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FUZZY LOGIC APPROACH IN FAILURE MODE AND EFFECTS ANALYSIS FOR RISK ASSESSMENT

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Abstract: Considering the increasing competitiveness of the ceramic industry within the country, export volumes, and the standards it must meet, the quality expectations of customers have increased. In this field, quality tools, such as FMEA (Failure Mode and Effects Analysis), are used to quantify the risk levels of existing defects, identify and prioritize them, and guide corrective measures. However, the lack of specialized technicians, the inefficiency of the visual inspection process, subjectivity, and qualitative failures involving uncertainty impose limitations on FMEA. The fuzzy FMEA approach is proposed to address the limitations of FMEA. The fuzzy FMEA system was identified through a case study of an industrial production unit. The RPN values of FMEA and fuzzy FMEA were evaluated and compared. The results show that the fuzzy FMEA method is effective at prioritizing product defects in ceramic sanitary ware production.

Keywords: Failure mode and effects analysis, Fuzzy logic, Manufacturing, Risk priority number, Fuzzy-FMEA

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1. Introduction

The desired quality level defined by the concepts of compliance with the purpose of use and with specifications and accepted as one definition of quality can be achieved, and continuous production at this quality level can be ensured through the use of quality techniques. Failure Mode and Effect Analysis (FMEA) is one such technique. In modern quality management, the concept of zero defects has gained increasing importance. FMEA, which prevents defective production by preventing its occurrence during the design or process phase, is an effective way to prevent it from reaching the customer.

A key component of an organization's strategy is risk management, which involves addressing process-related risks to secure long-term benefits from the activities they affect. This process may be either a service or a production process. Various studies should be conducted to ensure that the processes function effectively, produce useful output, and achieve customer satisfaction. In this context, the process FMEA is a powerful quality tool that can be used to better control product design or to eliminate variability in production processes. However, it has several important limitations. Several score combinations of Severity, Occurrence, and Detectability have been shown to yield the same RPN (Ben-Daya and Raouf, 1993; Bowles and Pela´ez, 1995; Pillay and Wang, 2003). The risk can differ even when the RPN is the same. In addition, the conventional method of determining the RPN ignores the relative importance of the three elements. To put it another way, the three criteria are considered to be equally important, but in reality, this could not be the case (Pillay and Wang, 2003). In fact, depending on the type of process or product, the three parameters' relative importance varies (Tay and Lim, 2006). A robust solution to this mathematical problem is to incorporate fuzzy logic into the FMEA framework.

The use of artificial intelligence techniques to solve engineering problems is increasing due to their demonstrated effectiveness and reliability. Examples include fuzzy systems and fuzzy logic techniques used in risk analysis. Fuzzy logic allows us to model by representing human reasoning and reflecting human linguistics because of its fuzzy rule base (Wan et al., 2019). Accurately evaluating the signs, severity (S), detection (D), and probability of the event occurring (P) is frequently challenging. Many potential values are disregarded in FMEA because these characteristics require precise numerical assignments. However, traditional FMEA lacks the flexibility to take experts' opinions into account (Mandal and Maiti, 2014). Fuzzy logic, which calculates the RPN using linguistic expressions, is used because humans are better at judging processes with linguistic expressions than with precise numerical scores. It offers mathematical techniques for translating verbal variables into numerical quantities. As a result, evaluating criticality using fuzzy logic makes it simple and natural to evaluate the risk related to failure types (Wan et al., 2019; Jahangoshai Rezaee et al., 2020).

Fuzzy FMEA has been applied to healthcare, steam valve systems, textile manufacturing, cyber-power grids, grinding wheels, shipbuilding, gas refineries, and service quality-internet banking (Liu et al., 2012; Tooranloo and Ayatollah, 2016; Liu et al., 2017; Li et al., 2019; Boral et al., 2020; Qin et al., 2020; Shahri et al., 2021; Cardiel Ortega and Serrato, 2023; Zuniga et al., 2023; Rong et al., 2024).

Razzad et al. (2024) used the fuzzy FMEA approach to analyze and eliminate 16 possible failure risks in the production of suction hoses for automobile air conditioning. To apply the specified method, a case study of the production process for automobile air-conditioning suction hoses was conducted. The results of traditional and fuzzy FMEA are compared. Mangla et al. (2018) applied fuzzy FMEA to assess risk priority in a green supply chain, and the approach was implemented in an Indian plastic manufacturing facility. Liu and Tsai (2012) used fuzzy FMEA, ANP, and QFD methods to perform a risk assessment of occupational uniqueness in the construction industry. This study identified the hazard levels associated with the major types of hazards in the construction industry, their causes, and the prevention and improvement measures that can be taken to address them. Ekmekçioğlu and Kutlu (2012) applied the fuzzy process FMEA approach by developing a hybrid method with TOPSIS and fuzzy AHP methods in a spindle manufacturing process in the automotive industry. Guimaraes et al. (2004) applied fuzzy FMEA to a nuclear reliability engineering problem in a chemical and volume control system. The results demonstrated the potential of the inference system for this group of problems. Dağsuyu et al. (2016) applied traditional and fuzzy FMEA methods in a case study to examine risk factors, examine all failure modes, and eliminate or reduce the highest risk priority failures in sterilization units at hospitals. Balarajuet al. (2019) applied fuzzy FMEA using root cause analysis in the mining machinery industry and identified 16 possible hazards using a Mamdani inference model. The input variables were defined using Gaussian membership functions, the output variables were defined using triangular membership functions, and max–min operators were employed. Gupta and Mishra (2020) conducted a risk analysis that included the fuzzy aspect to produce the parts of a lathe machine. The results demonstrate the superiority of the fuzzy FMEA approach in criticality analysis.

At the ceramic sanitary ware company where this study was conducted, the process FMEA was implemented because the production processes for ceramic products could not meet the customer's quality expectations, that is, the delivery of useful output at the desired level. It aims, through process FMEA, to bring production processes to the level required to meet customers' demands and expectations. A fuzzy-logic-based risk assessment system will provide significant benefits to users in the ceramic industry by enabling the determination of risk priorities and solution approaches. in determining risk priorities and therefore solution approaches.

