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# A Hybrid Fuzzy Decision-Making Algorithm for Prioritization of the 8D Problem-Solving Methodology Using FBWM and FSREM

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**Abstract**

This study developed a hybrid fuzzy decision-making algorithm based on the Fuzzy Best-Worst Method (FBWM) and the Fuzzy Square-Root-based Evaluation Method (FSREM). Despite the widespread application of the 8D methodology in engineering practice, the importance of its disciplines has not been sufficiently investigated; therefore, the aim of this study is to determine their significance and priority. The proposed fuzzy algorithm was applied to three companies operating within the automotive supply chain. FBWM was used to determine the criteria weights, while FSREM was applied to rank the 8D disciplines. Sensitivity analysis showed that the expert teams from the three considered companies perceived the problem in a very similar manner. The results of applying the proposed algorithm in all three companies showed that the discipline Identify and Verify Root Cause (D4) has the greatest influence on problem-solving effectiveness. In two of the three companies, Prevent Recurrence (D7) was ranked as the second most influential discipline, while in one company Define Permanent Corrective Actions (D5) was identified as the second most influential discipline. It can be concluded that the results demonstrated a high degree of consistency, while minor ranking deviations can be attributed to different quality management system approaches within each company.

**Keywords:** 8D methodology; problem-solving; FBWM; FSREM; automotive industry



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## 1. Introduction

The automotive industry in the modern business environment is based on connecting companies into supply chains, starting from basic raw materials, through components and assemblies, all the way to finished products, i.e., vehicles. Therefore, it can be said that these companies are mutually dependent and share the same priorities, primarily a high-quality final product and end-user satisfaction. Problem solving and the management of nonconformities in the production process represent one of the prerequisites for the supply chain to deliver a product of acceptable quality. For this reason, the identification, analysis, and resolution of potential problems are very important tasks faced by every company within the supply chain. Any nonconforming product originating from one company may cause serious problems in the next company within the chain and may permanently affect both profit and reputation.

In every complex and precision-driven industry, problems may be of various natures, ranging from improving the technical characteristics of products and engineering materials [1], optimizing manufacturing processes [2], ensuring product and process safety [3], enhancing product quality [4], and achieving more rational use of resources [5], among others. In today's automotive practice, the 8D (Eight Disciplines) method is most commonly used for problem solving. This method represents a standardized, systematic, and team-oriented approach to solving, most often recurring, problems [6]. The methodology is based on the implementation of eight disciplines or phases, each having its own role and purpose within the process. There are various situations in which this method can be applied. Primarily, it has been used for resolving customer complaints [7], with particular emphasis on root cause analysis [2,8]. However, it can also be applied in situations where there is a production problem (most often a recurring one), when product nonconformity exists, when the problem generates high costs, etc.

Although the method originated in the Ford company, contemporary research has shown that 8D can be successfully applied in various industrial sectors, ranging from forged material processing [4], plastic injection molding [9], to semiconductor manufacturing [8].

Despite the widespread application of the 8D methodology, especially in the automotive industry, there is still uncertainty regarding whether each of these disciplines has equal importance, i.e., an equal impact on solving the considered problem. Companies primarily apply 8D as a strictly defined procedure, going through each of these disciplines or phases without taking into account their actual significance. As a consequence of such practice, quality management, as well as other teams using the method, often allocate time and resources intuitively, relying exclusively on subjective judgment and personal experience. Such an approach almost certainly means that certain disciplines are implemented merely formally, without adequate analysis. Consequently, disciplines that have a significant impact on the reliability and sustainability of the proposed solution may be neglected. It should also be considered that the efficiency of the 8D methodology largely depends on the complexity of the process and the competence of the team implementing the methodology [10,11].

In the relevant literature, the 8D method is often applied in combination with other tools, such as Failure Mode and Effects Analysis (FMEA) (see [12,13]) or Value Stream Mapping (VSM) (see [14,15]), where the methods complement each other and can be highly compatible [16]. FMEA is a method that integrates very well with 8D, for example through updating FMEA risk databases by incorporating resolved complaints processed through the 8D methodology [17]. In addition, one of the issues addressed in the literature is the digitalization and automation of the 8D methodology, as well as its integration with Industry 4.0 tools, in order to make it an even more efficient and reliable tool [18].

Based on the aforementioned considerations, the need emerged for defining a Multi-Criteria Decision-Making (MCDM) model that could be used to determine the priority of disciplines within the 8D methodology, primarily from the perspective of the contribution of each discipline to the final problem resolution. Such a model would enable the identification of those disciplines that have the greatest impact on the problem-solving process, allowing problem-solving teams to allocate time and resources more reliably in the right direction and toward useful activities.

If the considered problem is observed through the structure of an MCDM problem, the alternatives analyzed in this paper are the disciplines within the 8D methodology themselves. Although the name of the method suggests that it consists of eight disciplines, there are actually nine, since there is also the so-called zero discipline, or D0, which refers to the preparation phase of the methodology implementation. The disciplines, as alternatives, are evaluated according to criteria defined in accordance with the opinions of experts from three automotive industry companies. All three companies are tier-1 suppliers within the supply chain. More details regarding the alternatives and criteria are provided in the section related to the problem description.

For solving the MCDM problem defined in this paper, a hybrid approach was used, based on two MCDM methods extended through the application of fuzzy set theory [19,20]. The first method is the Best-Worst Method (BWM) [21], which is used for determining the vector of criteria weights. The second method, used for ranking the alternatives, i.e., the disciplines, is the Square-Root based Evaluation Method (SREM) [22].

Both of the aforementioned methods were extended through the application of fuzzy logic in order to model imprecise and uncertain data, i.e., expert evaluations. The application of the BWM, and also Fuzzy Best-Worst Method (FBWM) is not unfamiliar in the literature, and many authors have highlighted the advantages of this approach [23–25]. Above all, FBWM has been used and proven to be a very effective decision-support tool in various engineering problems, such as supplier selection [26,27], supply chain risk analysis [28], infrastructure condition assessment [29], as well as industrial equipment selection [30].

In addition, FBWM has also been applied in the automotive industry, particularly in combination with other MCDM methods used for alternative ranking. Thus, within the domain of problem solving in the automotive industry, this method has been used for the selection of FMEA team members [31] and for integration with FMEA [32,33]. Although there are numerous methods with a different, more objective foundation based on data [34–36], including other approaches, such as machine learning and optimization approaches [37,38], FBWM was considered suitable in this study because it is a relatively simple and understandable method for decision-makers, while at the same time being appropriate for decisions based on subjective evaluations. It should be noted that there are important studies in which complex decision-making problems under uncertainty have been solved through the application of intuitionistic fuzzy sets and aggregation operators [39] or by using other advanced approaches for uncertainty modeling [40–42].

Unlike the FBWM, which has already been widely applied in the literature, the SREM first appeared in the study [22]. So far, this method has not been extended through the application of fuzzy set theory; therefore, one of the contributions of this paper is the extension of the method through the application of fuzzy numbers. In this way, a fuzzy extension of the SREM method, referred to as the Fuzzy Square-Root based Evaluation Method (FSREM), is defined.

Although there is a large number of studies in the relevant literature analyzing the 8D methodology [43], as well as studies in which FBWM has been applied to various engineering problems [44,45], the problem considered in this paper has not yet been addressed in the literature. Even within the automotive industry domain, research has mainly focused on FMEA [46–48], vehicle evaluation [49], supplier selection [50,51], and similar topics, while no studies have addressed this specific issue.

