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Advancing PFMEA Decision-Making: FRADAR Based Prioritization of Failure Modes Using AP, RPN, and Multi-Attribute Assessment in the Automotive Industry

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Abstract: This research proposes a novel way to improve Process Failure Modes and Effects Analysis (PFMEA) by using the Fuzzy RAnking based on the Distances And Range (FRADAR) method to prioritize activities for mitigating or eliminating failure modes in the automotive industry. The suggested approach seeks to improve classic PFMEA by using fuzzy sets to better assess risk-related criteria and their inherent uncertainty. The criteria used to prioritize actions for mitigating failure modes include the Action Priority (AP) and Risk Priority Number (RPN) approach, as well as the cost-effectiveness of actions, the time required to resolve issues, and their impact on production, all of which are assessed by a PFMEA team using predefined linguistic terms and suggestions. Applied to a case study of a Tier-1 automotive supplier, the FRADAR method effectively ranks failure modes, providing a structured and precise approach for action prioritization. The results highlight the model's potential to enhance decision-making processes, offering a robust framework for implementing PFMEA recommendations in the automotive industry.

Keywords: Action Priority; Automotive industry; FRADAR; PFMEA; RPN

1 INTRODUCTION

One of the important tools for improving the reliability of the manufacturing process in the automotive industry is Failure Mode and Effect Analysis (FMEA), specifically its version related to the manufacturing process, Process Failure Mode and Effect Analysis (PFMEA). By applying this method, a specific methodological procedure is used to determine the priority of the considered failure modes, or those factors that may potentially disrupt the realization or affect the final outcome of the manufacturing process.

The importance of FMEA analysis in the automotive industry is also reflected in the fact that its application is mandatory and prescribed by the IATF 16949:2016 standard [1]. Therefore, the latest version of the handbook [2] provides joint guidelines for applying different types of FMEA analysis in the automotive industry. In addition, the new manual modifies the FMEA methodology for risk assessment/priority determination of failure modes, shifting from the traditional Risk Priority Number (RPN) approach to the Action Priority (AP) approach. Although the new approach definitely addresses some of the methodological issues and ambiguities of the old approach, there is still space for improvement, as explained in previous research [3, 4].

The traditional FMEA analysis determines the priority of failure modes based on three risk factors: Severity of failure mode consequence (S), occurrence or frequency of failure mode (O), and the possibility of detecting failure modes (D). Like RPN, the AP approach is based on the analysis of these three risk factors. In both cases, the FMEA team determines or evaluates the value of these risk factors, which are stated on a scale of (1-10). These three risk factors are multiplied to determine RPN, which has a value between 1 and 1000. The AP approach has predefined scenarios for each combination of the values of these three risk factors, which means that no calculation is required. The priority of failure modes in the RPN approach is determined based on its value, and the threshold values (which may vary) primarily depend on the type of product, while in the AP approach, priority can be defined as Low (L), Medium (M), or High (H) (see [2]).

Although the priority of failure modes, as determined by the RPN or AP approaches, gives useful information about the importance of each failure mode, neither approach provides recommendations on the sequence in which activities should be done to address the causes of their occurrence. Therefore, the problem discussed in this paper is to determine the sequence of actions at the failure mode level by applying the RPN parameter and considering additional criteria. The AP approach is used to perform the primary selection of failure modes (failure modes of L priority are not considered).

In this case, the traditional RPN approach is used rather than the AP approach, as the application of the RPN approach provides a numerical value, which corresponds to the problem being addressed. This type of problem has been scarcely discussed in the literature. A similar problem was only considered in the paper [5], where the authors extended the PFMEA analysis by applying the Interval Type-2 Fuzzy Analytic Hierarchy Process (IT2FAHP) to determine the importance of the risk factors S, O, and D. The priority of actions was determined using two heuristic methods, namely the Genetic Algorithm (GA) and Variable Neighborhood Search (VNS). Additional criteria for determining the sequence of actions included downtime costs and maintenance costs caused by the occurrence of the failure mode.

This study investigates the application of the RAnking Based on Distances And Range (RADAR) method to improve FMEA analysis for defining the sequence of actions during failure modes. This is a novel method developed in the studies [6, 7] and is part of the Multi-Attribute Decision-Making (MADM) methods based on distance. The author applied the method to determine the priority of failure modes [6]. Through a comparison with the RPN approach, the weighted RPN approach, and two MADM methods, it was demonstrated that the RADAR method produces results most similar to conventional FMEA analysis. This indicates that the RADAR method is suitable for this type of problem. Furthermore, in the study [7], the author applied the RADAR method, as well as its modification RADAR II, for equipment selection in the automotive industry. By comparing the results obtained using multiple MADM methods, it was found that the method provides reliable and robust solutions. For this reason, this research employs the RADAR method extended with the use of fuzzy sets theory [8, 9].

In this paper, triangular fuzzy numbers (TFNs) were used to describe uncertain values. Although various approaches for representing uncertainty have been used in combination with different MADM methods in the literature, such as type-2 fuzzy sets [10], intuitionistic fuzzy sets [11] or rough sets [12], the authors believe that triangular fuzzy numbers are the most suitable for this type of problem due to their simplicity. They do not require high computational complexity and user friendly for practical application.

The main goal of this paper is to enhance the traditional FMEA analysis by applying a methodology for prioritizing actions, specifically for determining the sequence of treatment or intervention on the causes of failure modes. For this purpose, the fuzzy RADAR (FRADAR) approach has been used.