The remainder of this paper is organized as follows: Section 2 covers FMEA and fuzzy-FMEA in the methodology. A case study is introduced in Section 3. The results are presented in Section 4. Finally, Section 5 presents the conclusion of this paper.

2. Materials and Methods

In this study, FMEA (Failure Mode and Effect Analysis) and Fuzzy- FMEA approaches were used to analyze the production process of a company operating in the ceramic sanitary ware sector. Based on the opinions and experiences of experts working in the determined company and on analyses of the obtained data, the RPN (Risk Priority Number) and FRPN (Fuzzy Risk Priority Number) values and the priorities of the errors were determined. The differences between the results obtained by the two methods were evaluated.

2.1. Failure Mode and Effect Analysis

Failure Mode and Effects Analysis (FMEA)is an analysis technique that includes identifying and evaluating the types of failures and causes that may arise in relation to the design and production of a product, determining the activities that will reduce or eliminate the chances of occurrence of errors that may arise and making these activities recorded (Subriadi and Najwa, 2020). The primary purpose of the FMEA is to identify and prevent known or possible problems based on past data. During the FMEA study, different problems are assumed to have different priorities. Determining priorities and taking measures according to priorities savings from time, money and labor (Crawley, 2020).

In the ceramic sanitary ware industry, defects such as casting cracks, stains, pinholes, matt surfaces, repair trails, boiling surfaces, and thin or thick glazes are frequently encountered. The impact of these defects on the customer (Severity), the probability of occurrence (Occurrence), and the detectability (Detectability) should be considered. Determining priorities among failures according to the specified criteria guides the studies to be carried out to eliminate them. For this reason, all possible failure types that may be encountered in the sanitary ware production process were identified, and their priorities were determined using the specified approach.

2.2. Failure Mode and Effect Analysis with Fuzzy Logic

The FMEA and Fuzzy-FMEA approaches were used to analyze the production process of a company producing ceramic sanitary ware. The RPN and Fuzzy-RPN (fuzzy risk priorities) values and the priorities of failures were determined through analysis of data obtained from the opinions and experiences of experts working at the indicated company. The differences between the results obtained by both methods were determined.

In the sanitary ware industry, failure types such as casting cracks, stains, pinholes, dull surfaces, repair trails, boiling surfaces, thin glazes, and thick glazes are frequently encountered. The impact of these failures on the customer, the probability of their occurrence, and the level of detection should be considered. Determining the priorities of failures according to the specified criteria guides the implementation of solutions to eliminate failures. For this reason, all possible failure types that may be encountered in the production of ceramic sanitary ware have been identified, and efforts have been made to determine their priorities using the indicated approach.

2.3. Fuzzy Failure Mode and Effect Analysis

In 1965, Zadeh introduced fuzzy set theory, which provides a flexible and effective method for evaluating the risk of component failures. Classical FMEA requires comprehensive knowledge of the subject matter. It is important to handle related confusing information in a consistent and reasonable manner (Sharma, 2005).

Fuzzy FMEA was applied to the production process examined in this study. FMEA, as a risk analysis method, requires numerical data and probabilistic values to determine risks. However, in general, the required data are not sufficient, reliable, or readily available, resulting in difficulties in performing risk analysis of the systems. In this case, the probability values are fuzzy data that are linguistic rather than numerical and are determined based on expert opinion. For this reason, using fuzzy logic in FMEA allows analysis to be performed with linguistic rather than numerical expressions. Advantages of the Fuzzy FMEA vs. the traditional FMEA are presented in Table 1.

Table 1. Traditional vs. Fuzzy FMEA - features and benefits

Feature	Traditional FMEA	Fuzzy FMEA Advantage	Authors
Data type	Crisp scores	Linguistic and uncertain info	(Boral et al., 2020; Fattahi and Khalilzadeh, 2018;Dinmohammadi and Shafiee, 2020; Testik and Unlu,2022)
Factor weights	Usually equal	Fuzzy, data-driven weights	(Boral et al., 2020; Fattahi and Khalilzadeh, 2018;Chen et al., 2025; Tian et al., 2018)
RPN issues	Duplicates, crude	Rich fuzzy/rule-based rankings	(Zhu et al., 2022; Jiang et al., 2017; Zúñiga et al.,2023; Shi et al., 2019)
Expert Subjectivity	Poorly modeled	Explicitly modeled and aggregated	(Zhu et al., 2022; Pokorádi et al., 2021; Jiao et al.,2025)

Fuzzy-FMEA handles uncertainty, vagueness, and linguistic judgments. Experts often cannot give precise 1–10 scores; they think in linguistic terms(“low”, “medium”, “high”).Fuzzy sets model these linguistic ratings directly, capturing vagueness and incomplete data. Fuzzy membership functions or advanced fuzzy sets explicitly represent hesitation and randomness in evaluations. This makes fuzzy FMEA particularly suitable when statistical failure data are scarce or unreliable. Case studies(aircraft landing systems, steel plant, grinding wheel, ship fire safety, labs)show that fuzzy FMEA yields more discriminative and reliable rankings than traditional FMEA, often aligns better with engineering judgment, and demonstrates effective reductions in risk indices after actions.

Fuzzy logic, in which the RPN is computed using linguistic terms, is used because humans are better at analyzing processes using linguistic expressions than when using direct numerical ratings. It offers mathematical techniques for translating linguistic variables into numerical values. As a result, the evaluation of criticality using fuzzy logic makes it possible to naturally and simply quantify the risk related to failure modes (Wan et a., 2019; Jahangoshai Rezaee et al., 2020).

Many failure types, causes, and effects can be found in systems, designs, processes, and services. In this case, the failure types must be evaluated, ranked, and prioritized according to the risks or hazards. In this regard, the FMEA technique evaluates error types using a numerical quantity called the Risk Priority Number (RPN = severity x occurrence x detectability). RPN is obtained by multiplying three risk factors: severity, occurrence, and detection. The steps of the solution method are illustrated in Figure 1.

