2, 3.5, 7, 10)$
    end
  end
  Step 5: Determine the Negative ideal solution $(NIS_i^k = (l_i^-, m_i^-, r_i^-)$ 1
  The same equations given in Step 4 are used. If Cost take maximum, else take minimum. **Step 6:** Calculate the distances to positive ideal solution D_j^* for each alternative by using the following equation
  $D(x_j, PIS_i) = \sum_{i=1}^{n} d(x_i, PIS_i) = \frac{\left(\left|x_{ij} - l_i^*\right| + \left|x_{ij} - m_i^*\right| + \left|x_{ij} - r_i^*\right|\right)}{3}$
  Step 7: Calculate the distances to negative ideal solution D_j^- for each alternative by using equation which is given in Step 6 by replacing $*$ with $-$ values which are calculated in Step 4 and Step 5.
end
Step 8: Calculate the scores by using the following equation $s_j^k = \frac{D_j^-}{D_j^- + D_j^*}$

The results of the TOPSIS methods are used as inputs of the FIS.

Fuzzy inference system

For the applications of fuzzy logic, fuzzy sets theory, and their extensions, fuzzy inference systems (FISs) are one of the most appropriate, and most used applications. There is two types of FISs: Mamdani's FIS and Tagaki-Sugeno' FIS [61,62]. They can be practical to fulfill the many objectives in decision-making such as ranking and classification tasks, offline process simulation and diagnosis, online decision support tools, and process control [63]. In our study, Mamdani's FIS is used for the application, since they are mostly appropriate for the expert system applications where the rules are generated from the experts' knowledge.

In this work, we constructed a inference system based on rule generation technique with linguistic concepts to utilize the results of the fuzzy TOPSIS methods. The outputs of the TOPSIS methods are used as inputs of the rule based system.

Since the score values in three TOPSIS methods are labeled as probability, detectability, and frequency parameter, these values are converted to membership degrees using

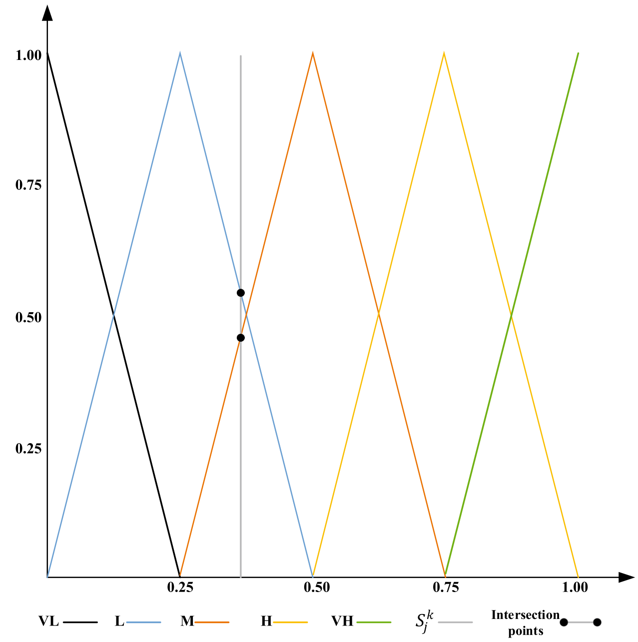

Fig. 1 Process of assigning membership values

Fig. 1. In the figure, x- and y-axis score of the risk with respect to FMEA parameter and membership degree, respectively.

After that, the membership degrees are used as inputs with respect to each FMEA parameter in rule-based system instead of scalar multiplication. To achieve this, the minimum of membership degree of each dimension are taken, respectively, as in Eq. (3):

$$X_{PDS} = \min\left((\mu_s)_j^P, (\mu_s)_j^D, (\mu_s)_j^S\right), \tag{3}$$

where μ_s represents fuzzy input of rule-based system of j^{th} risk with respect to dimension P, D, or S.

Then, the risk classes are determined which are *Ng* (Negligible), *Mi* (Minor), *Md* (Medium), *Ma* (Major), *Cr* (Critical), and *Ct* (Catastrophic).

For each class, maximum values of X_{PDS} are determined using the Eqs. (4–9):

$$Ng = max\,(X_{PDS})\ \forall X_{PDS} \in \textbf{Negligible Class} \tag{4}$$
$$Mi = max\,(X_{PDS})\ \forall X_{PDS} \in \textbf{Minor Class} \tag{5}$$
$$Md = max(X_{PDS})\ \forall X_{PDS} \in \textbf{Medium Class} \tag{6}$$
$$Ma = max(X_{PDS})\ \forall X_{PDS} \in \textbf{Major Class} \tag{7}$$
$$Cr = max(X_{PDS})\ \forall X_{PDS} \in \textbf{Critical Class} \tag{8}$$
$$Ct = max(X_{PDS})\ \forall X_{PDS} \in \textbf{Catastrophic Class}. \tag{9}$$

Defuzzify the *Ng*, *Mi*, *Md*, *Ma*, *Cr*, and *Ct* values using Eq. (10) to obtain the risk magnitudes (RMs) [64]:

$$RM = \frac{1 \times Ng + 3 \times Mi + 5 \times Md + 7 \times Ma + 9 \times Cr + 10 \times Ct}{Ng + Mi + Md + Ma + Cr + Ct}. \tag{10}$$

Finally, prioritize the risks according to results and determine the possible development steps to reduce it.

Proposed methodology

Based on the above methods, we developed an FMEA model to evaluate risks.

During the observations in the production plant, experts could not assign an exact value for their evaluations. In most of the cases, contrary to the ordinary FMEA analysis, they assign linguistic terms, which are created from the literature to evaluate the risk as in Table 3. Since the fuzzy sets are one of the most appropriate way of representing linguistic terms with their corresponded fuzzy numbers in the mathematical formulations, ordinary fuzzy sets are utilized to the proposed methodology to reflect the data with highest level.

Since the proposed methodology based on expert system evaluation, determining experts' weights is a vital and important phase for the results. Through that, in terms of their academic degree, work experience, and their study in the field, based on the comparison with respect to managerial consensus evaluation, Buckley's fuzzy AHP is conducted to obtain the weight of the experts.

