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ANALIZA FAKTORA KOJI UTIČU NA UNAPREĐENJE KVALITETA I DOSTIZANJE NIVOA ZRELOSTI PFMEA 4.0

Key words:
PFMEA;
quality enhancement;
maturity level;
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ANALYSIS OF FACTORS INFLUENCING THE QUALITY ENHANCEMENT AND ACHIEVEMENT OF PFMEA 4.0 MATURITY LEVEL

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Procesna analiza efekata i načina otkaza (engl. Process Failure Mode and Effect Analysis, PFMEA) predstavlja izuzetno koristan analitički alat za upravljanje kvalitetom, koji omogućava procenu potencijalnih načina otkaza i rizika koji mogu nastati u proizvodnom procesu. U automobilskoj industriji, primena PFMEA je obavezna, a propisana je standardom IATF 16949:2016 i pratećim procedurama. Kada je reč o samom proizvodnom procesu, PFMEA ima ključnu ulogu u obezbeđivanju pouzdanosti procesa. Međutim, brojne ograničavajuće okolnosti, poput finansijskih ograničenja, raspoloživosti radne snage, tehničkih uslova, veština i znanja, mogu značajno uticati na efikasnost implementacije PFMEA. Iz tog razloga, savremene industrijske prakse teže ka većem stepenu automatizacije PFMEA, smanjujući ljudske greške i subjektivnost u procenama, što je u skladu sa principima Industrije 4.0. Cilj ovog istraživanja je evaluacija i rangiranje faktora koji utiču na unapređenje PFMEA i potencijalno dostizanje nivoa PFMEA 4.0, na osnovu relevantnih kriterijuma, kako bi se utvrdilo koji faktori predstavljaju najveće izazove i najzahtevniji su za rešavanje u praksi. U tu svrhu, korišćen je kombinovani, višeatributivni pristup odlučivanja (engl. Multi-Attribute Decision-Making, MADM). Istraživanje je sprovedeno u saradnji sa liderima PFMEA timova iz tri kompanije automobilske industrije koje posluju u Srbiji.

The Process Failure Mode and Effect Analysis (PFMEA) is a highly useful analytical quality management tool for assessing potential failure modes and risks that may arise in the production process. In the automotive industry, PFMEA is mandatory, and its use is prescribed by the IATF 16949:2016 standard and related procedures. Regarding the manufacturing process itself, PFMEA plays a crucial role in ensuring process reliability. However, numerous limitations, such as financial constraints, workforce availability, technical conditions, skills, and knowledge, can significantly impact the effectiveness of PFMEA implementation. For this reason, modern industrial practices strive for a higher degree of PFMEA automation, minimizing human errors and reducing subjectivity in assessments, which is in line with the principles of Industry 4.0. The objec-

tive of this study is to evaluate and rank the factors influencing PFMEA improvement and the potential achievement of PFMEA 4.0, based on relevant criteria, to determine which factors pose the greatest challenges and are the most difficult to address in practice. For this purpose, a combined Multi-Attribute Decision-Making (MADM) approach was used. The research was conducted in collaboration with PFMEA team leaders from three automotive industry companies operating in Serbia.

1. Introduction

The Fourth Industrial Revolution, commonly known as Industry 4.0, has introduced significant transformations in the operations of industrial enterprises. Concepts such as the Internet of Things (IoT), artificial intelligence, cloud computing, Big Data, collaborative robotics, and additive manufacturing have become integral to modern production processes. The automotive industry, as a key contributor to the GDP of many countries and a crucial component of contemporary industrial systems, has also been profoundly impacted by these advancements. Every company strives to automate its business processes within its capabilities, enhancing their efficiency and effectiveness. The same applies to manufacturing processes, which are undeniably the most critical aspect of a company's success in the automotive sector.

One of the essential elements of the manufacturing process in automotive enterprises that necessitates the application of Industry 4.0 tools and concepts is Process Failure Mode and Effect Analysis (PFMEA). The implementation of PFMEA in the automotive industry is mandated by the IATF 16949:2016 standard [1]. However, PFMEA has several limitations [2], [3], some of which can be mitigated or effectively compensated for through the adoption of Industry 4.0 technologies. For instance, challenges such as the subjectivity of decision-makers and the assessment of risk factor values can be addressed through the application of artificial intelligence and Big Data analytics. Additionally, interdependencies between failure modes can be analyzed using machine learning techniques and cyber-physical systems (CPS).

