A Fuzzy FMEA-Resilience Approach for Maintenance Planning in a Plastics Industry

Abbas Al-Refaie[1*] and Hedayeh Aljundi[2]
[1*] *Department of Industrial Engineering, University of Jordan, Amman, 11942.*
abbas.alrefai@ju.edu.jo
[2] *Industrial Engineer, Received Master's Degree in Industrial Engineering, University of Jordan.*

ABSTRACT

The productivity and efficiency of industrial systems are highly affected by failures and machine breakdowns. Further, in asset-intensive industries, unexpected failures are considered the primary source of operational risk. In response, the maintenance department strives to calculate reliable estimates of the risk levels associated with such failures and develop resilient maintenance strategies that enable it to respond effectively to equipment failures. The research developed a framework for integrating fuzzy failure mode and effects analysis (FFMEA) with resilience engineering (RE) concepts for maintenance planning. The framework consists of four main stages: FFMEA, Risk iso-surface (RI), resilience assessment, and maintenance planning. In FFMEA, multiple sub-factors were considered for each main risk factor and evaluated using fuzzy logic. Then, in the RI stage, the risk priority number (RPN) was calculated through a fuzzy approach that considered the order of the importance of the main three risk factors. The fuzzy resilience assessment was applied through a survey of fifty-one questions related to the main four RE potentials to determine the need for resilient maintenance strategies. Finally, the RPN-Resilience diagram was employed to classify maintenance activities into six main maintenance strategies. A case study from a production line of plastic bags was used for illustration. The main advantage of the proposed FFMEA is that it divides the main risk criteria into sub-criteria to increase the accuracy of risk assessment and evaluate resilience potentials under fuzziness. In conclusion, the integration of the risk-resilience evaluation is a valuable tool for effectively planning maintenance activities.

Keywords: FMEA, Resilience, Fuzzy, Maintenance, Plastics industry.

1. INTRODUCTION

Industrial systems are continuously subjected to failures and breakdowns that affect the capability of physical assets by increasing maintenance costs, reducing productivity and equipment availability, and decreasing the ability to maintain a satisfactory level of quality and safety (Al-Refaie et al., 2020a; Jonge and Scarf, 2020). Maintenance can be defined as a combination of technical, administrative, and managerial actions that are implemented to maintain or recreate a perfect condition during the lifecycle of a unit to perform the required function. Generally, maintenance is classified into three main types: corrective maintenance, preventive maintenance, and predictive maintenance (Al-Refaie & Hamdieh, 2024; Ma, et al., 2020; Bumblauskas, 2017; Bashiri, et al., 2011).

Maintenance planning is becoming more and more vital to organizations since effectiveness, product quality, maintenance service, and safety are becoming as important as the availability of machines and maintenance costs (Al-Refaie & Al-Hawadi, 2024; Al-Refaie & Al-Hawadi, 2023; Al-Refaie et al., 2023; Piller, 2015). To reduce the adverse effects due to equipment failures, proper maintenance decisions have to be taken after a careful study of failure risks and available maintenance resources. Risk-based maintenance (RBM) is a maintenance strategy that combines risk assessment and maintenance planning by making use of the knowledge of failures to reduce maintenance costs, increase safety, and achieve tolerable risk levels by reducing failure probabilities and their consequences (Al-Refaie et al., 2022a; Al-Refaie and Almowas, 2021). Risk assessment helps in prioritizing failures according to their occurrence frequency, consequences, and the ability to detect them. Then, the decision about the maintenance type and frequency is made based on the risk assessment results (Al-Refaie and Al-Hawadi, 2022; Arunraj and Maiti, 2007).

Several quantitative and qualitative risk assessment tools have been used in maintenance planning, such as failure mode effect criticality analysis, event tree analysis, fault tree analysis, Delphi technique, and failure mode and effects analysis (FMEA). The FMEA is a widely-used quantitative risk assessment tool that evaluates potential failure modes (FMs) and then prioritizes them to determine the required maintenance actions and support the decision-making process about maintenance policies (Dinmohammadi and

----

https://doi.org/10.36001/IJPHM.2024.v15i2.3851

Shafiee, 2013). FMEA usually ranks FMs according to their risk priority number (RPN) which is the product of the three main risk factors: occurrence (O), severity (S), and detection (D) of a failure, where O is a measure of the failure frequency or probability (Smadi, 2014), while S assesses the impact and consequence of the failure (Balaraju, et al., 2019), and D refers to the probability of detecting the failure before it happens (Jamshidi, et al., 2015). However, FMEA usually uses a 10-point scale for evaluating risk factors, producing RPN values that lie between 1 and 1000. Equal RPN values can result from different combination sets of O, S, and D (Keskin and Özkan 2009), and thereby the difference in the importance of the three factors is not distinguished (Xiao et al., 2011). Furthermore, describing the three risk factors of failures based on crisp numbers is unreliable. Consequently, the experts' evaluation may include uncertainty that affects maintenance decisions. Instead, linguistic scales can be used in the risk assessment using the terms, high, low, and moderate to describe the risk factors for a given FM. To overcome the imprecise judgment and uncertainty that arise from experts' evaluations due to using a linguistic scale during risk assessment, the fuzzy logic theory helps to translate the linguistic scale into a final crisp number by assigning a membership function (MF) for each linguistic term (Al-Refaie et al., 2021a; Al-Refaie et al., 2019a; Geramian, et al., 2017).

In practice, it is impossible to prevent all failures from happening. Hence, resilience engineering has gained significant importance as a characteristic of the process industry, to react robustly to disruptive events and recover from failures rather than preventing them (Al-Refaie et al., 2022b; Al-Refaie et al., 2020b; Dinh, et al., 2012). According to Hollnagel (2011), resilience is the intrinsic ability of a system to adjust its functioning before, during, or following changes and disturbances, so that it can sustain required operations under both expected and unexpected conditions (Al-Refaie & Kokash, 2023; Al-Refaie et al., 2022c; Al-Refaie & Abedalqader, 2022; Al-Refaie & Abedalqader, 2021). Implementing resilient maintenance strategies helps reduce the adverse consequences associated with failures; such as delays, increased cost, and severe effects on machines and workers, supports conducting more responsive and efficient maintenance actions, and facilitates the coordination and communication between the maintenance department and other departments. Resilience engineering (RE) comprises four main potentials: the potential to respond (PR), the potential to monitor (PM), the potential to learn (PL), and the potential to anticipate (PA) (Hollnagel, 2009). The PR refers to the system's ability to react or respond to any threat or hazard correctly by activating prepared actions, while the PM refers to the system's ability to monitor internal and external signals that can positively or negatively affect the system's performance in the short or long term. Further, the PL indicates the system's ability to learn from previous experiences and hazards (Shirali et al., 2012). Finally, the PA refers to the system's ability to predict and expect future events and developments; such as fluctuating operating conditions and potential disruptions (Bukowski and Werbińska-Wojciechowska, 2020a).

Fuzzy logic includes three main steps; fuzzification, fuzzy inference system (FIS), and defuzzification (Al-Refaie et al., 2021b; Al-Refaie et al., 2019b; Gallab et al., 2019; Al-Refaie et al., 2018). In fuzzy logic, both the inputs and outputs are represented by fuzzy sets with associated MFs that are determined based on experts' knowledge and experiences. The FIS consists of a fuzzy rule base used to process the inputs and produce a fuzzy output. The experts' knowledge and experiences about the interactions between the inputs and output are translated through fuzzy rules in the form of "*if-then* rules". *If* refers to an antecedent which is the input and *then* refers to a consequent which is the output. The Mamdani inference system is the preferable system to express human knowledge because it offers two operators for the conjunction of the rules: AND (minimum) and OR (maximum). Finally, defuzzification is used to convert the fuzzy FIS output into a meaningful crisp number. Defuzzification methods include the max-membership principle, centroid method, and weighted average method. This research employs the centroid method for defuzzification (Zeng et al., 2007).

In asset-intensive industries, unexpected failures are the primary source of operational risk (Moerman et al., 2017). Thus, the maintenance department strives to develop resilient maintenance strategies to respond effectively to failures and recover equipment as soon as possible. Consequently, this research develops a FFMEA-resilience framework for maintenance planning under fuzziness. The proposed framework helps organizations determine the appropriate maintenance policy and identify the resilience level in dealing with machine failures. The remainder of the research including the introduction is structured in the following sequence. Section 2 reviews the relevant previous studies on risk assessment and resilience. Section 3 develops the integrated FMEA-resilience framework. Section 4 presents a case study to illustrate the proposed framework. Section 5 summarizes research conclusions and directions for future research.

2. LITERATURE REVIEW

FMEA was utilized in assessing risk in several research studies. For example, Braglia et al. (2007) proposed a methodology for performing built-in reliability as an extension of the Quality Functional Deployment using FMEA. The FMEA was used to translate customers' requirements into functional requirements for the product. Taghipour et al. (2011) used the Analytical Hierarchy Process (AHP) to introduce a multi-criteria decision-making model to prioritize medical devices according to their criticality. The model included six main criteria: function, age, mission criticality, risk, recalls and hazard alerts, and maintenance requirements. The failure consequence was divided into operational (e.g. downtime), non-operational (e.g. cost of repair), and safety and environment. Geum et al. (2011) integrated FMEA with grey relational analysis (GRA) to evaluate FMs in service sectors. The FMEA stage encompasses 19 sub-criteria, O includes four sub-criteria: frequency, repeatability, visibility, and single point failure, while D was divided into four sub-criteria: chance of non-detection, method of systematic detection, customer/ employee detection, and hardness of proactive inspection. S was divided into three main dimensions: basic, customer, and process. The basic dimension includes impact, core process, typicality, and affected range, while the customer dimension includes customer participation, customer contact, service encounter, and process dimension includes interdependency, bottleneck possibility, hardness of isolation, and resource distribution. Liu et al. (2017) developed an FMEA approach that integrated cloud model theory with GRA. Cloud model theory was used to express the uncertainty of the linguistic assessment in the FMEA and GRA was used to prioritize FMs. Carpitella et al. (2018) combined failure mode effects and criticality analysis with a fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) in prioritizing FMs and planning maintenance activities in a street-cleaning vehicle. The FMs were prioritized according to the operational time, the modality of the maintenance action execution, and the frequency of occurrence. Can (2018) combined FMEA and the weighted aggregated sum product assessment. The approach used an intuitionistic scale to deal with uncertainty and hesitancy in the assessment process. A medium-voltage cell assembly line was employed for illustration. Additional factors were included in computing the intuitionistic fuzzy RPN involving cost, exposure duration, and system safety. Eyuboglu et al. (2020) proposed an FMEA model to prevent power transformer failures while considering equipment aging. Each risk factor was divided into three weighted subdivisions. Failure severity was measured by damage, repair, and duration, while occurrence was assessed by location, failure type, and failure causes. Finally, detectability was evaluated by protection, monitoring, and inspection.