After that, for the evaluation of the failures, three TOPSIS decision matrices are constructed based on the experts' evaluations. Each decision matrix are corresponded to each parameter of FMEA, which are Probability, Frequency, and Detectability. Different from the ordinary TOPSIS method context, experts are utilized as the evaluation criteria and the failures are the evaluated alternatives. Therefore, outputs of the TOPSIS methods are the scores of the failures based on the expert evaluations with respect to each FMEA parameter. Based on these calculations, inputs of the FMEA are calculated by considering uncertainty.

For the last phase of the methodology, a reasonable outcome, which is entitled as risk magnitude, is obtained using a fuzzy rule based system. Even the scores with respect to each parameter for the failures are calculated flawlessly, utilizing scalar multiplication leads to a misleading result for the risk analysis in practical risk management because of the different combinations of the risk parameters' scores may produce the same risk degree in classical FMEA method. Moreover, classical FMEA has a limitation in the weight determining process, since it assigns the equal weight for each risk parameter. In rule-based systems, based on the field experiences, and expert knowledge in the area, experts create a pattern that

Table 4 Type of failures encountered in textile mills

Main area	Risk sources
F1—Failures resulting from the weaving machine	Temple mark —F11
	Foot ladder—F12
	Stop marks—F13
	Shrunk selvedge—F14
	Baggy selvedge—F15
	Bowed selvedge—F16
	Thick–thin selvedge—F17
	Weft pattern failure—F18
F2—Weaving preparation failures	Interlacing point— F21
	Drawing-in, pattern, repeat failure—F22
	Sliver marks—F23
	Reed marks—F24
F3—wrap & Weft failures	Wrap breaks—F31
	Hollow wrap—F32
	Double wrap—F33
	Loose wrap thread—F34
	Tight wrap thread—F35
	Thin or thick wrap—F36
	Thread irregularity in the wrap—F37
	Pile - F38
	Selvedge mark—F39
	Mesh—F310
	Breaking of weft thread—F311
	Shuttle slap—F312
	Tight, loose weft—F313
	Unraveled weft mark—F314
	Crushed weft thread—F315
	Weft ladder—F316
	Weft loop—F317
	Weft skip—F318
	Weft deformity (defect)—F319
	Weft column (weft band)—F320

Table 5 Pairwise comparison matrix for expert evaluation

Goal	Exp1	Exp2	Exp3	Exp4	Exp5
Exp1	EEI	EEI	WHI	HI	HI
Exp2	EEI	EEI	WHI	HI	HI
Exp3	WLI	WLI	EEI	WHI	WHI
Exp4	LI	LI	WLI	EEI	EEI
Exp5	LI	LI	WLI	EEI	EEI

Table 6 Decision matrix for Probability (P) parameter

	E1	E2	E3	E4	E5		E1	E2	E3	E4	E5
F11	ER	ER	QP	RP	UU	F35	UU	QP	ML	PI	UU
F12	RP	PI	ER	PI	ER	F36	RP	QP	RP	QP	PI
F13	ER	QP	RP	PI	ML	F37	QP	ML	RP	ER	PI
F14	UU	ML	UU	ER	UU	F38	RP	RP	QP	UU	RP
F15	PI	ML	RP	UU	RP	F39	RP	RP	ML	QP	PI
F16	ML	ML	RP	ER	RP	F310	UU	UU	ML	ER	ER
F17	QP	ER	PI	RP	PI	F311	PI	UU	QP	QP	ML
F18	PI	UU	ER	UU	QP	F312	QP	ER	RP	ML	QP
F21	ML	RP	UU	UU	ML	F313	ML	ER	QP	UU	ML
F22	ML	ML	PI	ML	PI	F314	PI	ML	ER	ML	ML
F23	RP	QP	QP	QP	RP	F315	QP	PI	ML	ML	QP
F24	ML	PI	ML	ER	ER	F316	PI	PI	QP	PI	UU
F31	QP	RP	UU	PI	QP	F317	ER	ML	ER	PI	UU
F32	UU	RP	RP	PI	QP	F318	PI	QP	RP	RP	ML
F33	ER	ER	ML	ER	QP	F319	UU	PI	PI	ML	PI
F34	ML	RP	RP	ER	PI	F320	RP	UU	QP	PI	PI

