algorithms

MDPI

Article

Optimization of PFMEA Team Composition in the Automotive Industry Using the IPF-RADAR Approach

Nikola Komatina [1,*] and Dragan Marinković [2,3]

1 Faculty of Engineering, University of Kragujevac, Sestre Janjić 6, 34000 Kragujevac, Serbia
2 Faculty of Mechanical Engineering and Transport Systems, Technical University Berlin, 10623 Berlin, Germany; dragan.marinkovic@tu-berlin.de
3 Mechanical Science Institute, Vilnius Gediminas Technical University-VILNIUS TECH, Plytinės st. 25, LT-10105 Vilnius, Lithuania
* Correspondence: nkomatina@kg.ac.rs

Abstract: In the automotive industry, the implementation of Process Failure Mode and Effect Analysis (PFMEA) is conducted by a PFMEA team comprising employees who are connected to the production process or a specific product. Core PFMEA team members are actively engaged in PFMEA execution through meetings, analysis, and the implementation of corrective actions. Although the current handbook provides guidelines on the potential composition of the PFMEA team, it does not strictly define its members, allowing companies the flexibility to determine the team structure independently. This study aims to identify the core PFMEA team members by adhering to criteria based on the recommended knowledge and competencies outlined in the current handbook. By applying the RAnking based on the Distances and Range (RADAR) approach, extended with Interval-Valued Pythagorean Fuzzy Numbers (IVPFNs), a ranking of potential candidates was conducted. A case study was performed in a Tier-1 supplier company within the automotive supply chain.

Keywords: automotive industry; PFMEA; PFMEA team; RADAR; IVPFNs

Academic Editors: Alicia Cordero and Juan Ramón Torregrosa Sánchez

Received: 16 May 2025
Revised: 29 May 2025
Accepted: 3 June 2025
Published: 4 June 2025

Citation: Komatina, N.; Marinković, D. Optimization of PFMEA Team Composition in the Automotive Industry Using the IPF-RADAR Approach. *Algorithms* **2025**, *18*, 342. https://doi.org/10.3390/a18060342

1. Introduction

In automotive industry companies, the team responsible for conducting Process Failure Mode and Effect Analysis (PFMEA), commonly referred to as the PFMEA team, represents one of the most important multidisciplinary teams within the organization, as its work can significantly impact the reliability of the production process. Regardless of the type of product or the supplier level within the automotive supply chain, the PFMEA team is an essential and vital link in achieving the strategic and operational objectives of the production process. The responsibilities and tasks of the PFMEA team, as well as those of the team leader (facilitator), are focused on the preparation, execution, and evaluation of the implemented PFMEA activities.

In addition to planning and coordinating activities related to PFMEA, team members often perform other tasks associated with their primary job roles. Only in large and complex business systems is the PFMEA team composed of members for whom this role is their primary position. In most cases, participation in the PFMEA team is an additional responsibility alongside their main job tasks.

PFMEA team members should possess technical expertise, be familiar with the workstations or production lines they are analyzing, be capable of effectively perceiving and identifying potential problems, and be communicative and open to collaboration with employees.

The application of PFMEA in the automotive industry is mandatory according to the IATF 16949:2016 standard [1]. To ensure uniformity and consistency in the implementation of PFMEA, the Automotive Industry Action Group (AIAG) and the German Association of the Automotive Industry (Ger. Verband der Automobilindustrie, VDA) developed a joint handbook [2], which serves as a basis for applying not only PFMEA but also its design-focused version (DFMEA) and the version for monitoring and system response (FMEA-MSR).

The AIAG&VDA Handbook provides certain guidelines and recommendations for the formation and work of PFMEA teams. However, it does not strictly define who should or can be a team member. The recommendations suggest that the core team should consist of [2] a facilitator (team leader), a process/manufacturing engineer, an ergonomic engineer, a process validation engineer, a quality/reliability engineer, and other personnel responsible for process development and planning.

The same handbook also proposes who may be part of the extended team, which is involved as needed and does not regularly participate in PFMEA meetings. It is recommended that occasional members include [2] a design engineer, technical experts, a service engineer, a project manager, maintenance staff, line workers, purchasing personnel, suppliers, and other individuals who may be relevant to specific aspects of the production process.

As the composition of the core PFMEA team is not strictly defined in the handbook, the subject of this study is the optimization of its composition, disregarding the formal positions of potential candidates within the company's hierarchy and focusing solely on their skills and characteristics.

The aim of this research is to evaluate and rank candidates for inclusion in the core PFMEA team by applying a multi-attribute approach in a Pythagorean fuzzy environment. In this way, a mathematically grounded and reliable tool is provided to company management for solving the problem under consideration.

The criteria for evaluating candidates are based on the recommended characteristics of the team members and facilitator outlined in the handbook [2], which are as follows: (1) knowledge of the considered process/product, (2) experience working in a PFMEA team, (3) interdisciplinary expertise, and (4) communication skills and teamwork abilities.

The selected criteria were chosen in collaboration with the management of the company where the case study was conducted. The company's management considered these four criteria to be the most effective for evaluating potential candidates. Although additional relevant criteria, such as interest in participating in the PFMEA team and workload in the primary job position, should be taken into account when selecting PFMEA team members, in this case, all candidates were first interviewed and asked whether they were willing and able to participate in the PFMEA team activities. Besides the additional responsibility, it is common practice in the company that this assignment brings benefits such as a monetary bonus on the monthly salary, opportunities for faster promotion, access to additional training, the possibility to collaborate with colleagues from other departments, increased recognition within the company, and more.

To address the problem under consideration, a Multi-Attribute Decision-Making (MADM) approach was employed. MADM, broadly speaking, falls under the group of Multi-Criteria Decision-Making (MCDM) methods and is used for solving optimization problems in various engineering domains, such as advanced manufacturing [3,4], logistics [5,6], material selection [7,8], failure analysis [9,10], energy sector [11,12], supplier selection [13,14], selection of electric vehicles [15,16], etc.

In this case, the MADM approach was extended by the application of Interval-Valued Pythagorean Fuzzy Numbers (IVPFNs). The MADM method used for ranking potential candidates in this study was the Ranking based on the Distances And Range (RADAR) method [17,18].

In the literature, there are two variations of the RADAR method, namely RADAR and RADAR II, which differ in the way values are normalized. The RADAR method favours the stability of an alternative by mitigating the influence of extremely high values across a small number of criteria, whereas the RADAR II method evaluates alternatives more objectively. However, in this study, due to the limitations of fuzzy algebra for IVPFNs, which does not recognize classical mathematical operations, such as subtraction and division, distances between two IVPFNs were used instead of these operations.

Therefore, two variants of the RADAR method extended by the application of IVPFNs were used in this study, referred to as the IPF-RADAR approach. For the purposes of the case study, a shift manager, HR specialist, and production supervisor were engaged as independent experts in the decision-making process. All other individuals who were potential candidates for PFMEA team membership, or who were already part of the existing PFMEA team within the company, were considered as candidates. The case study was conducted in a Tier-1 company in the automotive supply chain, primarily producing rubber components, along with certain plastic parts for automobiles.

This paper is organized as follows: The introductory chapter provides fundamental considerations regarding the research problem, presents the objective of the study, and outlines the applied methodology. The second chapter offers a literature review on the application of MADM methods for solving personnel/candidate selection problems. The third chapter explains the employed methodology, starting with the fundamentals of IVPFNs and continuing to the applied IPF-RADAR approach. The fourth chapter presents the practical implementation of the proposed model, while the final chapter highlights the key conclusions of the research.

2. Literature Review

The problem of determining the composition of a PFMEA team can, more broadly, be viewed as a personnel selection problem. This chapter is divided into two sections. The first refers to the analysis of the personnel selection problem in the relevant literature, while the second focuses on previous applications of the RADAR method.