However, the traditional FMEA fails to deal with the fuzziness and vagueness in the evaluation information due to the uncertainty of experts' assessment and human thinking (Milašinović et al., 2023; Liu et al., 2019). Therefore, several studies combined fuzzy logic with FMEA. Jamshidi et al. (2013) developed a fuzzy-based risk assessment model to assess pipeline failures. Failure probability included third-party damage, corrosion, design, and incorrect operation. While failure consequences covered product hazard, leak volume, dispersion, and receptors. Jee et al. (2015) introduced a fuzzy-based RPN approach utilizing genetic algorithm and monotonicity for prioritizing failures for a semiconductor manufacturing plant. Sankpal et al. (2015) used an integer linear programming approach to determine the appropriate maintenance strategy for failures identified using FFMEA. The aim was to maximize the reduction of RPN of each failure while considering the cost of each strategy, the compatibility constraint between failures and policies, and the available monetary resources. Nazeri and Jamshidi et al. (2015) developed a fuzzy risk assessment model to determine the appropriate maintenance policy for medical devices. Failure occurrence was assessed by repeatability, visibility, and mean time between failures (MTBF), while severity was measured by patient safety, the potential risk for the device operator and maintenance personnel, mean time to repair (MTTR), and economic loss. The detectability was evaluated by the probability of non-detection and the method of detection. Wang et al. (2016) integrated FMEA with a complex proportional assessment and analytic process to evaluate FMs under interval-valued intuitionistic fuzzy context in a hospital service setting. In FMEA, occurrence was assessed by repeatability and frequency, while severity was measured by impact, customer participation, and interdependency. Finally, the detectability was evaluated by the chance of non-detection and method of systematic detection. Naderikia (2017) proposed an approach to develop the maintenance strategy for railway tamping equipment using FFMEA and fuzzy decision-making trial and evaluation laboratory technique. Yazdi (2018) integrated FMEA, AHP, and entropy techniques to assess failures in a piping area for the construction industry. The fuzzy AHP was adopted to assign expert weights, find the most important specific activity, and determine a subjective weighing of severity, occurrence, and detection, while the entropy technique was adopted to calculate objective weights of the three risk factors. Expert weights were assessed based on job position, job experience, and education level. Liu et al. (2019) integrated cloud model theory and hierarchical technique for order of preference by similarity to the ideal solution (TOPSIS) method to produce an FMEA model that combined fuzziness and randomness of linguistic assessments and the advantages of hierarchical TOPSIS in solving complex decision-making problems. Kumar, et al. (2018) replaced the rule base development in FFMEA with a multi-criteria decision-making problem approach using Grey relational analysis to assess and prioritize different FMs in an auto Liquefied Petrol Gas dispensing station. Gallab et al. (2019) proposed a fuzzy risk assessment approach for three different equipment in the Liquefied Petrol Gas site. Jaderi et al. (2019) used both traditional and fuzzy risk-based maintenance (RBM) to evaluate asset failures in a petrochemical company to determine the criticality level of the company and identify the appropriate decisions regarding its maintenance strategy. Results revealed that the fuzzy RBM was more accurate than the traditional one. Wang et al. (2019) introduced an FMEA approach that took into consideration the psychological behavior of the decision-makers and the interaction relationships among risk factors using the prospect theory and Choquet integral, respectively.

An aircraft landing system was used to illustrate the approach and a comparison between other FMEA models and the developed FFMEA was conducted. Godina et al. (2021) integrated FFMEA with the design, measure, analyze, improve, and control cycle and applied it to a production line in an automotive industrial unit. In the define phase, all defects and potential failures were identified and classified to exclude the obvious defects. The number of FM occurrences was determined in the measure phase and the FFMEA was implemented in the analyze phase. According to the FFMEA results, improvements were suggested in the improvement phase, then, implemented and monitored in the control phase. Ribas et al. (2021) presented a two-stage FFMEA approach in the assessment of FMs of a hydroelectric earth dam. The first stage included the severity and occurrence as inputs to the FIS and the risk criticality index as an output. After that, the risk criticality index and detection are inputs to another FIS to obtain FIS-RPN. Reza et al. (2021) used FFMEA to identify failures in an apartment building and their causes and determine RPN for each failure to suggest risk mitigation actions for the most critical ones. Yeganeh et al. (2021) proposed a FFMEA approach for risk management implementation in light steel frame systems. In addition to failure occurrence and its consequences, the risk criticality number included another factor related to the ability to control the risk. Cardiel-Ortega & Baeza-Serrato (2023) proposed a fuzzy logic evaluation system with a solid mathematical basis in the defuzzification stage of RPN values by adjusting the centroid method and treating each set individually. Simulations were carried out to determine the system's best structure. A system of knitting machines in a textile company in southern Guanajuato was employed for validation.

In the context of resilience, Azadeh et al. (2014) introduced four new factors: self-organization, teamwork, redundancy, and fault-tolerant to evaluate the performance of RE in a petrochemical factory using data envelopment analysis, in addition to the six resilience indices introduced by Wreathall (2006) for high-reliability organizations (HRO) (i.e. management commitment, reporting culture, learning culture, awareness, preparedness, and flexibility). Dinh et al. (2012) differentiated between resilience strategies and principles, they introduced three resilience strategies to control disturbances: failure probability minimization, failure consequences minimization, and minimization of recovery time and restoration, while the resilience principles are: flexibility, controllability, early detection, minimization of failure, limitation of effects, and administrative controls and procedures. Wang et al. (2015) introduced the resilience concept into preventive maintenance scheduling for multi-aging production lines using a semi-Markov decision processes model. They aimed to minimize the system's average cost per unit of time under constrained preventive maintenance resources. Moerman et al. (2017) integrated RE and HRO concepts in a model to take into account engineering and organizational perspectives respectively in managing unexpected failures of a railway pit stop system. Jain et al. (2018) stated that resilience analysis is an important method in risk assessment and is divided into three phases; avoidance, survival, and recovery, which were represented by twenty-four resilience metrics. A survey was then conducted to identify the most important resilience metrics in each phase from the views of respondents from the chemical processes, and oil and gas fields. Bukowski and Werbińska-Wojciechowska (2020a) evaluated the maintenance capability level using a fuzzy-based method integrated with resilience potentials: PR, PM, PL, and PL. Two maintenance support parameters; potential readiness level and process regency, were introduced for each resilience potential. Bukowski and Werbińska-Wojciechowska (2020b) utilized resilience concepts and FMEA to investigate whether an automotive air conditioning compressors manufacturer followed RBM concepts.

However, little research was reported on the integration of FFMEA and resilience engineering to determine the appropriate maintenance policy. Moreover, prioritizing the RPN components; severity, detection, and occurrence, during PRN calculation was not considered. This research, therefore, contributes to the ongoing research on fuzzy risk assessment by developing a framework that integrates FFMEA with resilience under fuzziness. The proposed FFMEA differs from the traditional FMEA by dividing the main risk criteria into main sub-criteria to increase the accuracy of the risk assessment process and consider the order of importance of the three risk factors. Moreover, the resilience potentials and their characteristics are evaluated to determine the need for resilient maintenance strategies under fuzziness. Collectively, the developed combination of the FFMEA and fuzzy resilience shall greatly help decision-makers and maintenance experts assess the risk level associated with failures and determine the appropriate maintenance policies.

3. FMEA-RESILIENCE INTEGRATION

The methodology includes four stages, including FFMEA, resilience assessment, and maintenance planning. These stages are presented as follows.

3.1 FFMEA assessment

A typical production line usually consists of n machines; where each machine is subjected to several FMs. The FMEA is used to identify the system and sub-systems and then determine potential FMs, their causes, effects, and the current maintenance strategies. For each FM, the three risk factors O, S, and D have to be evaluated. In this research, each of the three risk factors is divided into sub-criteria as shown in Figure 1. The evaluation of failure risk using FFMEA is shown in Figure 2.

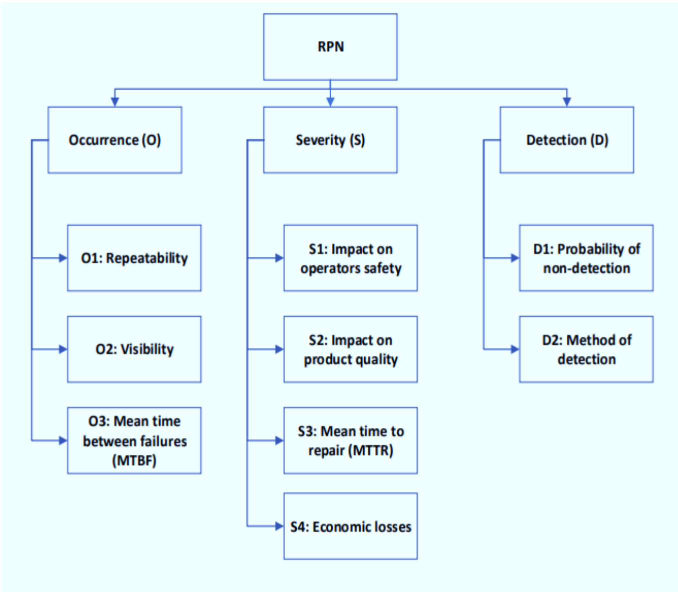

Figure 1. FMEA criteria and sub-criteria.