The probability used to calculate RPN corresponds to the frequency of failure occurrence. Severity is the effect of failure on the customer or the reaction it causes. The non-discovery value is the probability of a failure reaching the customer (the situation in which the error is assumed to have occurred and cannot be detected before shipment by existing controls). In the Fuzzy-FMEA approach, the specified risk factors are not stated as exact numerical values but as linguistic expressions and membership functions defined using expert opinion.

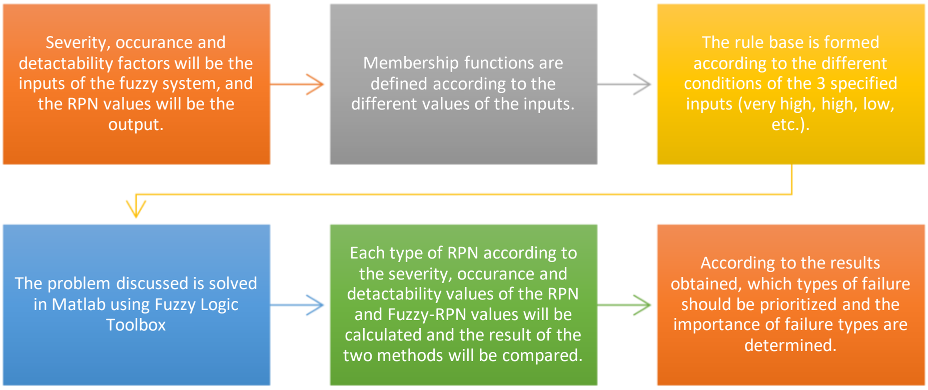


Figure 1. Steps followed in the solution method.

2.4. Case Study: Ceramic Industry

Fuzzy FMEA was applied to a ceramic sanitary ware company. The company operates in the technology sector, employing a fully automatic oven and modern glazing lines. The company's products are generally washbasins for bathroom cabinets and bathroom sets (washbasin, pedestal, closet, cistern). The expert team for FMEA and Fuzzy-FMEA comprises a ceramic engineer, a glaze-firing supervisor, and a shaping supervisor. Some of documents required for the FMEA study were considered, including process flow charts, failure record forms, and tables containing the failure criteria.

2.4.1. Application of FMEA

In this study, a probability-rating table (Table 2) was used to present the probabilities corresponding to each error type and to detect their occurrence. The probability rating is determined by giving a score between 1 and 10 (Akın, 1998). First, the failure rate was calculated to obtain the failure probability. The failure rate was calculated by dividing the number of defects by the total number of failures (for example, for casting crack: Failure rate for Casting crack= Number of Casting crack defect/ total number of all failures), and the failure probability was calculated by dividing the number of defects by the total production quantity (Failure probability of Casting crack= Failure rate for Casting crack/ Total production quantity). The severity rating (Table 3) is used to assess the impact on the customer of the type of error likely to occur. The impact on the customer is rated on a scale from 1 to 10. These ratings are associated with the impact of the error types (Akın, 1998).

According to the general decision of the FMEA team: casting crack, loading crack, unloading crack, scraper crack, unshaped product, thick glaze, shocked surface, and bursted part defects were assigned 7 points; retouching, stain, sticking, dull surface, repair trail, bubble surface, part under glaze, thin glaze, and non-glazed surface defects were assigned 6 points; skewness and boiling surface defects were assigned 5 points; and pinhole and collapsed product defects were assigned 4 points.

Table 2. Percentages and probability scores of error types

Failure type	Failure probability	Occurrence level	Failure type	Failure probability	Occurrence level
Casting crack	0.0564	7	Collapsed product	0.0046	5
Boiling surface	0.0454	6	Thin glaze	0.0089	5
Stain	0.0280	6	Thick glaze	0.0022	4
Sticking	0.0108	6	Shocked surface	0.0082	5
Loading cracks	0.0113	6	Repair trail	0.0004	3
Skewness	0.0128	6	Non-glazed surface	0.0007	4
Retouch	0.0026	5	Bursted part	0.0022	4
Pinhole	0.0048	5	Bubble surface	0.0003	3
Unloading cracks	0.0031	5	Dull surface	0.0000	1
Scraper crack	0.0032	5	Part of the glaze	0.0000	1
Unshaped product	0.0038	5			

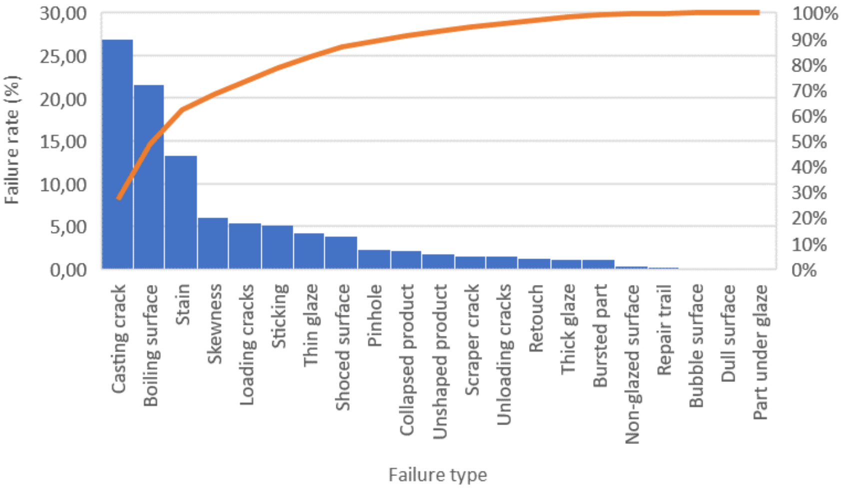


Figure 2. Pareto diagram of error-type percentages

Table 3. Severity rating table

Danger	Safety-related malfunction: a malfunction that does not comply with the law. The error occurs without any warning.	10
Serious	Safety-related fault: a noncompliant fault. The error occurs with a warning.	9
Very big	The entire production process can be scrapped. The product becomes unusable and loses its basic functions. Customers express great dissatisfaction.	8
Big	Major impact on the product/process. Production has to be sorted, and part of it is scrapped. Customer displeased.	7
Important	Causes of rework/repair of the part. Product performance degraded. Customers are dissatisfied.	6
Middle	Moderate impact on product performance or process. Customers experience discomfort when using the product. Some parts that provide convenience or comfort perform poorly.	5
Small	Minor impact on product performance or process. A defect is recognized by the customer, and there is some inconvenience in using the product.	4
Unimportant	Insignificant impact on product performance or process. Customers may notice a defect.	3
Very insignificant	Very minor impact on product performance or process. The error is not recognized by customers.	2
No impact	No impact on product performance or process.	1