2.1. Personnel Selection Problem

Personnel selection is one of the significant and contemporary research problems in the relevant literature. A considerable number of studies can be found in which the authors have conducted the selection of employees for specific positions or job roles, or the selection of candidates during the hiring process using various fuzzy MADM approaches. However, there is still a lack of studies addressing the selection of PFMEA team members, which gives particular importance to the proposed model.

In the study by Chen and Hung [19], the authors employed the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [20] and entropy methods to identify unsuitable applicants, while the Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) [21], extended through the use of two-tuple linguistic variables, was applied to evaluate suitable candidates. The coefficients obtained from TOPSIS and PROMETHEE were then aggregated to produce the final ranking of candidates. The study focused on the selection of the best candidate for the position of an overseas marketing manager.

The problem of selecting IT personnel was examined in the study by Mishra et al. [22], where the objective was to choose the best IT personnel candidate. For this purpose, the authors employed the Additive Ratio Assessment (ARAS) method [23], extended by the application of Intuitionistic Fuzzy Sets (IFSs). To model uncertainty, IFSs were also used in the study by Krishankumar et al. [24], where the authors applied the Multi-Criteria Optimization and Compromise Solution (VIKOR) [25] to choose suitable candidates for a project.

For evaluating candidates who applied for a sales job, the study by Biswas et al. [26] utilized the Logarithmic Percentage Change-driven Objective Weighting (LOPCOW) method, extended through the use of spherical fuzzy sets.

For personnel selection in the textile industry, Ozgormus et al. [27] employed a hybrid Quality Function Deployment (QFD)–MCDM framework, where the Trial and Evaluation Laboratory (DEMATEL) [28] method was used to determine the weights of the criteria, while the Grey Relational Analysis (GRA) [29] method was applied to rank the candidates. To represent uncertain values, triangular fuzzy numbers were utilized.

Although a considerable number of studies in the literature have addressed personnel selection using combined fuzzy MADM approaches, none of the authors have applied Pythagorean Fuzzy Sets (PFSs) for modelling uncertainty. Consequently, the personnel selection problem solved using this approach can be found, among others, in the studies [30–33].

Essentially, PFSs represent an extension of IFSs, offering a broader range for describing uncertainty. For this reason, some authors favour PFSs over IFSs [34]. A specific form of IFSs, known as IVPFNs, which were also used in this study, have membership and non-membership degrees within a defined range. This allows for a more accurate representation of uncertainty and imprecision.

In the literature, IVPFNs have been applied in various forms and combined with different optimization methods to address a wide range of problems. Some of the fields where IVPFNs have been used include economics [35], energy systems [36], tourism [37], and project management [38]. Therefore, it can be concluded that applying this approach to solve the personnel selection problem would offer practical contributions, an objective achieved in this study.

2.2. RADAR Method

As stated in the introductory chapter, the RADAR method was first introduced in the paper [17], while the RADAR II version was presented for the first time in the paper [18]. The fundamental characteristics of the method from a mathematical perspective are given in the paper [39], which provides a mathematical proof of the consistency of the rankings obtained using the RADAR and RADAR II methods through the presentation of their basic features.

In the paper [17], the author applied the RADAR method to determine the priority of failure modes. In addition, a comparison was made between the results obtained using the RADAR method and those obtained using the TOPSIS and ARAS methods, as well as the basic Risk Priority Number (RPN), including weighted RPN values (considering the importance of risk factors). A comparative analysis using the WS ranking similarity coefficient [40] showed a moderate to high level of overlap with the rankings obtained by TOPSIS and ARAS. When compared with the RPN and weighted RPN approach, this overlap was almost complete.

In the paper [41], the authors addressed a similar problem but used a combined Action Priority (AP) and RPN approach, introducing three additional criteria to determine the sequence for addressing failure modes. These additional criteria were the cost-effectiveness of mitigation actions, the time necessary to remedy the issue, and the impact on production process realization. To describe the uncertainty in this problem, pre-defined linguistic terms were used and modelled with triangular fuzzy numbers. In this way, the activities of the PFMEA team were optimized.

A comparison of results obtained by applying RADAR and RADAR II with those from other MADM methods was performed in the paper [18]. The author proposed a new model for equipment selection in the automotive industry and compared the results of the RADAR and RADAR II methods with those of TOPSIS, COmplex PRoportional Assessment (COPRAS) [42], VIKOR, ARAS, and EDAS [43] (Evaluation based on Distance from Average Solution). According to the WS ranking similarity coefficient, the degree of agreement between RADAR and RADAR II was very high (sometimes even absolute). Only the RADAR II method showed a moderate level of similarity with the EDAS method. Thus, only small variations were observed, which largely depended on the nature of each method.

In the paper presenting the mathematical foundations of the RADAR and RADAR II methods [39], a comparison of these two methods was performed using three numerical examples. Although the rankings were largely similar, there were cases where deviations occurred. The basic characteristic of the RADAR method is that it "favours" alternatives that are stable across multiple criteria. When an alternative is "below average" across several criteria, its chances of achieving a high rank are significantly reduced. Naturally, the ranking also strongly depends on the weights of the criteria themselves, and both RADAR and RADAR II tend to favour alternatives that are "stable" with respect to the more important criteria. All this indicates that both methods are suitable for risk and reliability analysis problems. However, the study showed that the basic RADAR method is somewhat more flexible than the RADAR II version. In other words, the basic RADAR method allows for slightly greater negative deviations of an alternative from the "average" values.

Since this paper addresses a personnel selection problem, the RADAR method was chosen in order to select candidates who outperform others across multiple criteria. Moreover, it favours candidates who perform well with respect to the most important criteria while reducing the effect of a candidate's extreme strength in a single criterion in cases where they do not meet the expected standards in other areas.

Based on the above, it can be concluded that although methods such as TOPSIS, VIKOR, and others are widely used in the literature for solving various types of problems, the RADAR method was selected due to its specific advantages that align with the nature of the problem under consideration. The key features of the RADAR method are particularly suitable for the personnel selection problem, as a candidate's competence is reflected through their knowledge and qualifications across multiple domains. Therefore, the method is well suited for situations in which versatile candidates must be selected, and the PFMEA team is inherently expected to be both interdisciplinary and multidisciplinary.

Furthermore, even in a fuzzy environment, the method's logic, grounded in the principle of stability, remains applicable. As demonstrated in previous studies [17,18,39], RADAR produces results that are highly consistent with those of other methods, with only minor deviations. At the same time, the method's underlying logic ensures that candidates with significant shortcomings in certain criteria are less likely to be selected. This is particularly valuable in contexts where the goal is to minimize risk. Hence, it can be concluded that RADAR provides a more cautious and robust decision-making framework, which is essential for the problem at hand.

3. Methodology

This chapter presents the fundamental considerations and basic computational operations (fuzzy algebra rules) with IVPFNs, as well as the modelling of uncertain values for determining the weights of criteria and the uncertain values of alternatives for each criterion. The proposed algorithm is presented at the end of the chapter.

3.1. Fundamentals of IVPFNs and Basic Computational Operations

An Interval-Valued Pythagorean Fuzzy Number (IVPFN) can be defined as a special form of Pythagorean Fuzzy Number (PFN) whose membership degree and non-membership degree lie between two values (within a range). IVPFN, $\tilde{A}$, can be mathematically expressed as follows [44]:

$$\tilde{A} = \{x, [\mu_{\tilde{A}_L}(x), \mu_{\tilde{A}_U}(x)], [\nu_{\tilde{A}_L}(x), \nu_{\tilde{A}_U}(x)]; x \in X\}$$

In this case, $\mu_{\tilde{A}}(x)$ denotes the membership degree, while $\nu_{\tilde{A}}(x)$ o represents the non-membership degree. The lower bound of the membership degree is denoted as $\mu_{\tilde{A}_L}(x)$, while the upper bound is denoted as $\mu_{\tilde{A}_U}(x)$. Similarly, the lower bound of the non-membership degree is denoted as $\nu_{\tilde{A}_L}(x)$, while the upper bound is denoted as $\nu_{\tilde{A}_U}(x)$.