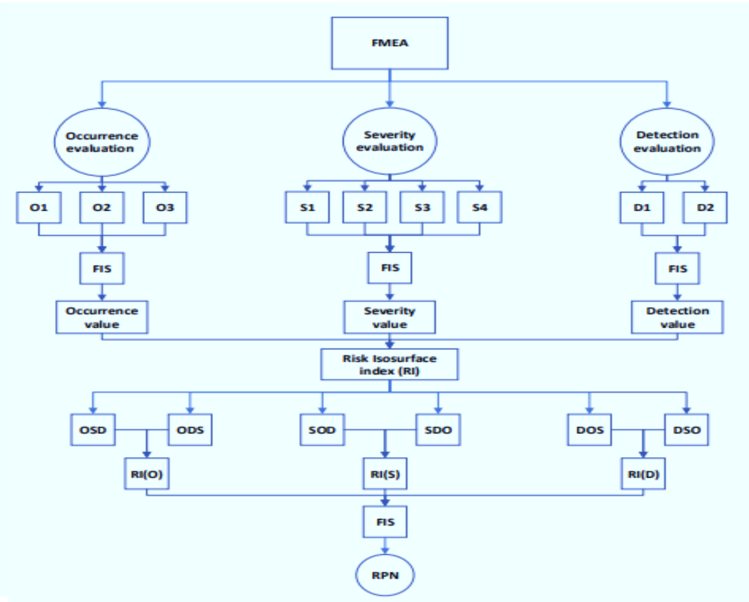

Figure 2. FFMEA approach.

The risk factors are described as follows:

1. The O factor donates the probability of a failure to happen or the frequency of failure occurrence. To evaluate O more accurately, it can be divided into two sub-criteria: repeatability (O1), MTBF (O2), and visibility (O3). Repeatability represents the frequency of failure occurrence due to the same source within a period (Geum et al., 2011), while the MTBF is a measure of reliability engineering and is defined as the expected time between two successive failures from the same type for the same machine. Visibility is another important factor in measuring the occurrence since it determines whether the failure is visible to the operators or maintenance experts during operating, inspection, or maintenance activities. Table 1 shows the linguistic terms used to evaluate the occurrence of sub-criteria and the corresponding fuzzy numbers.
2. The S factor refers to all the adverse consequences associated with the failure in terms of delay, cost, safety, and environment. In this study, severity is divided into four sub-criteria: operators and maintenance team safety (S1), product quality (S2), MTTR (S3), and economic loss (S4). It is important to investigate the effect of the failures on human wellbeing because some failures may lead to severe injuries or even death; thus S1 represents the impact of the failure on the safety of operators and maintenance personnel. Also, failures may have adverse on the produced product, thus, S2 is concerned about the impact of the failure on the product quality. MTTR is another measure of reliability that refers to the average time taken to define failure causes and get the equipment repaired (Kaur and Bahl, 2014). Moreover, there are economic losses associated with each failure, mainly due to reduced machine utilization, delay, and maintenance-related activities. In this study, the economic losses are due to maintenance labor and material costs and the loss of production. Table 2 shows the linguistic terms used to evaluate severity sub-criteria and the corresponding fuzzy numbers.
3. The D criterion refers to the ability to detect the failure before happening and it is divided into two sub-criteria: the probability of not detecting a failure (D_1) and the method of failure detection (D_2). D_1 is concerned about the ability of maintenance personnel to detect the failure and this is influenced by failure visibility, whether it can be detected through the naked eye or scheduled inspection or with the aid of diagnostic tools; such as automatic controls, alarms, and sensors (Sharma et al., 2005). While, D_2 refers to the method used in detecting the failure, whether it is detected through automated or manual inspection or cannot be detected at all. Tables 3 and 4 illustrate how D1 and D2 are evaluated using linguistic terms and the corresponding fuzzy numbers based on experts' experiences, respectively.

Experts are requested to evaluate FMs using linguistic terms that describe each sub-criterion. Then, the evaluation of experts is converted into triangular fuzzy numbers (TFNs) as follows (Yucel et al., 2011):

$$TFN = \sum_{i=1}^{n} w_i \, . MF_i \tag{1}$$

where TFN is the fuzzy number of the sub-criteria, n is the number of experts, w_i is the weight of expert i, and MF_i is the MF corresponding to the linguistic term chosen by expert i in the evaluation. The resulting TFNs are transformed into crisp values as follows (Jamshidi, et al., 2015):

$$D = \frac{1}{3}((U - L) + (M - L)) + L \quad (2)$$

where D is the defuzzified value of sub-criteria, U, L, and M are the upper, lower, and middle numbers of TFN, respectively. The defuzzified values of the sub-criteria are then inserted into the FIS of the main criteria using MATLAB to obtain the crisp values of O, S, and D for each FM utilizing Table 5. The next step is to calculate the RPN of each FM. In most cases, the three risk factors may differ in their importance. The RI function aims to involve this difference in RPN calculation and FM prioritization. Anes et al. (2018) introduced Eqs. (3) and (4) for calculating the RI for two and three risk factors with different importance, respectively.

$$RI\ (A, B)_{A>B} = \alpha . A + \mathrm{B} - \alpha \quad (3)$$

$$RI(A, B, C)_{C>A>B} = \alpha . A + B - \alpha + (C - 1) * \alpha^2 \quad (4)$$

where A, B, and C are risk factors, and α is the scale length of the risk factors. Because there are three risk factors involved in FMEA analysis (O, S, and D), six combinations will result according to the order of importance: SOD, SDO, OSD, ODS, DOS, and DSO. For example, the combination OSD means that O is more important than S, and S is more important than D. Based on an evaluation scale of 10 points, the RI is calculated as:

$$RI(OSD)_{O>S>D} = (O - 1). 10^2 + S. 10 + (D - 10) \quad (5)$$

Table 1. Description and fuzzy rating of O sub-criteria.

Fuzzy rating	O1: Repeatability (Gargama and Chaturvedi, 2011)	O2: MTBF (Braglia, 2000)	O3: Visibility (Jamshidi, et al., 2015)	Rating
Very high (VH)	Failure is almost happening (< 1 month)	< 3 months	It is not visible at all	(8,10,10)
High (H)	Repeated failure (1-6 months)	3-6 months	Visible while using the machine	(6,7.5,9)
Moderate (M)	Occasional failure (6-12 months)	6-24 months	Visible between two inspection intervals	(3.5,5,6.5)
Low (L)	Relatively few failures (12-24 months)	2-10 years	Visible while inspecting	(1,2.5,4)
Very low (VL)	Failure is unlikely (>2 years)	> 10 years	Visible before an inspection	(0,0,2)

Table 2. Description and fuzzy rating of S sub-criteria.

Fuzzy rating	S_1: Impact on operators and maintenance team safety. (Jamshidi, et al., 2015)	S_2: Impact on product quality (based on experts' experiences)	S_3: MTTR (Sharma, et al., 2005)	S_4: Economic loss (based on experts experiences)	Rating
VH	Death	Serious effect (product is scraped and cannot be recycled)	Production line shut down.	Economic loss ≥ \$10,000	(8,10,10)
H	Serious long-term injury	Significant effect (product is scraped but can be recycled)	External intervention for repairs	\$7000 ≤ Economic loss < \$10,000	(6, 7.5, 9)
M	Moderate injury	Moderate effect (product can be reworked)	1 day ≤MTTR< 4 days	\$4000 ≤ Economic loss < \$7000	(3.5 ,5, 6.5)
L	Minor injury	Minor effect (product can be sold at a lower price)	1hour ≤ MTTR< 1 day	\$1000<Economic loss <\$4000	(1, 2.5 ,4)
VL	Less or no effect	Less or no effect (product quality is not affected)	MTTR<1 hour	Economic loss< \$1000	(0, 0, 2)

Table 3. Description and fuzzy rating of D_1.

Fuzzy rating	Visible to the naked eye			Detection via automatic diagnostic aids			Detection after an inspection		Rating
	Yes	Partially	No	Directly	Indirectly	No	Yes	No	
Almost certain (AC)	X								(0.5, 1.5, 2.5)
High (H)		X		X			X		(1.5, 3 ,4.5)
Moderate (M)			X		X		X		(3,4.5, 6)
Low (L)			X		X			X	(4.5, 6, 7.5)
Remote (R)			X			X	X		(6, 7.5, 9)
Almost uncertain (AU)			X			X		X	(8,9,10)

Table 4. Description and fuzzy rating of D_2.

Rating	Description	Rating
VL	100% automatic inspection.	(0 ,0 ,2)
L	100% manual inspection.	(1, 2.5 ,4)
M	Manual inspection for some components.	(3.5,5,6.5)
H	No inspection for failure and it is allowed to occur.	(6, 7.5, 9)
VH	No known inspection process and it is hard to detect failure.	(8,10,10)

Table 5. Fuzzy rating of O, S, and D.