The motivation for conducting this research arises from the need to optimize the decision-making process within the 8D methodology by making it more reliable and efficient. Through the developed model and the research results, it is necessary to overcome the perspective of applying the 8D methodology merely as a formal procedure, without a clear understanding of the importance of each discipline that constitutes this methodology. As a result of the research, practitioners in the automotive industry are provided with a clear guideline regarding priorities in the implementation of the 8D methodology. In this way, human resources, time, and other organizational capacities can be directed toward the most important activities, which is also in accordance with modern manufacturing philosophies.

The main objective of this research is to define a hybrid MCDM model in a fuzzy environment in order to determine the priority of disciplines within the 8D methodology. Primarily, since the model was tested in automotive industry companies, the proposed model is mainly focused on application in this industrial sector. In addition to this objective, another goal is to define a set of criteria for evaluating 8D disciplines, which could also serve as a basis for future research in this domain.

The paper is organized as follows: after the introductory section, a problem description is provided. The third section presents the proposed hybrid MCDM algorithm, with emphasis on its mathematical background and the main steps of the approach. The fourth section presents the case study, while the discussion of the obtained results is given in the fifth section. Finally, the sixth section provides the most important conclusions of the research.

## 2. Problem Formulation

In this section, an explanation of the considered problem is provided. Specifically, the decision-makers (experts from companies) involved in this research are formally introduced, and the method of expressing evaluations is explained, i.e., the modeling of existing uncertainty and imprecision through the application of fuzzy set theory. In addition, the set of criteria and alternatives is defined.

### *2.1. Definition of the Set of Experts Participating in the Research*

This research involves experts from three companies (A, B, and C) in the automotive industry, i.e., enterprises that are tier-1 suppliers within the automotive supply chain. The aim was to include experts who have previously used the 8D methodology as a problem-solving tool, i.e., who have experience and the necessary knowledge in this domain. Formally, the group of experts from each company (see Figure 1) can be represented by the set of indices $\{1, \ldots, e, \ldots, E\}$. From company A $(e = 1)$, the participants were: (1) a Quality Manager, (2) a Supplier Quality Engineer, and (3) a Quality Control Specialist. From company B $(e = 2)$, the participants were: (1) a Continuous Improvement Manager, (2) a Quality Manager, and (3) a Technology Specialist. From company C $(e = 3)$, the participants were: (1) a Manufacturing Engineer, (2) a Quality Control Specialist, and (3) a Professional Maintenance Engineer.


**Figure 1.** Composition of expert groups by companies.

The aim was to assemble an experienced team of experts, while at the same time ensuring sufficient heterogeneity so that the problem is not observed from a single perspective only. The experts expressed their assessments through consensus, both for evaluating the relative importance of the criteria and for assessing the alternatives with respect to the considered criteria.

### *2.2. Definition of the Set of Criteria*

The criteria used for evaluating the disciplines within the 8D methodology were defined based on the relevant literature, as well as in cooperation with the experts participating in the research. Formally, the set of criteria can be represented by the set of indices $\{1, \ldots, c, \ldots, C\}$. The first criterion can be denoted as the impact of the considered discipline on the remaining disciplines $(c = 1)$. In fact, the literature states that if one discipline is not implemented adequately, it may affect the execution of another discipline [17]. The second criterion can be defined as the impact on solution quality $(c = 2)$. This actually represents the essence of the engineering approach within the 8D methodology, namely the effectiveness of the implemented corrective actions [6]. The third criterion is the time required for the implementation of the discipline (as a phase) $(c = 3)$, while the fourth criterion refers to the resources required for the implementation of the discipline $(c = 4)$. In fact, these two criteria can be observed as the business aspect of the considered problem, since time and resources in companies are often limited [7]. The fifth criterion is the impact of the discipline on customer or end-user satisfaction $(c = 5)$. The authors proposed this set of criteria to the experts, who accepted them and additionally refined them into their current form.

### *2.3. Definition of the Set of Alternatives*

In this research, the alternatives are the disciplines that constitute the 8D methodology. Formally, they can be represented by the set of indices $\{1, \ldots, i, \ldots, I\}$, and they are as follows [10,16–18,43]: D0—Preparation and Planning $(i = 1)$, D1—Form the Team $(i = 2)$, D2—Describe the Problem $(i = 3)$, D3—Develop Interim Containment Actions $(i = 4)$, D4—Identify and Verify Root Cause $(i = 5)$, D5—Define Permanent Corrective Actions $(i = 6)$, D6—Implement Permanent Corrective Actions $(i = 7)$, D7—Prevent Recurrence $(i = 8)$, and D8—Congratulate the Team/Closure $(i = 9)$.

### *2.4. Assessment of the Relative Importance of Criteria*

The relative importance of the criteria was evaluated by the experts using predefined linguistic terms modeled by triangular fuzzy numbers (TFNs). A total of five linguistic terms were used, and the domain of the fuzzy numbers is defined on a scale from 1 to 9, which is consistent with the standard BWM methodology. The following linguistic terms were used:

- Equal importance (W1): (1, 1, 1);
- Weak importance (W2): (1, 2.5, 4);
- Moderate importance (W3): (2.5, 5, 7.5);
- Strong importance (W4): (6, 7.5, 9);
- Extreme importance (W5): (9, 9, 9).

The linguistic terms W1 and W5 represent extreme values and are therefore modeled as crisp numbers. Equal importance between two criteria is represented by the value 1, whereas the absolute dominance of one criterion over another is represented by the value 9. The remaining three linguistic terms are modeled as TFNs. W3 has the widest interval because it represents a moderate level of preference of one criterion over another, and it is precisely at this level that the greatest uncertainty in expert judgments is expected. As the central linguistic term, it is positioned at the midpoint of the domain. The linguistic terms W2 and W4 are modeled with narrower intervals than W3, reflecting the expectation of lower uncertainty in expert assessments. Furthermore, they are defined symmetrically with respect to the extreme values W1 and W5, as well as the central term W3.

### *2.5. Assessment of Alternatives with Respect to the Criteria*

The evaluation of alternatives with respect to the considered criteria is also performed by the experts using predefined linguistic terms modeled by TFNs. In this case, the following linguistic terms were used:

- Very low (VL): (1, 1, 3);
- Low (L): (1, 3, 5);
- Medium (M): (3, 5, 7);
- High (H): (5, 7, 9);
- Very high (VH): (7, 9, 9).

In contrast to the linguistic terms used for assessing the relative importance of criteria, in this case the linguistic terms are symmetrically modeled due to the fact that the nature of evaluating alternative performance with respect to the considered criteria is evenly distributed.

## 3. Hybrid FBWM-FSREM Algorithm

As already stated in the previous section, the model developed in this paper is based on the application of a hybrid fuzzy MCDM model. The FBWM was used for determining the criteria weights, while the FSREM was used for ranking the alternatives. Figure 2 presents the algorithm of the proposed approach, followed by the mathematical model with its main steps.