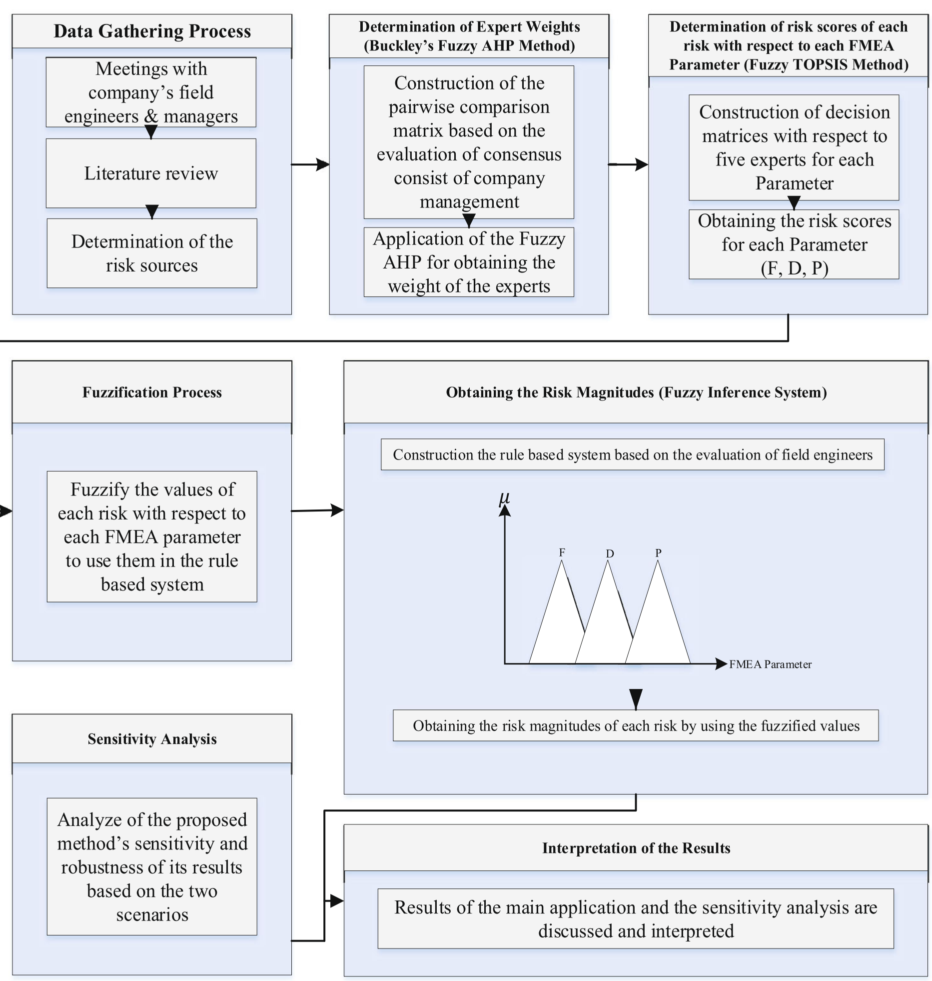

Fig. 2 Framework of the proposed methodology

Table 7 Decision matrix for Detectability (D) parameter

	E1	E2	E3	E4	E5		E1	E2	E3	E4	E5
F11	AC	AC	VE	EtD	DtD	F35	AC	AC	VE	AI	AC
F12	AI	VE	EtD	VE	AI	F36	EtD	VE	DtD	AC	VD
F13	DtD	AI	AI	DtD	EtD	F37	AC	AC	AI	EtD	AC
F14	DtD	AC	DtD	VD	EtD	F38	AC	DtD	VD	EtD	EtD
F15	DtD	AC	VE	DtD	DtD	F39	AC	EtD	VD	AC	VE
F16	AC	AC	DtD	AC	EtD	F310	EtD	DtD	VD	EtD	VE
F17	VE	DtD	EtD	AI	AC	F311	DtD	AI	AC	VE	VE
F18	DtD	EtD	EtD	AI	AI	F312	AI	EtD	DtD	VE	AC
F21	AC	DtD	AC	AC	VE	F313	EtD	AC	VD	VD	EtD
F22	AC	VD	VE	AC	AC	F314	EtD	AI	EtD	AC	DtD
F23	AC	DtD	EtD	DtD	DtD	F315	AI	VE	VD	DtD	VE
F24	VD	EtD	VE	DtD	DtD	F316	VE	AC	VD	VE	AI
F31	DtD	VD	AI	VE	VE	F317	EtD	VD	VD	DtD	DtD
F32	VD	AI	DtD	EtD	VE	F318	DtD	AI	EtD	VE	DtD
F33	VD	VD	VE	VE	AC	F319	DtD	VE	EtD	VE	AC
F34	DtD	VE	DtD	EtD	AC	F320	EtD	EtD	DtD	VD	EtD

aims to evaluate the failures efficiently. Therefore, a fuzzy inference system based on expert assessments is constructed to obtain more valid results. To interpret the results of the proposed approach, sensitivity analyses are conducted. The framework of the proposed methodology is given in Fig. 2.

Application

Risk analysis is an essential approach, especially in labor-intensive industries, to increase quality and to take precautions before failures occur. At this point, one of the frequently encountered approaches is the FMEA method. However, this method has some handicaps. To avoid these handicaps, they are usually used with fuzzy sets. It is also used with MCDM methods to increase the effectiveness of the method. Thus, it is ensured that RPNs can be calculated more accurately and efficiently. In this paper, the failures encountered in textile companies producing woven fabrics were investigated extensively and a risk assessment study was carried out to take precautions about them before the failures occurred in a textile mill as a case study. At this point, RPNs were calculated for each failures and it was tried to find out which failures constitute a higher risk. First, all the failures encountered in the related textile mills were investigated, and it was tried to make sure that all the failures were handled by also discussing with the textile workshop employees to be involved in the case study as decision-makers.

The decision matrix for Detectability parameter is given in Table 7.

Finally, the decision matrix for frequency parameter is constructed as in Table 8.

Woven fabric is created by connecting wrap and weft at right angles to each other with a specific system called “knitting”. Wraps from these two yarn groups can be called “active” yarn system; wefts can be called “passive” yarn system [65,66]. During weaving, three basic movements and two complementary actions are made to ensure that the wrap and weft threads intersect with each other [65]. 1. Shedding: By separating the wrap wires into two layers, large enough to pass the weft carrier element, called shed is the creation of a tunnel. 2. Weft insertion: It is the transportation of the weft thread along the shed [65]. 3. Tufting (tamping): It is the inclusion of the weft, which is moved to the mouthpiece, to the fabric formation line, to the previously woven fabric [65]. These three operations are called basic movements of the fabric and should be applied in the order given above [65]. 4. Wrap release: In this movement, the wrap is released from the weaving beam at the required speed, at a suitable and constant tension, and is transferred to the weaving area [65]. 5. Fabric wrapping: In this movement, the fabric is pulled from the weaving area to provide the desired weft density and wrapped around the fabric beam [65]. When these processes are completed, a weaving cycle is completed [65].

This hybrid risk analysis approach has been applied to be valid for woven fabric products manufactured in the textile mill and it is aimed to carry out a detailed, comprehensive, and holistic analysis by taking into account the failures encountered in all production stages of the product. In other words, a total quality improvement is aimed throughout the mill by considering all failures for all products.