In the study by [4], the authors developed a model for assessing the maturity level of PFMEA implementation, categorizing it into four levels: primitive, basic, proficient, and advanced. The highest level, referred to as PFMEA 4.0, represents a state of PFMEA development that integrates Enterprise Resource Planning (ERP), Manufacturing Execution Systems (MES), artificial intelligence, and other Industry 4.0 concepts.

In recent years, various studies have explored the integration of Industry 4.0 tools and concepts with PFMEA analysis. One such study was conducted by [5], in which the authors developed a mathematical model linking potential risks to the Six Sigma framework by assessing risks within the context of Quality 4.0. Similarly, [6] provided a detailed examination of the enhancement of Failure Mode and Effect Analysis (FMEA) through the application of Industry 4.0 technologies for automating risk assessment, presenting a case study from the construction industry.

In general, when linking Industry 4.0 with PFMEA or, more broadly, with Failure Mode and Effect Analysis (FMEA), the most commonly discussed approach in the relevant literature involves the application of artificial intelligence as a tool for enhancing the analysis and overcoming its fundamental limitations. Neural networks, as one of the key artificial intelligence tools, have been utilized in studies such as those by [7], [8]. Machine learning has been applied in the papers of [9–12].

However, the most extensive body of research on the integration of intelligent systems and FMEA analysis pertains to the application of fuzzy logic. FMEA has been extended through fuzzy logic and Multi-Attribute Decision Making (MADM) approaches in studies by [13–17].

Nevertheless, automotive industry companies, at least those operating in the Republic of Serbia, remain far from achieving the FMEA 4.0 level. A study by [18], conducted on a sample of 46 automotive companies in Serbia, revealed that the implementation of any Industry 4.0 concept is rare and that the use of specialized FMEA software remains at a low level.

The objective of this study is to examine the key factors preventing PFMEA analysis in automotive industry enterprises in the Republic of Serbia from reaching the 4.0 level. The factors analyzed in this study were defined by [4] and include: (1) Digitalization of PFMEA completion, (2) Inclusion of cost analysis, (3) Level of process automation, (4) Organization of PFMEA documentation, (5) Risk assessment methodology, (6) Control and data monitoring system, (7) Team readiness for PFMEA, and (8) Culture of continuous improvement. These factors were evaluated based on five criteria, which were defined in consultation with FMEA practitioners participating in this study: (1) Implementation costs, (2) Implementation complexity, (3) Employee resistance to change, (4) Lack of skills and knowledge, and (5) Lack of operational capacity.

To determine the weights of the considered criteria, the Analytic Hierarchy Process (AHP) method was applied [19], [20]. Although some other methods are also used for this purpose in the literature, such as the Best-Worst Method (BWM) [21], Defining Interrelationships Between Ranked criteria (DIBR) [22], Level Based Weight Assessment (LBWA) [23], the AHP method was chosen as one of the oldest and most commonly used methods in the relevant literature (see [24], [25]).

For ranking the factors, five Multi-Attribute Decision-Making (MADM) methods were used: Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [26], Simple Additive Weighting (SAW) (see [27], [28]), Evaluation based on Distance from Average Solution (EDAS) [29], Ranking based on the Distances And Range (RADAR) [30], and RADAR II [31]. The obtained results were compared and analyzed.

Following the introductory chapter, which also provides a brief overview of the relationship between PFMEA analysis and Industry 4.0 concepts, Chapter 2 describes the problem under consideration. Chapter 3 explains the applied methodology, while Chapter 4 presents the problem-solving process. The final chapter outlines the research conclusions.

2. Problem description

Achieving the highest PFMEA maturity level is a highly challenging and currently difficult goal for automotive industry enterprises in the Republic of Serbia. However, the primary objective is not merely to reach the PFMEA 4.0 level but to sufficiently automate and enhance the PFMEA process to make its application simpler, more effective, and more reliable. The goal is to minimize subjectivity in the assessments of PFMEA team members, reduce the risk of incorrect evaluations due to insufficient knowledge, and streamline the method into routine steps.