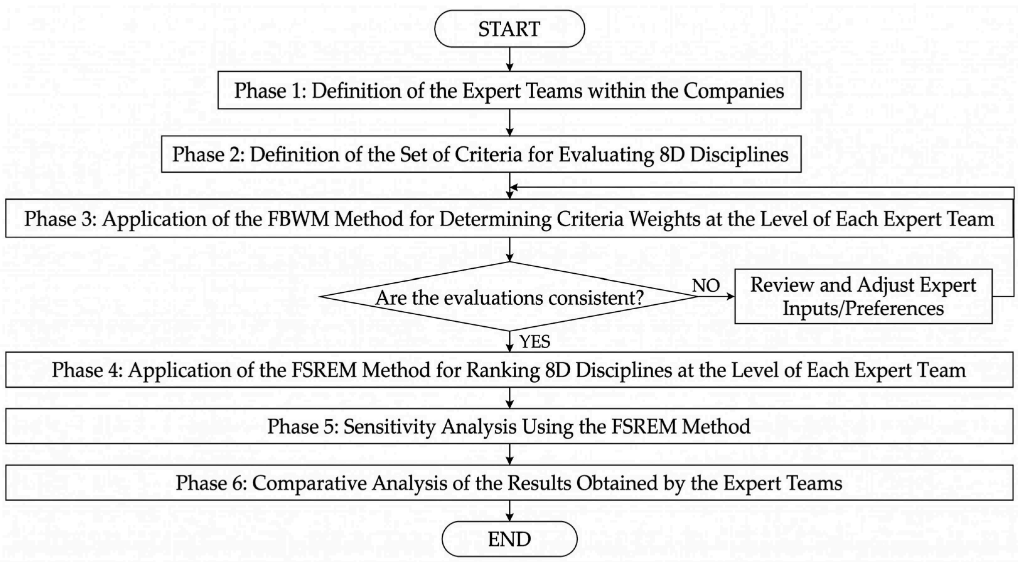


**Figure 2.** The algorithm of the proposed approach.

The same methodology was separately applied to the evaluations provided by experts from each individual company. It is important to emphasize that all mathematical operations with TFNs were performed in accordance with the rules of fuzzy algebra defined in [19,20].

### *3.1. Implementation Procedure of the FBWM*

The application of the FBWM was carried out through the following steps according to the procedure defined in [52]:

Step 1. Definition of the best and worst criteria. Then, the comparison of the best criterion with all other criteria is performed at the level of each expert team, $\widetilde{A}_B$, followed by the comparison of all other criteria with the worst criterion at the level of each expert team, $\widetilde{A}_W$. The evaluations can be formally expressed as follows:

$$\widetilde{A}_B = \left(\widetilde{a}_{B1}, \ldots, \widetilde{a}_{Bc}, \ldots, \widetilde{a}_{BC}\right) \tag{1}$$

$$\widetilde{A}_W = \left(\widetilde{a}_{1W}, \ldots, \widetilde{a}_{cW}, \ldots, \widetilde{a}_{CW}\right)^T \tag{2}$$

Step 2. Using the mathematical model defined in [53], the optimal weights of the criteria $\left(\widetilde{\omega}_1^*, \ldots, \widetilde{\omega}_c^*, \ldots \widetilde{\omega}_C^*\right)$ are determined:

Objective function:

$$min \max_{1=1,\ldots,C} \left\{ \left| \frac{\widetilde{\omega}_B}{\widetilde{\omega}_c} - \widetilde{a}_{Bc} \right|, \left| \frac{\widetilde{\omega}_c}{\widetilde{\omega}_W} - \widetilde{a}_{cW} \right| \right\} \tag{3}$$

Subject to:

$$\sum\nolimits_{c=1}^{C} \omega_c^M = 1 \tag{4}$$

where the fuzzy weights are presented using triangular fuzzy numbers:

$$\widetilde{\omega}_c = \left(\omega_c^L, \omega_c^M, \omega_c^U\right) \tag{5}$$

Subject to the following constraints:

$$\omega_c^L \leq \omega_c^M \leq \omega_c^U \quad c, c = 1, \ldots C \tag{6}$$

$$\omega_c^L, \omega_c^M, \omega_c^U \geq 0 \tag{7}$$

Step 3. The proposed mathematical model can be transformed into a linear programming problem by minimizing the absolute gap, denoted as ($\varphi^*$, $\varphi^*$, $\varphi^*$):

Objective function:

$$\min \varphi^* \tag{8}$$

Subject to:

$$\begin{array}{ll} \left|\omega_B^U - \omega_c^U \cdot a_{Bc}^U\right| \leq \varphi^*, & \forall c \\ \left|\omega_c^U - \omega_W^U \cdot a_{cW}^U\right| \leq \varphi^*, & \forall c \\ \left|\omega_B^L - \omega_c^L \cdot a_{Bc}^L\right| \leq \varphi^*, & \forall c \\ \left|\omega_c^L - \omega_W^L \cdot a_{cW}^L\right| \leq \varphi^*, & \forall c \end{array} \tag{9}$$

Step 4. The consistency check is performed after the defuzzification procedure [54] of the preference values. In this way, the procedure defined in the standard BWM is applied [21].

Step 5. In the final step, defuzzification of the fuzzy criteria weights is performed in order to obtain crisp values as input to the FSREM, $\omega_c$.

### *3.2. Implementation Procedure of the FSREM*

For the ranking of 8D disciplines, the FSREM was used, which represents an extension of the basic SREM method [22] and is implemented according to the following steps:

Step 1. Construction of the fuzzy decision matrix based on expert evaluations:

$$\left[\widetilde{D}_{ic}\right]_{I \times C} \tag{10}$$

Step 2. Formation of the fuzzy normalized decision matrix using the percentage normalization method, applying fuzzy algebra rules (all criteria are of a benefit-type):

$$\left[\tilde{M}_{ic}\right]_{I\times C} \tag{11}$$

where

$$\tilde{m}_{ic} = \frac{\tilde{d}_{ic}}{\sum_{i=1}^{I}\tilde{d}_{ic}}\cdot 100 \tag{12}$$

Step 3. Formation of the fuzzy squared-transformed normalized matrix:

$$\left[\tilde{S}_{ic}\right]_{I\times C} \tag{13}$$

where:

$$\tilde{S}_{ic} = \frac{\tilde{m}_{ic}^{2}}{\sum_{i=1}^{I}\tilde{m}_{ic}^{2}} \tag{14}$$

Step 4. Formation of the fuzzy root-transformed normalized matrix:

$$\left[\tilde{R}_{ic}\right]_{I\times C} \tag{15}$$

where:

$$\tilde{R}_{ic} = \frac{\sqrt{\tilde{m}_{ic}}}{\sum_{i=1}^{I}\sqrt{\tilde{m}_{ic}}} \tag{16}$$

Step 5. Normalization [54] of the values of the fuzzy squared-transformed normalized matrix and the fuzzy root-transformed normalized matrix, respectively:

$$[S_{ic}]_{I\times C} \tag{17}$$

$$[R_{ic}]_{I\times C} \tag{18}$$

Step 6. Formation of the $\alpha$-fused matrix:

$$[A_{ic}]_{I\times C} \tag{19}$$

where:

$$a_{ic} = \alpha\cdot S_{ic} + (1-\alpha)\cdot R_{ic} \tag{20}$$

The value of the parameter $\alpha$ indicates the extent to which decision-makers balance their assessments. If the value is closer to 0, the values from the root-transformed normalized matrix dominate, while values closer to 1 indicate dominance of the squared-transformed normalized matrix. In the first case, the mechanism is designed to favor alternatives that are more stable across all criteria, without giving too much weight to extreme values. In the second case, the focus is on favoring excellence, i.e., alternatives that are extremely good with respect to the most important criteria are rewarded.

Step 7. Formation of the weighted $\alpha$-fused matrix:

$$[N_{ic}]_{I\times C} \tag{21}$$

where:

$$n_{ic} = a_{ic}\cdot\omega_c \tag{22}$$

Step 8. Calculating the final ranking index, $F_i$:

$$F_i = \sum_{c=1}^{C} n_{ic} \tag{23}$$

The ranking of alternatives is performed according to this parameter, so that the first-ranked alternative is the one with the highest value, while the last-ranked alternative is the one with the lowest value of this parameter.

## 4. Case Study

In the previous section of the paper, it was mentioned that the case study was conducted in three companies that are tier-1 suppliers within the automotive supply chain. The companies manufacture different components for the automotive industry. Company A has a production facility located in central Serbia and is engaged in the production of rubber and plastic parts integrated into subassemblies. Company B is located in southern Serbia and manufactures leather and fabric covers for vehicle interiors. Company C has a production facility in southwestern Serbia and produces metal components for various applications.