For each IVPFN, the following rules apply [44]:

$$\begin{gathered} 0 \le \mu_{\tilde{A}_L}(x), \mu_{\tilde{A}_U}(x), \nu_{\tilde{A}_L}(x), \nu_{\tilde{A}_U}(x) \le 1 \\ \mu_{\tilde{A}_L}(x)^2 + \nu_{\tilde{A}_L}(x)^2 \le 1; x \in X \end{gathered} \tag{1}$$

If two IVPFNs, $\tilde{A}$ and $\tilde{B}$, as well as a crisp value c, are considered, the following fuzzy algebra rules can be applied [44,45]:

$$\tilde{A} \oplus \tilde{B} = \left(\begin{bmatrix} \sqrt{(\mu_1^L)^2 + (\mu_2^L)^2 - (\mu_1^L)^2(\mu_2^L)^2}, \\ \sqrt{(\mu_1^U)^2 + (\mu_2^U)^2 - (\mu_1^U)^2(\mu_2^U)^2} \end{bmatrix}, [\nu_1^L\nu_2^L, \nu_1^U\nu_2^U] \right) \tag{2}$$

$$\tilde{A} \otimes \tilde{B} = \left([\mu_1^L\mu_2^L, \mu_1^U\mu_2^U], \begin{bmatrix} \sqrt{(\nu_1^L)^2 + (\nu_2^L)^2 - (\nu_1^L)^2(\nu_2^L)^2}, \\ \sqrt{(\nu_1^U)^2 + (\nu_2^U)^2 - (\nu_1^U)^2(\nu_2^U)^2} \end{bmatrix} \right) \tag{3}$$

$$c\tilde{A} = \left(\begin{bmatrix} \sqrt{1 - (1 - (\mu_1^L)^2)^c}, \\ \sqrt{1 - (1 - (\mu_1^U)^2)^c} \end{bmatrix}, [(\nu_1^L)^c, (\nu_1^U)^c] \right) \tag{4}$$

$$\tilde{A}^c = \left([(\mu_1^L)^c, (\mu_1^U)^c], \begin{bmatrix} \sqrt{1 - (1 - (\nu_1^L)^2)^c}, \\ \sqrt{1 - (1 - (\nu_1^U)^2)^c} \end{bmatrix} \right) \tag{5}$$

The distance between two IVPFNs, $d(\tilde{A}, \tilde{B})$, can be calculated as follows [45]:

$$d(\tilde{A}, \tilde{B}) = \frac{1}{2} \sqrt{\left(\begin{gathered} ((\mu_1^L)^2 - (\mu_2^L)^2)\left(1 - \frac{\pi_1^L - \pi_2^L}{2}\right) + \\ \sqrt{((\mu_1^U)^2 - (\mu_2^U)^2)\left(1 - \frac{\pi_1^U - \pi_2^U}{2}\right)} \end{gathered} \right)} \tag{6}$$

The values π^L and π^U are called the hesitancy degrees of the lower and upper points, respectively. They are calculated as follows:

$$\pi^L = \sqrt{1 - (\mu_U^2 + \nu_U^2)} \tag{7}$$

$$\pi^U = \sqrt{1 - (\mu_L^2 + \nu_L^2)} \tag{8}$$

The defuzzification of $\tilde{A}$, i.e., the determination of its crisp value, can be calculated as follows [46]:

$$\begin{gathered} defuzz(\tilde{A}) = \\ \frac{1}{6}\Big(\mu_L^2 + \mu_U^2 + (1 - \pi_L^4 - \nu_L^2) + (1 - \pi_U^4 - \nu_U^2) + \mu_L\mu_U + \\ \sqrt[4]{(1 - \pi_L^4 - \nu_L^2)(1 - \pi_U^4 - \nu_U^2)}\Big) \end{gathered} \tag{9}$$

As the focus of this study is not on advancing IVPFN algebra but solely on applying this approach, the mathematical operations presented are fundamental or sufficient for the implementation of the RADAR method.

3.2. Modelling Uncertain Values of Criteria Weights

The determination of criterion weights can be performed in various ways. If the results are reliable and the problem under consideration corresponds to a problem from the literature, the weights can be adopted from such a source [17]. Another approach is direct estimation, which is most commonly used when there is a single decision-maker. Furthermore, weights can be determined by aggregating the assessments of decision-makers, as applied in [47–49]. Another method involves applying various MADM techniques, as demonstrated in [18,50–52].

In this study, the criteria weights were determined by aggregating the assessments of decision-makers, $e, e = 1, \ldots, E$ using the fuzzy addition operator, where the sum of the assessments was divided by the total number of decision-makers, E. As already stated in the introductory chapter, the decision-makers were as follows: a shift manager $(e = 1)$, an HR specialist $(e = 2)$, and a production supervisor $(e = 3)$. The decision-makers provided their assessments of criteria importance independently in written form via email.

Based on the recommendations of the AIAG&VDA Handbook [2] regarding the knowledge and skills of PFMEA team members, and in collaboration with the decision-makers, the following criteria were defined: knowledge of the considered process/product $(k = 1)$, experience working in a PFMEA team $(k = 2)$, interdisciplinary expertise $(k = 3)$, and communication skills and teamwork abilities $(k = 4)$. It is important to emphasize that all criteria are of a benefit type.

For expressing their assessments, the decision-makers used the following linguistic terms modelled using IVPFNs:

- Completely unimportant criterion (C1): $\{[0.0, 0.2], [0.8, 1.0]\}$;
- Unimportant criterion (C2): $\{[0.2, 0.4], [0.6, 0.8]\}$;
- Moderately important criterion (C3): $\{[0.4, 0.6], [0.4, 0.6]\}$;
- Important criterion (C4): $\{[0.6, 0.8], [0.2, 0.4]\}$;
- Very important criterion (C5): $\{[0.8, 1.0], [0.0, 0.2]\}$.

As can be seen, the domain of IVPFNs is within the interval from 0 to 1. A membership degree value closer to 1 indicates a higher criteria importance, and vice versa. The opposite rule applies to the non-membership degree.

3.3. Modelling Uncertain Values of Alternatives According to the Considered Criteria

Unlike the assessment of criteria importance, the evaluation of candidates, $i, i = 1, \ldots, I$, based on each considered criterion, $k, k = 1, \ldots, K$ was conducted collectively by the decision-makers, $e, e = 1, \ldots, E$, through consensus. It was assumed that through dialogue and the exchange of opinions, the decision-makers would evaluate the candidates more effectively than if they had provided individual assessments.

For candidate evaluation, the decision-makers used the following linguistic terms modelled using IVPFNs:

- Extremely poor (S1): $\{[0.0, 0.2], [0.8, 1.0]\}$;
- Very poor (S2): $\{[0.2, 0.3], [0.7, 0.8]\}$;
- Poor (S3): $\{[0.3, 0.4], [0.6, 0.7]\}$;
- Moderate (S4): $\{[0.4, 0.6], [0.4, 0.6]\}$;
- Good (S5): $\{[0.6, 0.7], [0.3, 0.4]\}$;
- Very good (S6): $\{[0.7, 0.8], [0.2, 0.3]\}$;

- Excellent (S7): $\{[0.8, 1.0], [0.0, 0.2]\}$.

As with the assessment of criterion importance, the values of IVPFNs range from 0 to 1. The same rules also apply to the membership and non-membership degrees.

3.4. The Proposed IPF-RADAR Algorithm

The process of candidate evaluation and selection of PFMEA team members, according to the proposed model, is carried out through the following steps:

Step 1. After defining the criteria, $k, k = 1, \dots, K$, based on the recommendations from the AIAG&VDA Handbook, the decision-makers, $e, e = 1, \dots, E$, make their assessments of the importance of each criterion.

Step 2. By applying the fuzzy addition mathematical operation, the assessments obtained at the level of each decision-maker, $\widetilde{w}_k^e$, are aggregated, resulting in a unique unnormalized weight for each criterion, $\widetilde{\omega}_k$. The fuzzy values are ultimately transformed into crisp values by applying the defuzzification procedure [46], and normalized by applying a linear normalization procedure to obtain crisp criteria weights, ω_k.