Fuzzy rating	Fuzzy number
VL	(0, 0, 2.5)
L	(0, 2.5, 5)
M	(2.5, 5, 7)
H	(5, 7.5, 10)
VH	(7.5,10, 10)

However, getting six RI values from the six combinations does not provide an accurate RPN to prioritize all FMs based on one combination. Therefore, three fuzzy numbers are generated from the six combinations, one when S is the most critical factor (SOD and SDO), one when O is the most important factor (OSD and ODS), and one when D is the most critical factor (DOS and DSO). Assuming that RI is represented by triangular MFs, the TFN of RI is generated from two RI combinations using Eq. (6).

$$\widetilde{RI} = (\bar{X} - s,\, \bar{X}, \bar{X} + s) \tag{6}$$

where $\widetilde{RI}$ is the TFN of RI resulting from two combinations, $\bar{X}$ and s are the average and estimated standard deviation of two RI combinations of the same risk factor, respectively. For instance, the TFN for O combinations (OSD and ODS) is given as:

$$\widetilde{RI}(O) = (\bar{X} - s\,, \bar{X}\,, \bar{X} + s) \tag{7}$$

where $\widetilde{RI}(O)$ is the TFN of RI when O is the most important factor, $\bar{X}$ and s are the average and standard deviation of OSD and ODS, respectively. As a result, each FM has three $\widetilde{RI}$ TFNs, as shown in Figure 3 are then introduced into FIS to obtain a crisp RPN. The interaction between the three RIs is represented using the fuzzy rule base in the form of IF-THEN rules. Since the TFNs are numerical values, they should be converted into matching fuzzy sets to become compatible with the IF-THEN fuzzy rules that are constructed using linguistic terms. Table 6 displays the linguistic terms used to describe the RPN. The matching fuzzy sets are obtained from the intersection between TFN and the MF of the corresponding $\widetilde{RI}$ as shown in Figure 4.

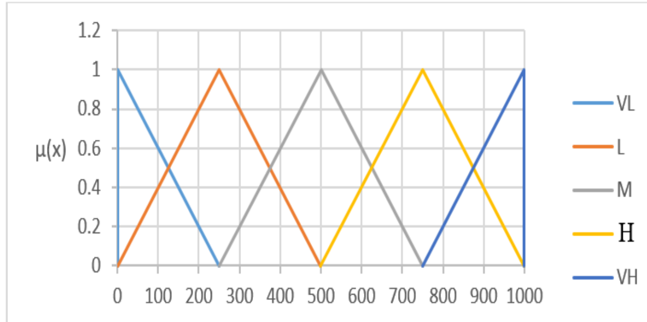

Figure 3. MFs of $\widetilde{RI(O)}$, $\widetilde{RI(S)}$and $\widetilde{RI(D)}$.

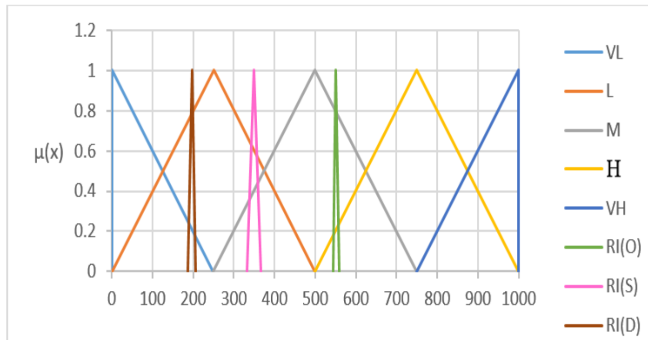

Figure 4. Matching fuzzy sets of $\widetilde{RI(O)}$, $\widetilde{RI(S)}$ and $\widetilde{RI(D)}$.

Table 6. Linguistic variables and MFs of $\widetilde{RPN}$.

Fuzzy rating	Fuzzy number
None (N)	(0, 0, 200)
Very low (VL)	(100, 200, 300)
Low (L)	(200, 300, 400)
High Low (HL)	(300, 400, 500)
Low Moderate (LM)	(400, 500, 600)
Moderate (M)	(500, 600, 700)
High Moderate (HM)	(600, 700, 800)
Low High (LH)	(700, 800, 900)
High (H)	(800, 900, 1000)
Very high (VH)	(900, 1000, 1000)

After that, the strength of the fire rules is obtained using fuzzy intersection (minimum) operation as

$$\mu_R = \mu_{\widetilde{RI}(O)}(x_1) \wedge \mu_{\widetilde{RI}(S)}(x_2) \wedge \mu_{\widetilde{RI}(D)}(x_3) \wedge \mu_{RPN}(y) \tag{8}$$

where μ_R is the MF of the rule, $\mu_{\widetilde{RI}(O)}$, $\mu_{\widetilde{RI}(S)}$, $\mu_{\widetilde{RI}(D)}$, μ_{RPN} are the MF of $\widetilde{RI(O)}$, $\widetilde{RI(S)}$ and $\widetilde{RI(D)}$, and RPN, respectively, $x_1 \in X_1$, $x_2 \in X_2$, $x_3 \in X_3$, $y \in U$, X_1, X_2, X_3, and U represent the universe of $\widetilde{RI(O)}$, $\widetilde{RI(S)}$, $\widetilde{RI(D)}$, and $\widetilde{RPN}$, respectively. Then, the MF of the output is obtained using the fuzzy union (maximum) operation using Eq. (9):

$$\mu_{RPN} = \vee_{i=1}^{k} R^k(x, y) \tag{9}$$

where μ_{RPN} is the MF of the output (RPN), k is the number of rules, and R^k is the strength of rule k. Table 9 displays the MFs of $\widehat{RPN}$. Finally, the fuzzy RPN is defuzzified using the centroid method as stated in Eq. (10).

$$Output = \frac{\sum_{i=1}^{q} \mu_i(y_i).Y_i}{\sum_{i=1}^{q} \mu_i(y_i)} \quad (10)$$

3.2 Resilience assessment

This research considers four resilience potentials proposed by Hollnagel (2011), including PR, PM, PL, and PA as shown in Figure 5. The resilience characteristics, measures, and concepts are classified under the four resilience potentials. Seven PR characteristics are considered including rapidity (Cai et al., 2018), emergency preparedness (Jain et al., 2018, Van der Beek and Schraagen, 2015, Tadic et al., 2014), robustness (Guo, et al., 2021, Attoh-Okine et al., 2009), recoverability (Muller, 2012), resource availability (Van der Beek and Schraagen, 2015), redundancy: (Yodo and Wang, 2016; Okoh and Haugen, 2015; Carvalho et al., 2012) and flexibility: (Woods 2006; Woods and wreath, 2003). Further, four PM characteristics are examined including controllability (Dinh et al., 2012), minimization of failure, resourcefulness (Bruneau et al. 2003), and limitation of effect. Furthermore, six PL characteristics are assessed involving adaptability (Tong et al., 2020), agility (Muller, 2012), administration controls and procedures (Dinh et al., 2012), learning capability (Park et al., 2012; Mentes and Turan, 2018), and reporting culture (Azadeh and Salehi, 2014, Costella et al., 2009, Woods and wreath, 2003) Communicating culture (Jain, et al., 2018). Finally, three PA characteristics are investigated including early detection (Sheffi and Rice, 2005; Jain et al., 2018, Tadic et al., 2014), anticipation/ forecast capability, and proactivity/ preparedness (Shirali, et al., 2013). A five-level Likert scale is used to assess RPN elements and resilience potentials. The fuzzy logic follows to aggregate the experts' evaluation and obtain a final resilience index using Eq. (10) that describes the need for resilience maintenance strategies. Table 7 displays the linguistic terms for PR, PM, PL, PA, and resilience index.

Table 7. MFs of Resilience potentials.

Linguistic term	Fuzzy number
VL	(0,0,0.3)
L	(0.1,0.3,0.5)
M	(0.3,0.5,0.7)
H	(0.5,0.7,0.9)
VH	(0.7,1,1)

3.3 Maintenance Planning

FMEA helps to determine the criticality of FMs, the higher the RPN, the more proactive maintenance strategy is required. For instance, an FM with high RPN may require predictive or preventive maintenance while a FM with low RPN may require corrective maintenance. However, the resilience index is used to determine whether the maintenance policy chosen based on RPN should be resilient or not. Moreover, FMEA is used to make improvements and adjustments based on O, S, and D values to reduce the risks of FMs. Also, the four resilience potentials are used to determine the critical resilience aspects and needed improvements. Figure 6 shows the resilience-RPN diagram which can be utilized to determine the maintenance strategies.

4. APPLICATION

A production line that produces plastic bags with different types of shopping bags, food packaging, multilayer bags, and heavy-duty bags is employed to illustrate the developed framework. The main goal of the factory is to respond effectively to customers' demands, in terms of delivery on time, cost, and product quality. To achieve this goal, the maintenance team should maintain continuous production with minimum interruptions and failures affecting production capacity. Thus, having resilient maintenance strategies with risk-based thinking will drive the production process to be more resilient and robust against undesired events. The required data were collected from two maintenance experts: the head of the department and the maintenance engineer and they were given equal weights (i.e. w_1=0.5 and w_2=0.5). The production line consists of three main machines: a plastic filming machine, a Flexo printing machine, and a cutting machine. First, the granular raw materials are transformed into plain plastic rolls using the plastic filming machine. Then, the plain, unprinted roll is driven into a Flexo printing machine to print the required design on the roll. Finally, the cutting machine cuts the printed roll into identical bags of the desired dimensions.