Additionally, the time required for the method's implementation is a crucial factor, and efforts are directed toward its reduction. To provide a clearer understanding of the research problem, a graphical representation of the study is presented in Figure 1.

The core of this research involves analyzing factors, i, $i = 1,\dots,I$, defined in the study by [4]. The criteria, j, $j = 1,\dots,J$, based on which these factors are evaluated, were determined in collaboration with PFMEA team members from three automotive industry companies operating in the Republic of Serbia. The weight of each criterion was determined using the AHP method, while the ranking of the factors was conducted using five MADM methods, as explained in the following chapter.

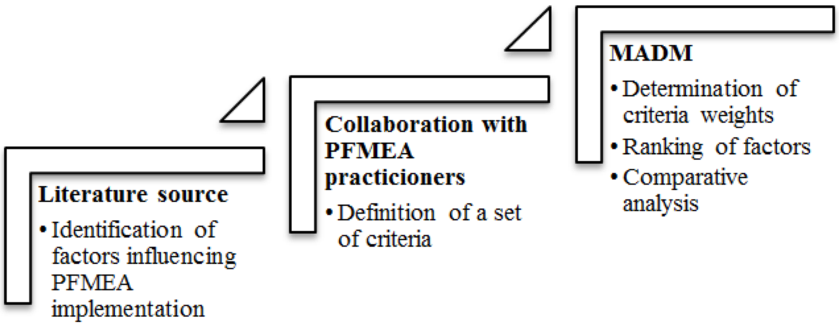

Figure 1. Problem description

3. Materials and methods

This research utilized a total of six MADM methods. AHP was applied for determining the criterion weights, while TOPSIS, SAW, EDAS, RADAR, and RADAR II were used for ranking the factors influencing the achievement of the PFMEA 4.0 maturity level. Since the focus of the study is not on improving or extending these methods but rather on assessing the significance of the considered factors, the basic versions of these methods were employed.

3.1. Determination of criteria weights using the AHP method

The AHP method is based on pairwise comparison of criteria through a pairwise comparison matrix, which can be formally represented as follows: $[W_{jj'}]_{J\times J}$

Such that: $j, j' = 1,...,J, j \neq j'$.

In this case, PFMEA team leaders, e, $e = 1,...,E$, from three different automotive industry companies provided their assessments of the relative importance of the criteria. In this case, three PFMEA team leaders were selected from three different automotive companies with production facilities located in the Republic of Serbia. Each of the chosen decision-makers has over 10 years of work experience in the automotive industry, as well as more than five years of experience working in PFMEA teams. Besides leading PFMEA teams, their primary positions within their companies are Maintenance Specialist, Manufacturing Engineer, and Quality Engineer.

For their evaluations, they used the standard Saaty's fundamental measurement scale [19]:

- 1 – two criteria are equally important (prioritized);
- 3 – one criterion has slightly greater importance compared to the other;
- 5 – one criterion has significantly greater importance compared to the other;
- 7 – one criterion has very much greater importance compared to the other;
- 9 – one criterion has absolutely and extremely greater importance compared to the other;
- 2, 4, 6, and 8 – intermediate values representing a compromise between the defined values.

The consistency check of the assessments was performed using the Eigenvector method [32], by calculating the Consistency Index (CI).

By applying the steps of the conventional AHP method, the criterion weights were determined at the level of each decision-maker, ω_j^e.

The geometric mean operator was then used to determine the unique criterion weight, ω_j:

$$\omega_j = \sqrt[E]{\prod_{e=1}^{E} \omega_j^e} \tag{1}$$

In this way, the criterion weights obtained based on each decision-maker individually were aggregated into a single value.

3.2. Ranking of factors influencing the achievement of the PFMEA 4.0 maturity level

The problem of determining the most significant factors that obstruct or pose the greatest challenge for achieving PFMEA 4.0 maturity level in automotive industry companies in Serbia was addressed in this study using five MADM methods. Specifically, the TOPSIS, SAW, EDAS, and two variations of the RADAR method (RADAR and RADAR II) were applied. As previously mentioned, the original versions of these methods were used.