Step 3. The candidates, $i, i = 1, \dots, I$, are evaluated based on the considered criteria, $k, k = 1, \dots, K$. The decision-makers assess the candidates by consensus. Based on these assessments, a fuzzy decision matrix is formed, $\left[\widetilde{M}_{ik}\right]_{I \times K}$.

The steps of the basic RADAR method were further extended using IVPFNs algebra rules [44,45]. For the computational operation of subtraction, the distance between two IVPFNs was used.

Step 4. The maximum proportion matrix, α, is generated:

$$[\alpha_{ik}]_{I \times K} \tag{10}$$

such that

$$\alpha_{ik} = d\left(d\left(\max_i \widetilde{M}_{ik}, \widetilde{M}_{ik}\right); \left(d\left(\max_i \widetilde{M}_{ik}, \widetilde{M}_{ik}\right) + d\left(\widetilde{M}_{ik}, \min_i \widetilde{M}_{ik}\right)\right)\right) \tag{11}$$

Step 5. The minimum proportion matrix, β, is generated:

$$[\beta_{ik}]_{I \times K} \tag{12}$$

such that

$$\beta_{ik} = d\left(d\left(\widetilde{M}_{ik}, \min_i \widetilde{M}_{ik}\right); \left(d\left(\max_i \widetilde{M}_{ik}, \widetilde{M}_{ik}\right) + d\left(\widetilde{M}_{ik}, \min_i \widetilde{M}_{ik}\right)\right)\right) \tag{13}$$

Considering the fact that all evaluated criteria are of the benefit type, the calculation formulas for cost-type criteria according to the RADAR method are not presented in this paper.

The maximum and minimum values are taken as the highest and lowest assessments given by the decision-makers for each criterion, respectively.

Step 6. The empty range matrix is generated:

$$[E_{ik}]_{I \times K} \tag{14}$$

such that

$$E_{ik} = |\alpha_{ik} - \beta_{ik}| \tag{15}$$

Step 7. The relative relationship matrix, $[RR_{ik}]_{I \times K}$, is generated:

$$RR_{ik} = \frac{\alpha_{ik}}{\beta_{ik} + E_{ik}} \tag{16}$$

Step 8. The weighted relative relationship matrix, $[WRR_{ik}]_{I \times K}$, is generated:

$$WRR_{ik} = RR_{ik} \cdot \omega_k \tag{17}$$

Step 9. The aggregated ranking index, RI_i, is calculated:

$$RI_i = \frac{\min \sum_{k=1}^{K} WRR_i}{\sum_{k=1}^{K} WRR_i} \tag{18}$$

Step 10. The candidates are ranked using the RADAR method.

The graphical representation of the proposed methodology is shown in Figure 1. The presented algorithm includes the main steps of the developed mathematical model.

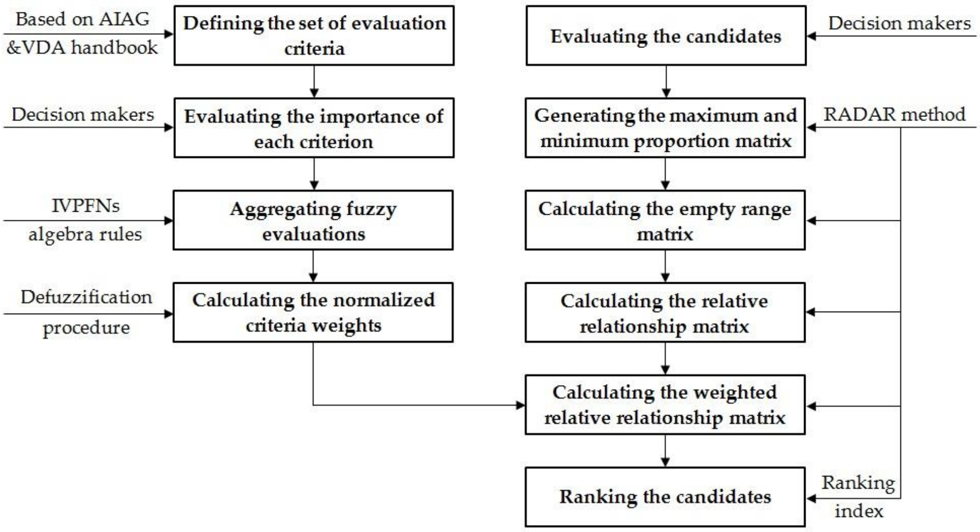

Figure 1. The proposed algorithm.

4. Practical Implementation of the Proposed IPF-RADAR

This chapter presents the practical implementation of the proposed model. Out of a total of 13 candidates, 6 members of the core PFMEA team needed to be selected. Formal positions within the company's hierarchy, as well as the candidates' job titles, were not considered and, therefore, are not mentioned in the paper. As previously stated, the case study was conducted in a company that is a Tier-1 supplier in the automotive supply chain.

According to Step 1 of the proposed algorithm, the decision-makers expressed their assessments of the importance of the considered criteria:

- Shift manager: $\widetilde{w}_1^1 = V4$; $\widetilde{w}_2^1 = V5$; $\widetilde{w}_3^1 = V3$; $\widetilde{w}_4^1 = V2$;
- HR specialist: $\widetilde{w}_1^2 = V5$; $\widetilde{w}_2^2 = V4$; $\widetilde{w}_3^2 = V3$; $\widetilde{w}_4^2 = V4$;
- Production supervisor: $\widetilde{w}_1^3 = V5$; $\widetilde{w}_2^3 = V3$; $\widetilde{w}_3^3 = V2$; $\widetilde{w}_4^3 = V3$.

The aggregated (summed) values of the relative importance weights of criteria were determined by applying the IVPFN algebra rules (Step 2):

$$\widetilde{w}_1 = \{[0.92, 1.00], [0.00, 0.03]\}$$

$$\widetilde{w}_2 = \{[0.90, 1.00], [0.00, 0.05]\}$$

$$\widetilde{w}_3 = \{[0.57, 0.81], [0.10, 0.29]\}$$

$$\widetilde{w}_4 = \{[0.70, 0.90], [0.05, 0.19]\}$$

The defuzzified and normalized criterion weights were as follows:

$$\omega_1 = 0.29$$

$$\omega_2 = 0.28$$

$$\omega_3 = 0.19$$

$$\omega_4 = 0.23$$

According to Step 3 of the proposed algorithm, the decision-makers evaluated the considered candidates by consensus, which is presented through the fuzzy decision matrix (Table 1).

Table 1. The fuzzy decision matrix.

Candidate, i	$k = 1$	$k = 2$	$k = 3$	$k = 4$
$i = 1$	S6	S2	S2	S4
$i = 2$	S2	S5	S5	S2
$i = 3$	S7	S3	S5	S7
$i = 4$	S2	S5	S5	S2
$i = 5$	S4	S7	S5	S4
$i = 6$	S5	S5	S7	S7
$i = 7$	S6	S7	S3	S5
$i = 8$	S2	S6	S2	S4
$i = 9$	S7	S3	S5	S7
$i = 10$	S7	S6	S4	S3
$i = 11$	S6	S1	S6	S4
$i = 12$	S3	S4	S7	S7
$i = 13$	S4	S6	S3	S6

Based on Steps 4 and 5, determination of the maximum and minimum proportion matrices was performed, respectively. Both of these matrices are presented in Table 2.