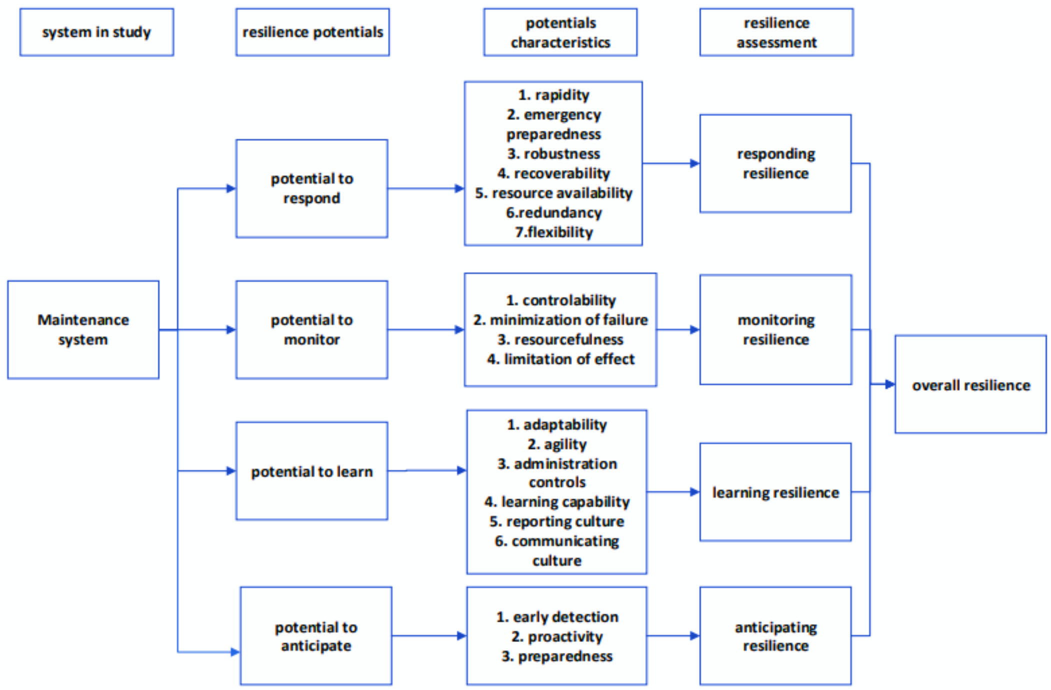

Figure 5. Resilience assessment framework.

4.1 FFMEA results

The FMs, effects, and current maintenance strategy are represented in Table 8. Two experts evaluated the RPN and resilience sub-criteria. For illustration, the experts evaluated O for FM1 of machine 1 (FM_{11}) as shown in Table 9. In Table 9, O1 was evaluated by E1 and E2 as H (6, 7.5, 9) and M (3, 4.5, 6), respectively. Then, the evaluation of O1 was converted into TFN using Eq. (1) as follows:

$$\mathrm{TFN}(O_1) = (6, 7.5, 9) \otimes 0.5 \oplus (6, 7.5, 9) \otimes 0.5 = (6, 7.5, 9)$$

The defuzzified TFN of O1 was calculated as follows:

$$D(O_1) = \frac{1}{3}.\big((9-6) + (7.5-6)\big) + 6 = 7.5$$

Similarly, the evaluation was performed for the remaining sub-criteria. The aggregated TFNs of the O, S, and D sub-criteria are displayed in Table 11. The six RI combinations SOD, SDO, OSD, ODS, DOS, and DSO were calculated using Eq. (4) and then shown in Table 12. Then, the six RI values were converted into three TFNs; $\widetilde{RI(O)}$, $\widetilde{RI(S)}$, and $\widetilde{RI(D)}$ as also listed in Table 12.

Table 8. FMEA of plastic bags production line.

Machine	Failure mode	Failure effect	Current maintenance
Plastic filming	FM_{11}: The sensor was not placed properly leading to an inaccurate temperature reading	Defective products	Predictive
	FM_{12}: Improper lubrication of bearing	Work accidents	Preventive
	FM_{13}: Air sensor failure	Defective products	Corrective
Flexo-printing	FM_{21}: Tension controller failure due to load cell error	Solid ink leading to unprinted roll	Corrective
	FM_{22}: Inoperative door sensor	Work accidents	Predictive
	FM_{23}: Worn bearing	Work accidents	Preventive
Cutting	FM_{31}: Photocell error	Defective products and accumulated materials may lead to fire	Corrective
	FM_{32}: Rubber Cylinder cut	Defective products and accumulated materials may lead to fire	Preventive
	FM_{33}: Damaged heater	Defective products	Corrective

Table 9. An illustrative evaluation of O for FM_{11}.

FM	Expert	O1	O2	O3
FM_{11}	E1	H	VH	VH
FM_{11}	E2	H	VH	H

Table 10. Aggregated TFNs of O, S, and D sub-criteria.

FM	Occurrence			Severity				Detection	
	O1	O2	O3	S1	S2	S3	S4	D1	D2
FM11	(6, 7.5,9)	(8,10,10)	(7,8.75,9.5)	(0.5,1.25, 3)	(0.5,1.25, 3)	(0.5,1.25, 3)	(3.5,5,6.5)	(1,2.25,3.5)	(2.25,3.75,5.25)
FM12	(4.75,6.25,7.75)	(7,8.75,9.5)	(6,7.5,9)	(6,7.5,9)	(6,7.5,9)	(6,7.5,9)	(2.25,3.75,5.25)	(0.5,1.5,2.5)	(2.25,3.75,5.25)
FM13	(2.25,3.75,5.25)	(0.5,1.25, 3)	(3.5,5,6.5)	(0,0,2)	(0,0,2)	(0,0,2)	(3.5,5,6.5)	(0.5,1.5,2.5)	(0,0,2)
FM21	(2.25,3.75,5.25)	(3.5,5,6.5)	(2.25,3.75,5.25)	(0.5,1.25, 3)	(0.5,1.25, 3)	(0.5,1.25, 3)	(3.5,5,6.5)	(3,4.5,6)	(2.25,3.75,5.25)
FM22	(4.75,6.25,7.75)	(8,10,10)	(4.75,6.25,7.75)	(8,10,10)	(8,10,10)	(8,10,10)	(6,7.5,9)	(5.25,6.75.8.25)	(6,7.5,9)
FM23	(4.75,6.25,7.75)	(6,7.5,9)	(4.75,6.25,7.75)	(2.25,3.75,5.25)	(2.25,3.75,5.25)	(2.25,3.75,5.25)	(2.25,3.75,5.25)	(0.5,1.5,2.5)	(6,7.5,9)
FM31	(7,8.75,9.5)	(6,7.5,9)	(7,8.75,9.5)	(3.5,5,6.5)	(3.5,5,6.5)	(3.5,5,6.5)	(2.25,3.75,5.25)	(2.25,3.75,5.25)	(2.25,3.75,5.25)
FM32	(0.5,1.25, 3)	(7,8.75,9.5)	(0.5,1.25, 3)	(2.25,3.75,5.25)	(2.25,3.75,5.25)	(2.25,3.75,5.25)	(3.5,5,6.5)	(6,7.5,9)	(3.5,5,6.5)
FM33	(4.75,6.25,7.75)	(6,7.5,9)	(4.75,6.25,7.75)	(3.5,5,6.5)	(3.5,5,6.5)	(3.5,5,6.5)	(4.75,6.25,7.75)	(6,7.5,9)	(3.5,5,6.5)

Table 11. Defuzzified values of O, S, and D sub-criteria.

FM	Occurrence			O	Severity				S	Detection		D
	O1	O2	O3		S1	S2	S3	S4		D1	D2	
FM11	7.5	9.3	8.4	9	1.58	9.3	3.75	5	5	2.25	3.75	2.5
FM12	6.25	8.4	7.5	7.63	7.5	0.67	5	3.75	5	1.5	3.75	2.5
FM13	3.75	1.6	5	3.62	0.67	9.3	1.58	5	5	1.5	0.67	0.88
FM21	3.75	5	3.75	3.75	1.6	9.3	5	5	5	4.5	3.75	2.5
FM22	6.25	9.3	6.25	7.63	9.3	1.58	6.25	7.5	7.5	6.75	7.5	6.25
FM23	6.25	7.5	6.25	7.63	3.75	5	5	3.75	5	1.5	7.5	2.5
FM31	8.4	7.5	8.4	9	5	7.5	2.5	3.75	5	3.75	3.75	2.5
FM32	1.6	8.4	1.6	4.12	3.75	7.5	5	5	5	7.5	5	7.5
FM33	6.25	7.5	6.25	7.63	5	8.41	5	6.25	6.25	7.5	5	7.5

Table 12. SOD, SDO, OSD, ODS, DOS, and DSO values.

FM	SOD	SDO	OSD	ODS	DOS	DSO	$\widetilde{RI(O)}$	$\widetilde{RI(S)}$	$\widetilde{RI(D)}$	RPN
FM_{11}	843	820	482.5	424	235	199	(820, 831.3, 842.5)	(424, 453.3, 482.5)	(199, 217, 235)	457
FM_{12}	706	683	469	423	221	198	(683, 694.3, 705.5)	(422.6, 445.7, 468.8)	(197.6, 209.5, 221.3)	409
FM_{13}	303	266	427	402	19	31	(265.8, 284.3, 302.9)	(402.4, 414.7, 427.1)	(18.8, 25.0, 31.2)	244
FM_{21}	318	295	430	419	183	194	(295, 306.3, 317.5)	(418.8, 424.4, 430)	(182.5, 188.1, 193.8)	289
FM_{22}	734	723	723	710	599	598	(723, 728.6, 734.3)	(710.1, 716.3, 722.6)	(597.6, 598.2, 598.8)	702
FM_{23}	706	683	469	423	221	198	(683, 694.3, 705.5)	(422.6, 445.7, 468.8)	(197.6, 209.5, 221.3)	408
FM_{31}	843	820	483	424	235	199	(820, 831.3, 842.5)	(424, 453.3, 482.5)	(199, 217, 235)	380
FM_{32}	360	382	439	469	686	694	(359.5, 370.8, 382)	(438.7, 453.9, 469.1)	(686.2, 690.2, 694.1)	586
FM_{33}	723	734	599	598	723	710	(723, 728.6, 734.3)	(597.6, 598.2, 598.8)	(710.1, 716.3, 722.55)	702

The TFNs were then converted to matching fuzzy sets. For illustration, the matching sets for FM_{11} are shown in Figure 6.