The detectability of failures before the product or part leaves the production or assembly line. It is assumed here that a failure has already occurred, and the possibility of preventing the delivery of a part exhibiting that type of failure using the available control capabilities is evaluated. Once again, a rating between one and ten is applied. Detectability ratings are 1 for the casting-crack defect, 2 for the unshaped-product defect, and 3 for the remaining failure types.

2.4.2. Application of Fuzzy-FMEA

In this part of the study, the Fuzzy-FMEA approach was applied to the production process of a company in the ceramic sanitary ware sector. Based on the analyses using the opinions and experiences of three company experts, FRPN (Fuzzy Risk Priority Number) values were determined, and failures were ranked by priority. MATLAB was used to evaluate the FRPN values using the Mamdani (Min-Max) method via the Fuzzy Logic Toolbox (Figure 3).

The fuzzy control system (Figure 4) consists of a fuzzification unit, an information base, an inference (decision-making) unit, and defuzzification (clarification) unit.

Fuzzification: the linguistic terms from expert opinions were considered, and the outputs for severity, occurrence, detectability, and risk were defined. The intervals and membership function values are obtained for linguistic terms such as VL, L, M, H, and VH.

Based on expert opinion, a five-level linguistic scale ("very low," "low," "medium," "high," and "very high") was defined for each variable, and appropriate membership functions representing these scale levels were established. Evaluations reflecting three experts were assigned specific statistical weights by their experience w_1=0.4 level w_2=0.3 w_3=0.3; these weights are detailed in Tables 5–7. Figure 5 shows one of the membership-function values for severity, calculated from averaged expert opinions.

Table 4. Detectability rating table

Impossible	No detection possibility	10
Very difficult	It is very difficult for controls to identify the error types	9
Difficult	Difficult for controls to identify error types	8
Less	Few controls identify the type of error	7
Very little	Few controls identify the type of error	6
Middle	Controls are used to identify the type of error medium.	5
Above average	Controls identify errors above average	4
High	Controls are high to identify the type of error	3
Very high	Controls are too high to identify the error type	2
Exactly	Controls are nearly certain to identify the error type	1

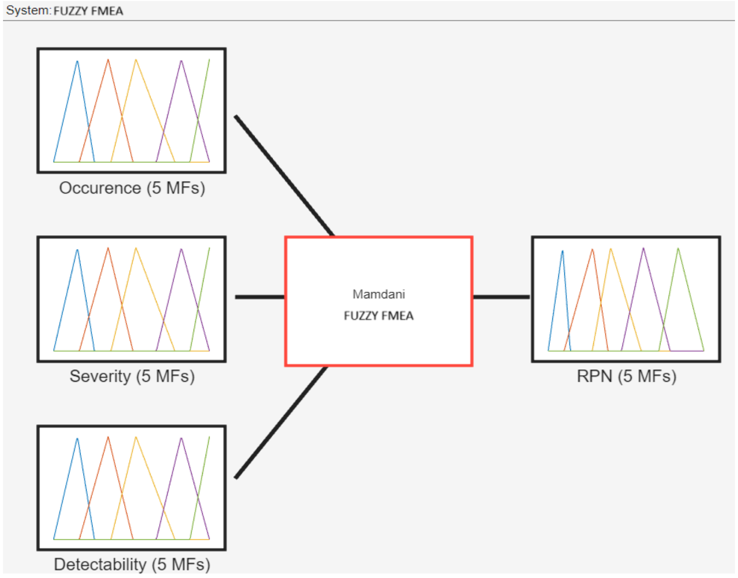


Figure 3. General overview of the fuzzy logic model created in MATLAB.

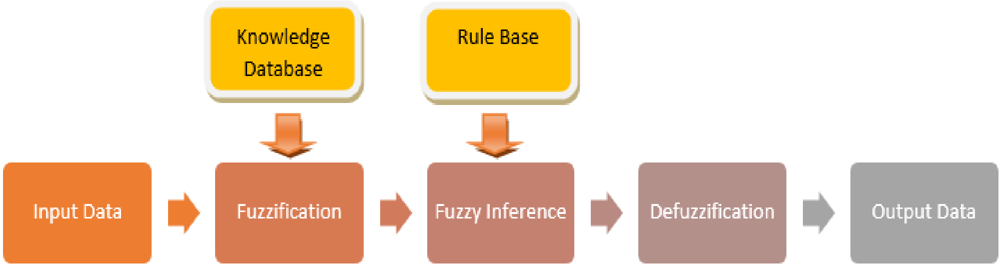


Figure 4. Fuzzy controller system.