The authors initially contacted employees from the quality departments of these companies. In agreement with them, expert teams consisting of three members were formed within each company. The requirement was that the experts had experience in the application of the 8D methodology and were willing to participate in the research. The authors distributed the questionnaire to the experts via email, and the experts returned their evaluations using the same communication channel.

### *4.1. Determination of Criteria Weights Using the Proposed FBWM Procedure*

The expert teams expressed their evaluations through consensus. The relative importance of the criteria was assessed by the expert teams as follows (Step 1 of the FBWM procedure):

- Company A ($e = 1$):

$$A_B = \begin{bmatrix} W1 & W2 & W3 & W4 & W1 \end{bmatrix} \qquad A_W = \begin{bmatrix} W4 & W3 & W2 & W1 & W4 \end{bmatrix}$$

- Company B ($e = 2$):

$$A_B = \begin{bmatrix} W3 & W1 & W3 & W5 & W2 \end{bmatrix} \qquad A_W = \begin{bmatrix} W2 & W5 & W2 & W1 & W3 \end{bmatrix}$$

- Company C ($e = 3$):

$$A_B = \begin{bmatrix} W2 & W1 & W4 & W4 & W2 \end{bmatrix} \qquad A_W = \begin{bmatrix} W3 & W4 & W2 & W1 & W3 \end{bmatrix}$$

Using the consistency verification procedure [21], the following Consistency Ratio (CR) values were obtained (Step 4): 0.06, 0.10, and 0.10. The expert assessments from Company A can be considered highly consistent, while the assessments of the other two expert groups are considered acceptably consistent.

The calculation procedure will be demonstrated only for the Case Study of Company A, as the procedure remains identical for the other two companies. For Company A, the mathematical model can be presented as follows (Step 2 of the FBWM procedure):

$$\left|\frac{\omega_1^L}{\omega_2^L} - 1\right| \le \varphi \qquad \left|\frac{\omega_1^M}{\omega_2^M} - 2.5\right| \le \varphi \qquad \left|\frac{\omega_1^U}{\omega_2^U} - 4\right| \le \varphi$$

$$\left|\frac{\omega_1^L}{\omega_3^L} - 2.5\right| \le \varphi \qquad \left|\frac{\omega_1^M}{\omega_3^M} - 5\right| \le \varphi \qquad \left|\frac{\omega_1^U}{\omega_3^U} - 7.5\right| \le \varphi$$

$$\left|\frac{\omega_1^L}{\omega_4^L} - 6\right| \le \varphi \qquad \left|\frac{\omega_1^M}{\omega_4^M} - 7.5\right| \le \varphi \qquad \left|\frac{\omega_1^U}{\omega_4^U} - 9\right| \le \varphi$$

$$\left|\frac{\omega_1^L}{\omega_5^L}-1\right|\le\varphi \qquad \left|\frac{\omega_1^M}{\omega_5^M}-1\right|\le\varphi \qquad \left|\frac{\omega_1^U}{\omega_5^U}-1\right|\le\varphi$$
$$\left|\frac{\omega_2^L}{\omega_4^L}-2.5\right|\le\varphi \qquad \left|\frac{\omega_2^M}{\omega_4^M}-5\right|\le\varphi \qquad \left|\frac{\omega_2^U}{\omega_4^U}-7.5\right|\le\varphi$$
$$\left|\frac{\omega_3^L}{\omega_4^L}-1\right|\le\varphi \qquad \left|\frac{\omega_3^M}{\omega_4^M}-2.5\right|\le\varphi \qquad \left|\frac{\omega_3^U}{\omega_4^U}-4\right|\le\varphi$$
$$\left|\frac{\omega_5^L}{\omega_4^L}-6\right|\le\varphi \qquad \left|\frac{\omega_5^M}{\omega_4^M}-7.5\right|\le\varphi \qquad \left|\frac{\omega_5^U}{\omega_4^U}-9\right|\le\varphi$$
$$\omega_1^L\le\omega_1^M\le\omega_1^U \qquad \omega_2^L\le\omega_2^M\le\omega_2^U \qquad \omega_3^L\le\omega_3^M\le\omega_3^U$$
$$\omega_4^L\le\omega_4^M\le\omega_4^U \qquad \omega_5^L\le\omega_5^M\le\omega_5^U$$
$$\omega_1^L\ge 0 \qquad \omega_2^L\ge 0 \qquad \omega_3^L\ge 0 \qquad \omega_4^L\ge 0 \qquad \omega_5^L\ge 0$$

The fuzzy values of the criteria weights were obtained according to Step 3 of the FBWM procedure for Company A. In order to solve the linear programming problem, the Lingo 22.0 software [55] was used. The fuzzy criteria weights are:

$$\tilde{\omega}_1^1=(0.06,0.45,0.45)$$
$$\tilde{\omega}_2^1=(0.12,0.12,0.15)$$
$$\tilde{\omega}_3^1=(0.00,0.08,0.08)$$
$$\tilde{\omega}_4^1=(0.02,0.04,0.04)$$
$$\tilde{\omega}_5^1=(0.20,0.30,0.30)$$

By applying the centroid method, crisp values of the criteria weights were obtained, which were subsequently normalized using the arithmetic mean operator (based on the assessments of experts from Company A):

$$\omega_1^1=0.40 \qquad \omega_2^1=0.16 \qquad \omega_3^1=0.06 \qquad \omega_4^1=0.04 \qquad \omega_5^1=0.34$$

In the same manner, fuzzy criteria weights were also calculated based on the assessments of the expert teams from Company B and Company C, respectively:

$$\tilde{\omega}_1^2=(0.12,0.12,0.31) \qquad \tilde{\omega}_1^3=(0.00,0.23,0.23)$$
$$\tilde{\omega}_2^2=(0.06,0.48,0.48) \qquad \tilde{\omega}_2^3=(0.38,0.38,0.75)$$
$$\tilde{\omega}_3^2=(0.08,0.12,0.12) \qquad \tilde{\omega}_3^3=(0.02,0.08,0.11)$$
$$\tilde{\omega}_4^2=(0.03,0.06,0.06) \qquad \tilde{\omega}_4^3=(0.02,0.06,0.06)$$
$$\tilde{\omega}_5^2=(0.20,0.22,0.22) \qquad \tilde{\omega}_5^3=(0.23,0.25,0.25)$$

The crisp values of the criteria weights are:

$$\omega_1^2=0.21 \qquad \omega_2^2=0.38 \qquad \omega_3^2=0.12 \qquad \omega_4^2=0.06 \qquad \omega_5^2=0.24$$
$$\omega_1^3=0.15 \qquad \omega_2^3=0.50 \qquad \omega_3^3=0.07 \qquad \omega_4^3=0.05 \qquad \omega_5^3=0.24$$

The defuzzification of the criteria weights was performed in accordance with Step 5 of the proposed FBWM procedure. Figure 3 presents a graphical representation of the criteria weight values obtained by all three expert teams.

Based on Figure 3, it is evident that $c = 3$ and $c = 4$ have the lowest importance according to the assessments of all three expert teams. Minor discrepancies in the assessments are observed for the remaining three criteria. Specifically, the expert team from Company A considers criterion $c = 1$ to be the most important, whereas the experts from the other two companies consider criterion $c = 2$ to be the most important.

### *4.2. Ranking of 8D Disciplines Using the Proposed FSREM Procedure*

In the Step 1 of the proposed FSREM procedure, a fuzzy decision matrix is formed based on the assessments of the expert teams. Tables 1–3 present the assessments provided by the expert teams from Companies A, B, and C, respectively.