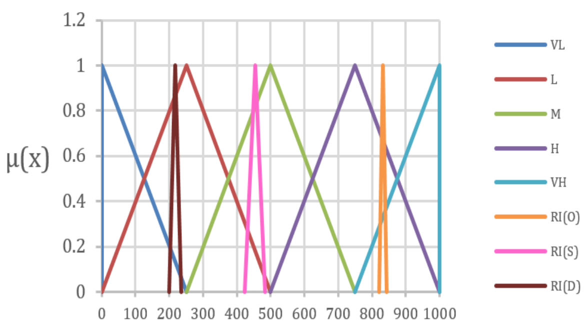

Figure 6. The matching sets for FM_{11}.

The TFNs of $\widetilde{RI(O)}$, $\widetilde{RI(S)}$, and $\widetilde{RI(D)}$ are (544.12,551.41,558.7), (333.25, 350.125, 367), and (187.45, 197.035, 206.62), respectively. Table 13 displays the matching sets for FM_{11}. The fuzzy RPN (= 457) was then defuzzified using Eq. (10).

Table 13. The outputs of the fired rules and RPN for FM_{11}.

RI(O)		RI(S)		RI(D)				RPN	
				VL	0.19	L	0.88		
H	0.69	L	0.27	L	0.19	HL	0.27	L	0.19
		M	0.83	HL	0.19	LM	0.69	HL	0.27
VH	0.35	L	0.27	HL	0.19	LM	0.27	LM	0.69
		M	0.83	LM	0.19	M	0.35	M	0.35

Table 12 shows that the highest RPN values correspond to FM_{22} and FM_{33}, whereas the lowest RPN values correspond to FM13 and FM_{21}. Accordingly, FM_{22} and FM_{33} require a more proactive maintenance policy than FM_{13} and FM_{21}.

4.2 Fuzzy resilience results

The experts were requested to fill out a survey of 51 questions regarding the four resilience potentials and their characteristics for each FM separately. Table 14 displays the corresponding TFNs and defuzzified values of PR, PM, PL, and PA. Finally, the values of the defuzzified potentials were set inputs to the resilience FIS to calculate the resilience index for all FMs as also listed in Table 14, where it is found that FM_{11}, FM_{12}, FM_{31}, FM_{32}, and FM_{33} require resilient maintenance policies.

4.3 RPN-Resilience results

The RPN-Resilience diagram is shown in Figure 7, which reveals that a corrective maintenance strategy should be applied to FM_{13}, however, resilient corrective maintenance is the appropriate maintenance policy for FM_{21}. Moreover, preventive maintenance should be performed for FM_{31} and FM_{32}, while resilient preventive maintenance should be used for FM_{11}, FM_{12}, and FM_{23}. Furthermore, the appropriate policies for FM_{33} and FM_{22} are predictive maintenance and resilient predictive maintenance, respectively. Finally, the required maintenance strategies and improvements that could be implemented to improve the performance of the maintenance department are provided in Table 15.

Table 14. Defuzzified PR, PM, PL, PA, and RI.

FM	PR	PM	PL	PA	PR	RI
FM_{11}	(0.394, 0.605, 0.786)	(0.363, 0.575, 0.750)	(0.379, 0.579, 0.779)	(0.405, 0.605, 0.805)	(0.394, 0.605, 0.786)	0.594
FM_{12}	(0.517, 0.744, 0.889)	(0.408, 0.608, 0.808)	(0.453, 0.667, 0.839)	(0.483, 0.689, 0.877)	(0.517, 0.744, 0.889)	0.646
FM_{13}	(0.245, 0.444, 0.645)	(0.233, 0.433, 0.633)	(0.218, 0.410, 0.610)	(0.233, 0.433, 0.633)	(0.245, 0.444, 0.645)	0.428
FM_{21}	(0.417, 0.619. 0.819)	(0.300, 0.500, 0.700)	(0.308, 0.500, 0.700)	(0.322, 0.522, 0.722)	(0.417, 0.619. 0.819)	0.532
FM_{22}	(0.508, 0.736, 0.883)	(0.450, 0.656, 0.844)	(0.469, 0.721, 0.854)	(0.450, 0.655, 0.844)	(0.508, 0.736, 0.883)	0.634
FM_{23}	(0.403, 0.609, 0.800)	(0.383, 0.583, 0.783)	(0.388, 0.624, 0.788)	(0.366, 0.566, 0.766)	(0.403, 0.609, 0.800)	0.587
FM_{31}	(0.321, 0.520, 0.720)	(0.267, 0.467, 0.654)	(0.226, 0.389, 0.597)	(0.161, 0.350, 0.555)	(0.321, 0.520, 0.720)	0.409
FM_{32}	(0.178, 0.359, 0.569)	(0.179, 0.354, 0.567)	(0.150, 0.333, 0.542)	(0.166, 0.333, 0.550)	(0.178, 0.359, 0.569)	0.369
FM_{33}	(0.124, 0.249, 0.470)	(0.165, 0.308, 0.533)	(0.226, 0.376, 0.589)	(0.061, 0.161, 0.411)	(0.124, 0.249, 0.470)	0.334

Table 15. Suggested improvements for FM maintenance.

Machine	FMs	Current maintenance	Suggested maintenance	Suggested actions
Plastic filming	FM_{11}	Preventive	Moderate resilient preventive	Conduct pre-startup review, use checklists, conduct regular inspections, monitor deviations, and near-misses, review operational and maintenance procedures
	FM_{12}	Preventive	Moderate resilient preventive	Continuous inspection, improving shift handover communications, conducting pre-startup review, defining authorities and responsibilities.
	FM_{13}	Corrective	Low resilient corrective	Maintain resource availability and redundant tools and spare parts, develop contingency plans, and employee training, using previous experiences in future corrective actions.
Flexo printing	FM_{21}	Corrective	Moderate resilient corrective	Train employees to deal with failure, keep redundant tools and spare parts, and define emergency and contingency plans.
	FM_{22}	Predictive	Moderate resilient predictive	Observe and interpret signals of failures, facilitate failure reporting, and review operational and maintenance procedures.
	FM_{23}	Preventive	Moderate resilient preventive	Regular inspection, conduct a pre-startup review, and define authorities and responsibilities.
Cutting machine	FM_{31}	Corrective	Low resilient preventive	Routine inspection, regular cleaning, plan for maintenance activities, and continuous monitoring.
	FM_{32}	Preventive	Low resilient preventive	Conduct pre-startup review, continuous inspection, monitor deviations, improve shift handover communications, and review operational and maintenance procedures.
	FM_{33}	Corrective	Low resilient predictive	Gather data and information, consistent condition monitoring, define procedures for failure detection, anticipate the obsolescence of components and equipment

4.4 Comparison with previous studies

Compared to the reported approaches in previous literature, the proposed framework for risk and resilience assessment using fuzzy FMEA-resilience indices has the following benefits: (1) obtaining a risk-resilience index by fuzzy assessment of various FMEA components and resilience potentials; (2) utilizing the risk and resilience indices to determine the appropriate maintenance policy under uncertainty, and (3) developing iso-surface and matching sets to determine the resultant RPN that was employed to prioritize the importance of occurrence, detection, and severity. In practice, the proposed framework can provide a valuable evaluation of risk and resilience indices that can support maintenance engineering in enhancing maintenance performance by improving operational safety, productivity, and availability of machines. These advantages can significantly reduce maintenance costs, failure probabilities, and failure consequences.

5. CONCLUSIONS

This research proposed a framework that integrates FFMEA and resilience engineering for fuzzy maintenance planning. In FFMEA, the main risk factors O, S, and D were divided into sub-factors. Then, the fuzzy logic approach was used to estimate RPNs, taking into account the order of importance of O, S, and D. In resilience assessment, a survey of fifty-one questions was developed to help experts evaluate the need for resilient maintenance strategies for potential FMs. The expert evaluation was analyzed using a fuzzy logic approach. Finally, the appropriate maintenance strategies for FMs were selected according to the results of FFMEA and resilience assessment through the Resilience-RPN diagram. A case study of the plastic bags production line in a plastic factory was conducted to illustrate the proposed framework and identify the appropriate maintenance policies with the suggested actions for regular and resilient corrective, preventive, and predictive maintenance. Results showed that the proposed framework is effective in handling the vagueness and uncertainty of experts' judgment, calculating RPN through the Fuzzy iso-surface approach, and determining the proper resilience characteristics and principles for the main resilience potentials. In conclusion, the benefits of the developed framework make it a valuable tool for maintenance engineering for reducing the probability and impacts of failures, reducing economic losses due to maintenance activities and production interruptions, and increasing production capacity and profit. However, the main limitation of this framework is that it requires a good understanding of statistical and mathematical techniques, experience in failure assessment, and knowledge of fuzzy sets and theory. Future research considers implementing machine learning for failure detection and maintenance planning.

REFERENCES

Al-Refaie, A., & Hamdieh, B. A. (2024). A data mining framework for maintenance prediction of faulty products under warranty. *Journal of Advanced Manufacturing Systems*, 23(01), 35-59.

Al-Refaie, A., & Al-Hawadi, A. (2024). Blockchain design for optimal joint production and maintenance over multiple periods for oil-filling production lines. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, 09544054241252854.

Al-Refaie, A., Abu Hamdieh, B., & Lepkova, N. (2023). Prediction of maintenance activities using generalized sequential pattern and association rules in data mining. *Buildings*, 13(4), 946.

Al-Refaie, A., & Al-Hawadi, A. (2023). A proposed eFSR blockchain system for optimal planning of facility services with probabilistic arrivals and stochastic service durations. *Buildings*, 13(1), 240.

Al-Refaie, A., & Kokash, T. (2023). Optimization of sustainable reverse logistics network with multi-objectives under uncertainty. *Journal of Remanufacturing*, 13(1), 1-23.

Al-Refaie, A., Al-Hawadi, A., & Lepkova, N. (2022a). Blockchain design with optimal maintenance planning. *Buildings,* 12(11), 1902.