This paper is structured as follows: Section 1 introduces the research issue and discusses the study's objectives and importance. Section 2 provides a literature review that summarizes relevant studies and approaches in the topic. Section 3 outlines the methodology, including the FRADAR approach used in the study. Section 4 includes a case study demonstrating the suggested model's use in the automotive industry. Finally, Section 5 presents conclusions, discusses the findings, and suggests future study areas.

2 LITERATURE REVIEW

As previously stated, the subject of prioritizing failure mode activities, that is, selecting the sequence in which to treat the causes or mitigate the impacts of failure modes, has not received much attention in the literature. However, multiple studies have been conducted in which FMEA analysis or another production issue has been improved through the use of various MADM techniques [13-15].

This study primarily focuses on using a fuzzy MADM methodology to improve FMEA. The relevant literature identifies many methodologies and domains of application for fuzzy and fuzzy MADM concepts [16-18]. Some authors [19, 20] expand the FMEA analysis by employing fuzzy sets theory, specifically TFNs, to characterize risk factor values and/or weights. On the other hand, in paper [21] authors employ a combination of triangular and trapezoidal fuzzy numbers to represent uncertain values. In the study [22] the authors applied a similar principle; however, they used the VIKOR method for ranking failure modes.

FMEA analysis combined with the VIKOR method (Serb. VIšekriterijumsko KOmpromisno Rangiranje) [23] also can be found in the papers of [24, 25]. In both studies, the authors use triangular fuzzy numbers to describe uncertainties.

Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [26], being one of the most widely used methods in various MADM domains [27, 28], is also combined with FMEA analysis in several studies [29-31]. All of these studies utilize triangular fuzzy numbers. It is worth noting that [24] applied the TOPSIS method in combination with fuzzy sets theory to test the results obtained by the VIKOR method.

Besides these two methods, the Decision-Making Trial and Evaluation Laboratory (DEMATEL) [32, 33] method was used in combination with triangular fuzzy numbers in the study by Liu et al. [34], while it was applied with the Evaluation based on Distance from Average Solution (EDAS) [35] method in the paper of [36]. In studies by [31, 36], the Analytic Hierarchy Process (AHP) [37] method was employed to determine the weights of risk factors. The criteria weights (or risk factors, in this case), as in this study, can be directly assessed by decision-makers and aggregated using an appropriate operator. However, numerous other methods can also be used for this purpose, as has been done in various types of optimization problems [7, 38-40].

When it comes to the application domain, it is quite broad regarding fuzzy FMEA analysis. In addition to the automotive industry [21], it is applied in the food industry [20], electronics [34], agriculture [31], transportation [24], enterprise architecture [25], well drilling [29], renewable energy investments [36], industrial processes [30], project risk management [19], floating production storage and offloading [22] and more.

As previously mentioned in the earlier sections of this paper, each of these applications focused on prioritization or risk assessment. However, no one in the relevant literature has addressed the problem of determining the sequence in which failure modes should be addressed. In this study, this issue is tackled through the application of a combined PFMEA-FRADAR approach.

3 METHODOLOGY

In this study, the traditional PFMEA analysis was extended by the application of the FRADAR approach to determine the specific sequence of addressing failure modes i, $i = 1, \ldots, I$. This approach streamlines the implementation of proposed activities for PFMEA team members. Given that PFMEA recommends focusing on removing or minimizing the causes of failure modes with high (H) and medium (M) priority, only these failure modes were investigated in this study.

In Fig. 1, the proposed methodology is presented, while the explanation of the phases shown in the figure is provided later in this chapter.

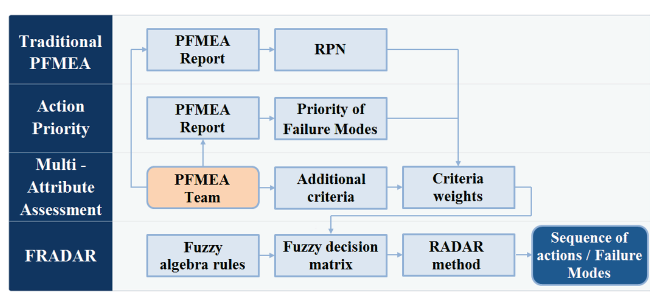

Figure 1 The proposed methodology

The failures' priority was identified using the AP technique. The RPN parameter value was then calculated for each failure mode and used to determine the failure mode value using the RPN criterion.

The criteria used to determine the sequence of actions are k, $k = 1, \dots, K$: RPN value ($k = 1$), cost-effectiveness of mitigation actions ($k = 2$), time required to resolve the issue ($k = 3$), and impact on production process realization ($k = 4$).

The criteria were defined in collaboration with the PFMEA team of an automotive industry company. The company is a Tier-1 supplier in the automotive supply chain, with its production facility located in the Republic of Serbia.

The first criterion pertains to the RPN parameter value, traditionally calculated by multiplying the risk factor values S (Severity), O (Occurrence), and D (Detection). The second criterion represents the cost-effectiveness of mitigation actions for the considered failure mode. The third criterion refers to the time required to resolve the issue, as estimated by the PFMEA team members. Finally, the fourth criterion considers the impact of the proposed actions on potentially halting certain production phases or even the entire production process.

3.1 Determination of Criteria Weights

A total of 5 members of the PFMEA team participated in the research, where e, $e = 1, \dots, E$. Each of them assessed the importance of the considered criteria based on pre-defined linguistic statements. The linguistic expressions used were:

- Absolutely unimportant criterion (L1): (0, 0, 0.3),
- Slightly important criterion (L2): (0.1, 0.3, 0.5),
- Moderately important criterion (L3): (0.25, 0.5, 0.75),
- Very important criterion (L4): (0.5, 0.7, 0.9),
- Absolutely important criterion (L5): (0.7, 1, 1).

