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A Hybrid Interval Type-2 Fuzzy DEMATEL-MABAC Approach for Strategic Failure Management in Automotive Manufacturing

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Abstract: In the context of today's rapidly evolving automotive market, improving the reliability and efficiency of manufacturing processes remains a critical challenge for industry players. This study introduces a hybrid multi-attribute decision-making model that integrates Failure Mode and Effects Analysis (FMEA) with interval type-2 fuzzy set theory to classify and prioritize process failures. The approach enables the FMEA team to systematically identify and rank failure modes, facilitating the timely implementation of corrective actions aimed at enhancing process reliability. A key feature of the proposed model is the utilization of interval type-2 triangular fuzzy numbers (IT2TFNs), which capture the inherent uncertainty in expert assessments of risk factors (RFs). These fuzzy values are aggregated using the fuzzy harmonic mean, and the total relation matrix is derived by applying fuzzy algebraic operations, followed by defuzzification and distance calculations between fuzzy numbers. The modified Decision-Making Trial and Evaluation Laboratory (DEMATEL) method is employed to determine the relative weights of identified RFs, while the Multi-Attributive Border Approximation Area Comparison (MABAC) technique is used to rank failure modes based on their impact on manufacturing process reliability. The model's effectiveness is demonstrated through its application to real-world data from an automotive supply chain, highlighting its superior capability compared to conventional approaches. This research contributes to the advancement of failure management strategies, providing a comprehensive and robust framework for decision-making in complex manufacturing environments.

Keywords: Manufacturing process; FMEA; Interval type-2 fuzzy numbers; DEMATEL; MABAC; Automotive supply chain

1 Introduction

The rapid and continuous transformations in the market, driven by the emergence and application of new technologies, evolving environmental protection regulations, and, notably, the shifting demands of customers—such as the need for products of high quality, reasonable prices, and on-time delivery—necessitate that management takes appropriate actions to enhance the manufacturing process. In the automotive industry, the manufacturing process represents a critical business function, and its effectiveness and reliability are directly linked to the achievement of key business objectives, including profitability, competitiveness, and long-term sustainability. Consequently, improvements in manufacturing process reliability are integral to fostering the growth of national economies, given that the automotive sector is one of the largest and most significant contributors to the gross national income in many countries worldwide.

It has been widely acknowledged that failures occurring during production are primary causes of the failure to meet established business goals. Therefore, enhancing the reliability of the manufacturing process is contingent upon the identification, elimination, or reduction of these failures throughout the production cycle. Over recent decades, numerous techniques, tools, and methods have been developed to prevent or mitigate such failures. One of the most widely recognized and adopted methods in practice is FMEA, which is employed to systematically detect, analyze, and assess potential failures within the production process. The mandatory application of FMEA within the automotive industry is stipulated by the IATF 16949 standard, which underscores its critical role in ensuring quality management and continuous improvement in manufacturing operations [1].

In conventional FMEA, the evaluation of identified failures is performed according to three RFs: severity, occurrence of failure realisation, and difficulty of detecting the failure. The following assumptions are introduced: (i) RFs have equal weights, (ii) the values of RFs are assessed by decision-makers (DMs) using a standard measurement scale defined in the interval [1–10], and (iii) the rank of failures corresponds to the risk priority number (RPN), which is calculated using the proposed mathematical formulation. The elimination of identified failures is based on the obtained rank; it is considered that this approach eliminates failures that have the greatest impact on the reliability of the manufacturing process, given the limitations of the available budget.

In the literature, numerous papers can be found advocating that there are existing disadvantages of conventional FMEA [2, 3]. Some of the important shortcomings of FMEA include: (i) DMs express their assessments better using linguistic statements rather than precise numbers; (ii) the weights of RFs are different; and (iii) the formula for calculating RPN lacks mathematical justification. Therefore, many authors emphasize different approaches that have been proposed to eliminate the shortcomings of FMEA, including approaches that integrate Multi-Criteria Decision-Making (MCDM) methods and fuzzy sets theory [4–6]. Additionally, other methods, such as Pareto analysis [7] could also be used.