Al-Refaie, A., Lepkova, N., & Camlibel, M. E. (2022b). The relationships between the pillars of TPM and TQM and manufacturing performance using structural equation modeling. *Sustainability*, 14(3), 1497.

Al-Refaie, A., & Abedalqader, H. (2022). Optimal berth scheduling and sequencing under unexpected events. *Journal of the Operational Research Society*, 73(2), 430-444.

Al-Refaie, A., & Al-Hawadi, A. (2022). Optimal fuzzy repairs' scheduling and sequencing of failure types over multiple periods. *Journal of Ambient Intelligence and Humanized Computing*, 13(1), 201-217.

Al-Refaie, A. and Almowas, H. (2021). Multi-objective maintenance planning under preventive maintenance. *Journal of Quality in Maintenance Engineering*, Vol. ahead-of-print No. ahead-of-print. https://doi.org/10.1108/JQME-05-2021-0035

Al-Refaie, A., & Abedalqader, H. (2021). Optimal berth allocation under regular and emergent vessel arrivals. *Proceedings of the Institution of Mechanical Engineers, Part M: Journal of Engineering for the Maritime Environment*, 235(2), 642-656.

Al-Refaie, A., Abdullah, R., & Domi, G. B. (2021a). A genetic-fuzzy procedure for solving fuzzy multiresponses problem: genetic-fuzzy procedure for solving fuzzy multiresponses problem. *International Journal of Intelligent Systems and Applications in Engineering*, 9(3), 81-90.

Al-Refaie, A., Abbasi, G., & Ghanim, D. (2021b). Proposed α-cut CUSUM and EWMA control charts for fuzzy response observations. *International Journal of Reliability, Quality and Safety Engineering*, 28(02), 2150012.

Al-Refaie, A., Qapaja, A., & Al-Hawadi, A. (2021c). Optimal fuzzy scheduling and sequencing of work-intensive multiple projects under normal and unexpected events. *International Journal of Information Technology Project Management* (IJITPM), 12(3), 64-89.

Al-Refaie, A., Lepkova, N., Abbasi, G., & Bani Domi, G. (2020a). Optimization of process performance by multiple pentagon fuzzy responses: Case studies of wire-electrical discharge machining and sputtering process. *Advances in Production Engineering & Management*, 15(3), 307-317

Al-Refaie, A., Al-Tahat, M., & Lepkova, N. (2020b). Modelling relationships between agility, lean, resilient, green practices in cold supply chains using ISM approach. *Technological and Economic Development of Economy*, 26(4), 675-694.

Al-Refaie, A., Obaidat, A., Fouad, R. H., & Hanayneh, B. (2019a). A fuzzy-logic approach for developing variables control charts and process capability indices under linguistic measurements. *ARPN Journal of Engineering and Applied Sciences*, 14(6), 1120-1139.

Al-Refaie, A., Bani Domi, G., & Abdullah, R. (2019b). A fuzzy goal programming-regression approach to optimize process performance of multiple responses under uncertainty. *International Journal of Management Science and Engineering Management*, 14(1), 20-32.

Al-Refaie, A., Judeh, M., & Li, M. H. (2018). Optimal fuzzy scheduling and sequencing of multiple-period operating room. *AI EDAM*, 32(1), 108-121.

Arunraj, N. S. and Maiti, J. (2007). Risk-based maintenance—Techniques and applications. *Journal of Hazardous Materials*, 142 (3), 653-661.

Anes, V., Henriques, E., Freitas, M., and Reis, L. (2018). A new risk prioritization model for failure mode and effects analysis. *Quality and Reliability Engineering International*, 34(4), 516–528.

Attoh-Okine, N. O., Cooper, A. T., and Mensah, S. A. (2009). Formulation of Resilience Index of Urban Infrastructure Using Belief Functions. *IEEE Systems Journal*, 3(2), 147–153.

Azadeh, A., and Salehi, V. (2014). Modeling and optimizing efficiency gap between managers and operators in integrated resilient systems: The case of a petrochemical plant. *Process Safety and Environmental Protection*, 92(6), 766–778.

Azadeh, A., Salehi, V., Ashjari, B., and Saberi, M. (2014). Performance evaluation of integrated resilience engineering factors by data envelopment analysis: The case of a petrochemical plant. *Process Safety and Environmental Protection*, 92(3), 231–241.

Balaraju, J., Govinda Raj, M. G., and Murthy, C. S. (2019). Fuzzy-FMEA Risk Evaluation Approach for LHD Machine-A Case Study. *Journal of Sustainable Mining*, 18(4), 257-268.

Bashiri, M., Badri, H., and Hejazi, T. H. (2011). Selecting optimum maintenance strategy by fuzzy interactive linear assignment method. *Applied Mathematical Modelling*, 35(1), 152–164.

Braglia, Marcello (2000). MAFMA: multi-attribute failure mode analysis. *International Journal of Quality & Reliability Management*, 17(9), 1017–1033.

Braglia, M., Fantoni, G. and Frosolini, M. (2007). The house of reliability. *International Journal of Quality & Reliability Management*. 24(4), 420-440

Bruneau, M., Chang, S. E., Eguchi, R. T., Lee, G. C., O'Rourke, T. D., Reinhorn, A. M., Shinozuka, M., Tierney, K., Wallace, W. A. and Winterfeldt, D. V. (2003). A Framework to Quantitatively Assess and Enhance the Seismic Resilience of Communities. *Earthquake Spectra*, 19(4), 733–752.

Bukowski, L. and Werbińska-Wojciechowska, S. (2020a). Using fuzzy logic to support maintenance decisions according to Resilience-Based Maintenance concept. *Maintenance and Reliability*, 23(2), 294–307.

Bukowski, L. and Werbińska-Wojciechowska, S. (2020b). Resilience based maintenance: a conceptual approach. *Proceedings of the 30th European Safety and Reliability Conference and the 15th Probabilistic Safety Assessment and Management Conference*, Venice, Italy. doi:10.3850/978-981-14-8593-0_4450-cd.

Bumblauskas, D., Gemmill, D., Igou, A., & Anzengruber, J. (2017). Smart Maintenance Decision Support Systems (SMDSS) based on corporate big data analytics. *Expert Systems with Applications*, 90, 303–317.

Cai, B., Xie, M., Liu, Y., Liu, Y., and Feng, Q. (2018). Availability-based engineering resilience metric and its corresponding evaluation methodology. *Reliability Engineering & System Safety*, 172, 216–224.

Can, Gülin Feryal. (2018). An intutionistic approach based on failure mode and effect analysis for prioritizing corrective and preventive strategies. *Human Factors and Ergonomics in Manufacturing & Service Industries*, 28(3), 130-147.

Cardiel-Ortega, J. J., & Baeza-Serrato, R. (2023). Failure mode and effect analysis with a Fuzzy Logic approach. *Systems*, 11(7), 348.

Carpitella, S., Certa, A., Izquierdo, J., and La Fata, C. M. (2018). A combined multi-criteria approach to support FMECA analyses: A real-world case. *Reliability Engineering & System Safety*, 169, 394–402.

Carvalho, H., Barroso, A. P., Machado, V. H., Azevedo, S., and Cruz-Machado, V. (2012). Supply chain redesign for resilience using simulation. *Computers & Industrial Engineering*, 62(1), 329–341.

Costella, M. F., Saurin, T. A., and de Macedo Guimarães, L. B. (2009). A method for assessing health and safety management systems from the resilience engineering perspective. *Safety Science*, 47(8), 1056–1067.

Dinh, L. T. T., Pasman, H., Gao, X. and Mannan, M. S. (2012). Resilience engineering of industrial processes: Principles and contributing factors. *Journal of Loss Prevention in The Process Industries*, 25 (2), 233-241.

Dinmohammadi, F. and Shafiee, M. (2013). A Fuzzy-FMEA Risk Assessment Approach for Offshore Wind Turbines.