To evaluate the values of alternatives (factors) based on each considered criterion, decision-makers used the following measurement scale:

- 1 – the improvement of the factor does not depend on the considered criterion;
- 2 – the improvement of the factor slightly depends on the considered criterion;
- 3 – the improvement of the factor moderately depends on the considered criterion;
- 4 – the improvement of the factor largely depends on the considered criterion;
- 5 – the improvement of the factor absolutely depends on the considered criterion.

Each decision-maker, e, $e = 1,\ldots,E$, provides their assessments independently, which are then aggregated (summed) to obtain a single value.

3.3. The proposed algorithm

The developed model in this study can also be represented through an algorithm, i.e., implementation steps (Figure 2).

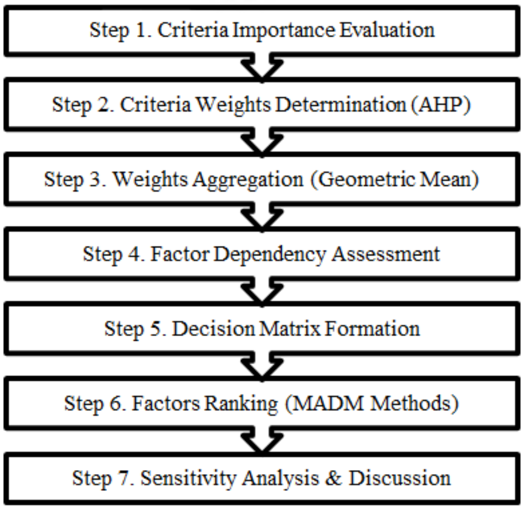

Figure 2. The proposed algorithm

In Figure 2, the following steps of the proposed algorithm can be observed:

Step 1. Evaluation of the relative importance of criteria at the level of each decision-maker, $\lfloor W_{jj'} \rfloor_{J \times J}$.

Step 2. Determination of criteria weights using the conventional AHP method at the level of each decision-maker, ω_j^e.

Step 3. Aggregation of criteria weights into a single value using the geometric mean operator, ω_j.

Step 4. Assessment of the dependency values of factors on the considered criterion at the level of each decision-maker, $\lfloor M_{ij}^e \rfloor_{I \times J}$.

Step 5. Summation of the assessed values into a single score to form the decision matrix, $\lfloor M_{ij} \rfloor_{I \times J}$.

Step 6. Application of the basic versions of the TOPSIS, SAW, EDAS, RADAR, and RADAR II methods for ranking factors. Since the basic versions of the considered MADM methods were used in this study, and the focus of the paper is not on their modification or improvement, the methodological steps are omitted to keep the paper concise.

Step 7. Sensitivity analysis and discussion of the obtained results.

4. Determining the impact of factors on improving PFMEA maturity level

As already mentioned in this study, the dimensions of the considered problem include 8 alternatives and 5 criteria. The considered alternatives, i.e., the factors being ranked, are: Digitalization of PFMEA completion (i = 1), Inclusion of cost analysis (i = 2), Level of process automation (i = 3), Organization of PFMEA documentation (i = 4), Risk assessment methodology (i = 5), Control and data monitoring system (i = 6), Team readiness for PFMEA (i = 7), and Culture of continuous improvement (i = 8). The criteria based on which these alternatives are evaluated are: Implementation costs (j = 1), Implementation complexity (j = 2), Employee resistance to change (j = 3), Lack of skills and knowledge (j = 4), and Lack of operational capacity (j = 5).