Many authors believe that DMs more easily and accurately express their estimates using natural language words rather than precise numbers. The development of mathematical theories, such as type-2 fuzzy sets theory [8], allows vagueness, uncertainty, and imprecision to be represented more accurately in quantitative terms. Mendel [8] suggests that using type-2 fuzzy sets minimises the effects of uncertainties by better modelling them. It is important to note that the modelling of existing uncertainty in IT2FSs is not limited only to linguistic variables but also extends to the definition of membership functions [9]. Therefore, many authors [10] suggest using IT2TFNs, which capture the uncertainties of natural language in an adequately accurate manner while simultaneously requiring less computational complexity than interval type-2 fuzzy numbers with more complex membership function shapes. In this research, uncertainties related to internal impact RFs are modelled using IT2TFNs.

In this research, a fuzzy two-stage model for rating and ranking failures identified in the manufacturing process of an automotive company is proposed. There are many papers in the relevant literature that propose various subjective MCDM methods with interval type-2 fuzzy numbers for determining weight vectors, such as: (i) AHP [11] with IT2TFNs [4, 12, 13] (ii) Best Worst Method developed by Rezaei [14], which has been modified with IT2TFNs [15, 16], and DEMATEL with IT2TFNs [17–21], as in this research. In the second stage, the classification and ranking of identified failures are performed using the modified MABAC. MABAC was developed by Pamučar and Ćirović [22] and applied to solve management problems in different domains [23–25].

The FMEA team undertakes management initiatives based on the obtained priority of failures. It is crucial that the priority of failures is determined in an exact manner, which is significantly less influenced by the subjective attitudes of the FMEA team, leading to a greater improvement in the reliability of the manufacturing process. In the literature, there are few manuscripts where the solution to the considered problem has been found by applying FMEA combined with MCDM and type-2 fuzzy sets theory [26]. The motivation for this research comes from the aforementioned facts.

The wider objective of this research may be interpreted as: (i) modelling of existing uncertainties using IT2TFNs, (ii) expressing the internal impact of RFs as fuzzy group decision-making, with aggregated values of the internal impact matrix provided using fuzzy harmonic means, (iii) determining the weights of risk RFs using IT2FDEMATEL, and (iv) classifying and ranking failures that have the greatest impact on the reliability of the production process in the automotive enterprise using the proposed MABAC method. The authors believe that the proposed methodology can significantly assist the FMEA team in taking the necessary management measures within a shorter period of time to eliminate the identified failures.

The paper is organized as follows: The proposed methodology is introduced in Section 2. Section 3 illustrates the methodology with real-life data. Conclusions are provided in Section 4.

2 Methodology

In order to understand the problem, a review of some background on IT2TFNs is provided in Section 2.1.

2.1 Basic Definition of IT2TFNs

In this Section, some basic definitions related to fuzzy algebra rules of the IT2TFNs are presented [8, 27, 28].

Definition 1. If the upper membership function and lower membership function of $\widetilde{\widetilde{\mathrm{A}}}$ are two triangular type-1 fuzzy numbers, than $\widetilde{\widetilde{A}}$ is referred to as a triangular interval type-2 fuzzy number, $\widetilde{\widetilde{\mathrm{A}}} = \left(\widetilde{\mathrm{A}}^{U}, \widetilde{\mathrm{A}}^{L}\right)$ so that:

$$\widetilde{\widetilde{\mathrm{A}}} = \left(\widetilde{A}^{\mathrm{U}}, \widetilde{A}^{\mathrm{L}}\right) = \left(\left(\mathrm{a}_1^{\mathrm{U}}, \mathrm{a}_2^{\mathrm{U}}, \mathrm{a}_3^{\mathrm{U}}, \alpha\right), \left(\mathrm{a}_1^{\mathrm{L}}, \mathrm{a}_2^{\mathrm{L}}, \mathrm{a}_3^{\mathrm{L}}, \beta\right)\right)$$

where,

The lower and upper bounds in the domain are denoted as a_1^U, a_3^U respectively, and a_1^L, a_3^L respectively. The modal values are a_2^U, respectively, and a_2^L, respectively. The values of the membership function are defined as:

$$(\alpha, \beta) \in [0, 1]$$

Definition 2. Assume two IT2TFNs, $\tilde{\tilde{A}}$, and $\tilde{\tilde{B}}$

$$\tilde{\tilde{A}} = \left(\left(a_1^U, a_2^U, a_3^U, \alpha_1\right), \left(a_1^L, a_2^L, a_3^L, \beta_1\right)\right)$$
$$\tilde{\tilde{B}} = \left(\left(b_1^U,\ b_2^U,\ b_3^U, \alpha_2\right), \left(b_1^L,\ b_2^L,\ b_3^L, \beta_2\right)\right)$$