Table 8 Decision matrix for Frequency (F) parameter

	E1	E2	E3	E4	E5		E1	E2	E3	E4	E5
F11	Occ	Rae	Vra	Occ	Unu	F35	Fre	Occ	Occ	Vra	Fre
F12	Fre	Occ	Rae	Occ	Unu	F36	Fre	Occ	Vra	Con	Rae
F13	Unu	Rae	Unu	Occ	Unu	F37	Vra	Unu	Con	Occ	Occ
F14	Fre	Unu	Fre	Rae	Rae	F38	Unu	Fre	Unu	Occ	Occ
F15	Vra	Occ	Fre	Rae	Unu	F39	Unu	Rae	Vra	Occ	Vra
F16	Occ	Rae	Rae	Occ	Rae	F310	Occ	Fre	Con	Fre	Rae
F17	Vra	Fre	Vra	Occ	Vra	F311	Rae	Occ	Occ	Rae	Vra
F18	Fre	Vra	Occ	Unu	Unu	F312	Rae	Rae	Unu	Rae	Rae
F21	Fre	Occ	Rae	Unu	Unu	F313	Fre	Vra	Unu	Rae	Unu
F22	Unu	Fre	Fre	Unu	Fre	F314	Occ	Rae	Occ	Rae	Occ
F23	Unu	Unu	Vra	Unu	Fre	F315	Fre	Rae	Unu	Vra	Fre
F24	Occ	Rae	Fre	Fre	Occ	F316	Occ	Rae	Occ	Unu	Occ
F31	Rae	Fre	Fre	Unu	Fre	F317	Vra	Occ	Rae	Vra	Rae
F32	Fre	Rae	Vra	Unu	Unu	F318	Occ	Fre	Unu	Occ	Unu
F33	Rae	Rae	Fre	Fre	Occ	F319	Occ	Rae	Occ	Rae	Occ
F34	Con	Occ	Rae	Rae	Fre	F320	Con	Con	Unu	Rae	Unu

According to the explanations of decision-makers and related literature, 32 types of failures are determined as in Table 4.

The application starts with the determination of the experts' weights. The experts have been selected from among white collar workers in the textile mill. Experts are textile, industrial, and other engineers working in the respective enterprise. All of them are working in various management units. Therefore, the age-related experience factor came to the fore as the determinable difference between the experts in the mill who have knowledge about risk management and work on this subject. For this reason, an age-based weight assessment was carried out among engineers working on risk management in the mill. The values are assigned based on the mentioned criteria. The linguistic pairwise comparison matrix is constructed using the scale given in Table 2 as in Table 5.

The Algorithm 1 is applied to the pairwise comparison matrix and the weights are calculated as follows: Exp1= 0.347, Exp2=0.347, Exp3= 0.169, Exp4= 0.068, and Exp5= 0.068.

After that, we constructed the decision matrices for each FMEA parameter. The decision matrix for Probability parameter is given in Table 6.

After applying the Algorithm 2, the scores of each risk based on each parameter are calculated as in Table 9.

Table 9 shows the calculation results for fuzzy TOPSIS in crisp version for probability, detectability, and frequency. These results constitute the inputs for the FIS calculations. These results are the inputs of FIS process. During the process, each FMEA parameter for every risks is defuzzified using the conversion function which is represented in Fig. 1. For an illustrative example, defuzzifications of FMEA parameters for **F11-Temple Mark** risk are given as follows.

For the Probability, the result of TOPSIS is equal to 0.84. This value is used in the conversion function to find the intersection points with the limits. Through the calculation, the defuzzified value is equal to 0.67 for High (H), and 0.37 for Very High (VH). The values for Detectability are 0.66 for High (H), and 0.34 for Very High (VH). Finally, for Frequency, it is 0.67 for High (H), and 0.37 for Very High (VH). These are the final values for the input of FIS with respect to **F11-Temple Mark** risk. The constructed FIS based on three decision-makers is given in Table 10.

Table 10 shows the structure created for the proposed FIS process. The outputs of the FIS process for different levels for probability, detectability, and frequency inputs can be seen from this table. These inputs are run and the risk magnitudes are obtained as in Table 11.

Table 11 shows the RPN degrees of each risk source in the applied FIS-based hybrid risk analysis approach. As can be seen from the table, failures with high RPN are Foot Ladder–F12, Stop Marks–F13, Weft Pattern Fault–F18, Hollow Warp–F32 Double Warp–F33, Selvedge Mark–F39, Breaking of Weft Thread–F311, Shuttle Slap–F312, Unraveled Weft Mark–F314, Weft Loop–F317, and Weft Deformity (Defect)–F319.

The most crucial risks encountered in the textile mill which are marked in red in Table 11 are foot ladder, stop marks, weft pattern failure, hollow wrap, double wrap, selvedge mark, breaking of weft thread, shuttle slap, unraveled weft mark, weft loop, and weft deformity. To deal

Table 9 Results of the TOPSIS methods based on each FMEA parameter

Magnitudes based on probability		Magnitudes based on detectability		Magnitudes based on FREQUENCY	
Risk	Magnitude	Risk	Magnitude	Risk	Magnitude
F11	0.827	F11	0.835	F11	0.842
F12	0.954	F12	0.331	F12	0.62
F13	0.669	F13	0.064	F13	0.903
F14	0.459	F14	0.424	F14	0.617
F15	0.607	F15	0.508	F15	0.765
F16	0.279	F16	0.802	F16	0.838
F17	0.748	F17	0.389	F17	0.748
F18	0.812	F18	0.203	F18	0.701
F21	0.472	F21	0.665	F21	0.636
F22	0.238	F22	0.612	F22	0.57
F23	0.57	F23	0.451	F23	0.878
F24	0.478	F24	0.255	F24	0.691
F31	0.634	F31	0.141	F31	0.59
F32	0.789	F32	0.1	F32	0.741
F33	0.751	F33	0.257	F33	0.789
F34	0.598	F34	0.373	F34	0.484
F35	0.465	F35	0.875	F35	0.556
F36	0.672	F36	0.432	F36	0.586
F37	0.403	F37	0.785	F37	0.751
F38	0.788	F38	0.434	F38	0.673
F39	0.715	F39	0.581	F39	0.927
F310	0.598	F310	0.223	F310	0.439
F311	0.661	F311	0.295	F311	0.813
F312	0.624	F312	0.244	F312	0.946
F313	0.435	F313	0.493	F313	0.743
F314	0.509	F314	0.244	F314	0.791
F315	0.487	F315	0.29	F315	0.692
F316	0.865	F316	0.63	F316	0.787
F317	0.608	F317	0.15	F317	0.876
F318	0.678	F318	0.143	F318	0.611
F319	0.819	F319	0.434	F319	0.791
F320	0.74	F320	0.269	F320	0.279