The domain of fuzzy numbers is defined on the measurement scale (0-1). The evaluations of the PFMEA team members were aggregated using the fuzzy arithmetic mean operator [41]. In this way, the weights of the considered criteria were determined.

3.2 Modelling of Uncertain Values of Criteria

Unlike determining the criteria weights, where the assessments of the PFMEA team members are aggregated using the fuzzy arithmetic mean operator, in this case, the assessments are made by consensus. Using predefined linguistic expressions (Tab. 1), the PFMEA team members evaluate the values for each considered failure mode i, $i = 1, \dots, I$, according to each criterion k, $k = 1, \dots, K$. The domain of fuzzy numbers is defined on the measurement scale (1-10).

In this context, the RPN value ($k = 1$) is considered as a benefit-type criterion, as higher RPN values suggest a higher priority for addressing failure modes, implying that steps should be taken to limit the risks associated with these modes. This guarantees that failure modes with higher RPN values receive priority for corrective measures. Similarly, the cost-effectiveness of mitigation actions ($k = 2$) is a benefit-type criterion since it assesses the efficiency of risk reduction in terms of cost, with the goal of maximizing benefits while minimizing expenses. On the other side, both the time necessary to remedy the issue ($k = 3$) and the impact on production process realization ($k = 3$) are cost-type criteria, as they relate to the possible rise in costs due to longer resolution timeframes or larger impact on production process.

Table 1 Linguistic expressions modelled using triangular fuzzy numbers for evaluating the values of failure modes according to the considered criteria

Fuzzy number notation	TFN	Cost-effectiveness of mitigation actions ($k = 2$)	Time required to resolve the issue ($k = 3$)	Impact on production process realization ($k = 4$)
		Description		
Very low value (V1)	(1, 1, 3.5)	Actions are extremely costly, with little to no benefit in terms of risk reduction.	Very quick actions that require minimal time and effort to implement.	The issue has a negligible impact on the production process.
Low value (V2)	(2, 3.5, 5)	Actions provide some cost-effectiveness but with limited benefit.	Actions that require a short amount of time to implement but are still relatively simple.	The issue may slightly disrupt the production process but does not halt it.
Medium value (V3)	(4, 5.5, 7)	Actions provide balanced cost-effectiveness with noticeable risk reduction.	Actions requiring a moderate amount of time and effort to implement.	The issue may cause moderate disruption but can be managed without halting the process.
High value (V4)	(6, 7.5, 9)	Actions are very cost-effective, significantly reducing risks and costs.	Actions that require considerable time and resources to implement.	The issue can cause significant disruption to the production process, requiring attention to avoid delays.
Very high value (V5)	(7.5, 10, 10)	Actions are extremely cost-effective, almost eliminating risks and costs.	Actions that require a substantial amount of time and effort to fully implement.	The issue has a severe impact, potentially halting the production process and requiring immediate resolution.

3.3 Proposed Algorithm

In this research, a model for determining the priority sequence of actions to address failure modes in an automobile industry company was developed and tested. The proposed model can be given using the following algorithm:

Step 1. Data collection on failure modes from the existing PFMEA report. Based on the application of the AP methodology, failure modes of H and M priority categories were selected, i, $i = 1, \dots, I$.

Step 2. In collaboration with the members of the PFMEA team from a Tier-1 company in the automotive supply chain, a set of criteria was defined, k, $k = 1, \dots, K$.

Step 3. The importance of the considered criteria, $\tilde{w}_k^e$, was assessed by the members of the PFMEA team, e, $e = 1, \dots, E$. Their assessments, were aggregated using the fuzzy arithmetic mean operator to determine criteria weights, $\tilde{\omega}_k$.

Step 4. Based on the assessments made by the PFMEA team members, which were reached through consensus, a fuzzy decision matrix is formed:

$$\left[\tilde{M}_{ik}\right]_{I \times K} \tag{1}$$

The next steps of the proposed algorithm represent an extension of the RADAR method [6, 7] through the application of fuzzy set theory and fuzzy algebra rules [9, 42]:

Step 5. Construct the fuzzy maximum proportion matrix, $\tilde{\alpha}$:

$$\left[\tilde{\alpha}_{ik}\right]_{I\times K} \tag{2}$$

For the benefit type of criteria:

$$\tilde{\alpha}_{ik}=\frac{\dfrac{\max_i \tilde{M}_{ik}}{\tilde{M}_{ik}}}{\left[\left(\dfrac{\max_i \tilde{M}_{ik}}{\tilde{M}_{ik}}\right)+\left(\dfrac{\tilde{M}_{ik}}{\min_i \tilde{M}_{ik}}\right)\right]} \tag{3}$$

For the cost type of criteria:

$$\tilde{\alpha}_{ik}=\frac{\dfrac{\tilde{M}_{ik}}{\min_i \tilde{M}_{ik}}}{\left[\left(\dfrac{\max_i \tilde{M}_{ik}}{\tilde{M}_{ik}}\right)+\left(\dfrac{\tilde{M}_{ik}}{\min_i \tilde{M}_{ik}}\right)\right]} \tag{4}$$

Step 6. Construct the fuzzy minimum proportion matrix, $\tilde{\beta}$:

$$\left[\tilde{\beta}_{ik}\right]_{I\times K} \tag{5}$$

For the benefit type of criteria:

$$\tilde{\beta}_{ik}=\frac{\dfrac{\tilde{M}_{ik}}{\min_i \tilde{M}_{ik}}}{\left[\left(\dfrac{\max_i \tilde{M}_{ik}}{\tilde{M}_{ik}}\right)+\left(\dfrac{\tilde{M}_{ik}}{\min_i \tilde{M}_{ik}}\right)\right]} \tag{6}$$