Based on the first step of the proposed algorithm, the decision-makers provided their assessments of the relative importance of the criteria:

$$e = 1 \qquad \begin{bmatrix} 1 & 1/3 & 1/4 & 1/7 & 1/9 \\ & 1 & 2 & 1/3 & 1/2 \\ & & 1 & 1/3 & 1/2 \\ & & & 1 & 2 \\ & & & & 1 \end{bmatrix} \qquad CI = 0.04$$

$$e = 2 \qquad \begin{bmatrix} 1 & 1 & 1/2 & 1/3 & 1/5 \\ & 1 & 1 & 1/2 & 1/3 \\ & & 1 & 1/4 & 1/4 \\ & & & 1 & 1 \\ & & & & 1 \end{bmatrix} \qquad CI = 0.04$$

$$e = 3 \qquad \begin{bmatrix} 1 & 1/2 & 1/3 & 1/8 & 1/6 \\ & 1 & 1/2 & 1/4 & 1/3 \\ & & 1 & 1/2 & 1/2 \\ & & & 1 & 2 \\ & & & & 1 \end{bmatrix} \qquad CI = 0.02$$

In all three cases, the decision makers' evaluations are consistent, meaning that the condition $CI \leq 0.1$ is met. By applying the AHP method (Step 2), the following criteria weights were obtained at the level of each decision maker (Table 1).

Table 1. Criteria weights at the level of each decision maker

e = 1	**e = 2**	**e = 3**
$\omega_1^1 = 0.04$	$\omega_1^2 = 0.09$	$\omega_1^3 = 0.05$
$\omega_2^1 = 0.16$	$\omega_2^2 = 0.12$	$\omega_2^3 = 0.09$
$\omega_3^1 = 0.13$	$\omega_3^2 = 0.11$	$\omega_3^3 = 0.17$
$\omega_4^1 = 0.40$	$\omega_4^2 = 0.31$	$\omega_4^3 = 0.41$
$\omega_5^1 = 0.27$	$\omega_5^2 = 0.37$	$\omega_5^3 = 0.28$

The aggregated value of the criteria weights (Step 3), determined using the geometric mean operator, is:

$\omega_1 = 0.06$ $\omega_2 = 0.12$ $\omega_3 = 0.13$ $\omega_4 = 0.37$ $\omega_5 = 0.30$

According to step 4, the assessment of the dependency values of factors on the considered criterion was performed at the level of each decision-maker (Table 2). Then, by applying step 5, the summation/aggregation of the assessed values into a single score was carried out to form the decision matrix, which is presented in Table 3.

Table 2. Assessment of the dependency values of factors on the considered criterion was performed at the level of each decision-maker

Factor	$j = 1$	$j = 2$	$j = 3$	$j = 4$	$j = 5$
$i = 1$	3, 3, 2	4, 5, 4	3, 4, 3	5, 5, 4	4, 5, 5
$i = 2$	3, 4, 4	2, 1, 2	2, 2, 2	3, 3, 3	2, 2, 2
$i = 3$	4, 5, 5	5, 5, 5	4, 4, 4	5, 5, 5	5, 5, 5
$i = 4$	2, 2, 3	3, 3, 4	3, 3, 4	3, 3, 3	2, 2, 2
$i = 5$	2, 3, 4	3, 4, 5	3, 3, 3	4, 5, 3	3, 4, 4
$i = 6$	4, 3, 4	5, 5, 2	3, 2, 4	5, 4, 5	5, 5, 5
$i = 7$	1, 2, 1	2, 2, 3	5, 5, 5	5, 3, 5	2, 2, 2
$i = 8$	1, 2, 2	2, 3, 4	4, 5, 4	3, 4, 2	3, 2, 4

Table 3. Decision matrix

Factor	$j = 1$	$j = 2$	$j = 3$	$j = 4$	$j = 5$
$i = 1$	8	13	10	14	14
$i = 2$	11	5	6	9	6
$i = 3$	14	15	12	15	15
$i = 4$	7	10	10	9	6
$i = 5$	9	12	9	12	11
$i = 6$	11	12	9	14	15
$i = 7$	4	7	15	13	6
$i = 8$	5	9	13	9	9

By applying step 6, the ranking of the considered factors was performed, as shown in Table 4.

Table 4. Ranking of the considered factors using MADM methods

Factor	Rank				
	TOPSIS	SAW	EDAS	RADAR	RADAR II
$i = 1$	3	3	3	3	3
$i = 2$	8	8	6	8	7
$i = 3$	1	1	1	1	1
$i = 4$	7	7	8	7	8
$i = 5$	4	4	5	4	5
$i = 6$	2	2	2	2	2
$i = 7$	5	5	4	5	4
$i = 8$	6	6	7	6	6

In step 7 of the proposed algorithm, a sensitivity analysis and discussion of the obtained results are conducted. To make the analysis clearer and more effective, the ranking of alternatives is graphically presented in Figure 3.