The arithmetic operations are introduced:

The addition operation, which is denoted as, $\tilde{\tilde{A}} + \tilde{\tilde{B}}$ can be defined as:

$$\tilde{\tilde{A}} + \tilde{\tilde{B}} = \begin{pmatrix} \left(a_1^U + b_1^U, a_2^U + b_2^U, a_3^U + b_3^U; \min\left(\alpha_1, \alpha_2\right), \min\left(\beta_1, \beta_2\right)\right) \\ \left(a_1^L + b_1^L, a_2^L + b_2^L, a_3^L + b_3^L; \min\left(\alpha_1, \alpha_2\right), \min\left(\beta_1, \beta_2\right)\right) \end{pmatrix}$$

The subtraction operation, which is denoted as, $\tilde{\tilde{A}} - \tilde{\tilde{B}}$ can be defined as:

$$\tilde{\tilde{A}} - \tilde{\tilde{B}} = \begin{pmatrix} \left(a_1^U - b_3^U, a_2^U - b_2^U, a_3^U - b_1^U; \min\left(\alpha_1, \alpha_2\right), \min\left(\beta_1, \beta_2\right)\right) \\ \left(a_1^L - b_3^L, a_2^L - b_{32}^L, a_3^L - b_1^L; \min\left(\alpha_1, \alpha_2\right), \min\left(\beta_1, \beta_2\right)\right) \end{pmatrix}$$

The multiplication operation, which is denoted as, $\tilde{\tilde{A}} - \tilde{\tilde{B}}$ can be defined as:

$$\tilde{\tilde{A}} \cdot \tilde{\tilde{B}} = \begin{pmatrix} \left(a_1^U \cdot\ b_1^U, a_2^U \cdot\ b_2^U, a_3^U \cdot\ b_3^U; \min\left(\alpha_1, \alpha_2\right), \min\left(\beta_1, \beta_2\right)\right) \\ \left(a_1^L \cdot\ b_1^L, a_2^L \cdot\ b_2^L, a_3^L \cdot\ b_3^L; \min\left(\alpha_1, \alpha_2\right), \min\left(\beta_1, \beta_2\right)\right) \end{pmatrix}$$

The division operation, which is denoted as, $\tilde{\tilde{A}} - \tilde{\tilde{B}}$ can be defined as:

$$\tilde{\tilde{A}} : \tilde{\tilde{B}} = \begin{pmatrix} \left(a_1^U : b_3^U, a_2^U : b_2^U, a_3^U : b_1^U; \min\left(\alpha_1, \alpha_2\right), \min\left(\beta_1, \beta_2\right)\right) \\ \left(a_1^L : b_3^L, a_2^L : b_2^L, a_3^L : b_1^L; \min\left(\alpha_1, \alpha_2\right), \min\left(\beta_1, \beta_2\right)\right) \end{pmatrix}$$

Definition 3. Let us discuss the triangular interval type-2 fuzzy number $\approx \tilde{\tilde{A}}$, and the crisp value k [8, 27, 28]:

$$k \cdot \tilde{\tilde{A}} = \begin{pmatrix} \left(k \cdot a_1^U, k \cdot a_2^U, k \cdot a_3^U; \alpha_1\right), \\ \left(k \cdot a_1^L, k \cdot a_2^L, k \cdot a_3^L; \beta_1\right) \end{pmatrix}$$
$$(\tilde{\tilde{A}})^{-1} = \begin{pmatrix} \left(\frac{1}{a_3^U}, \frac{1}{a_2^U}, \frac{1}{a_1^U}; \alpha_1\right) \\ \left(\frac{1}{a_3^L}, \frac{1}{a_2^L}, \frac{1}{a_1^L}; \beta_1\right) \end{pmatrix}$$

Definition 4. The defuzzified Triangular type-2 fuzzy numbers approach (DTriT) is proposed [29]:

$$DTriT = \frac{1}{2}\left\{\frac{\left(a_3^U - a_1^U\right) + \left(\alpha_2 - a_1^U\right)}{3} + a_1^U + \left[\beta\frac{\left(a_3^L - a_1^L\right) + \left(a_2^L - a_1^L\right)}{3} + a_1^L\right]\right\}$$