For the cost type of criteria:

$$\tilde{\beta}_{ik}=\frac{\dfrac{\max_i \tilde{M}_{ik}}{\tilde{M}_{ik}}}{\left[\left(\dfrac{\max_i \tilde{M}_{ik}}{\tilde{M}_{ik}}\right)+\left(\dfrac{\tilde{M}_{ik}}{\min_i \tilde{M}_{ik}}\right)\right]} \tag{7}$$

Step 7. Construct the empty range matrix:

$$\left[E_{ik}\right]_{I\times K} \tag{8}$$

where:

$$E_{ik}=\left|\alpha_{ik}-\beta_{ik}\right| \tag{9}$$

where: α_{ik} is defuzzified value of $\tilde{\alpha}_{ik}$, and β_{ik} is defuzzified value of $\tilde{\beta}_{ik}$. Defuzzification of this values is performed by procedure defined in [43].

Step 8. Construct the fuzzy relative relationship matrix:

$$\left[\widetilde{RR}_{ik}\right]_{I\times K} \tag{10}$$

where:

$$\widetilde{RR}_{ik}=\frac{\tilde{\alpha}_{ik}}{\tilde{\beta}_{ik}+E_{ik}} \tag{11}$$

Step 9. Construct the fuzzy weighted relative relationship matrix:

$$\left[\widetilde{WRR}_{ik}\right]_{I\times K} \tag{12}$$

where:

$$\widetilde{WRR}_{ik}=\widetilde{RR}_{ik}\cdot\tilde{\omega}_k \tag{13}$$

Step 10. Aggregated ranking index, RI_i:

$$RI_i=\frac{\min\sum_{k=1}^{K} defuzz\,\widetilde{WRR}_i}{\sum_{k=1}^{K} defuzz\,\widetilde{WRR}_i} \tag{14}$$

Defuzzification of $\widetilde{WRR}_i$ is performed using the defuzzification procedure defined in the [43].

Afterward, the ranking of the considered failure modes is determined, where the highest value of RI_i indicates the failure mode that should be addressed first. The reverse is also true. In the next section, the proposed algorithm is tested on a case study from the automotive industry.

4 CASE STUDY

The case study used to test the developed model was conducted in a company that is a Tier-1 supplier in the automotive supply chain. The company specializes in manufacturing leather upholstery for automobile interiors. Data from the PFMEA report were collected from the sewing production process phase. The considered failure modes, related to the sewing machine, (with H and M priority) are presented in Tab. 2, along with their S, O, and D values, AP approach category, and RPN values (step 1 of the proposed algorithm).

Out of a total of 27 identified failure modes for considered production phase, 16 with H or M priority are shown in Tab. 2. The remaining failure modes have L priority and were therefore not considered in this analysis. Of course, if financial resources and other resources are available, the PFMEA team may choose to include them for consideration.

In this case, the limitation is the available resources, which is why failure modes with L priority were not considered.

According to the new AP approach, the priority of failure modes is determined. It can be seen in Tab. 2 that this priority is not always compatible with the RPN value. Some failure modes, such as (i = 5), have a higher RPN value compared to, for example, (i = 10), even though (i = 10) has a H priority and (i = 5) has a M priority. This is because the AP approach prioritizes Severity over the other two risk factors. In this study, the set of failure modes under consideration was selected according to the AP approach, but the RPN value was used in the decision matrix, as it allows for the quantitative expression of priority/risk.

Table 2 Identified failure modes and their priority according to AP and RPN approaches

Number of failure mode	Failure mode	S	O	D	AP	RPN
i = 1	Misaligned stitching	8	6	6	H	288
i = 2	Thread breakage	9	6	7	H	378
i = 3	Skipped stitches	8	6	5	H	240
i = 4	Needle damage	9	4	4	H	144
i = 5	Incorrect thread tension	7	5	6	M	210
i = 6	Material slippage during sewing	8	5	5	M	200
i = 7	Uneven stitch length	7	4	6	M	168
i = 8	Puckering of fabric	8	5	6	M	240
i = 9	Loose stitches	7	4	6	M	168
i = 10	Sewing machine's feed mechanism failure	9	4	4	H	144
i = 11	Incorrect alignment of panels	7	5	5	M	175
i = 12	Fabric tearing during stitching	9	5	7	H	315
i = 13	Color mismatch in stitching	6	4	7	M	168
i = 14	Excessive thread wastage	7	5	4	M	140
i = 15	Needle overheating	8	4	5	M	160
i = 16	Damage to embroidery patterns	6	6	5	M	180

As already mentioned, and as presented in Step 2 of the proposed algorithm, a set of criteria has been defined: RPN value (k = 1), cost-effectiveness of mitigation actions (k = 2), time required to resolve the issue (k = 3), and impact on production process realization (k = 4).

The criteria were defined in collaboration with the members of the PFMEA team during a panel discussion. During the same panel discussion, the PFMEA team members expressed their assessments regarding the importance of each criterion, as well as the value of each failure mode according to each considered criterion.