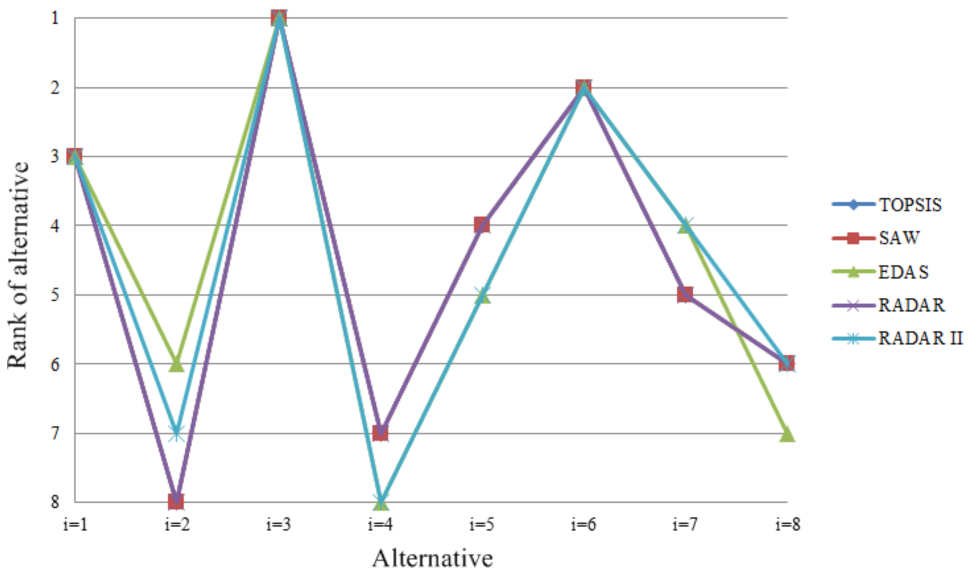

Figure 3. Rank of alternatives (factors)

From Table 4, as well as from Figure 3, it is evident that the application of different MADM methods results in a very similar ranking of factors influencing the improvement of the PFMEA maturity level. The results obtained using these methods are largely consistent, especially concerning the top three ranked factors.

In Figure 3, numerous overlaps in the ranking of alternatives can be observed, i.e., the curves are of very similar shape and frequently coincide. Even where deviations exist, they are very small. To further examine the reliability of the obtained results, a comparison of the rankings was performed using Spearman's rank correlation coefficient, as shown in Table 5. Spearman's rank correlation coefficient between the rankings obtained by different MADM methods was calculated using the Data Analysis function in Microsoft Office Excel.

Table 5. Comparative analysis of alternative rankings using Spearman's rank correlation coefficient

	TOPSIS	SAW	EDAS	RADAR	RADAR II
TOPSIS	**1.00**				
SAW	1.00	**1.00**			
EDAS	0.90	0.90	**1.00**		
RADAR	1.00	1.00	0.90	**1.00**	
RADAR II	0.95	0.95	0.98	0.95	**1.00**

Table 5 clearly shows that the TOPSIS, SAW, and RADAR methods produce identical rankings of the alternatives (correlation coefficient equal to 1). In all other cases, the correlation coefficient is 0.9 or higher, indicating a high degree of correlation, meaning the rankings of the alternatives are very similar. This confirms the previously stated assumptions that all methods yielded stable results.

In all considered cases, Level of process automation (i = 3) is ranked first, Control and data monitoring system (i = 6) is ranked second, while Digitalization of PFMEA completion (i = 1) holds third place in the ranking.

Risk assessment methodology (i = 5) and Team readiness for PFMEA (i = 7) alternate between fourth and fifth place, depending on the method applied. Thus, minor variations exist, which depend on the nature of the specific MADM method.