Definition 5. The Vertex method can be adapted in the following way [30]:

$$d_V(\tilde{A}, \tilde{B}) = \left\{\frac{1}{8}\left[\ (a_1^u - b_1^u)^2 + 2 \cdot (a_2^u - b_2^u)^2 + (a_3^u - b_3^u)^2 + \left(a_1^l - b_1^l\right)^2 + 2 \cdot \left(a_2^l - b_2^l\right)^2 + \left(a_3^l - b_3^l\right)^2 \right.\right.$$
$$+ \left(\alpha_1\left(\tilde{A}^U\right) - \alpha_1\left(\tilde{B}^U\right)\right)^2 + \left(\alpha_2\left(\tilde{A}^U\right) - \alpha_2\left(\tilde{B}^U\right)\right)^2 + \left(\beta_1\left(\tilde{A}^U\right) - \beta_1\left(\tilde{B}^U\right)\right)^2$$
$$\left.\left. + \left(\beta_2\left(\tilde{A}^U\right) - \beta_2\left(\tilde{B}^U\right)\right)^2\right]\right\}^{\frac{1}{2}}$$

2.2 Defining Set of DMs

The DMs participating in this research are members of the FMEA team. They possess adequate knowledge in the domain of manufacturing and maintenance business processes. Formally, the DMs are represented by the set of indices $\{1, \ldots, e, \ldots, E\}$. The total number of DM is denoted as E. The index of a DM is denoted as E, where $e, e = 1, \ldots, E$.

In this research, the FMEA team includes the production manager, quality manager, and maintenance manager.

2.3 Definition of a Finite Set of RFs

In general, failures that may occur in the manufacturing process, which lead to a reduction in the effectiveness and reliability of the process, can be assessed according to various attributes. These RFs can be formally represented by a set of indices $\{1, \ldots, k, \ldots, K\}$, where K is the total number of RFs and $k, k = 1, \ldots, K$, is the index of a RF.

In accordance with the IATF16949 standard [1], which is applied in automotive companies, it can be concluded that the FMEA team evaluates identified failures based on three attributes: severity, occurrence, and detection.

2.4 Definition of a Finite Set of Identified Failures

In this research, the manufacturing process in a company that is part of the automotive supply chain is considered. This manufacturing process is carried out through two phases: laser cutting and carbon welding. The FMEA team has identified a set of failures based on evidence data and their experience. Generally, the considered failures may be represented by the set of indices $\{1, \ldots, i, \ldots, I\}$, where I represents the total number of failures, and the index of a failure is denoted as iii, where $i, i = 1, \ldots, I$.

The values of identified failures are assessed by the FMEA team as presented in tables. It should be noted that all considered attributes are benefit-type.

2.5 Choice of Appropriate Linguistic Variables for Describing the Relative Importance of RFs

In this research, the impact of RFs is described using linguistic expressions that are modelled by IT2TFNs. The authors believe that type-2 fuzzy numbers adequately capture the uncertainties and imprecisions of natural language. The basic characteristics of fuzzy numbers are: membership function, granulation, and domain. Based on literature data, it can be concluded that using a triangular membership function provides sufficiently accurate results without reducing the accuracy of the results. In the literature, many authors suggest IT2TFNs for describing uncertain data in different management problems, as in this research.

There is no specific recommendation or rule in the literature on how to determine the granulation and domain of fuzzy numbers. Granulation is most often determined depending on the problem size. However, many authors suggest that the maximum number of linguistic terms used for assessing uncertain data should not exceed seven [13, 31, 32]. In this research, a seven-point scale is used. The domains of fuzzy numbers are defined on the real line within different intervals.

The linguistic expressions and their corresponding IT2TFNs for describing the relative importance of evaluation criteria are represented as follows:

- Low importance (W_1) : $((1, 1, 2.5; 1), (1, 1, 2; 0.75))$
- Fairly low importance (W_2) : $((1, 2.5, 5; 1), (1.5, 2.5, 4.5; 0.75))$
- Medium importance (W_3) : $((3, 5, 7; 1), (3.5, 5, 6.5; 0.75))$
- Fairly high importance (W_4) : $((6, 7.5, 9; 1), (6.5, 7.5, 8.5; 0.75))$
- High importance (W_5) : $((7.5, 9, 9; 1), (8, 9, 9; 0.75))$

The value of 1 or 9 denotes that the relative importance of RFs is the smallest or largest, respectively.