According to Step 3 of the proposed algorithm, the importance of the considered criteria is evaluated by the members of the PFMEA team. Their assessments are:

$$\tilde{w}_1^1 = L4 \quad \tilde{w}_2^1 = L3 \quad \tilde{w}_3^1 = L2 \quad \tilde{w}_4^1 = L3$$
$$\tilde{w}_1^2 = L4 \quad \tilde{w}_2^2 = L2 \quad \tilde{w}_3^2 = L1 \quad \tilde{w}_4^2 = L3$$
$$\tilde{w}_1^3 = L3 \quad \tilde{w}_2^3 = L3 \quad \tilde{w}_3^3 = L2 \quad \tilde{w}_4^3 = L3$$
$$\tilde{w}_1^4 = L4 \quad \tilde{w}_2^4 = L4 \quad \tilde{w}_3^4 = L3 \quad \tilde{w}_4^4 = L3$$
$$\tilde{w}_1^5 = L5 \quad \tilde{w}_2^5 = L3 \quad \tilde{w}_3^5 = L2 \quad \tilde{w}_4^5 = L2$$

The aggregated and normalized weight values of the criteria are:

$$\tilde{\omega}_1 = (0.17,\ 0.37,\ 0.82) \qquad \tilde{\omega}_2 = (0.10,\ 0.26,\ 0.67)$$
$$\tilde{\omega}_3 = (0.04,\ 0.14,\ 0.47) \qquad \tilde{\omega}_4 = (0.08,\ 0.23,\ 0.64)$$

According to Step 4 of the proposed algorithm, the PFMEA team members provided consensus-based evaluations for the value of each failure mode against each considered criterion. The only exception is the RPN value, which was directly taken from the PFMEA report previously developed by the same PFMEA team. The fuzzy decision matrix is presented in Tab. 3.

Each of the five PFMEA team members recorded their assessments on paper for later discussion and deliberation. A compromise solution was reached through agreement, or, in cases where consensus could not be achieved, an average score (assessment) was calculated. Such cases were very rare. In most instances, their assessments largely coincided and were consistent.

Table 3 The fuzzy decision matrix

	k = 1	k = 2	k = 2	k = 2
i = 1	288	V4	V3	V4
i = 2	378	V3	V3	V4
i = 3	240	V4	V3	V5
i = 4	144	V2	V2	V3
i = 5	210	V3	V3	V4
i = 6	200	V3	V3	V4
i = 7	168	V3	V2	V3
i = 8	240	V4	V3	V4
i = 9	168	V3	V3	V4
i = 10	144	V4	V4	V5
i = 11	175	V4	V3	V4
i = 12	315	V5	V3	V5
i = 13	168	V3	V2	V4
i = 14	140	V2	V2	V2
i = 15	160	V2	V2	V3
i = 16	180	V4	V3	V4

By applying step 5 of the proposed algorithm, the fuzzy maximum proportion matrix, $\tilde{\alpha}$, is formed. Given that the minimum and maximum values are clearly identifiable due to the linguistic terms being arranged in a gradient, there is no need for comparing fuzzy numbers in this step.

The first element of the fuzzy maximum proportion matrix, $\tilde{\alpha}$, is calculated as follows:

$$\tilde{\alpha}_{11} = \frac{\dfrac{\max_i \tilde{M}_{i1}}{\tilde{M}_{11}}}{\left[\left(\dfrac{\max_i \tilde{M}_{i1}}{\tilde{M}_{11}}\right) + \left(\dfrac{\tilde{M}_{11}}{\min_i \tilde{M}_{i1}}\right)\right]} = \frac{\dfrac{378}{288}}{\dfrac{378}{288} + \dfrac{288}{140}} = 0.39$$

A crisp value can also be represented as a fuzzy number:

$$\tilde{\alpha}_{11} = (0.39,\ 0.39,\ 039)$$

Tab. 4 presents the remaining values of the fuzzy maximum proportion matrix, $\tilde{\alpha}$. Fuzzy algebra rules were applied for operations with fuzzy numbers.

Tab. 5 presents values of the fuzzy minimum proportion matrix, $\tilde{\beta}$ (Step 6 of the proposed algorithm). Also, fuzzy algebra rules were applied for operations with fuzzy numbers.

By applying the procedure shown in step 7, the empty range matrix, E_{ik} (Tab. 6), was determined. In order to determine the values of the elements of this matrix, the values of the matrices $\tilde{\alpha}$ and $\tilde{\beta}$ were defuzzified. The subsequent steps of the proposed algorithm continue using fuzzy numbers and fuzzy algebra rules.