Table 2. The maximum proportion matrix, $\boldsymbol{\alpha}$, and the minimum proportion matrix, $\boldsymbol{\beta}$.

i	$\boldsymbol{\alpha}$				$\boldsymbol{\beta}$			
	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 1$	$k = 2$	$k = 3$	$k = 4$
$i = 1$	0.43	0.73	1.00	0.60	0.57	0.27	0.00	0.40
$i = 2$	1.00	0.49	0.51	1.00	0.00	0.51	0.49	0.00
$i = 3$	0.00	0.67	0.51	0.00	1.00	0.33	0.49	1.00
$i = 4$	1.00	0.49	0.51	1.00	0.00	0.51	0.49	0.00
$i = 5$	0.60	0.00	0.51	0.60	0.40	1.00	0.49	0.40
$i = 6$	0.51	0.49	0.00	0.00	0.49	0.51	1.00	1.00
$i = 7$	0.43	0.00	0.71	0.51	0.57	1.00	0.29	0.49
$i = 8$	1.00	0.42	1.00	0.60	0.00	0.58	0.00	0.40
$i = 9$	0.00	0.67	0.51	0.00	1.00	0.33	0.49	1.00
$i = 10$	0.00	0.42	0.60	0.71	1.00	0.58	0.40	0.29
$i = 11$	0.43	1.00	0.43	0.60	0.57	0.00	0.57	0.40
$i = 12$	0.71	0.58	0.00	0.00	0.29	0.42	1.00	1.00
$i = 13$	0.60	0.42	0.71	0.43	0.40	0.58	0.29	0.57

According to Step 6 of the proposed algorithm, the empty range matrix was formed, while applying Step 7 resulted in the formation of the relative relationship matrix, which is presented in Table 3.

Table 3. The relative relationship matrix.

Candidate, i	$k = 1$	$k = 2$	$k = 3$	$k = 4$
$i = 1$	0.61	1.00	1.00	1.00
$i = 2$	1.00	0.94	1.00	1.00
$i = 3$	0.00	1.00	1.00	0.00

$i = 4$	1.00	0.94	1.00	1.00
$i = 5$	1.00	0.00	1.00	1.00
$i = 6$	1.00	0.94	0.00	0.00
$i = 7$	0.61	0.00	1.00	1.00
$i = 8$	1.00	0.57	1.00	1.00
$i = 9$	0.00	1.00	1.00	0.00
$i = 10$	0.00	0.57	1.00	1.00
$i = 11$	0.61	1.00	0.61	1.00
$i = 12$	1.00	1.00	0.00	0.00
$i = 13$	1.00	0.57	1.00	0.61

By applying Step 8 of the proposed algorithm, the weighted relative relationship matrix was determined, while Step 9 resulted in the aggregated ranking index, which was used for candidate ranking (Step 10). These values are presented in Table 4.

Table 4. Ranking of candidates using the RADAR method.

Candidate, i	Weighted Relative Relationship Matrix				RI_i	Rank
	$k = 1$	$k = 2$	$k = 3$	$k = 4$		
$i = 1$	0.18	0.28	0.19	0.23	0.54	10–11
$i = 2$	0.29	0.26	0.19	0.23	0.48	12–13
$i = 3$	0.00	0.28	0.19	0.00	1.00	1–2
$i = 4$	0.29	0.26	0.19	0.23	0.48	12–13
$i = 5$	0.29	0.00	0.19	0.23	0.66	7
$i = 6$	0.29	0.26	0.00	0.00	0.85	3
$i = 7$	0.18	0.00	0.19	0.23	0.79	6
$i = 8$	0.29	0.16	0.19	0.23	0.54	10–11
$i = 9$	0.00	0.28	0.19	0.00	1.00	1–2
$i = 10$	0.00	0.16	0.19	0.23	0.81	5
$i = 11$	0.18	0.28	0.12	0.23	0.59	9
$i = 12$	0.29	0.28	0.00	0.00	0.82	4
$i = 13$	0.29	0.16	0.19	0.14	0.60	8

From the presented results, it can be seen that the candidates who would be included in the PFMEA team were $i = 3$, $i = 9$, $i = 6$, $i = 12$, $i = 10$, and $i = 7$. In this way, a PFMEA team of six members would be formed.

Candidates $i = 3$ and $i = 9$ received equal evaluations across all considered criteria, making it logical that they shared first and second place. These candidates had the highest scores for the first and fourth criteria. They were slightly below average for the second criterion, while they performed fairly well for the third criterion. Candidate $i = 6$ had the highest scores for the third and fourth criteria and was also rated well for the first and second criteria. However, slightly lower ratings in these two criteria, which are the most important, placed this candidate in third position.

The last place was shared by $i = 2$ and $i = 4$, who received the lowest relative scores for the first and fourth criteria. Although they were above average for the remaining two criteria, the very low scores in the two most influential criteria significantly impacted their final ranking.

It would be interesting to see how the ranking of candidates would change if the criterion weights were determined based on individual evaluations by each decision-maker. Based on these results, a sensitivity analysis of the proposed model was conducted.

Sensitivity Analysis

Based on the individual assessments of the relative importance of each criterion by the decision-makers, defuzzification and normalization were performed. As a result, the decision-makers estimated the following criterion weights:

- Shift manager: $[0.28, 0.36, 0.21, 0.15]$;
- HR specialist: $[0.32, 0.25, 0.18, 0.25]$;
- Production supervisor: $[0.39, 0.23, 0.16, 0.23]$.

Table 5 presents the ranking of alternatives in four cases: when the decision-makers' assessments are aggregated and in three cases when they are considered individually.

Table 5. Sensitivity analysis.

Candidate, i	Rank of Candidates			
	Aggregated Weights	$e = 1$	$e = 2$	$e = 3$
$i = 1$	10–11	11	10	10
$i = 2$	12–13	12–13	12–13	12–13
$i = 3$	1–2	3–4	1–2	1–2
$i = 4$	12–13	12–13	12–13	12–13
$i = 5$	7	6–7	7	7
$i = 6$	3	5	3	4
$i = 7$	6	1	6	6
$i = 8$	10–11	10	11	11
$i = 9$	1–2	3–4	1–2	1–2
$i = 10$	5	2	4–5	3
$i = 11$	9	9	9	8
$i = 12$	4	6–7	4–5	5
$i = 13$	8	8	8	9

By examining Table 5, it can be concluded that changes in the criteria weights lead to certain ranking variations; however, these deviations are generally negligible. When criteria weights are considered based solely on the evaluations of the shift manager ($e = 1$), candidate $i = 7$ attains the highest rank, followed by candidate $i = 10$ in second place. Meanwhile, candidates $i = 3$ and $i = 9$, who share the top rank in all other scenarios, are ranked jointly in third place in this case. This outcome is due to the fact that these two candidates performed exceptionally well according to the first and second criteria, which were highly rated by this decision-maker. On the other hand, the weight of the fourth criterion was significantly lower, reducing the prominence of alternatives $i = 3$ and $i = 9$. To enhance clarity and facilitate comparison, Figure 2 provides a graphical representation of all four ranking variations.

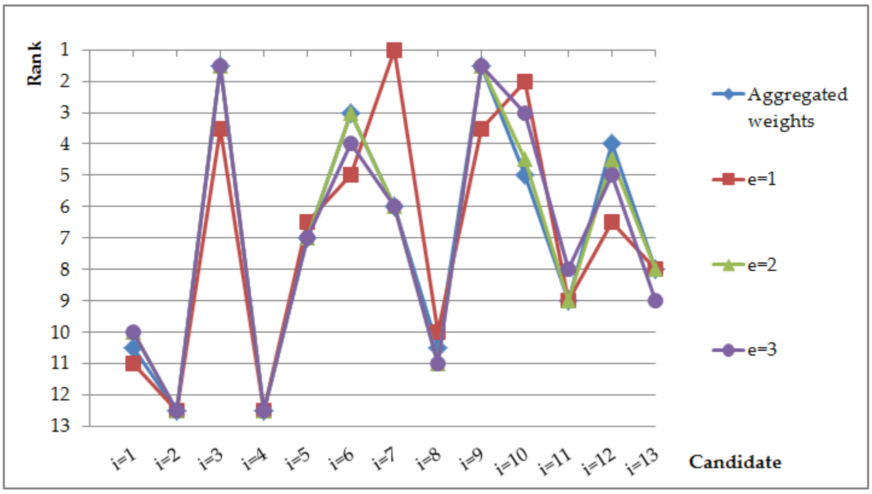

Figure 2. Graphical representation of ranking deviations among candidates.