2.6 The Proposed IT2FDEMATEL

The original DEMATEL, proposed by the Geneva Research Center at the Battelle Memorial Institute, presents a particularly pragmatic tool for visualizing the structure of complex causal relationships [33]. Authors [34] modified the original DEMATEL by representing the relationships between the criteria using a direct-relation matrix. Many researchers have extended the modified DEMATEL [34] with type-2 fuzzy sets theory [17–21], as in this research.

A brief comparative analysis of the works found in the literature and the proposed IT2FDEMATEL in this research will be provided below.

In all analyzed papers, the elements of the initial direct relation matrix are described by interval type 2 trapezoidal fuzzy numbers (IT2TrFNs). In this research, the impact values of RFs are described by IT2TFNs. The use of IT2TrFNs requires complex calculations. In contrast, the use of IT2TFNs is significantly simpler, and the obtained solutions are sufficiently accurate.

The domains of IT2TrFNs in the analyzed papers are defined on the interval [0-1]. In this research, the authors defined the domains of the IT2FNs on a common measurement scale [11], as many authors suggest in the relevant literature. Baykasoğlu and Gölcük [18] suggested a seven-point scale, as used in this research. In the rest of the analyzed papers, a five-point scale is used.

The determination of the values of the elements in the initial direct relation matrix is stated as a fuzzy group decision-making problem, as in this research. Aggregation of fuzzy ratings from DMs is performed in the analyzed papers. In this research, the authors suggested using the fuzzy harmonic mean, which represents a difference and, in the authors' opinion, an advantage over the considered manuscripts.

In this paper, all treated RFs are benefit-type, so it was not necessary to transform the initial relation matrix into the normalized initial relation decision matrix. Compared to the other analyzed papers, the proposed procedure requires significantly less computation.

In many papers [17, 18, 20], the total relation matrix is constructed according to the procedure developed in modified DEMATEL combined with type 2 fuzzy sets theory [8]. The transformation of the fuzzy total relation matrix into the total relation matrix is given by using different proposed procedures [19, 21].

In this research, matrix calculations are combined with fuzzy algebra rules [8], defuzzification, and distance measures. In this way, the total relation matrix is obtained. The weight vector is calculated according to the procedure proposed in the modified DEMATEL.

The application domains of the proposed IT2FDEMATEL vary. For instance, software engineering [21], industrial management [17, 18, 20], and the primary industry sector [19].

In this research, the proposed IT2FDEMATEL is used to determine the weight vector in the domain of production management. The algorithm for implementing the IT2FDEMATEL method is carried out through the following steps:

Step 1. Establish the causal dependencies of RFs at the level of each DM:

$$\tilde{\tilde{X}}^e = [\tilde{\tilde{x}}^e_{kk'}]_{KxK}$$

Step 2. Determine the aggregated causal relationship matrix of RFs:

$$\tilde{\tilde{X}} = [\tilde{\tilde{x}}_{kk'}]_{KxK}$$

where,

$$\tilde{\tilde{x}}_{kk'} = \frac{E}{\sum_{e=1,\ldots,E} \tilde{\tilde{x}}^e_{kk'}}$$

Step 3. Determine the index $\tilde{\tilde{\theta}}$:

$$\tilde{\tilde{\theta}} = \max \left\{ \frac{1}{\max \sum_{k'=1,\ldots,K} \tilde{\tilde{x}}_{kk'}}, \frac{1}{\max \sum_{k=1,\ldots,K} \tilde{\tilde{x}}_{kk'}} \right\}$$

The ranking of IT2TFNs is performed according to the procedure developed by Lee and Chen [27].

Step 4. The direct relation matrix, $\widetilde{D}$ is determined according to the expression:

$$\tilde{\tilde{D}} = \tilde{\tilde{\theta}} \cdot \tilde{\tilde{X}} = \left[\tilde{\tilde{d}}_{kk'}\right]_{KxK}$$

Step 5. Determine the total relation matrix:

$$T = \text{defuzz}(\tilde{\tilde{D}}) \cdot (\tilde{\tilde{I}} - \tilde{\tilde{D}})^{-1} = [t_{kk'}]_{KxK}$$

where,

$\tilde{\tilde{I}}$ is the identity matrix, so the values of the elements on the main diagonal are described by IT2TFNs.