Table 4 The fuzzy maximum proportion matrix, $\tilde{\alpha}$

i	k = 1	k = 2	k = 2	k = 2
i = 1	(0.39, 0.39, 0.39)	(0.14, 0.38, 0.82)	(0.14, 0.54, 7.19)	(0.19, 0.62, 5.14)
i = 2	(0.27, 0.27, 0.27)	(0.18, 0.54, 1.34)	(0.14, 0.54, 7.19)	(0.19, 0.62, 5.14)
i = 3	(0.48, 0.48, 0.48)	(0.14, 0.38, 0.82)	(0.14, 0.54, 7.19)	(0.24, 0.74, 4.22)
i = 4	(0.72, 0.72, 0.72)	(0.20, 0.74, 2.63)	(0.06, 0.32, 17.50)	(0.13, 0.46, 7.50)
i = 5	(0.55, 0.55, 0.55)	(0.18, 0.54, 1.34)	(0.14, 0.54, 7.19)	(0.19, 0.62, 5.14)
i = 6	(0.57, 0.57, 0.57)	(0.18, 0.54, 1.34)	(0.14, 0.54, 7.19)	(0.19, 0.62, 5.14)
i = 7	(0.65, 0.65, 0.65)	(0.18, 0.54, 1.34)	(0.06, 0.32, 17.50)	(0.13, 0.46, 7.50)
i = 8	(0.48, 0.48, 0.48)	(0.14, 0.38, 0.82)	(0.14, 0.54, 7.19)	(0.19, 0.62, 5.14)
i = 9	(0.65, 0.65, 0.65)	(0.18, 0.54, 1.34)	(0.14, 0.54, 7.19)	(0.19, 0.62, 5.14)
i = 10	(0.72, 0.72, 0.72)	(0.14, 0.38, 0.82)	(0.20, 0.68, 5.00)	(0.24, 0.74, 4.22)
i = 11	(0.63, 0.63, 0.63)	(0.14, 0.38, 0.82)	(0.14, 0.54, 7.19)	(0.19, 0.62, 5.14)
i = 12	(0.35, 0.35, 0.35)	(0.12, 0.26, 0.59)	(0.14, 0.54, 7.19)	(0.24, 0.74, 4.22)
i = 13	(0.65, 0.65, 0.65)	(0.18, 0.54, 1.34)	(0.06, 0.32, 17.50)	(0.19, 0.62, 5.14)
i = 14	(0.73, 0.73, 0.73)	(0.20, 0.74, 2.63)	(0.06, 0.32, 17.50)	(0.05, 0.26, 18.75)
i = 15	(0.67, 0.67, 0.67)	(0.20, 0.74, 2.63)	(0.06, 0.32, 17.50)	(0.13, 0.46, 7.50)
i = 16	(0.62, 0.62, 0.62)	(0.18, 0.54, 1.34)	(0.14, 0.54, 7.19)	(0.19, 0.62, 5.14)

Table 5 The fuzzy minimum proportion matrix, $\tilde{\beta}$

i	k = 1	k = 2	k = 2	k = 2
i = 1	(0.61, 0.61, 0.61)	(0.19, 0.62, 5.14)	(0.15, 0.46, 1.36)	(0.14,0.38,0.82)
i = 2	(0.73, 0.73, 0.73)	(0.13, 0.46, 7.50)	(0.15, 0.46, 1.36)	(0.14,0.38,0.82)
i = 3	(0.52, 0.52, 0.52)	(0.19, 0.62, 5.14)	(0.15, 0.46, 1.36)	(0.12,0.26,0.59)
i = 4	(0.28, 0.28, 0.28)	(0.05, 0.26, 18.75)	(0.17, 0.68, 2.81)	(0.18,0.54,1.34)
i = 5	(0.45, 0.45, 0.45)	(0.13, 0.46, 7.50)	(0.15, 0.46, 1.36)	(0.14,0.38,0.82)
i = 6	(0.43, 0.43, 0.43)	(0.13, 0.46, 7.50)	(0.15, 0.46, 1.36)	(0.14,0.38,0.82)
i = 7	(0.35, 0.35, 0.35)	(0.13, 0.46, 7.50)	(0.17, 0.68, 2.81)	(0.18,0.54,1.34)
i = 8	(0.52, 0.52, 0.52)	(0.19, 0.62, 5.14)	(0.15, 0.46, 1.36)	(0.14,0.38,0.82)
i = 9	(0.35, 0.35, 0.35)	(0.13, 0.46, 7.50)	(0.15, 0.46, 1.36)	(0.14,0.38,0.82)
i = 10	(0.28, 0.28, 0.28)	(0.19, 0.62, 5.14)	(0.11, 0.32, 0.80)	(0.12,0.26,0.59)
i = 11	(0.37, 0.37, 0.37)	(0.19, 0.62, 5.14)	(0.15, 0.46, 1.36)	(0.14,0.38,0.82)
i = 12	(0.65, 0.65, 0.65)	(0.24, 0.74, 4.22)	(0.15, 0.46, 1.36)	(0.12,0.26,0.59)
i = 13	(0.35, 0.35, 0.35)	(0.13, 0.46, 7.50)	(0.17, 0.68, 2.81)	(0.14,0.38,0.82)
i = 14	(0.27, 0.27, 0.27)	(0.05, 0.26, 18.75)	(0.17, 0.68, 2.81)	(0.20,0.74,2.63)
i = 15	(0.33, 0.33, 0.33)	(0.05, 0.26, 18.75)	(0.17, 0.68, 2.81)	(0.18,0.54,1.34)
i = 16	(0.38, 0.38, 0.38)	(0.13, 0.46, 7.50)	(0.15, 0.46, 1.36)	(0.14,0.38,0.82)

Table 6 The empty range matrix, E_{ik}

i	k = 1	k = 2	k = 2	k = 2
i = 1	0.22	1.54	1.96	1.54
i = 2	0.46	2.02	1.96	1.54
i = 3	0.04	1.54	1.96	1.41
i = 4	0.44	5.16	4.74	2.02
i = 5	0.09	2.02	1.96	1.54
i = 6	0.14	2.02	1.96	1.54
i = 7	0.30	2.02	4.74	2.02
i = 8	0.04	1.54	1.96	1.54
i = 9	0.30	2.02	1.96	1.54
i = 10	0.44	1.54	1.55	1.41
i = 11	0.27	1.54	1.96	1.54
i = 12	0.30	1.41	1.96	1.41
i = 13	0.30	2.02	4.74	1.54
i = 14	0.46	5.16	4.74	5.16
i = 15	0.35	5.16	4.74	2.02
i = 16	0.24	2.02	1.96	1.54

By applying the procedure presented in step 8 of the proposed algorithm, the values of the elements of the fuzzy relative relationship matrix (Tab. 7) are calculated.