Since the calculation procedure is performed identically for the assessments of all three expert teams, only the calculation process and detailed steps of the FSREM application for the assessments of the expert team from Company A will be presented below. For the other two companies, only the final ranking of the alternatives will be provided.

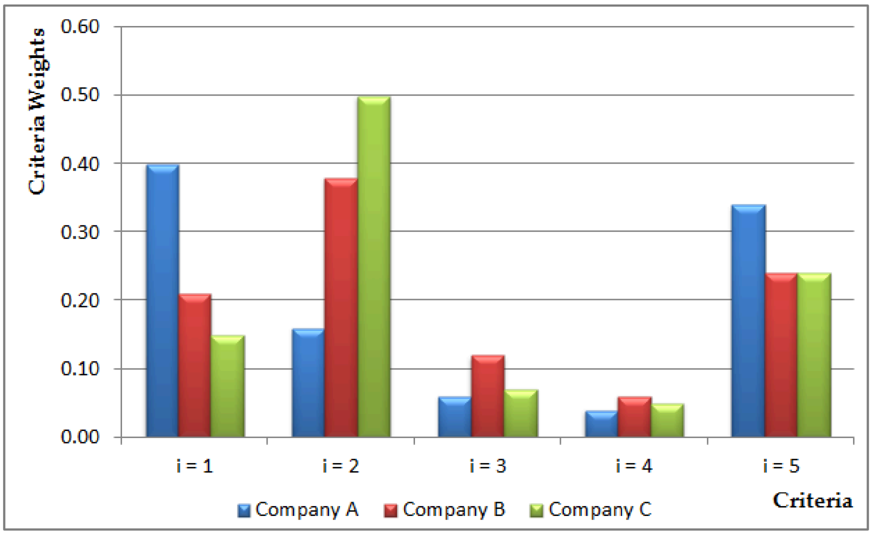


**Figure 3.** Graphical representation of criteria weights obtained by all three expert teams.

**Table 1.** Fuzzy decision matrix based on the assessments of the expert team from Company A.

| *i* | *c*=1 | *c*=2 | *c*=3 | *c*=4 | *c*=5 |
|---|---|---|---|---|---|
| $i = 1$ | VL | VL | L | VL | VL |
| $i = 2$ | L | L | M | L | L |
| $i = 3$ | M | M | L | L | M |
| $i = 4$ | H | M | M | L | H |
| $i = 5$ | VH | VH | H | M | VH |
| $i = 6$ | VH | H | M | M | VH |
| $i = 7$ | H | H | M | L | H |
| $i = 8$ | VH | VH | M | M | H |
| $i = 9$ | L | VL | L | VL | M |

**Table 2.** Fuzzy decision matrix based on the assessments of the expert team from Company B.

| | *c*=1 | *c*=2 | *c*=3 | *c*=4 | *c*=5 |
|---|---|---|---|---|---|
| $i = 1$ | VL | VL | VL | VL | VL |
| $i = 2$ | L | M | L | L | L |
| $i = 3$ | M | M | M | L | M |
| $i = 4$ | M | H | M | M | H |
| $i = 5$ | H | VH | H | M | VH |
| $i = 6$ | H | VH | M | M | H |
| $i = 7$ | H | H | M | L | H |
| $i = 8$ | VH | VH | M | M | H |
| $i = 9$ | L | L | L | VL | M |

Table 4 presents the fuzzy normalized decision matrix (Step 2 of the proposed FSREM procedure) for the assessments of the expert group from Company A.

Example of calculating the first element of the fuzzy normalized decision matrix:

$$\tilde{m}_{11} = \frac{(1,1,3)}{(37,53,65)} \cdot 100 = (1.538, 1.887, 8.108)$$

By applying Steps 3 and 4 of the proposed FSREM procedure, the fuzzy squared-transformed normalized decision matrix (Table 5) and the fuzzy root-transformed normalized decision matrix (Table 6) were obtained, respectively.

**Table 3.** Fuzzy decision matrix based on the assessments of the expert team from Company C.

| $i$ | $c$=1 | $c$=2 | $c$=3 | $c$=4 | $c$=5 |
|---|---|---|---|---|---|
| $i = 1$ | VL | VL | VL | VL | VL |
| $i = 2$ | L | M | L | VL | L |
| $i = 3$ | M | M | L | L | M |
| $i = 4$ | M | H | M | M | H |
| $i = 5$ | H | VH | H | M | VH |
| $i = 6$ | M | VH | M | M | VH |
| $i = 7$ | H | H | M | L | H |
| $i = 8$ | H | VH | M | M | VH |
| $i = 9$ | L | L | VL | VL | M |

**Table 4.** Fuzzy normalized decision matrix for Company A.

| $i$ | $c$=1 | $c$=2 | $c$=3 | $c$=4 | $c$=5 |
|---|---|---|---|---|---|
| $i = 1$ | (1.538, 1.887, 8.108) | (1.639, 2.128, 9.091) | (1.695, 7.317, 21.739) | (2.128, 3.448, 20.000) | (1.493, 1.887, 8.108) |
| $i = 2$ | (1.538, 5.660, 13.514) | (1.639, 6.383, 15.152) | (5.085, 12.195, 30.435) | (2.128, 10.345, 33.333) | (1.493, 5.660, 13.514) |
| $i = 3$ | (4.615, 9.434, 18.919) | (4.918, 10.638, 21.212) | (1.695, 7.317, 21.739) | (2.128, 10.345, 33.333) | (4.478, 9.434, 18.919) |
| $i = 4$ | (7.692, 13.208, 24.324) | (4.918, 10.638, 21.212) | (5.085, 12.195, 30.435) | (2.128, 10.345, 33.333) | (7.463, 13.208, 24.324) |
| $i = 5$ | (10.769, 16.981, 24.324) | (11.475, 19.149, 27.273) | (8.475, 17.073, 39.130) | (6.383, 17.241, 46.667) | (10.448, 16.981, 24.324) |
| $i = 6$ | (10.769, 16.981, 24.324) | (8.197, 14.894, 27.273) | (5.085, 12.195, 30.435) | (6.383, 17.241, 46.667) | (10.448, 16.981, 24.324) |
| $i = 7$ | (7.692, 13.208, 24.324) | (8.197, 14.894, 27.273) | (5.085, 12.195, 30.435) | (2.128, 10.345, 33.333) | (7.463, 13.208, 24.324) |
| $i = 8$ | (10.769, 16.981, 24.324) | (11.475, 19.149, 27.273) | (5.085, 12.195, 30.435) | (6.383, 17.241, 46.667) | (7.463, 13.208, 24.324) |
| $i = 9$ | (1.538, 5.660, 13.514) | (1.639, 2.128, 9.091) | (1.695, 7.317, 21.739) | (2.128, 3.448, 20.000) | (4.478, 9.434, 18.919) |