with the risks encountered in the textile mill successfully, a two-sided approach has been proposed. The first side is the operational dimension and the second is the management dimension. Operational dimension includes technical recommendations regarding raw materials, semi-finished products, or machines. The second dimension is the training activities and induction program efforts to be provided by the management. The following preventive measures can be listed for operational dimension. Through literature review and expert advice, ongoing measures are proposed for each critical source of risk [28,67–69]. The first important risk foot ladder failure is caused by the feet not moving upwards due to the failure of the magnets in the weaving machine. As a measure, the maintenance of the weaving machine should be done at frequent intervals and replacement of the machine should be also made if necessary. Stop mark failure happens if the loom stops and restarts with strike or carding errors may occur, as the loom will give the wrong apron. As a preventive action, the keel settings must be set correctly. Weft pattern failure caused by making different colors and numbers of wefts from the weft color report. To prevent this, the drawing should be done carefully and the drawing plan accuracy and weft report should be checked. Hollow wrap occurs caused when hollow ends during one or more weft threads caused by falling of one or more frames. Maintenance and repairs related to the weaving machine should be again done properly. Breaking of weft thread failure happens if there is a burr or something to cause snagging in the parts where the thread used in the loom passes, the weft breaks, and the machine stops. To prevent this risk, feeders, brakes, and other devices should be controlled. Double wrap when a broken warp end is wrapped around the adjacent end and the loom begins to make the same movement without stopping. It is a failure generally caused by the weaver. Selvedge marks are the failures caused by the bending or folding of one edge of the fabric. It may occur due to incorrect threading of the weft thread, incorrect loom settings, or the temple setup and mostly originates from the weaver. Breaking of weft thread failure is the formation of gap in that part of the fabric as a result of a weft thread breakage. Weft bobbins and machine settings should be checked to prevent this failure. Shuttle slap occurs when the shuttle breaks several wraps or wefts on the shuttle looms. Weft loop failures are the small loops formed by the weft thread on its surface because of excessive twisting or failure of the braking function in the thread. Weft deformity is the error caused by deformation in the weft thread. Working with higher quality yarns can be preventive for this failure. Apart from these technical suggestions, training of employees and having an occupational health and safety specialist in the mill to analyze risks are also administrative preventive measures. Measures should be taken in both dimensions for the risks with high RPN, as shown in Table 11.

Discussion

To check the effects of the experts' weights, we constructed two different scenarios based on the case of equal weighted experts, and case of evaluating working experience together with being in an FMEA study before. For the first one, weights of the experts are directly assigned as 0.2. For the second one, a new comparison matrix is added to evaluation process of Buckley's fuzzy AHP, and then, experts' weights are re-calculated. Through the scenarios, fuzzy TOPSIS and FIS calculations are re-made, and then, results are discussed.

Sensitivity analysis

Scenario-1 Case of equal weighted experts

First, the experts weights are assigned as equal values. After that, TOPSIS algorithm is re-run with respect to each FMEA parameter. Therefore, risk scores are re-calculated, which are given in Table 12.

Based on the new risk score values, inputs of FIS are changed and the new risk magnitudes are obtained as in Table 13.

Scenario-2 Case of being in an FMEA study before situation

Since the being an FMEA study before is a Yes or No question, following aggregation procedure of two evaluations (work experience comparison matrix, and the being an FMEA study before) is applied.

The responses and the results of the evaluations based on the work experience are presented in Table 17.

Based on the discussions with the managerial consensus, the weights of the evaluation areas are determined as 0.75 and 0.25, respectively. Also, since the total number of experts, which being in an FMEA study is equal to 2, "Yes" is assigned as 0.5 and "No" is assigned as 0 for the aggregation procedure. Therefore, the new weights of the experts are calculated as follows: Exp1=0.260, Exp2=0.385, Exp3=0.252, Exp4=0.051, and Exp5=0.051.

Based on the new weights, TOPSIS is re-run for each FMEA parameter. The results of them are presented in Table 14.

Similarly to Scenario-1, new risk new inputs of FIS are re-run and the risk magnitudes are re-obtained as in Table 15.

Interpretation of the results

Based on the main findings of our application, a sensitivity analysis is carried out with respect to two scenarios. Comparison of the scenarios with the main findings are given in Table 16.

F320-Weft Column (Weft Band) is the most affected risk based on the Scenario-1 with 0.32 increase rate. On the contrary, F318-Weft Skip is the least affected risk with 0.018 increase rate.

Similarly, based on the Scenario-2, F35-Tight Wrap Thread is the most affected risk with 0.21 decrease rate. On the contrary, F312- Shuttle Slap is the least affected risk with 0.09 increase rate.

Since the differences are based on the weights of the experts, the following aspects are observed. Based on the analysis, in both scenarios, risk magnitudes of the F11, F13, F24, F33, F38, F39, F311, F314, and F317 are decreased. When the weights are compared, it is certain that Expert-1 has a great impact on them, since the weight of it is decreased in both scenarios.

In a similar way, Expert-3 weight has a regular uptrend based on the main application, Scenario-1, and Scenario-2, respectively. When this trend is analyzing, F21, F22, F32, and F36 risks have the same trend. This concludes that Expert-3 has a great impact on them.