Example of calculating the element of the fuzzy relative relationship matrix:

$$\widetilde{RR}_{12}=\frac{\tilde{\alpha}_{12}}{\tilde{\beta}_{12}+E_{12}}=$$

$$=\frac{(0.14,\ 0.38,\ 0.82)}{(0.19,\ 0.62,\ 5.14)+(1.54,\ 1.54,\ 1.54)}=(0.02,\ 0.18,\ 0.47)$$

In step 9 of the proposed algorithm, the values are made more difficult, as shown in Tab. 8.

Example of calculating the element of the fuzzy weighted relative relationship matrix:

$$\widetilde{WRR}_{11} = \widetilde{RR}_{11} \cdot \tilde{\omega}_1 =$$
$$= (0.47,\ 0.47,\ 0.47) \cdot (0.17,\ 0.37,\ 0.82) = (0.08,\ 0.17,\ 0.38)$$

According to step 10 of the proposed algorithm, the aggregated ranking index, RI_i, is calculated. An example of the calculation for the first failure mode:

$$RI_1 = \frac{\min \sum_{k=1}^{K} defuzz\,\widetilde{WRR}_i}{\sum_{k=1}^{K} defuzz\,\widetilde{WRR}_i} = \frac{1.39}{1.56} = 0.89$$

The value of the aggregated ranking index, RI_i, for the remaining failure modes, as well as the ranking of failure modes, is shown in Tab. 9.

Table 7 The fuzzy relative relationship matrix, $\left[\widetilde{RR}_{ik}\right]_{I \times K}$

i	$k = 1$	$k = 2$	$k = 2$	$k = 2$
$i = 1$	(0.47, 0.47, 0.47)	(0.02, 0.18, 0.47)	(0.04, 0.22, 3.40)	(0.08, 0.32, 3.07)
$i = 2$	(0.28, 0.28, 0.28)	(0.02, 0.27, 0.80)	(0.04, 0.22, 3.40)	(0.08, 0.32, 3.07)
$i = 3$	(0.65, 0.65, 0.65)	(0.02, 0.18, 0.47)	(0.04, 0.22, 3.40)	(0.11, 0.41, 2.55)
$i = 4$	(1.43, 1.43, 1.43)	(0.01, 0.41, 1.65)	(0.01, 0.12, 8.20)	(0.05, 0.22, 4.37)
$i = 5$	(0.81, 0.81, 0.81)	(0.02, 0.27, 0.80)	(0.04, 0.22, 3.40)	(0.08, 0.32, 3.07)
$i = 6$	(0.87, 0.87, 0.87)	(0.02, 0.27, 0.80)	(0.04, 0.22, 3.40)	(0.08, 0.32, 3.07)
$i = 7$	(1.15, 1.15, 1.15)	(0.02, 0.27, 0.80)	(0.01, 0.12, 8.20)	(0.05, 0.22, 4.37)
$i = 8$	(0.65, 0.65, 0.65)	(0.02, 0.18, 0.47)	(0.04, 0.22, 3.40)	(0.08, 0.32, 3.07)
$i = 9$	(1.15, 1.15, 1.15)	(0.02, 0.27, 0.80)	(0.04, 0.22, 3.40)	(0.08, 0.32, 3.07)
$i = 10$	(1.43, 1.43, 1.43)	(0.02, 0.18, 0.47)	(0.07, 0.30, 2.41)	(0.11, 0.41, 2.55)
$i = 11$	(1.08, 1.08, 1.08)	(0.02, 0.18, 0.47)	(0.04, 0.22, 3.40)	(0.08, 0.32, 3.07)
$i = 12$	(0.40, 0.40, 0.40)	(0.02, 0.11, 0.33)	(0.04, 0.22, 3.40)	(0.11, 0.41, 2.55)
$i = 13$	(1.15, 1.15, 1.15)	(0.02, 0.27, 0.80)	(0.01, 0.12, 8.20)	(0.08, 0.32, 3.07)
$i = 14$	(1.49, 1.49, 1.49)	(0.01, 0.41, 1.65)	(0.01, 0.12, 8.20)	(0.01, 0.11, 10.79)
$i = 15$	(1.23, 1.23, 1.23)	(0.01, 0.41, 1.65)	(0.01, 0.12, 8.20)	(0.05, 0.22, 4.37)
$i = 16$	(1.03, 1.03, 1.03)	(0.02, 0.27, 0.80)	(0.04, 0.22, 3.40)	(0.08, 0.32, 3.07)

Table 8 The fuzzy weighted relative relationship matrix, $\left[\widetilde{WRR}_{ik}\right]_{I \times K}$