**Table 5.** Fuzzy squared-transformed normalized decision matrix for Company A.

| $i$ | $c$=1 | $c$=2 | $c$=3 | $c$=4 | $c$=5 |
|---|---|---|---|---|---|
| $i = 1$ | (0.001, 0.003, 0.133) | (0.001, 0.003, 0.182) | (0.000, 0.045, 2.254) | (0.000, 0.009, 2.678) | (0.001, 0.003, 0.153) |
| $i = 2$ | (0.001, 0.023, 0.369) | (0.001, 0.028, 0.505) | (0.003, 0.124, 4.417) | (0.000, 0.080, 7.438) | (0.001, 0.024, 0.425) |
| $i = 3$ | (0.006, 0.065, 0.724) | (0.006, 0.078, 0.991) | (0.000, 0.045, 2.254) | (0.000, 0.080, 7.438) | (0.005, 0.068, 0.833) |
| $i = 4$ | (0.016, 0.127, 1.196) | (0.006, 0.078, 0.991) | (0.003, 0.124, 4.417) | (0.000, 0.080, 7.438) | (0.014, 0.133, 1.376) |
| $i = 5$ | (0.031, 0.210, 1.196) | (0.031, 0.252, 1.638) | (0.009, 0.244, 7.301) | (0.003, 0.221, 14.578) | (0.028, 0.220, 1.376) |
| $i = 6$ | (0.031, 0.210, 1.196) | (0.016, 0.153, 1.638) | (0.003, 0.124, 4.417) | (0.003, 0.221, 14.578) | (0.028, 0.220, 1.376) |
| $i = 7$ | (0.016, 0.127, 1.196) | (0.016, 0.153, 1.638) | (0.003, 0.124, 4.417) | (0.000, 0.080, 7.438) | (0.014, 0.133, 1.376) |
| $i = 8$ | (0.031, 0.210, 1.196) | (0.031, 0.252, 1.638) | (0.003, 0.124, 4.417) | (0.003, 0.221, 14.578) | (0.014, 0.133, 1.376) |
| $i = 9$ | (0.001, 0.023, 0.369) | (0.001, 0.003, 0.182) | (0.000, 0.045, 2.254) | (0.000, 0.009, 2.678) | (0.005, 0.068, 0.833) |

**Table 6.** Fuzzy root-transformed normalized decision matrix for Company A.

| $i$ | $c$=1 | $c$=2 | $c$=3 | $c$=4 | $c$=5 |
|---|---|---|---|---|---|
| $i = 1$ | (0.032, 0.048, 0.134) | (0.032, 0.051, 0.145) | (0.027, 0.091, 0.258) | (0.028, 0.064, 0.274) | (0.031, 0.047, 0.133) |
| $i = 2$ | (0.032, 0.083, 0.173) | (0.032, 0.089, 0.187) | (0.047, 0.118, 0.305) | (0.028, 0.111, 0.354) | (0.031, 0.082, 0.172) |
| $i = 3$ | (0.055, 0.107, 0.205) | (0.055, 0.115, 0.222) | (0.027, 0.091, 0.258) | (0.028, 0.111, 0.354) | (0.053, 0.106, 0.204) |
| $i = 4$ | (0.071, 0.126, 0.232) | (0.055, 0.115, 0.222) | (0.047, 0.118, 0.305) | (0.028, 0.111, 0.354) | (0.068, 0.125, 0.231) |
| $i = 5$ | (0.084, 0.143, 0.232) | (0.085, 0.154, 0.251) | (0.061, 0.139, 0.346) | (0.048, 0.143, 0.418) | (0.081, 0.142, 0.231) |
| $i = 6$ | (0.084, 0.143, 0.232) | (0.072, 0.136, 0.251) | (0.047, 0.118, 0.305) | (0.048, 0.143, 0.418) | (0.081, 0.142, 0.231) |
| $i = 7$ | (0.071, 0.126, 0.232) | (0.072, 0.136, 0.251) | (0.047, 0.118, 0.305) | (0.028, 0.111, 0.354) | (0.068, 0.125, 0.231) |
| $i = 8$ | (0.084, 0.143, 0.232) | (0.085, 0.154, 0.251) | (0.047, 0.118, 0.305) | (0.048, 0.143, 0.418) | (0.068, 0.125, 0.231) |
| $i = 9$ | (0.032, 0.083, 0.173) | (0.032, 0.051, 0.145) | (0.027, 0.091, 0.258) | (0.028, 0.064, 0.274) | (0.053, 0.106, 0.204) |

Example of calculating the first element of the fuzzy squared-transformed and fuzzy root-transformed normalized matrices, respectively:

$$\tilde{S}_{11} = \frac{\left(1.538^2, 1.887^2, 8.108^2\right)}{(494.675,\ 1370.595,\ 3747.261)} = (0.001, 0.003, 0.133)$$

$$\tilde{R}_{11} = \frac{\left(\sqrt{1.538}, \sqrt{1.887}, \sqrt{8.108}\right)}{(21.261,\ 28.834,\ 39.209)} = (0.032, 0.048, 0.134)$$

Then, normalization was performed using the centroid method in order to obtain the squared-transformed (Table 7) and root-transformed (Table 8) normalized matrices, respectively.

**Table 7.** Squared-transformed normalized decision matrix for Company A.

| *i* | *c*=1 | *c*=2 | *c*=3 | *c*=4 | *c*=5 |
|---|---|---|---|---|---|
| $i = 1$ | 0.045 | 0.062 | 0.766 | 0.896 | 0.052 |
| $i = 2$ | 0.131 | 0.178 | 1.515 | 2.506 | 0.150 |
| $i = 3$ | 0.265 | 0.358 | 0.766 | 2.506 | 0.302 |
| $i = 4$ | 0.446 | 0.358 | 1.515 | 2.506 | 0.508 |
| $i = 5$ | 0.479 | 0.640 | 2.518 | 4.934 | 0.541 |
| $i = 6$ | 0.479 | 0.602 | 1.515 | 4.934 | 0.541 |
| $i = 7$ | 0.446 | 0.602 | 1.515 | 2.506 | 0.508 |
| $i = 8$ | 0.479 | 0.640 | 1.515 | 4.934 | 0.508 |
| $i = 9$ | 0.131 | 0.062 | 0.766 | 0.896 | 0.302 |

**Table 8.** Root-transformed normalized decision matrix for Company A.

| *i* | *c*=1 | *c*=2 | *c*=3 | *c*=4 | *c*=5 |
|---|---|---|---|---|---|
| $i = 1$ | 0.071 | 0.076 | 0.125 | 0.122 | 0.070 |
| $i = 2$ | 0.096 | 0.103 | 0.157 | 0.164 | 0.095 |
| $i = 3$ | 0.122 | 0.131 | 0.125 | 0.164 | 0.121 |
| $i = 4$ | 0.143 | 0.131 | 0.157 | 0.164 | 0.142 |
| $i = 5$ | 0.153 | 0.163 | 0.182 | 0.203 | 0.151 |
| $i = 6$ | 0.153 | 0.153 | 0.157 | 0.203 | 0.151 |
| $i = 7$ | 0.143 | 0.153 | 0.157 | 0.164 | 0.142 |
| $i = 8$ | 0.153 | 0.163 | 0.157 | 0.203 | 0.142 |
| $i = 9$ | 0.096 | 0.076 | 0.125 | 0.122 | 0.121 |

After that, the $\alpha$-fused matrix is formed by applying Step 6 of the proposed FSREM procedure. Table 9 presents the matrix with $\alpha$ = 0.5. Table 10 presents the weighted $\alpha$-fused matrix (Step 7).