Based on Figure 2, it can be concluded that the ranking deviations are almost negligible. The only change that may influence the selection of PFMEA team members in this case is that candidate $i = 5$ shares the sixth position with candidate $i = 12$. However, given that candidate $i = 12$ ranks either fourth or fifth in all other cases, while candidate $i = 5$ consistently holds the seventh position, candidate $i = 12$ is given preference. Therefore, the ranking obtained using the approach based on aggregated decision-maker assessments of criteria weights can be considered sufficiently reliable.

The company management has adopted and confirmed the obtained results as authoritative, which can be considered a practical validation of the proposed model. In this way, the practical applicability of the model has also been confirmed.

5. Conclusions

In this study, a mathematical model for the precise selection of core PFMEA team members was presented and tested. The objective of the research was to select six core PFMEA team members through an objective decision-making approach, respecting relevant criteria defined in collaboration with decision-makers and based on the recommendations from the current AIAG&VDA Handbook regarding the knowledge and competencies of team members.

The primary reason for conducting this research stems from the fact that the automotive industry does not have strictly defined criteria for determining who can or cannot be a member of the PFMEA team. Although the current AIAG&VDA Handbook provides certain recommendations, the final decision on team composition is left to company management. Since the PFMEA team plays a crucial role in identifying and analyzing potential failure modes, which can significantly impact production process reliability and, consequently, the overall business performance of a manufacturing company, this research problem requires special attention.

In the relevant literature, numerous studies have addressed the problem of personnel/candidate selection for specific job positions within a company. However, no research has been conducted on the selection of PFMEA team members. This fact represents one of the practical contributions of this study.

To objectively determine the composition of the core PFMEA team, this study employed the RADAR method, extended through the use of Interval-Valued Pythagorean Fuzzy Numbers (IVPFNs), which have not been previously applied to describe uncertainty and imprecision in the domain of personnel/candidate selection. Candidates were evaluated based on criteria defined in collaboration with decision-makers from a Tier-1 company in the automotive supply chain. Additionally, the same decision-makers assessed a total of thirteen candidates, from which six were selected as core PFMEA team members.

The proposed model offers several contributions, both in general and in comparison to existing models in the relevant literature: (1) The problem of PFMEA team member selection has not been previously explored in the relevant literature. (2) The applied RADAR method is relatively new and has not been extensively utilized in the literature, yet it has been proven to be reliable and stable. (3) The RADAR method does not require complex comparisons of fuzzy numbers, as the weighting process is performed in one of the final steps of the method, and fuzzy numbers can be easily compared based on linguistic term gradation. (4) IVPFNs have been used, which have not previously been applied in the domain of personnel/candidate selection. (5) The model can be applied in other companies and across different industries. (6) Sensitivity analysis has confirmed the stability of the proposed model.

In addition, the RADAR method was selected for solving this problem because it is based on identifying the most stable solution across all considered criteria. In this way, candidates are selected who satisfy a larger number of criteria, with particular emphasis on those with higher importance. Most other MADM methods tend to favour objectivity in a way that allows candidates with extremely low ratings on certain criteria to still be part of the final selection.

The key advantage of the RADAR method compared to other existing approaches lies in the fact that an alternative—here, a candidate—is significantly penalized if they do not perform above average on the more important criteria. This approach enables the formation of a balanced, reliable, and versatile PFMEA team, which is highly desirable in practice.

In practical terms, the proposed model provides company management with an objective insight into which employees are the most competent to become members of the PFMEA team, regardless of their formal position within the organizational structure. In this way, it fundamentally contributes to the formation of a competent team with sufficient knowledge and experience, enabling the effective implementation of the PFMEA analysis. Moreover, the developed model can also be used by management for assembling other working teams within the organization, naturally with certain adjustments and modifications.

Despite these contributions, the proposed model also has certain limitations: (1) the unavoidable subjectivity of decision-makers; (2) the questionable competence of decision-makers; (3) the potential consideration of additional relevant criteria, such as interest in participating in the PFMEA team, workload at the primary job position, etc.; (4) the dynamic business environment and employee turnover, which can lead to changes in the composition of the PFMEA team over time; (5) limited practicality for application in smaller organizations.

The subjectivity of decision-makers' assessments can be highlighted as one of the most significant issues present in the considered case study. The goal in future research, building upon this study, is to evaluate candidates based on precise and measurable parameters. By introducing candidate testing, recording awards and achievements in their roles, as well as monitoring certain indicators, the influence of the decision-makers themselves will be reduced. However, it is important to emphasize that their influence cannot be completely eliminated.

To reduce the subjectivity of the proposed model, future research directions could explore the possibility of introducing statistical analysis of candidates. Additionally, increasing the number of decision-makers could enhance objectivity.

A limitation of the proposed model in practice is the potential dynamic nature of the problem, reflected in the constant fluctuation of employees, which can affect changes in the composition of the PFMEA team. Therefore, future research could focus on developing a dynamic model for selecting PFMEA team members.

Regarding the scope of application, the proposed model could be used in other industries where PFMEA analysis is frequently applied, such as the aerospace and pharmaceutical industries, as well as in other sectors where precision and production process reliability are of paramount importance.

From a methodological perspective, the proposed model could be extended by incorporating certain MADM methods for determining criterion weights or by comparing the obtained candidate ranking with rankings obtained from multiple MADM methods.

Author Contributions: Conceptualization, N.K. and D.M.; methodology, N.K.; validation, D.M., formal analysis, D.M.; investigation, N.K.; resources, N.K.; data curation, D.M.; writing—original draft preparation, N.K.; writing—review and editing, D.M.; visualization, N.K.; supervision, D.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AIAG	Automotive Industry Action Group
AP	Action Priority
ARAS	Additive Ratio Assessment
COPRAS	COmplex PRoportional ASsessment
DEMATEL	Decision-Making Trial and Evaluation Laboratory
DFMEA	Design Failure Mode and Effect Analysis
EDAS	Evaluation based on Distance from Average Solution
FMEA	Failure Mode and Effect Analysis
FMEA-MSR	Failure Mode and Effect Analysis–Monitoring and System Response
GRA	Grey Relational Analysis
IATF	International Automotive Task Force
IFSs	Intuitionistic Fuzzy Sets
IPF-RADAR	Interval-valued Pythagorean Fuzzy—–ADAR
IVPFNs	Interval-Valued Pythagorean Fuzzy Numbers
LOPCOW	Logarithmic Percentage Change-driven Objective Weighting
MADM	Multi-Attribute Decision-Making
MCDM	Multi-Criteria Decision-Making
PFMEA	Process Failure Mode and Effect Analysis
PFSs	Pythagorean Fuzzy Sets
PROMETHEE	Preference Ranking Organization METHod for Enrichment Evaluation
RPN	Risk Priority Number
QFD	Quality Function Deployment
RADAR	RAnking based on the Distances And Range
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
VDA	Verband der Automobilindustrie (eng. German Association of the Automotive Industry)
VIKOR	Multi-Criteria Optimization and Compromise Solution
WS	Weighted Similarity (Ranking Similarity Coefficient)