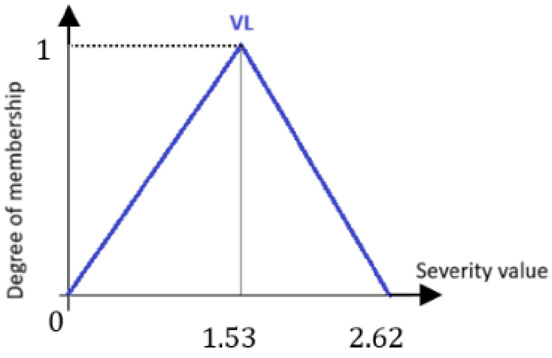
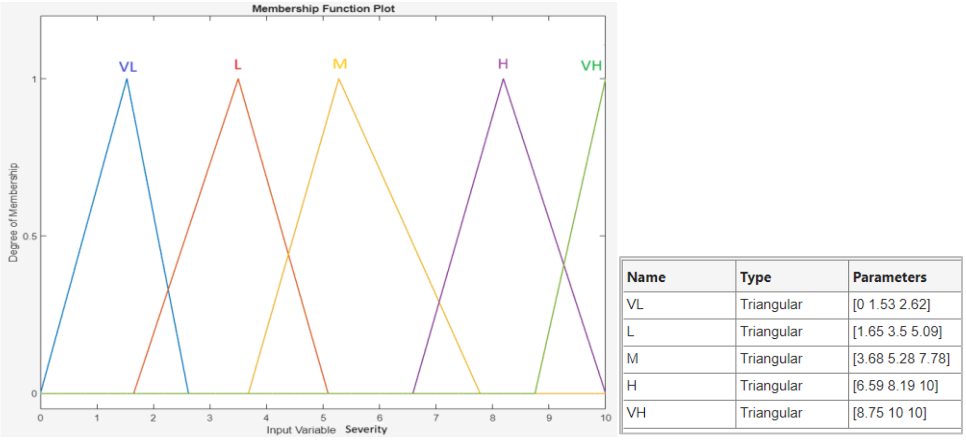


Figure 5. Triangular membership function for VL (very low) values of severity.

Severity values are calculated using expert opinions with their weights. For example, the VL value is calculated as (0.4*1.5)+(0.3*1.5)+(0.3*1.6)=1.53 for α=1. The experts were asked to identify membership function values using linguistic terms in the table below. The triangular membership functions were used to evaluate the three experts. A (α = 0) refers to the values they will receive when the membership function is 0; B (α = 1) is 1 when the membership function is 1; C (α = 0) is 0. Since more than one expert assessment was included in the analysis, a weight (w) was assigned to each expert. In Tables 5, 6, and 7, the severity, occurrence, and detectability, as assessed by experts' membership functions, are given as inputs, and the risk priority number (Table 8) is given as the output.

Table 5. Expert opinion synthesis for severity (S) parameter ranges

		α=0					α=1					α=0				
w	Expert	VL	L	M	H	VH	VL	L	M	H	VH	VL	L	M	H	VH
0.4	1	0	1.5	3.5	6.5	8.6	1.5	3.5	5.4	8.1	10	2.5	5.3	7.6	10	10
0.3	2	0	1.7	3.9	6.8	8.9	1.5	3.4	5.1	8.2	10	2.8	4.9	7.7	10	10
0.3	3	0	1.8	3.7	6.5	8.8	1.6	3.6	5.3	8.3	10	2.6	5.0	8.1	10	10
sum=1	Mean	0	1.65	3.68	6.59	8.75	1.53	3.5	5.28	8.19	10	2.62	5.09	7.78	10	10

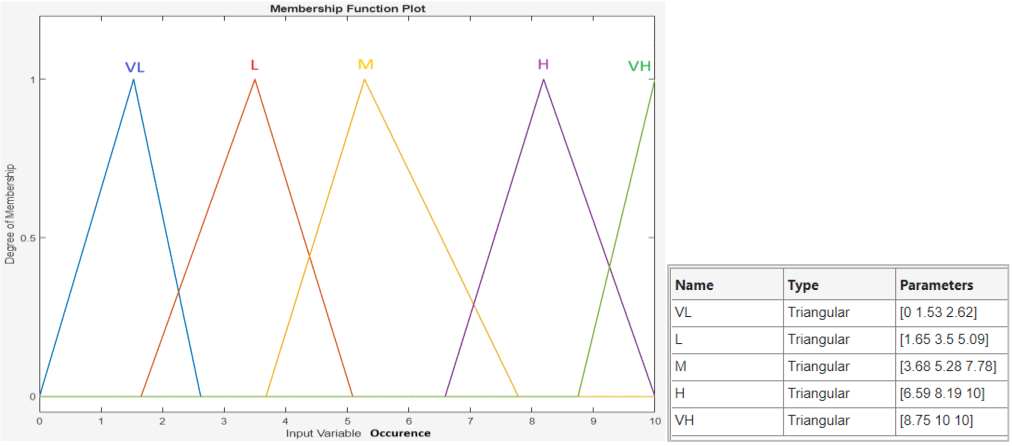


Name	Type	Parameters
VL	Triangular	[0 1.53 2.62]
L	Triangular	[1.65 3.5 5.09]
M	Triangular	[3.68 5.28 7.78]
H	Triangular	[6.59 8.19 10]
VH	Triangular	[8.75 10 10]

Figure 6. The membership function values determined by experts for severity.

Table 6. Expert opinion synthesis for occurrence (O) parameter ranges

		α=0					α=1					α=0				
w	Expert	VL	L	M	H	VH	VL	L	M	H	VH	VL	L	M	H	VH
0.4	1	0	1.5	3.5	6.5	8.6	1.5	3.5	5.4	8.1	10	2.5	5.3	7.6	10	10
0.3	2	0	1.7	3.9	6.8	8.9	1.5	3.4	5.1	8.2	10	2.8	4.9	7.7	10	10
0.3	3	0	1.8	3.7	6.5	8.8	1.6	3.6	5.3	8.3	10	2.6	5.0	8.1	10	10
sum=1	Mean	0	1.65	3.68	6.59	8.75	1.53	3.5	5.28	8.19	10	2.62	5.09	7.78	10	10