Table 10 Constructed FIS based on decision-makers

Frequency	Detectability	Probability VL	Probability L	Probability M	Probability H	Probability VH
VL	VL	Mi	Mi	Mi	Md	Ma
	L	Ng	Mi	Mi	Mi	Ma
	M	Ng	Ng	Ng	Mi	Md
	H	Ng	Ng	Ng	Mi	Md
	VH	Ng	Ng	Ng	Ng	Mi
L	VL	Mi	Mi	Md	Ma	Cr
		Mi	Mi	Md	Md	Ma
	M	Ng	Mi	Mi	Md	Ma
	H	Ng	Ng	Mi	Mi	Md
	VH	Ng	Ng	Mi	Mi	Md
M	VL	Mi	Md	Ma	Ma	Cr
	L	Mi	Mi	Md	Ma	Cr
	M	Mi	Mi	Mi	Md	Ma
	H	Ng	Mi	Mi	Md	Ma
	VH	Ng	Ng	Mi	Mi	Md
H	VL	Md	Md	Ma	Ma	Ct
	L	Mi	Md	Ma	Ma	Cr
	M	Mi	Mi	Md	Ma	Cr
	H	Mi	Mi	Md	Md	Ma
	VH	Ng	Mi	Md	Md	Ma
VH	VL	Md	Ma	Ma	Cr	Ct
	L	Md	Md	Ma	Cr	Ct
	M	Mi	Md	Ma	Ma	Cr
	H	Mi	Mi	Md	Ma	Cr
	VH	Mi	Mi	Md	Ma	Cr

Ng: negligible
Mi: minor
Md: medium
Ma: major
Cr: critical
Ct: catastrophic

Table 11 Results of the application

Risk and its obtained magnitude							
F11	6.508	F21	4.084	F35	3.621	F313	5.000
F12	7.503	F22	3.526	F36	5.049	F314	7.394
F13	8.876	F23	6.675	F37	4.234	F315	6.050
F14	4.644	F24	6.466	F38	6.734	F316	6.353
F15	6.029	F31	6.075	F39	7.593	F317	8.578
F16	4.050	F32	7.417	F310	5.242	F318	6.316
F17	6.902	F33	7.323	F311	7.134	F319	7.883
F18	7.494	F34	4.856	F312	8.450	F320	5.078

Table 12 Results of TOPSIS methods with respect to each parameter based on Scenario-1

Risk	Risk scores			Risk	Risk scores		
	F	D	P		F	D	P
F11	0.840	0.618	0.764	F35	0.604	0.733	0.537
F12	0.708	0.330	0.962	F36	0.593	0.427	0.694
F13	0.865	0.106	0.638	F37	0.649	0.665	0.638
F14	0.697	0.315	0.596	F38	0.697	0.360	0.742
F15	0.773	0.393	0.694	F39	0.906	0.607	0.627
F16	0.843	0.685	0.551	F310	0.461	0.292	0.652
F17	0.802	0.418	0.838	F311	0.852	0.485	0.470
F18	0.762	0.151	0.728	F312	0.944	0.418	0.506
F21	0.753	0.753	0.449	F313	0.818	0.348	0.393
F22	0.562	0.742	0.400	F314	0.787	0.351	0.391
F23	0.807	0.326	0.562	F315	0.706	0.294	0.335
F24	0.596	0.247	0.582	F316	0.775	0.474	0.802
F31	0.573	0.294	0.649	F317	0.917	0.124	0.717
F32	0.818	0.227	0.762	F318	0.697	0.238	0.627
F33	0.652	0.483	0.640	F319	0.787	0.551	0.735
F34	0.584	0.438	0.751	F320	0.551	0.225	0.782

Table 13 New outputs of FIS based on Scenario-1

Risk and its obtained risk magnitude							
F11	6.213	F21	4.596	F35	4.042	F313	5.258
F12	8.052	F22	3.584	F36	5.246	F314	5.231
F13	7.921	F23	6.875	F37	4.903	F315	5.275
F14	5.742	F24	5.764	F38	6.306	F316	7.655
F15	6.706	F31	5.714	F39	6.087	F317	8.206
F16	5.582	F32	7.655	F310	5.750	F318	6.408
F17	8.102	F33	5.242	F311	5.509	F319	6.596
F18	7.145	F34	5.682	F312	6.560	F320	7.545

When the results are interpreted, our model has ability to represent even small changes such as weight changes of Expert-4 and Expert-5. This reveals that it is very sensitive in the changes of the inputs. Also, the trends of the changes and their value affect the risk magnitudes with meaningful directions. This also proves that our decisions are robust based on the direction of the changes and their values.

Comparative analysis

To demonstrate the advantages of the proposed method, comparative analyses with classical FMEA method and weighted FMEA method are carried out. Based on the outputs of the TOPSIS methods, RPNs with respect to classical FMEA and weighted FMEA methods of the risk sources are calculated.

Table 14 Results of TOPSIS methods with respect to each parameter based on Scenario-2

Risk	Risk scores			Risk	Risk scores		
	F	D	P		F	D	P
F11	0.876	0.834	0.782	F35	0.586	0.864	0.391
F12	0.669	0.371	0.960	F36	0.648	0.419	0.659
F13	0.909	0.048	0.656	F37	0.676	0.713	0.415
F14	0.617	0.456	0.429	F38	0.659	0.344	0.746
F15	0.700	0.589	0.567	F39	0.940	0.482	0.649
F16	0.868	0.739	0.322	F310	0.372	0.186	0.533
F17	0.728	0.345	0.805	F311	0.778	0.346	0.622
F18	0.735	0.234	0.812	F312	0.941	0.236	0.699
F21	0.680	0.636	0.551	F313	0.795	0.500	0.487
F22	0.512	0.547	0.303	F314	0.797	0.223	0.501
F23	0.896	0.392	0.512	F315	0.751	0.306	0.490
F24	0.680	0.315	0.483	F316	0.794	0.603	0.816
F31	0.527	0.112	0.672	F317	0.861	0.124	0.575
F32	0.800	0.088	0.817	F318	0.612	0.148	0.663
F33	0.753	0.281	0.683	F319	0.797	0.449	0.864
F34	0.567	0.375	0.673	F320	0.322	0.255	0.681

Table 15 New outputs of FIS based on Scenario-2

Risk and its obtained magnitude							
F11	6.348	F21	4.852	F35	2.861	F313	5.243
F12	7.709	F22	3.116	F36	5.336	F314	7.009
F13	8.249	F23	6.284	F37	4.316	F315	6.419
F14	4.394	F24	5.734	F38	6.210	F316	6.767
F15	5.125	F31	6.282	F39	6.624	F317	7.746
F16	3.872	F32	8.129	F310	5.667	F318	6.408
F17	7.284	F33	6.741	F311	6.462	F319	8.241
F18	7.650	F34	5.293	F312	8.527	F320	5.525

For the first comparison, the results of the classical FMEA method are presented in Table 18.