**Table 9.** $\alpha$-fused matrix ($\alpha$ = 0) for Company A.

| *i* | *c*=1 | *c*=2 | *c*=3 | *c*=4 | *c*=5 |
|---|---|---|---|---|---|
| $i = 1$ | 0.058 | 0.069 | 0.446 | 0.509 | 0.061 |
| $i = 2$ | 0.113 | 0.140 | 0.836 | 1.335 | 0.122 |
| $i = 3$ | 0.193 | 0.244 | 0.446 | 1.335 | 0.211 |
| $i = 4$ | 0.295 | 0.244 | 0.836 | 1.335 | 0.325 |
| $i = 5$ | 0.316 | 0.402 | 1.350 | 2.569 | 0.346 |
| $i = 6$ | 0.316 | 0.377 | 0.836 | 2.569 | 0.346 |
| $i = 7$ | 0.295 | 0.377 | 0.836 | 1.335 | 0.325 |
| $i = 8$ | 0.316 | 0.402 | 0.836 | 2.569 | 0.325 |
| $i = 9$ | 0.113 | 0.069 | 0.446 | 0.509 | 0.211 |

**Table 10.** Weighted α-fused matrix (α = 0) for Company A.

| i | c=1 | c=2 | c=3 | c=4 | c=5 |
|---|---|---|---|---|---|
| $i = 1$ | 0.023 | 0.011 | 0.027 | 0.020 | 0.021 |
| $i = 2$ | 0.045 | 0.022 | 0.050 | 0.053 | 0.042 |
| $i = 3$ | 0.077 | 0.039 | 0.027 | 0.053 | 0.072 |
| $i = 4$ | 0.118 | 0.039 | 0.050 | 0.053 | 0.110 |
| $i = 5$ | 0.126 | 0.064 | 0.081 | 0.103 | 0.118 |
| $i = 6$ | 0.126 | 0.060 | 0.050 | 0.103 | 0.118 |
| $i = 7$ | 0.118 | 0.060 | 0.050 | 0.053 | 0.110 |
| $i = 8$ | 0.126 | 0.064 | 0.050 | 0.103 | 0.110 |
| $i = 9$ | 0.045 | 0.011 | 0.027 | 0.020 | 0.072 |

Example of calculating the first element of the α-fused matrix:

$$a_{11} = 0.5 \cdot 0.045 + (1 - 0.5) \cdot 0.071 = 0.058$$

Example of calculating the first element of the weighted α-fused matrix:

$$n_{11} = 0.058 \cdot 0.40 = 0.023$$

In the final step (Step 8), the final ranking index is calculated and the alternatives are ranked, as shown in Table 11.

**Table 11.** Final ranking index and ranking of alternatives (α = 0) for Company A.

| i | $F_i$ | Rank |
|---|---|---|
| $i = 1$ | 0.102 | 9 |
| $i = 2$ | 0.213 | 7 |
| $i = 3$ | 0.268 | 6 |
| $i = 4$ | 0.371 | 5 |
| $i = 5$ | 0.492 | 1 |
| $i = 6$ | 0.457 | 2 |
| $i = 7$ | 0.392 | 4 |
| $i = 8$ | 0.454 | 3 |
| $i = 9$ | 0.175 | 8 |

Example of calculating the final ranking index:

$$F_1 = 0.023 + 0.011 + 0.027 + 0.020 + 0.021 = 0.102$$

Tables 12–14 present the ranking for each company separately, with varying values of α: 0, 0.25, 0.5, 0.75, and 1.

**Table 12.** Compromise ranking of alternatives for Company A.

| | $F_i$ (α=0) | Rank | $F_i$ (α=0.25) | Rank | $F_i$ (α=0.5) | Rank | $F_i$ (α=0.75) | Rank | $F_i$ (α=1) | Rank |
|---|---|---|---|---|---|---|---|---|---|---|
| $i = 1$ | 0.077 | 9 | 0.090 | 9 | 0.102 | 9 | 0.115 | 9 | 0.128 | 9 |
| $i = 2$ | 0.103 | 8 | 0.158 | 7 | 0.213 | 7 | 0.268 | 7 | 0.323 | 7 |
| $i = 3$ | 0.125 | 6 | 0.197 | 6 | 0.268 | 6 | 0.340 | 6 | 0.412 | 6 |
| $i = 4$ | 0.142 | 5 | 0.257 | 5 | 0.371 | 5 | 0.485 | 5 | 0.600 | 5 |
| $i = 5$ | 0.158 | 1 | 0.325 | 1 | 0.492 | 1 | 0.659 | 1 | 0.827 | 1 |
| $i = 6$ | 0.155 | 2 | 0.306 | 2 | 0.457 | 2 | 0.609 | 2 | 0.760 | 2 |
| $i = 7$ | 0.146 | 4 | 0.269 | 4 | 0.392 | 4 | 0.515 | 4 | 0.639 | 4 |

**Table 12.** *Cont.*

| | $F_i$ ($\alpha$=0) | Rank | $F_i$ ($\alpha$=0.25) | Rank | $F_i$ ($\alpha$=0.5) | Rank | $F_i$ ($\alpha$=0.75) | Rank | $F_i$ ($\alpha$=1) | Rank |
|---|---|---|---|---|---|---|---|---|---|---|
| $i = 8$ | 0.153 | 3 | 0.303 | 3 | 0.454 | 3 | 0.604 | 3 | 0.755 | 3 |
| $i = 9$ | 0.104 | 7 | 0.140 | 8 | 0.175 | 8 | 0.211 | 8 | 0.247 | 8 |

**Table 13.** Compromise ranking of alternatives for Company B.

| | $F_i$ ($\alpha$=0) | Rank | $F_i$ ($\alpha$=0.25) | Rank | $F_i$ ($\alpha$=0.5) | Rank | $F_i$ ($\alpha$=0.75) | Rank | $F_i$ ($\alpha$=1) | Rank |
|---|---|---|---|---|---|---|---|---|---|---|
| $i = 1$ | 0.078 | 9 | 0.088 | 9 | 0.098 | 9 | 0.107 | 9 | 0.117 | 9 |
| $i = 2$ | 0.115 | 7 | 0.181 | 7 | 0.247 | 7 | 0.313 | 7 | 0.379 | 7 |
| $i = 3$ | 0.131 | 6 | 0.238 | 6 | 0.346 | 6 | 0.454 | 6 | 0.561 | 6 |
| $i = 4$ | 0.146 | 5 | 0.306 | 4 | 0.466 | 4 | 0.627 | 4 | 0.787 | 4 |
| $i = 5$ | 0.160 | 1 | 0.367 | 1 | 0.575 | 1 | 0.783 | 1 | 0.990 | 1 |
| $i = 6$ | 0.154 | 3 | 0.333 | 3 | 0.512 | 3 | 0.690 | 3 | 0.869 | 3 |
| $i = 7$ | 0.148 | 4 | 0.300 | 5 | 0.453 | 5 | 0.605 | 5 | 0.757 | 5 |
| $i = 8$ | 0.156 | 2 | 0.336 | 2 | 0.517 | 2 | 0.697 | 2 | 0.877 | 2 |
| $i = 9$ | 0.109 | 8 | 0.160 | 8 | 0.210 | 8 | 0.261 | 8 | 0.312 | 8 |

**Table 14.** Compromise ranking of alternatives for Company C.

| | $F_i$ ($\alpha$=0) | Rank | $F_i$ ($\alpha$=0.25) | Rank | $F_i$ ($\alpha$=0.5) | Rank | $F_i$ ($\alpha$=0.75) | Rank | $F_i$ ($\alpha$=1) | Rank |
|---|---|---|---|---|---|---|---|---|---|---|
| $i = 1$ | 0.076 | 9 | 0.082 | 9 | 0.089 | 9 | 0.095 | 9 | 0.102 | 9 |
| $i = 2$ | 0.113 | 7 | 0.160 | 7 | 0.207 | 7 | 0.254 | 7 | 0.301 | 7 |
| $i = 3$ | 0.126 | 6 | 0.205 | 6 | 0.284 | 6 | 0.364 | 6 | 0.443 | 6 |
| $i = 4$ | 0.145 | 5 | 0.284 | 5 | 0.423 | 5 | 0.562 | 5 | 0.702 | 5 |
| $i = 5$ | 0.157 | 1 | 0.339 | 1 | 0.521 | 1 | 0.703 | 1 | 0.885 | 1 |
| $i = 6$ | 0.152 | 3 | 0.295 | 3 | 0.439 | 3 | 0.582 | 3 | 0.725 | 3 |
| $i = 7$ | 0.146 | 4 | 0.287 | 4 | 0.427 | 4 | 0.568 | 4 | 0.708 | 4 |
| $i = 8$ | 0.156 | 2 | 0.319 | 2 | 0.482 | 2 | 0.645 | 2 | 0.808 | 2 |
| $i = 9$ | 0.104 | 8 | 0.136 | 8 | 0.167 | 8 | 0.199 | 8 | 0.231 | 8 |

As can be seen in Tables 12–14, two extreme values of $\alpha$ (0 and 1) were considered, as well as a compromise solution with $\alpha$ = 0.5 and two intermediate values, $\alpha$ = 0.25 and $\alpha$ = 0.75. The analysis of the obtained results is presented in the following section.