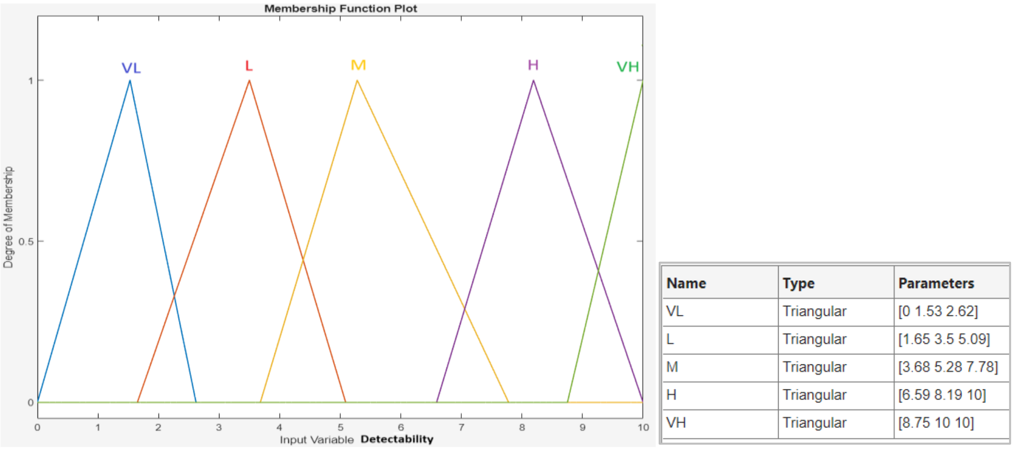


Name	Type	Parameters
VL	Triangular	[0 1.53 2.62]
L	Triangular	[1.65 3.5 5.09]
M	Triangular	[3.68 5.28 7.78]
H	Triangular	[6.59 8.19 10]
VH	Triangular	[8.75 10 10]

Figure 7. The membership function values determined by experts for occurrence.

Table 7. Expert opinion synthesis for detectability (D) parameter ranges

		α=0					α=1					α=0				
w	Expert	VL	L	M	H	VH	VL	L	M	H	VH	VL	L	M	H	VH
0.4	1	0	1.5	3.5	6.5	8.6	1.5	3.5	5.4	8.1	10	2.5	5.3	7.6	10	10
0.3	2	0	1.7	3.9	6.8	8.9	1.5	3.4	5.1	8.2	10	2.8	4.9	7.7	10	10
0.3	3	0	1.8	3.7	6.5	8.8	1.6	3.6	5.3	8.3	10	2.6	5.0	8.1	10	10
sum=1	Mean	0	1.65	3.68	6.59	8.75	1.53	3.5	5.28	8.19	10	2.62	5.09	7.78	10	10

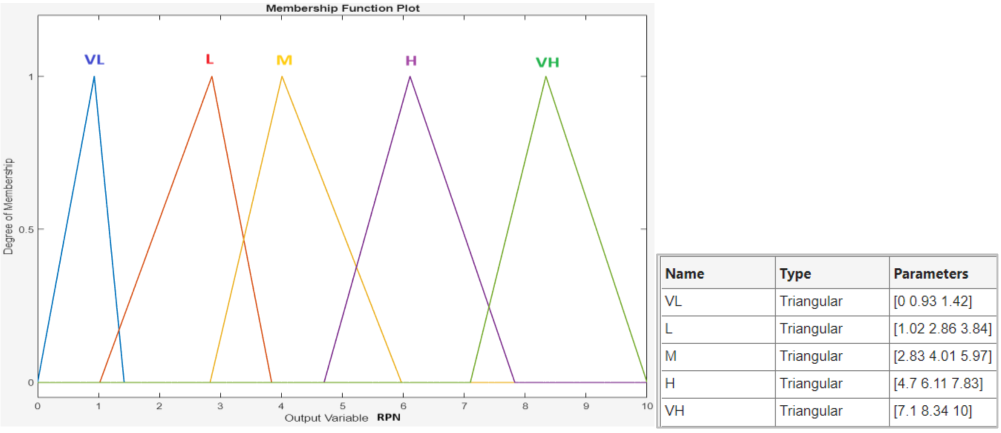


Name	Type	Parameters
VL	Triangular	[0 1.53 2.62]
L	Triangular	[1.65 3.5 5.09]
M	Triangular	[3.68 5.28 7.78]
H	Triangular	[6.59 8.19 10]
VH	Triangular	[8.75 10 10]

Figure 8. The membership function values determined by experts for Detectability

Table 8. The membership function values determined by experts for risk priority number

		α=0					α=1					α=0				
w	Expert	VL	L	M	H	VH	VL	L	M	H	VH	VL	L	M	H	VH
0,4	1	0	0.9	3.1	4.7	7.1	0.9	3.1	4.1	6.2	8.4	1.3	3.6	6.0	7.8	10
0,3	2	0	1.2	2.8	4.2	6.7	0.8	2.6	3.7	6.2	7.8	1.7	3.9	5.7	7.6	10
0,3	3	0	1.0	2.5	5.2	7.5	1.1	2.8	4.2	5.9	8.8	1.3	4.1	6.2	8.1	10
sum=1	Mean	0	1.02	2.83	4.7	7.1	0.93	2.86	4.01	6.11	8.34	1.42	3.84	5.97	7.83	10



Name	Type	Parameters
VL	Triangular	[0 0.93 1.42]
L	Triangular	[1.02 2.86 3.84]
M	Triangular	[2.83 4.01 5.97]
H	Triangular	[4.7 6.11 7.83]
VH	Triangular	[7.1 8.34 10]

Figure 9. The membership function values determined by experts for RPN.

In a Fuzzy Inference System (FIS), input weights are determined by logical inference rather than simple multiplication. A multi-input, single-output (MISO) rule base, constructed using IF-THEN logic, defines the relationship between inputs and the output risk level. A standard rule R_i in the system is expressed as equation 1 (Türkşen, 2012):

$$IF\ O\ is\ A_i\ AND\ S\ is\ B_i\ AND\ D\ is\ C_i\ THEN\ RPN\ is\ Z_i \qquad (1)$$

Where A_i, B_i and C_i are the linguistic terms for the inputs, and Z_i is the linguistic term for the resulting Fuzzy-RPN output. Given three input variables with five membership functions each, a comprehensive matrix of 5^3=125 rules was established to evaluate all potential failure scenarios. The Mamdani inference mechanism employs the min operator for the AND conjunction to determine the “firing strength” α_i of each rule (Bowles and Peláez, 1995) (equation 2):

$$\alpha_i = min\left(\mu_{A_i}(S),\, \mu_{B_i}(O),\, \mu_{C_i}(D)\right) \qquad (2)$$

Defuzzification: the collected fuzzy output generated by the rule base must be converted back into a crisp, actionable numerical value to definitively rank the failure modes (Tay and Lim, 2006). To achieve the highest degree of consistency and representation of the fuzzy set, the Centroid method was selected. The final crisp Fuzzy-RPN (F-RPN) value is calculated by finding the geometric center of the aggregated output membership function μ_C (Wang et al., 2009) (equation 3):

$$F - RPN = \frac{\int z \cdot \mu_C(z)\, dz}{\int \mu_C(z)\, dz} \qquad (3)$$

Where z represents the output variable (risk level) and μ_C (z)is the aggregated membership degree.