International Journal of Prognostics and Health Management, 4, 1-10.
Eyuboglu, O. H., Dindar, B., and Gul, O. (2020). Risk assessment by using failure modes and effects analysis (FMEA) based on power transformer aging for maintenance and replacement decision. 2020 2nd *Global Power, Energy and Communication Conference* 2020, Izmir, Turkey, 20-23 October, 2020, 251-255.
Gallab, M., Bouloiz, H., Alaoui, Y. L., and Tkiouat, M. (2019). Risk Assessment of Maintenance activities using Fuzzy Logic. *Procedia Computer Science*. 148. 226-235.
Gargama, H., and Chaturvedi, S. K. (2011). Criticality Assessment Models for Failure Mode Effects and Criticality Analysis Using Fuzzy Logic. *IEEE Transactions on Reliability*, 60(1), 102–110.
Geramian, A., Mehregan, M. R., Garousi Mokhtarzadeh, N., and Hemmati, M. (2017). Fuzzy inference system application for failure analyzing in automobile industry. *International Journal of Quality & Reliability Management*, 34(9), 1493–1507.
Geum, Y., Cho, Y., and Park, Y. (2011). A systematic approach for diagnosing service failure: Service-specific FMEA and grey relational analysis approach. *Mathematical and Computer Modelling*, 54(11-12), 3126–3142.
Godina, R., Silva, B.G.R. and Espadinha-Cruz, P. (2021). A DMAIC Integrated Fuzzy FMEA Model: A Case Study in the Automotive Industry. *Applied Sciences*, 11(8), 3726.
Guo, D., Shan, M. and Owusu, E. (2021). Resilience Assessment Frameworks of Critical Infrastructures: State-of-the-Art Review. *Buildings*, 11, 464.
Hollnagel, Erik (2009). The four cornerstones of resilience engineering. In: Nemeth, C.P., Hollnagel, E. and Dekker, S.W.A. (Eds), Resilience Engineering Perspectives, Volume 2: Preparation and Restoration. (pp. 117-134), UK, Ashgate.
Hollnagel, Erik (2011). Prologue: the scope of resilience engineering. In: Hollnagel, E., Paries, J., Woods, D.D. and Wreathall, J. (Eds.), Resilience Engineering in Practice: A Guidebook. UK, Ashgate.
Jaderi, F., Ibrahim, Z. Z. and Zahiri, M. R. (2019). Criticality analysis of petrochemical assets using risk based maintenance and the fuzzy inference system. *Process Safety and Environmental Protection*, 121, 312-325.
Jain, P., Mentzer, R. and Mannan, M. S. (2018). Resilience metrics for improved process-risk decision making: Survey, analysis and application. *Safety Science*, 108, 18-23.
Jamshidi, A., Yazdani-Chamzini, A., Yakhchali, S. H. and Khaleghi, S. (2013). Developing a new fuzzy inference system for pipeline risk assessment. *Journal of Loss Prevention in the Process Industries*, 26(1), 197-208.
Jamshidi, A., Rahimi, S. A., Ait-kadi, D. and Ruiz, A. (2015). A comprehensive fuzzy risk-based maintenance framework for prioritization of medical devices. *Applied Soft Computing*, 32, 322-334.
Jee, T. L., Tay, K. M., and Lim, C. P. (2015). A New Two-Stage Fuzzy Inference System-Based Approach to Prioritize Failures in Failure Mode and Effect Analysis. *IEEE Transactions on Reliability*, 64(3), 869–877.
Jonge, B. D. and Scarf, P. A. (2020). A review on maintenance optimization. *European Journal of Operational Research*, 285(3), 805-824.
Kaur, G. and Bahl, K. (2014). Software Reliability, Metrics, Reliability Improvement Using Agile Process. *International Journal of Innovative Science, Engineering & Technology*, 1(3).
Keskin, G. A. and Özkan, C. (2009). An alternative evaluation of FMEA: fuzzy ART algorithm. *Quality and Reliability Engineering International*, 25(6), 647-661.
Kumar, A. M., Rajakarunakaran, S., Pitchipoo, P. and Vimalesan, R. (2018). Fuzzy based risk prioritisation in an auto LPG dispensing station. *Safety Science*, 101, 231-247.
Liu, H., Wang, L., You, X., and Wu, S. (2017). Failure mode and effect analysis with extended grey relational analysis method in cloud setting. *Total Quality Management & Business Excellence*, 30(1), 1–23.
Liu, H., Wang, L., Li, Z. and Hu, Y. (2019). Improving Risk Evaluation in FMEA with Cloud Model and Hierarchical TOPSIS Method. *IEEE Transactions on Fuzzy Systems*, 27(1), 84-95.
Ma, Z., Ren, Y., Xiang, X., and Turk, Z. (2020). Data-driven decision-making for equipment maintenance. Automation in Construction, 112, 103103.
Mentes, A., and Turan, O. (2018). A new resilient risk management model for Offshore *Wind Turbine maintenance. Safety Science*, 119, 360-374.
Milašinović, M., Ivetić, D., Stojković, M., & Savić, D. (2023). Failure conditions assessment of complex water systems using fuzzy logic. Water *Resources Management*, 37(3), 1153-1182.
Moerman, J., Braaksma, J. and Dongen, L. V. (2017), Resilient performance in maintenance operations: managing unexpected failures. *24th International Annual EurOMA Conference 2017, Edinburgh, United Kingdom*, 1-5 July, 2017.
Muller, George. (2012). Fuzzy Architecture Assessment for Critical Infrastructure Resilience. *Procedia Computer Science*, 12, 367–372.
Nazeri, A., and Naderikia, R. (2017). A new fuzzy approach to identify the critical risk factors in maintenance management. *The International Journal of Advanced Manufacturing Technology*, 92(9-12), 3749–3783.
Okoh, P., and Haugen, S. (2015), Improving the robustness and resilience properties of maintenance. Process Safety and Environmental Protection, 94, 212–226.
Park, J., Seager, T. P., Rao, P. S. C., Convertino, M., & Linkov, I. (2012). Integrating Risk and Resilience Approaches to Catastrophe Management in Engineering Systems. *Risk Analysis*, 33(3), 356–367.

Piller, Christoph (2015). A Reference Model for Maintenance Processes. In: Fleischmann A., Schmidt W., Stary C. (Eds), S-BPM in the Wild. (pp. 153–169), Heidelberg, Springer, Cham. doi.org/10.1007/978-3-319-17542-3_9.

Reza, A., Vanany, I., and Machsus. (2021). Risk assessment for apartment building maintenance using Fuzzy-FMEA methods. *IOP Conference Series: Materials Science and Engineering, Joint International Conference of The 2nd International Conference on Industrial and System Engineering and The 7th Annual Conference on Industrial and System Engineering, 1072, Surabaya, Indonesia*, 22-23 July, 2020, 012001.

Ribas, J. R., Severo, J. C. R., Guimarães, L. F. and Perpetuo, K. P. C. (2021). A fuzzy FMEA assessment of hydroelectric earth dam failure modes: A case study in Central Brazil. *Energy Reports*, 7, 4412-4424.

Sankpal, P., Andrew, A. and Kumanan S. (2015). Maintenance Strategies selection using Fuzzy FMEA and Integer Programming. *Proceedings of the International Conference on Advances in Production and Industrial Engineering* 2015, 23-24 January, 2015, 503-509.

Sharma, R. K., Kumar, D., and Kumar, P. (2005). Systematic failure mode effect analysis (FMEA) using fuzzy linguistic modelling. *International Journal of Quality & Reliability Management*, 22(9), 986–1004.

Sheffi, Y. and Rice J. B. (2005). A Supply Chain View of the Resilient Enterprise. *MIT Sloan Management Review*, 47(1), 41-48.

Shirali, G. A., Mohammadfam, I., and Ebrahimipour, V. (2013). A new method for quantitative assessment of resilience engineering by PCA and NT approach: A case study in a process industry. *Reliability Engineering & System Safety*, 119, 88–94.

Shirali, G. H. A., Motamedzade, M., Mohammadfam, I., Ebrahimipour, V., and Moghimbeigi, A. (2012). Challenges in building resilience engineering (RE) and adaptive capacity: A field study in a chemical plant. *Process Safety and Environmental Protection*, 90(2), 83–90.

Smadi, Hazem J. (2014). Determining Occurrence in FMEA Using Hazard Function. *International Journal of Industrial and Manufacturing Engineering*, 8(9), 2885-2889.

Taghipour, S., Banjevic, D., and Jardine, A. K. S. (2011). Prioritization of medical equipment for maintenance decisions. *Journal of the Operational Research Society*, 62(9), 1666–1687.

Tadić, D., Aleksić, A., Stefanović, M., and Arsovski, S. (2014). Evaluation and Ranking of Organizational Resilience Factors by Using a Two-Step Fuzzy AHP and Fuzzy TOPSIS. *Mathematical Problems in Engineering*, 2014, 1–13.

Tong, Q., Yang, M., and Zinetullina, A. (2020). A Dynamic Bayesian Network-based approach to Resilience Assessment of Engineered Systems. *Journal of Loss Prevention in the Process Industries*, 65, 104152.

Van der Beek, D., and Schraagen, J. M. (2015). ADAPTER: Analysing and developing adaptability and performance in teams to enhance resilience. *Reliability Engineering & System Safety*, 141, 33–44.

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

Wang, W., Liu, X., Chen, X. and Qin, Y. (2019). Risk assessment based on hybrid FMEA framework by considering decision maker's psychological behavior character. *Computers & Industrial Engineering*, 136, 516-527.

Wang, X., Qi, C., Wang, H., Si, Q. and Zhang, G. (2015). Resilience-driven maintenance scheduling methodology for multi-agent production line system. 2015 27th Chinese Control and Decision Conference (CCDC), Qingdao, China 23-25 May, 2015, 614-619.

Woods, David D. (2006). Essential characteristics of resilience. In E. Hollnagel, D. D. Woods, & N. Levenson (Eds.), Resilience engineering. (pp. 21-34), Hampshire, Ashgate Publishing.

Woods, D. D. and Wreathall, J. (2003). Managing Risk Proactively: The Emergence of Resilience Engineering. Columbus, OH: Institute for Ergonomics, the Ohio State University

Wreathall, John (2006). Properties of resilient organizations: an initial view. In: Hollnagel, E., Woods, D., Leveson, N. (Eds.), Resilience Engineering: Concepts and Precepts. (pp. 275–286), UK, Ashgate.

Xiao, N., Huang, H.-Z., Li, Y., He, L., and Jin, T. (2011). Multiple failure modes analysis and weighted risk priority number evaluation in FMEA. *Engineering Failure Analysis*, 18(4), 1162–1170.

Yazdi, Mohammad. (2018). Improving failure mode and effect analysis (FMEA) with consideration of uncertainty handling as an interactive approach. *International Journal on Interactive Design and Manufacturing*, 13, 441–458.

Yeganeh, A., Heravi, M. Y., Razavian, S. B., Behzadian, K. and Shariatmadar,H. (2021). Applying a new systematic fuzzy FMEA technique for risk management in light steel frame systems. *Journal of Asian Architecture and Building Engineering*, (1-22). DOI: 10.1080/13467581.2021.1971994.

Yodo, N., and Wang, P. (2016). Engineering Resilience Quantification and System Design Implications: A Literature Survey. *Journal of Mechanical Design*, 138(11), 111408.

Yucel, G., Cebi, S., Hoege, B., and Ozok, A. F. (2012). A fuzzy risk assessment model for hospital information system implementation. *Expert Systems with Applications*, 39(1), 1211–1218.

Zeng, J., An, M., and Smith, N. J. (2007). Application of a fuzzy based decision making methodology to construction project risk assessment. *International Journal of Project Management*, 25(6), 589–600.