Based on the Table 18, F18—Weft Pattern Failure and F317—Weft Loop have the same RPN, even they have the different FMEA parameter values. Similar to this results, F12—-Foot Ladder and F311—Breaking of Weft Thread, F314—Unraveled Weft Mark and F38—Pile, F39—Selvedge Mark, and F23—Sliver Marks, F16—Bowed Selvedge, and F35—Tight Wrap Thread have very close RPN values with respect to very different parameter values. In this kind of analysis, the worst and the best risk sources with respect to the RPN numbers may be determined, but the risks cannot be categorized. Since the aim of the risk analysis studies is to categorize the risks using the available data with the highest accuracy,

Table 16 Comparison of scenarios with the main findings

Risk	Direction of change & rate	
	Scenario-1	Scenario-2
F11	Decreased, rate = 0.045	Decreased, rate = 0.025
F12	Increased, rate = 0.068	Increased, rate = 0.027
F13	Decreased, rate = 0.108	Decreased, rate = 0.071
F14	Increased, rate = 0.191	Decreased, rate = 0.054
F15	Increased, rate = 0.101	Decreased, rate = 0.15
F16	Increased, rate = 0.275	Decreased, rate = 0.044
F17	Increased, rate = 0.148	Increased, rate = 0.052
F18	Decreased, rate = 0.047	Increased, rate = 0.02
F21	Increased, rate = 0.111	Increased, rate = 0.158
F22	Increased, rate = 0.016	Decreased, rate = 0.116
F23	Increased, rate = 0.029	Decreased, rate = 0.059
F24	Decreased, rate = 0.109	Decreased, rate = 0.113
F31	Decreased, rate=0.059	Increased, rate = 0.033
F32	Increased, rate = 0.031	Increased, rate = 0.088
F33	Decreased, rate = 0.284	Decreased, rate = 0.079
F34	Increased, rate = 0.145	Increased, rate = 0.083
F35	Increased, rate = 0.104	Decreased, rate = 0.21
F36	Increased, rate = 0.038	Increased, rate = 0.054
F37	Increased, rate = 0.136	Increased, rate = 0.019
F38	Decreased, rate = 0.064	Decreased, rate=0.078
F39	Decreased, rate = 0.198	Decreased, rate = 0.128
F310	Increased, rate = 0.088	Increased, rate = 0.075
F311	Decreased, rate = 0.228	Decreased, rate = 0.094
F312	Decreased, rate = 0.224	Increased, rate = 0.009
F313	Increased, rate = 0.049	Increased, rate = 0.046
F314	Decreased, rate = 0.293	Decreased, rate = 0.052
F315	Decreased, rate = 0.128	Increased, rate = 0.058
F316	Increased, rate = 0.17	Increased, rate = 0.061
F317	Decreased, rate = 0.043	Decreased, rate = 0.097
F318	Increased, rate = 0.014	Increased, rate = 0.014
F319	Decreased, rate = 0.163	Increased, rate = 0.043
F320	Increased, rate = 0.327	Increased, rate = 0.081

Table 17 Scenario-2 expert values

Weights based on fuzzy AHP		Being in an FMEA study	
E1	0.347	E1	No
E2	0.347	E2	Yes
E3	0.169	E3	Yes
E4	0.068	E4	No
E5	0.068	E5	No

our proposed approach presents more appropriate result to consider.

For the second comparison, we checked the weighted FMEA results based on the different weights of the FMEA parameters to demonstrate the difficulty and uncertainty in each case results. Through that, the results of the weighted FMEA methods with respect to three cases are presented in Table 19.

Table 18 Results of the classical FMEA

Risk	RPN	Risk	RPN
F11	0.115	F35	0.032
F12	0.396	F36	0.224
F13	0.565	F37	0.065
F14	0.163	F38	0.300
F15	0.228	F39	0.278
F16	0.046	F310	0.204
F17	0.342	F311	0.379
F18	0.453	F312	0.446
F21	0.100	F313	0.164
F22	0.053	F314	0.304
F23	0.275	F315	0.239
F24	0.246	F316	0.252
F31	0.321	F317	0.453
F32	0.526	F318	0.355
F33	0.440	F319	0.366
F34	0.181	F320	0.151

Based on Table 19, the risk source such as F12—Foot Ladder has very similar RPNs with respect to different weight scenarios. Same case is also observed for the F13—Stop Marks, F18—Weft Pattern Failure, F32—Hollow Wrap, F317—Weft Loop, and F320—Weft Column (Weft Band) risk sources. Because of the different weights calculates the very similar results even same results in some cases, this creates an uncertain situation, which yields the importance of accurate weighting.

Another comparison is applied using an integrated BWM and MOORA methodology. BWM is used to determine experts' weights and MOORA method is conducted to calculate the risk magnitudes of the failures. As a result of the BWM, weights of the experts are calculated as 0.34, 0.34, 0.18, 0.07, and 0.07. After that, the same decision matrices are used for the MOORA method with respect to each FMEA parameter. Different from the TOPSIS, objectives are considered as FMEA parameters. Through that, experts evaluations for each FMEA parameter are aggregated using experts' weights for the applicability. Moreover, detectability is considered as beneficial objective and the others are considered as non-beneficial objectives. For the weights of the objectives, equal weighted rule is considered. Through that, objectives' weights are equal to 0.333. Through the calculations, scores are obtained. Using the min–max normalization, the scores are converted to risk magnitudes which spreads between the 0 and 10. The obtained results of the comparison are determined as in Table 20.