Table 9. Rule base for Fuzzy-FMEA

1.	If Occurence is VL and	Severity is	VL	and	Detectability is	VL	then	RPN is	VL
2.	If Occurence is VL and	Severity is	VL	and	Detectability is	L	then	RPN is	VL
3.	If Occurence is VL and	Severity is	VL	and	Detectability is	M	then	RPN is	VL
4.	If Occurence is VL and	Severity is	VL	and	Detectability is	H	then	RPN is	L
5.	If Occurence is VL and	Severity is	VL	and	Detectability is	VH	then	RPN is	M
6.	If Occurence is VL and	Severity is	L	and	Detectability is	H	then	RPN is	L
7.	If Occurence is VL and	Severity is	L	and	Detectability is	VH	then	RPN is	M
8.	If Occurence is VL and	Severity is	M	and	Detectability is	VL	then	RPN is	VL
9.	If Occurence is VL and	Severity is	M	and	Detectability is	L	then	RPN is	VL
10.	If Occurence is VL and	Severity is	M	and	Detectability is	M	then	RPN is	VL
11.	If Occurence is VL and	Severity is	M	and	Detectability is	H	then	RPN is	L
12.	If Occurence is VL and	Severity is	M	and	Detectability is	VH	then	RPN is	M
13.	If Occurence is VL and	Severity is	H	and	Detectability is	VL	then	RPN is	L
14.	If Occurence is VL and	Severity is	H	and	Detectability is	VL	then	RPN is	L
15.	If Occurence is VL and	Severity is	H	and	Detectability is	L	then	RPN is	L
111.	If Occurence is VH and	Severity is	L	and	Detectability is	VH	then	RPN is	H
112.	If Occurence is VH and	Severity is	M	and	Detectability is	VL	then	RPN is	M
113.	If Occurence is VH and	Severity is	M	and	Detectability is	L	then	RPN is	M
114.	If Occurence is VH and	Severity is	M	and	Detectability is	M	then	RPN is	H
115.	If Occurence is VH and	Severity is	M	and	Detectability is	M	then	RPN is	VH
116.	If Occurence is VH and	Severity is	M	and	Detectability is	VH	then	RPN is	VH
117.	If Occurence is VH and	Severity is	H	and	Detectability is	VL	then	RPN is	M
118.	If Occurence is VH and	Severity is	H	and	Detectability is	L	then	RPN is	H
119.	If Occurence is VH and	Severity is	H	and	Detectability is	M	then	RPN is	VH
120.	If Occurence is VH and	Severity is	H	and	Detectability is	H	then	RPN is	VH
121.	If Occurence is VH and	Severity is	H	and	Detectability is	VH	then	RPN is	VH
122.	If Occurence is VH and	Severity is	VH	and	Detectability is	VL	then	RPN is	H
123.	If Occurence is VH and	Severity is	VH	and	Detectability is	L	then	RPN is	VH
124.	If Occurence is VH and	Severity is	VH	and	Detectability is	M	then	RPN is	VH
125.	If Occurence is VH and	Severity is	VH	and	Detectability is	H	then	RPN is	VH

3. Results and Discussion

The comparison between the FRPN values obtained by the MATLAB code and the relative values obtained using the classical method is presented in the table below.

The traditional risk priority number (RPN)is obtained by multiplying the factor values in the fifth column. The fuzzy risk priority number(F-RPN) for each failure mode, as determined by the proposed evaluation system, is displayed in the sixth column. The final column of Table 10 lists the order of failure modes.

The values obtained from the traditional and new methods differ, except for certain failure priorities. For example, stains, thin glazes, unloading cracks, scraper cracks, and shocked surfaces have the same priority number for each method. Similarly, dull surfaces and parts under the glaze have the lowest priority (Figures 10 and 11). “Sticking” failure is in the 5th order when traditional method is used, but it is in the 1st order according to Fuzzy FMEA. On the other hand, “casting crack” failure is in the 13th order according to traditional method, but it is in the 3th order when Fuzzy FMEA is used. These changes demonstrate that the fuzzy logic model can increase risk perception by placing greater weight on situations in which the “severity” and “occurrence” parameters are high, as required for production safety.

Figures 10 and 11 show significant differences in the importance of the two results. Because experts' personal opinions and experiences are included in the F-FMEA approach, some special cases not considered in F-FMEA may also gain importance. Therefore, the priorities of some faults identified by the F-FMEA model may differ from those obtained by the FMEA model. In addition, to carry out the F-FMEA approach reliably, experts should perform the assessments and analyses.

Table 10. Failures and priorities according to RPN and FRPN scores

	Failures	O	S	D	RPN Score	FRPN Score	RPN Priority	FRPN Priority
1	Stain	6	6	4	144	5.00	1	1
2	Sticking	6	6	3	108	5.00	5	1
3	Boiling surface	6	5	4	120	3.49	4	4
4	Casting crack	7	7	1	49	3.52	13	3
5	Bursted part	4	7	3	84	3.49	8	4
6	Thin glaze	5	6	4	120	3.49	4	4
7	Retouch	5	6	3	90	3.49	7	4
8	Bubble surface	3	6	3	54	3.48	12	5
9	Non-glazed surface	4	6	3	72	3.48	9	5
10	Repair trail	3	6	4	72	3.48	9	5
11	Unloading cracks	5	7	3	105	2.86	6	6
12	Scraper crack	5	7	3	105	2.86	6	6
13	Thick glaze	4	7	5	140	4.91	2	2
14	Shocked surface	5	7	3	105	2.86	6	6
15	Unshaped product	5	7	2	70	2.7	10	7
16	Collapsed product	5	4	3	60	2.66	11	8
17	Pinhole	5	4	3	60	2.66	11	8
18	Loading cracks	6	7	3	126	2.48	3	9
19	Skewness	6	5	4	120	3.49	4	10
20	Dull surface	1	6	3	18	0.77	15	11
21	Part of the glaze	1	6	4	24	0.77	14	12