Culture of continuous improvement (i = 8) is ranked sixth in most cases, except in the EDAS method, where it is ranked seventh. Organization of PFMEA documentation (i = 4) is generally ranked seventh, except in the EDAS method, where it holds the last position. Inclusion of cost analysis (i = 2) is ranked last in the TOPSIS, SAW, and RADAR methods, sixth in EDAS, and seventh in RADAR II. However, the significance of this factor is negligible.

It can be concluded that the application of different MADM methods confirms the stability of the solution. In this sense, the most important factors influencing the potential improvement of the PFMEA analysis, or in other words, the ones that may hinder its advancement the most, are (i = 3), (i = 6), and (i = 1).

5. Conclusion

This study identifies the key factors influencing the enhancement of the PFMEA analysis to the PFMEA 4.0 level. The case study was conducted in collaboration with three automotive industry companies and three PFMEA team leaders. The significance of involving practitioners lies in the fact that they have the best understanding of the conditions within their companies and are familiar with their capabilities.

To address the research problem, a total of six MADM methods were employed. The AHP method was used to determine the weights of the criteria, which were previously established in collaboration with PFMEA practitioners who participated in the study. Additionally, the same respondents provided their assessments of the relative importance of the considered criteria, as well as the dependence of the analyzed factors on the defined criteria. For ranking the factors and determining their impact on the possibility of improving PFMEA implementation, five MADM methods were applied: TOPSIS, SAW, EDAS, RADAR, and RADAR II.

Based on the obtained ranking of the analyzed factors, the most important ones were identified as the Level of process automation (i = 3), Control and data monitoring system (i = 6), and Digitalization of PFMEA completion (i = 1). On the other hand, the least significant factors were the Culture of continuous improvement (i = 8), Organization of PFMEA documentation (i = 4), and Inclusion of cost analysis (i = 2).

The Level of process automation (i = 3) is a crucial factor, as it significantly facilitates the application of PFMEA analysis. Primarily, the automation of manufacturing activities reduces the likelihood of failure mode occurrence, which greatly impacts the overall PFMEA analysis. Additionally, automation enables better monitoring of process execution and the collection of data necessary for conducting the analysis.

The Control and data monitoring system (i = 6) is closely related to automation. A system that monitors and controls the occurrence of failure modes would significantly aid in identifying critical process points. This would enable faster responses to emerging issues and more effective implementation of preventive actions.

The Digitalization of PFMEA completion (i = 1) refers to the systematization of data entry and the generation of PFMEA reports. This process is primarily supported by appropriate PFMEA software, which helps standardize the application of PFMEA analysis within the company.

Furthermore, it is evident that the Culture of continuous improvement (i = 8), Organization of PFMEA documentation (i = 4), and Inclusion of cost analysis (i = 2) are less influential factors. Specifically, (i = 8) is a factor that can be relatively easily influenced through changes in organizational structure and leadership style, which can significantly contribute to its improvement. The factor (i = 4) pertains to PFMEA documentation itself, meaning that if data is accurate and the analysis is conducted properly, the organization of documentation can be easily improved. Lastly, the factor (i = 2) can be integrated into PFMEA analysis by adding an additional risk factor or incorporating a cost aspect within the severity risk factor.

The main contribution of this research is the application of a combined MADM approach, incorporating five different ranking methods, to identify key factors influencing the enhancement of PFMEA analysis. By employing five MADM methods, an objective ranking of alternatives was performed, confirming the stability of the obtained results. In this way, practitioners are provided with insights into the factors that require the most attention if a company aims to improve its PFMEA analysis to the 4.0 level.

The primary limitation of this study is the restricted data sample, as the research involved experts from only three companies. Since all three companies operate within the automotive industry, the results may not be fully applicable to other industrial sectors.

Future research could include a larger number of companies and extend beyond the automotive industry to other industrial and economic sectors. Additionally, from a methodological perspective, MADM methods could be expanded by applying fuzzy logic, and further sensitivity analysis could be conducted by varying the criterion weight values. Moreover, different approaches can be used for comparing the ranking of alternatives, as proposed in [33], [34]. Consideration could be given to incorporating additional factors for analysis, as well as introducing new evaluation criteria.

6. Acknowledgement

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