Table 19 Results of the weighted FMEA cases

Case 1: P = 0.4, D=0.3, F = 0.3		Case 2: P = 0.3, D = 0.4, F = 0.3		Case 3 P = 0.3, D = 0.3, F = 0.4	
Risk	RPN	Risk	RPN	Risk	RPN
F11	0.633	F11	0.634	F11	0.567
F12	0.769	F12	0.735	F12	0.740
F13	0.819	F13	0.843	F13	0.846
F14	0.541	F14	0.557	F14	0.553
F15	0.620	F15	0.635	F15	0.608
F16	0.423	F16	0.479	F16	0.415
F17	0.707	F17	0.707	F17	0.693
F18	0.774	F18	0.763	F18	0.772
F21	0.480	F21	0.496	F21	0.466
F22	0.383	F22	0.416	F22	0.398
F23	0.656	F23	0.687	F23	0.654
F24	0.622	F24	0.643	F24	0.649
F31	0.688	F31	0.684	F31	0.711
F32	0.808	F32	0.803	F32	0.819
F33	0.760	F33	0.764	F33	0.759
F34	0.572	F34	0.561	F34	0.575
F35	0.391	F35	0.400	F35	0.357
F36	0.615	F36	0.606	F36	0.605
F37	0.451	F37	0.486	F37	0.432
F38	0.687	F38	0.676	F38	0.665
F39	0.690	F39	0.711	F39	0.660
F310	0.604	F310	0.588	F310	0.622
F311	0.720	F311	0.735	F311	0.724
F312	0.760	F312	0.792	F312	0.773
F313	0.549	F313	0.580	F313	0.556
F314	0.668	F314	0.696	F314	0.692
F315	0.615	F315	0.636	F315	0.638
F316	0.693	F316	0.685	F316	0.644
F317	0.761	F317	0.788	F317	0.785
F318	0.711	F318	0.705	F318	0.729
F319	0.734	F319	0.732	F319	0.709
F320	0.599	F320	0.553	F320	0.598

Through the results, most of the failures are obtained in the same level when the proposed results are checked. However, there are also differences. We believe that this yields again the importance of assigning the most appropriate weights to the FMEA parameters. Moreover, since the scores can be negatives, we applied min–max normalization process to determine the risk level of the sources. It caused to obtain 0 and 10 risk magnitudes. Through that, the compared methodology can be a good example for ranking of risk modes for a comprehensive risk analysis.

In our proposed model, every rule is specifically constructed based on the expert knowledge with respect to the FMEA parameters to obtain the RPNs. This offers to researchers a wide assessment area to allocate the risk sources by considering even small changes. Thereby, it provides sustainable and robust results, where risk sources can be categorized appropriately and prioritized based on the RPNs.

Conclusion

Risk assessment approaches are frequently applied to consider the risk caused by failures, especially in labor-intensive enterprises. The FMEA approach used in risk assessment studies analyzes the system or process to identify possible failure modes and their causes and effects on system

Table 20 Results of the case of integrated BWM MOORA approach

	Scores	Normalization	Risk Magnitude
F11	0.407	1.000	0.000
F12	-0.061	0.468	5.321
F13	-0.091	0.434	5.660
F14	-0.240	0.265	7.346
F15	0.002	0.540	4.596
F16	0.017	0.557	4.425
F17	-0.006	0.531	4.691
F18	-0.086	0.440	5.602
F21	-0.031	0.502	4.975
F22	-0.343	0.148	8.521
F23	-0.023	0.511	4.887
F24	-0.257	0.245	7.546
F31	-0.252	0.251	7.489
F32	-0.092	0.433	5.667
F33	-0.051	0.479	5.207
F34	-0.269	0.232	7.678
F35	0.097	0.648	3.518
F36	-0.117	0.404	5.956
F37	0.073	0.621	3.789
F38	-0.015	0.520	4.797
F39	0.149	0.707	2.927
F310	-0.394	0.090	9.101
F311	-0.063	0.466	5.341
F312	-0.070	0.459	5.414
F313	-0.146	0.372	6.284
F314	-0.181	0.332	6.685
F315	-0.239	0.266	7.340
F316	0.196	0.760	2.399
F317	-0.114	0.409	5.914
F318	-0.207	0.303	6.971
F319	0.059	0.604	3.959
F320	-0.473	0.000	10.000

or process performance. Risk prioritization of failure modes is determined by calculating RPNs obtained by multiplying the probability of occurrence (O), severity of effects (S), and chance of detection (D). While determining the number of risk priorities in the traditional FMEA, these factors are determined as crisp numbers, but fuzzy logic is used to overcome this shortcoming of FMEA. In addition, due to the flexibility of decision-makers to overcome some of the traditional RPN's shortcomings, MCDM approaches have been used within the framework of fuzzy logic in risk assessment studies. In this paper, the failures encountered in textile companies producing woven fabrics were investigated extensively and a risk assessment study was carried out to take precautions about them before the failure occurred in a textile mill. For this purpose, integrated fuzzy decision-making methodology including fuzzy AHP, fuzzy TOPSIS, and FIS has been introduced to prioritize the risk sources. A case study is carried out with the method proposed in a textile mill, and it is determined which risks arising from failures are higher. In the proposed integrated approach, linguistic evaluations from experts have been converted to quantitative values for calculations via fuzzy logic and it is aimed to create an effective proactive risk calculator for managers or researchers to make useful inferences, judgments, and decisions about production processes, especially in sectors with high-quality variability, such as textiles. Thus, a comprehensive risk assessment study has been proposed in which it can reflect expert opinions to calculations in the best way and measures can be taken for risks arising from failures in risk analysis studies to take measures against failures in the process industries.

For future studies, different MCDM approaches or different extensions of fuzzy sets can be applied to conduct a comparative analysis. Furthermore, the proposed methodology can be applied to different manufacturing plants and a road map for the proactive behavior for the risk assessment can be constructed. The efficiency of the method can be measured using different distance calculations to calculate the distances between fuzzy numbers.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

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