i	$k = 1$	$k = 2$	$k = 2$	$k = 2$
$i = 1$	(0.08, 0.17, 0.38)	(0.002, 0.05, 0.32)	(0.002, 0.03, 1.60)	(0.01, 0.07, 1.97)
$i = 2$	(0.05, 0.11, 0.23)	(0.002, 0.07, 0.54)	(0.002, 0.03, 1.60)	(0.01, 0.07, 1.97)
$i = 3$	(0.11, 0.24, 0.53)	(0.002, 0.05, 0.32)	(0.002, 0.03, 1.60)	(0.01, 0.09, 1.63)
$i = 4$	(0.24, 0.53, 1.17)	(0.001, 0.11, 1.11)	(0.000, 0.02, 3.85)	(0.004, 0.05, 2.80)
$i = 5$	(0.14, 0.30, 0.66)	(0.002, 0.07, 0.54)	(0.002, 0.03, 1.60)	(0.01, 0.07, 1.97)
$i = 6$	(0.15, 0.32, 0.72)	(0.002, 0.07, 0.54)	(0.002, 0.03, 1.60)	(0.01, 0.07, 1.97)
$i = 7$	(0.19, 0.42, 0.94)	(0.002, 0.07, 0.54)	(0.000, 0.02, 3.85)	(0.004, 0.05, 2.80)
$i = 8$	(0.11, 0.24, 0.53)	(0.002, 0.05, 0.32)	(0.002, 0.03, 1.60)	(0.01, 0.07, 1.97)
$i = 9$	(0.19, 0.42, 0.94)	(0.002, 0.07, 0.54)	(0.002, 0.03, 1.60)	(0.01, 0.07, 1.97)
$i = 10$	(0.24, 0.53, 1.17)	(0.002, 0.05, 0.32)	(0.003, 0.04, 1.13)	(0.01, 0.09, 1.63)
$i = 11$	(0.18, 0.40, 0.88)	(0.002, 0.05, 0.32)	(0.002, 0.03, 1.60)	(0.01, 0.07, 1.97)
$i = 12$	(0.07, 0.15, 0.33)	(0.002, 0.03, 0.22)	(0.002, 0.03, 1.60)	(0.01, 0.09, 1.63)
$i = 13$	(0.19, 0.42, 0.94)	(0.002, 0.07, 0.54)	(0.000, 0.02, 3.85)	(0.01, 0.07, 1.97)
$i = 14$	(0.25, 0.55, 1.22)	(0.001, 0.11, 1.11)	(0.000, 0.02, 3.85)	(0.001, 0.03, 6.91)
$i = 15$	(0.21, 0.46, 1.01)	(0.001, 0.11, 1.11)	(0.000, 0.02, 3.85)	(0.004, 0.05, 2.80)
$i = 16$	(0.18, 0.38, 0.85)	(0.002, 0.07, 0.54)	(0.002, 0.03, 1.60)	(0.01, 0.07, 1.97)

Table 9 Order of taking actions for the considered failure modes (ranking)

i	RI_i	*Rank*
$i = 1$	0.89	3-4
$i = 2$	0.89	3-4
$i = 3$	0.90	2
$i = 4$	0.42	15
$i = 5$	0.77	7
$i = 6$	0.76	8-9
$i = 7$	0.47	13
$i = 8$	0.85	5
$i = 9$	0.71	11
$i = 10$	0.80	6
$i = 11$	0.76	8-9
$i = 12$	1.00	1
$i = 13$	0.52	12
$i = 14$	0.30	16
$i = 15$	0.43	14
$i = 16$	0.73	10

The presented rankings show the priority order in which the identified failure modes should be handled. Fabric tearing during stitching (i = 12) is given the highest priority, indicating its importance to the production process and overall quality. This is followed by skipped stitches (i = 3), with misaligned stitching (i = 1) and thread breakage (i = 2) tied for third place. These failure modes reveal severe concerns with sewing quality and machine functionality that need to be addressed immediately.

The results are reasonable and consistent with practical expectations, prioritizing failure modes with the greatest potential to interrupt production and damage product quality. Lower-priority failure modes, such as excessive thread wastage (i = 14) and needle damage (i = 4), are placed 15th and 16th, indicating that they have a less immediate impact than other issues. However, they should be addressed as part of a larger reform strategy. The suggested technique effectively distinguishes between failure modes, directing decision-makers to more targeted and economical mitigation actions.

If the obtained results are compared with the traditional RPN approach, as well as the new AP approach, certain similarities and differences can be observed in the considered case. According to the proposed approach, as well as the RPN parameter, the same top five failure modes are highlighted, but their rankings vary. The key reason for this occurrence is that the RPN criterion carries the greatest weight in this case study. However, changing the weights of the criteria can significantly influence the final ranking.

Although there are similarities, there are also significant differences. For example, failure mode (i = 10), which ranks sixth according to the proposed approach, is ranked fifteenth (second to last) according to RPN. Similarly, (i = 7), which is ranked thirteenth according to the proposed model, holds the tenth place according to RPN. There are also some minor variations (a change of one or two positions in the ranking), but these are not particularly significant.

When compared to the AP approach, certain differences can also be observed. For example, (i = 4), which has a priority rating of H, is ranked fifteenth according to the proposed model. The reason for this is the low cost-effectiveness of the proposed measures. Simply put, it is not economically viable for the company to allocate resources to eliminate the impact of this failure mode

5 CONCLUSION

The primary objective of this research was to improve traditional PFMEA by incorporating the FRADAR approach to properly prioritize failure modes during the manufacturing process. The suggested model addresses the shortcomings of the traditional RPN-based technique by introducing additional decision criteria and utilizing fuzzy set theory to handle uncertainty.

The proposed methodology, which was based on the FRADAR approach, included four essential criteria: RPN value, cost-effectiveness of mitigation actions, time required to resolve the issue, and impact on the production process. Fuzzy numbers represented the language assessments provided by PFMEA team members, ensuring accurate evaluations. The methodology was validated through a case study conducted in a Tier-1 automotive supplier, with a focus on leather seat cover production. The results showed rational prioritization, with higher-ranked failure types indicating their disruptive potential.

The proposed model has multiple advantages, including more flexibility in dealing with complex failure modes, higher precision in prioritization via fuzzy logic, and adaptability to different industrial environments. However, the dependence on expert judgment adds the possibility of subjectivity, and the fuzzy methodology may increase computational complexity.

Future study could concentrate on improving the model by incorporating criteria weight modifications, sophisticated computational methodologies, and expanding its application to other automobile manufacturing processes. This would improve the robustness of risk management systems and enable more effective decision-making in the automobile industry and beyond.

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