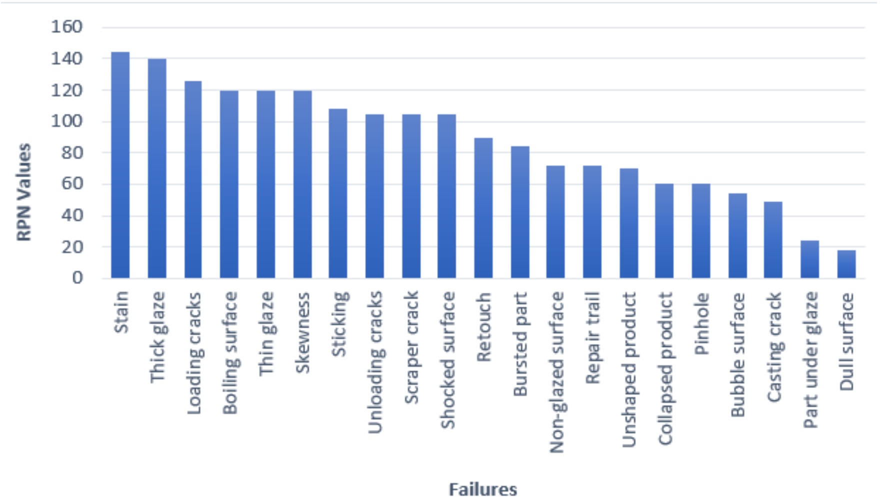


Figure 10. Failure types and RPN values.

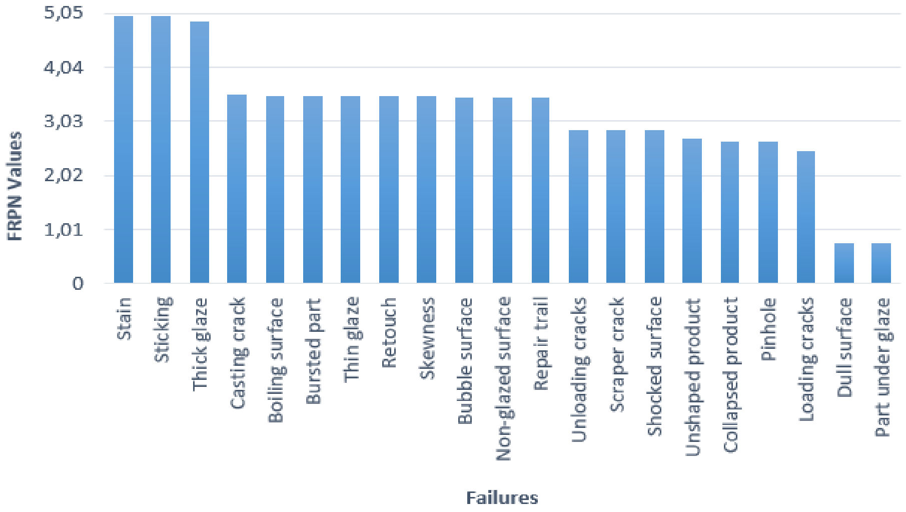


Figure 11. Failure types and FRPN values.

In the traditional FMEA method, risk assessment is performed using the RPN obtained by multiplying the severity, probability, and detectability values. However, using the traditional method, the multiplication of values representing severity, occurrence, and detectability can yield identical results, which may result in overlooked risks requiring further attention. A n FMEA incorporating fuzzy logic emerges as a powerful alternative. The results of the analysis indicate that the model enhanced with fuzzy logic facilitates prioritization by assessing risks on a broader scale.

4. Conclusion

This study addresses the FMEA requirements for failures detected by visual inspection by using parameters gathered from FMEA analysis to construct a fuzzy inference system (FIS). This tool will enable the development of mathematical models that consider issues involving high levels of uncertainty and do not ignore factors sometimes disregarded by conventional logic. In this study, traditional and fuzzy FMEA methods were compared with respect to risk priority numbers. Failures were prioritized using both methods. The fuzzy FMEA approach provided more reliable results and a means to rank failures. This approach enables prioritizing faults by tracing them to their source. To achieve this, quality experts should assist with data interpretation and define criteria to determine the risk of each failure mode. In this study, an attempt was made to eliminate the uncertainties and prioritization issues involved in the RPN (Risk Priority Number) calculation determined by traditional Failure Mode and Effect Analysis (FMEA). Within the scope of the study, the severity, occurrence, and detectability values were fuzzified using MATLAB's fuzzy logic module, and expert opinions were integrated into the system with an “if-then” rule base. The findings show that the fuzzy FMEA method can provide more accurate and more descriptive results than the traditional method for prioritizing risk factors. Overall, fuzzy FMEA enhances classical FMEA by representing uncertainty and linguistic judgment, weighting risk factors and experts more realistically, and producing more reliable, discriminative failure-mode rankings, especially valuable in data-poor or highly complex systems. In future studies, fuzzy FMEA can be applied in different sectors. In addition to process FMEA, design and system FMEA studies can be conducted using the same method.

Author Contributions

The percentages of the author' contributions are presented below. The author reviewed and approved the final version of the manuscript.

	G.Ö.G
C	100
D	100
S	100
DCP	100
DAI	100
L	100
W	100
CR	100
SR	100
PM	100
FA	100

C= concept, D= design, S= supervision, DCP= data collection and/or processing, DAI= data analysis and/or interpretation, L= literature search, W= writing, CR= critical review, SR= submission and revision, PM= project management, FA= funding acquisition.

Conflict of Interest

The author declare no conflict of interest.

Ethical Consideration

Ethics committee approval was not required for this study because it did not involve animals or humans.

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