## 5. Discussion

Based on the obtained research results and the evaluations of the expert teams from all three considered companies, it can be concluded that, although the 8D methodology is a standardized problem-solving procedure, the expert teams have different perceptions of priorities (see Figure 3), but with a generally high level of agreement, which can be observed in Figures 4 and 5.

According to the evaluations of all three expert teams, as well as in all three $\alpha$ variants, D4—Identify and Verify Root Cause $(i = 5)$ stands out as the dominant discipline. In fact, the root cause was recognized as a key element of problem-solving, and experts from all three teams agreed with these results.

The second most important discipline is D7—Prevent Recurrence $(i = 8)$. The expert teams from Companies B and C evaluated this discipline as second in importance because they believe that preventing the recurrence of problems is very important within the 8D methodology. In contrast, the experts from Company A ranked this discipline third, while they placed D5—Define Permanent Corrective Actions ($i = 6$) in second place. They emphasized that the transition from current (temporary) measures to a permanent solution is a very important aspect of this methodology.

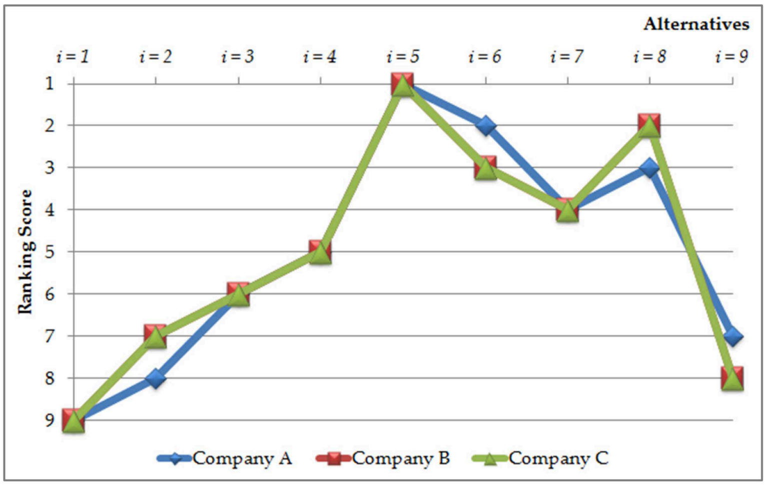


**Figure 4.** Ranking of alternatives for Companies A, B, and C (α = 0).

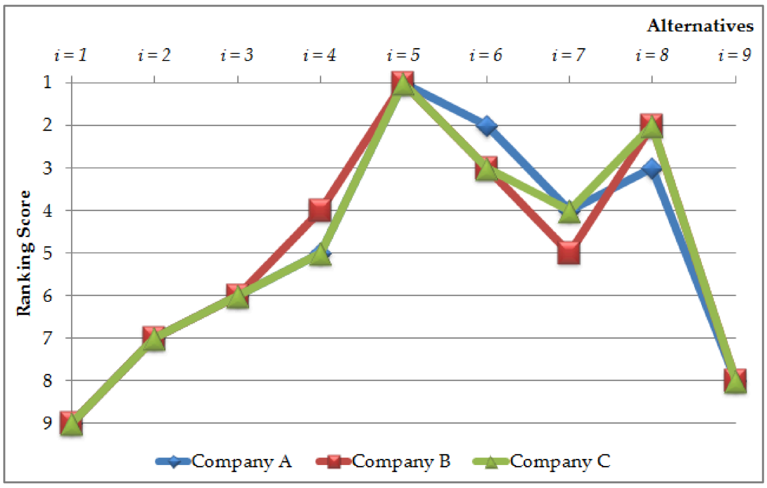


**Figure 5.** Ranking of alternatives for Companies A, B, and C (α = 0.5 and α = 1).

Although there are occasional deviations in ranking, the obtained solution is highly stable. The least important discipline is definitely D0—Preparation and Planning ($i = 1$). It is followed by D8—Congratulate the Team/Closure ($i = 9$) and D1—Form the Team ($i = 2$). The experts pointed out that these phases are largely formal and do not have a significant influence on the essence of problem-solving.

Additional confidence in the obtained solution is provided by the fact that the SREM was subjected to a comparative analysis with two well-known MCDM methods, namely Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) [56,57] and Simple Additive Weighting (SAW) [56,57], in the original study [22]. This comparative analysis demonstrated a high degree of consistency among the considered approaches, which was particularly evident in the compromise scenario (α = 0.5), where complete agreement in the ranking results was observed. Minor deviations were identified only for the extreme values of the parameter α, especially for α = 0. However, even these deviations were not observed in every analyzed scenario. Based on these findings, it can be concluded that the stability of the proposed approach and the reliability of the obtained results are not merely a consequence of employing a single MCDM method.

## 6. Conclusions

Within this research, a new hybrid algorithm for the evaluation and ranking of disciplines within the 8D methodology was developed and applied. The case study was focused on the automotive industry. The key scientific contribution of this paper can be identified as the integration of the FBWMs and FSREMs, which enabled the objective modeling of subjective expert evaluations. It should be particularly emphasized that, in this study, the SREM was extended through the application of fuzzy logic for the first time, demonstrating that the mathematical framework of this method is adaptable to modifications and applicable to complex decision-making problems.

The research showed that, within the 8D methodology, certain disciplines stand out because of their importance. In particular, these are D4—Identify and Verify Root Cause, D7—Prevent Recurrence, and D5—Define Permanent Corrective Actions. These disciplines can be identified as critical points in the implementation of the 8D methodology, while the developed MCDM algorithm can serve decision-makers in the automotive sector as a reliable tool for optimizing time and resources. The goal is to focus attention on those disciplines that have the greatest importance for processes, companies, and end users.

Despite the scientific and practical contributions of the study, the research also has certain limitations. The first limitation refers to the application domain. The obtained results can be considered reliable exclusively within the automotive industry, with a particular focus on Tier-1 suppliers. The second limitation relates to the model itself, which is based on the evaluations of a selected group of experts and therefore involves a certain degree of subjectivity.

In future research, the developed FSREM procedure should be applied to solving other management and engineering problems, both in the automotive industry and in other industrial sectors. In addition, the proposed model may be extended through the application of different uncertainty modeling concepts, such as intuitionistic fuzzy numbers [58], Pythagorean fuzzy numbers [40], neutrosophic numbers [41], and others.

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## Abbreviations

The following abbreviations are used in this manuscript:

| | |
|---|---|
| 8D | Eight Disciplines |
| BWM | Best-Worst Method |
| FMEA | Failure Mode and Effects Analysis |
| FBWM | Fuzzy Best-Worst Method |
| FSREM | Fuzzy Square-Root based Evaluation Method |

| | |
|---|---|
| MCDM | Multi-Criteria Decision-Making |
| SAW | Simple Additive Weighting |
| SREM | Square-Root based Evaluation Method |
| TFNs | Triangular Fuzzy Numbers |
| TOPSIS | Technique for Order Preference by Similarity to an Ideal Solution |
| VSM | Value Stream Mapping |

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