References

1. *IATF 16949:2016*; Quality Management System Requirements for Automotive Production and Relevant Service Parts Organizations, 1st Edition. International Automotive Task Force: Torino, Italy, 2017.
2. AIAG; VDA. *AIAG&VDA Failure Mode and Effects Analysis–FMEA Handbook: Design FMEA, Process FMEA, Supplemental FMEA for Monitoring & System Response*; Automotive Industry Action Group: Southfield, MI, USA, 2019.
3. Kawecka, E.; Perec, A.; Radomska-Zalas, A. Use of the Simple Multicriteria Decision-Making (MCDM) Method for Optimization of the High-Alloy Steel Cutting Processby the Abrasive Water Jet. *Spectr. Mech. Eng. Oper. Res.* **2024**, *1*, 111–120. https://doi.org/10.31181/smeor11202411.
4. Palanisamy, M.; Pugalendhi, A.; Ranganathan, R. Selection of Suitable Additive Manufacturing Machine and Materials through Best–Worst Method (BWM). *Int. J. Adv. Manuf. Technol.* **2020**, *107*, 2345–2362. https://doi.org/10.1007/s00170-020-05110-6.
5. Chakraborty, S.; Saha, A.K. Selection of Forklift Unit for Transport Handling Using Integrated MCDM under Neutrosophic Environment. *Facta Univ. Ser. Mech. Eng.* **2024**, *22*, 235. https://doi.org/10.22190/FUME220620039C.
6. Sumrit, D.; Keeratibhubordee, J. Risk Assessment Framework for Reverse Logistics in Waste Plastic Recycle Industry: A Hybrid Approach Incorporating FMEA Decision Model with AHP-LOPCOW-ARAS Under Trapezoidal Fuzzy Set. *Decis. Mak. Appl. Manag. Eng.* **2025**, *8*, 42–81. https://doi.org/10.31181/dmame812025984.
7. Więckowski, J.; Sałabun, W. Comparative Sensitivity Analysis in Composite Material Selection: Evaluating OAT and COMSAM Methods in Multi-Criteria Decision-Making. *Spectr. Mech. Eng. Oper. Res.* **2025**, *2*, 1–12. https://doi.org/10.31181/smeor21202524.
8. Alkan, R.; Yucesan, M.; Gul, M. A Multi-Attribute Decision-Making to Sustainable Construction Material Selection: A Bayesian BWM-SAW Hybrid Model. In *Advances in Best-Worst Method*; Rezaei, J., Brunelli, M., Mohammadi, M., Eds.; Lecture Notes in Operations Research; Springer International Publishing: Cham, Switzerland, 2022; pp. 67–78, ISBN 978-3-030-89794-9.
9. Kushwaha, D.K.; Panchal, D.; Sachdeva, A. A Modified FMEA Approach Based Integrated Decision Framework for Overcoming the Problems of Sudden Failure and Accidental Hazards in Turbine and Alternator Unit. *Facta Univ. Ser. Mech. Eng.* **2023**, *online first*. https://doi.org/10.22190/FUME221126010K.
10. Afzali Behbahani, N.; KhodadadiKarimvand, M.; Ahmadi, A. Environmental Risk Assessment Using FMEA and Entropy Based on TOPSIS Method: A Case Study Oil Wells Drilling. *Big Data Comput. Vis.* **2022**, *2*, 31–39. https://doi.org/10.22105/bdcv.2022.331778.1054.
11. Mishra, A.R.; Pamucar, D.; Rani, P.; Hezam, I.M. Single-Valued Neutrosophic Distance Measure-Based MEREC-RANCOM-WISP for Solving Sustainable Energy Storage Technology Problem. *Cogn. Comput.* **2025**, *17*, 87. https://doi.org/10.1007/s12559-025-10437-x.
12. Alshamrani, A.; Majumder, P.; Das, A.; Hezam, I.M.; Božanić, D. An Integrated BWM-TOPSIS-I Approach to Determine the Ranking of Alternatives and Application of Sustainability Analysis of Renewable Energy. *Axioms* **2023**, *12*, 159. https://doi.org/10.3390/axioms12020159.
13. Asadabadi, M.R.; Ahmadi, H.B.; Gupta, H.; Liou, J.J.H. Supplier Selection to Support Environmental Sustainability: The Stratified BWM TOPSIS Method. *Ann. Oper. Res.* **2023**, *322*, 321–344. https://doi.org/10.1007/s10479-022-04878-y.
14. Ecer, F. Multi-Criteria Decision Making for Green Supplier Selection Using Interval Type-2 Fuzzy AHP: A Case Study of a Home Appliance Manufacturer. *Oper. Res. Int. J.* **2022**, *22*, 199–233. https://doi.org/10.1007/s12351-020-00552-y.
15. Tadić, D.; Lukić, J.; Komatina, N.; Marinković, D.; Pamučar, D. A Fuzzy Decision-Making Approach to Electric Vehicle Evaluation and Ranking. *Teh. Vjesn./Tech. Gaz.* **2025**, *4*, 1066–1075. https://doi.org/10.17559/TV-20250223002410.
16. Stević, Ž.; Baydaş, M.; Kavacık, M.; Ayhan, E.; Marinković, D. Selection of Data Conversion Technique via Sensitivity-Performance Matching: Ranking of Small E-Vans with PROBID Method. *Facta Univ. Ser. Mech. Eng.* **2024**, *22*, 643–671. https://doi.org/10.22190/FUME240305023S.
17. Komatina, N. A Compromise-Based MADM Approach for Prioritizing Failures: Integrating the RADAR Method within the FMEA Framework. *J. Sist. Man. Industr.* **2024**, *8*, 73–88. https://doi.org/10.30656/jsmi.v8i2.9283.
18. Komatina, N. A Novel BWM-RADAR Approach for Multi-Attribute Selection of Equipment in the Automotive Industry. *Spectr. Mech. Eng. Oper. Res.* **2025**, *2*, 104–120. https://doi.org/10.31181/smeor21202531.
19. Chen, C.-T.; Hung, W.-Z. A Two-Phase Model for Personnel Selection Based on Multi-Type Fuzzy Information. *Mathematics* **2020**, *8*, 1703. https://doi.org/10.3390/math8101703.
20. Hwang, C.L.; Yoon, K. Methods for Multiple Attribute Decision Making. In *Multiple Attribute Decision Making: Methods and Applications a State-of-the-Art Survey*; Springer: Berlin/Heidelberg, Germany,1981; pp. 58–191.

21. Brans, J.P.; Vincke, Ph.; Mareschal, B. How to Select and How to Rank Projects: The Promethee Method. *Eur. J. Oper. Res.* **1986**, *24*, 228–238. https://doi.org/10.1016/0377-2217(86)90044-5.
22. Mishra, R.A.; Sisodia, G.; Pardasani, R.K.; Sharma, K. Multi-Criteria IT Personnel Selection on Intuitionistic Fuzzy Information Measures and ARAS Methodology. *Iran. J. Fuzzy Syst.* **2020**, *17*, 55–68.
23. Zavadskas, E.K.; Turskis, Z. A New Additive Ratio Assessment (ARAS) Method in Multicriteria Decision-making. *Technol. Econ. Dev. Econ.* **2010**, *16*, 159–172. https://doi.org/10.3846/tede.2010.10.
24. Krishankumar, R.; Premaladha, J.; Ravichandran, K.S.; Sekar, K.R.; Manikandan, R.; Gao, X.Z. A Novel Extension to VIKOR Method under Intuitionistic Fuzzy Context for Solving Personnel Selection Problem. *Soft Comput.* **2020**, *24*, 1063–1081. https://doi.org/10.1007/s00500-019-03943-2.
25. Opricovic, S.; Tzeng, G.-H. Extended VIKOR Method in Comparison with Outranking Methods. *Eur. J. Oper. Res.* **2007**, *178*, 514–529. https://doi.org/10.1016/j.ejor.2006.01.020.
26. Biswas, S.; Chatterjee, S.; Majumder, S. A Spherical Fuzzy Framework for Sales Personnel Selection. *J. Comput. Cogn. Eng.* **2022**, *3*, 373–394. https://doi.org/10.47852/bonviewJCCE2202357.
27. Ozgormus, E.; Guner Goren, H.; Senocak, A. An Integrated Fuzzy QFD-MCDM Framework for Personnel Selection Problem. *Sci. Iran.* **2021**, *28*, 2972–2986. https://doi.org/10.24200/sci.2019.52320.2657.
28. Falatoonitoosi, E.; Leman, Z.; Sorooshian, S.; Salimi, M. Decision-Making Trial and Evaluation Laboratory. *RJASET* **2013**, *5*, 3476–3480. https://doi.org/10.19026/rjaset.5.4475.
29. Ju-Long, D. Control Problems of Grey Systems. *Syst. Control Lett.* **1982**, *1*, 288–294. https://doi.org/10.1016/S0167-6911(82)80025-X.
30. Chuang, Y.-C.; Hu, S.-K.; Liou, J.J.H.; Tzeng, G.-H. A Data-Driven MADM Model Ofr Personnel Selection and Improvement. *Technol. Econ. Dev. Econ.* **2020**, *26*, 751–784. https://doi.org/10.3846/tede.2020.12366.
31. Dumnić, S.; Mostarac, K.; Ninović, M.; Jovanović, B.; Buhmiler, S. Application of the Choquet Integral: A Case Study on a Personnel Selection Problem. *Sustainability* **2022**, *14*, 5120. https://doi.org/10.3390/su14095120.
32. Kilic, H.S.; Demirci, A.E.; Delen, D. An Integrated Decision Analysis Methodology Based on IF-DEMATEL and IF-ELECTRE for Personnel Selection. *Decis. Support Syst.* **2020**, *137*, 113360. https://doi.org/10.1016/j.dss.2020.113360.
33. Tešić, D.; Delibašić, B.; Božanić, D.; Lojić, R.; Pamučar, D.; Eisingerné Balassa, B. Application of the FUCOM-FUZZY MAIRCA Model in Human Resource Management. *Acta Polytech. Hung.* **2023**, *20*, 231–249. https://doi.org/10.12700/APH.20.3.2023.3.14.
34. Ayyildiz, E.; Taskin Gumus, A. Interval-Valued Pythagorean Fuzzy AHP Method-Based Supply Chain Performance Evaluation by a New Extension of SCOR Model: SCOR 4.0. *Complex Intell. Syst.* **2021**, *7*, 559–576. https://doi.org/10.1007/s40747-020-00221-9.
35. Rahimi, M.; Kumar, P.; Moazzamigodarzi, M.; Mishra, A.R. Digital Transformation Challenges in Sustainable Financial Service Systems Using Novel Interval-Valued Pythagorean Fuzzy Double Normalization-Based Multiple Aggregation Approach. *Environ. Dev. Sustain.* **2022**, 1–33. https://doi.org/10.1007/s10668-022-02719-3.
36. Mishra, A.R.; Pamučar, D.; Hezam, I.M.; Chakrabortty, R.K.; Rani, P.; Božanić, D.; Ćirović, G. Interval-Valued Pythagorean Fuzzy Similarity Measure-Based Complex Proportional Assessment Method for Waste-to-Energy Technology Selection. *Processes* **2022**, *10*, 1015. https://doi.org/10.3390/pr10051015.
37. Wei, G.; Tang, Y.; Zhao, M.; Lin, R.; Wu, J. Selecting the Low-Carbon Tourism Destination: Based on Pythagorean Fuzzy Taxonomy Method. *Mathematics* **2020**, *8*, 832. https://doi.org/10.3390/math8050832.
38. Mohagheghi, V.; Mousavi, S.M. A New Multi-Period Optimization Model for Resilient-Sustainable Project Portfolio Evaluation under Interval-Valued Pythagorean Fuzzy Sets with a Case Study. *Int. J. Mach. Learn. Cybern.* **2021**, *12*, 3541–3560. https://doi.org/10.1007/s13042-021-01403-8.
39. Komatina, N.; Marinkovic, D.; Babič, M. Fundamental Characteristics and Applicability of the RADAR Method: Proof of Ranking Consistency. *Spectr. Oper. Res.* **2026**, *3*, 63–80. https://doi.org/10.31181/sor31202635.
40. Sałabun, W.; Urbaniak, K. A New Coefficient of Rankings Similarity in Decision-Making Problems. In Proceedings of the Computational Science–ICCS 2020: 20th International Conference, Amsterdam, The Netherlands, 3–5 June 2020; Springer International Publishing: Cham, Switzerland; pp. 632–645.
41. Komatina, N.; Marinković, D.; Tadić, D.; Pamučar, D. Advancing PFMEA Decision-Making: FRADAR Based Prioritization of Failure Modes Using AP, RPN, and Multi-Attribute Assessment in the Automotive Industry. *Teh. Glas./Tech. J.* **2025**, *19*, *accepted for publication*. https://doi.org/10.31803/tg-20250221185213.
42. Zavadskas, E.K.; Kaklauskas, A.; Peldschus, F.; Turskis, Z. Multi-Attribute Assessment of Road Design Solutions by Using the COPRAS Method. *Balt. J. Road Bridge Eng.* **2007**, *2*, 195–203.

43. Keshavarz Ghorabaee, M.; Zavadskas, E.K.; Olfat, L.; Turskis, Z. Multi-Criteria Inventory Classification Using a New Method of Evaluation Based on Distance from Average Solution (EDAS). *Informatica* **2015**, *26*, 435–451. https://doi.org/10.15388/Informatica.2015.57.
44. Garg, H. A Novel Accuracy Function under Interval-Valued Pythagorean Fuzzy Environment for Solving Multicriteria Decision Making Problem. *J. Intell. Fuzzy Syst.* **2016**, *31*, 529–540. https://doi.org/10.3233/IFS-162165.
45. Peng, X.; Yang, Y. Fundamental Properties of Interval-Valued Pythagorean Fuzzy Aggregation Operators: Interval-Valued Pythagorean Fuzzy Aggregation Operations. *Int. J. Intell. Syst.* **2016**, *31*, 444–487. https://doi.org/10.1002/int.21790.
46. Karasan, A.; Ilbahar, E.; Kahraman, C. A Novel Pythagorean Fuzzy AHP and Its Application to Landfill Site Selection Problem. *Soft Comput.* **2019**, *23*, 10953–10968. https://doi.org/10.1007/s00500-018-3649-0.
47. Mishra, A.R.; Rani, P.; Cavallaro, F.; Alrasheedi, A.F. Assessment of Sustainable Wastewater Treatment Technologies Using Interval-Valued Intuitionistic Fuzzy Distance Measure-Based MAIRCA Method. *Facta Univ. Ser. Mech. Eng.* **2023**, *21*, 359–386. https://doi.org/10.22190/FUME230901034M.
48. Nestić, S.; Gojković, R.; Petrović, T.; Tadić, D.; Mimović, P. Quality Performance Indicators Evaluation and Ranking by Using TOPSIS with the Interval-Intuitionistic Fuzzy Sets in Project-Oriented Manufacturing Companies. *Mathematics* **2022**, *10*, 4174. https://doi.org/10.3390/math10224174.
49. Mimović, P.; Tadić, D.; Borota-Tišma, A.; Nestić, S.; Lafuente, J. Evaluation and Ranking of Insurance Companies by Combining TOPSIS and the Interval Fuzzy Rough Sets. *Serbian J. Manag.* **2021**, *16*, 279–299. https://doi.org/10.5937/sjm16-27672.
50. Božanić, D.; Epler, I.; Puška, A.; Biswas, S.; Marinković, D.; Koprivica, S. Application of the DIBR II–Rough MABAC Decision-Making Model for Ranking Methods and Techniques of Lean Organization Systems Management in the Process of Technical Maintenance. *Facta Univ. Ser. Mech. Eng.* **2024**, *22*, 101–123. https://doi.org/10.22190/FUME230614026B.
51. Kizielewicz, B.; Sałabun, W. SITW Method: A New Approach to Re-Identifying Multi-Criteria Weights in Complex Decision Analysis. *Spectr. Mech. Eng. Oper. Res.* **2024**, *1*, 215–226. https://doi.org/10.31181/smeor11202419.
52. Rakić, M.; Žižović, M.M.; Miljković, B.; Njeguš, A.; Žižović, M.R.; Đorđević, I. Multi-Criteria Selection of Standards for System Analyst Activities in Organizations. *Facta Univ. Ser. Mech. Eng.* **2023**, *21*, 433–451. https://doi.org/10.22190/FUME230521023R.