$$((1, 1, 1; 1), (1, 1, 1; 0.75))$$

Formally, the identity matrix can be represented as:

$$\tilde{\tilde{I}} = \left[\tilde{\tilde{i}}_{kk'}\right]_{KxK}$$

The difference between the two matrices $(\tilde{\tilde{I}} - \tilde{\tilde{D}})$ is calculated using matrix operations and fuzzy algebra rules [8], such that:

$$\tilde{\tilde{A}} = (\tilde{\tilde{I}} - \tilde{\tilde{D}}) = \left[\tilde{\tilde{a}}_{kk'}\right]_{KxK}$$

The determination of the values of the elements in the adjugated matrix $\tilde{\tilde{A}}$, and its determinant is based on the application of matrix operations and the distance between two IT2TFNs. Consequently, the values of the inverse matrix $\tilde{\tilde{A}}$ are described by crisp values.

Step 6. The determination of the RFs' weights is based on the modified expression proposed in the conventional DEMATEL method:

$$W_k = \sqrt{(S_k + C_k)^2 + (S_k - C_k)^2}$$

where,

$$S_k = \sum_{k'=1,\ldots K} t_{kk'}$$

$$C_k = \sum_{k=1,\ldots K} t_{kk'}$$

Step 7. The normalized weight vector is obtained by applying fuzzy algebra rules:

$$[\omega_k]_{Kx1}$$

where,

$$\omega_k = \frac{W_k}{\sum_{k=1,.,K} W_k}$$

2.7 The Proposed MABAC

In the conventional MABAC method [22], the normalized decision matrix is constructed using Weitendorf's linear normalization [35]. The principle of the product is used to construct the weighted normalized decision matrix. The border approximation area (BAA) matrix is determined by applying the geometric mean. The distance of the weighted normalized decision matrix elements from the BAA is calculated according to the proposed procedure. In the literature, many manuscripts utilize conventional MABAC for ranking alternatives within approximation areas [23–25]. Alternatives belonging to the BAA and upper approximation area are ranked according to the values of the criterion functions calculated for these alternatives.

In this paper, the conventional MABAC method has been modified as follows: (i) the values of the elements in the decision matrix are normalized using the Max-Min method [35]; this normalization procedure requires simpler calculations compared to the normalization procedure used in conventional MABAC. Since all RFs in this research are benefit-type and assessed on a scale from 1 to 10, the authors believe that using a simpler normalization procedure is justified as it does not reduce the accuracy of the results; (ii) the weighted normalized decision matrix is constructed using the principle of exponentiation. The choice of the exponentiation principle for normalizing the decision matrix can be considered a problem in itself.

The proposed MABAC can be realized through the following steps:

Step 1. The decision matrix is stated:

$$[x_{ik}]_{IxK}$$

where,

x_{ik} is the value of RF $k, k = 1, \ldots, K$ for failure $i, i = 1, \ldots, I$; these values are obtained from the FMEA report and are described by precise numbers.

Step 2. Constructing the normalized decision matrix:

$$r_{ik} = \frac{x_{ik}}{x^{\max}}$$

where,

$x^{\max}$ is the maximum value of the RF .

Step 3. The weighted decision matrix is constructed:

$$[z_{ik}]_{IxK}$$

where,

$$z_{ik} = (r_{ik})^{\omega_k}$$

Step 4. Construct the matrix, where $[\mathrm{v_{ik}}]_{\mathrm{I\times K}}$, $\mathrm{i} = 1, \ldots, \mathrm{I}$ and $\mathrm{k} = 1, \ldots,$ K. The elements of this matrix are determined by applying the fuzzy algebra rules [8]:

$$v_{ik} = z_{ik} + \omega_k$$

Step 5. Construct the column matrix, $[g_{\mathrm{k}}]_{1\times\mathrm{K}}$, $\mathrm{k} = 1, \ldots,$ K. The elements of this matrix are determined by applying the geometric mean:

$$g_k = \sqrt[I]{v_{ik}}$$

Step 6. Determine whether failure $i, i = 1, \ldots, I$ belongs to the approximate area, G^+at the level of each RF $k, k = 1, \ldots, K$ according to the modified procedure proposed by Pamučar and Ćirović [22]:

$$i \in \left\{ \begin{array}{ll} G^+ & if \quad S_i = \sum_{k=1,\ldots.K} q_{ik} \geq 0 \quad q_{ik} = v_{ik} - g_k \\ G^- & otherwise \end{array} \right\}$$

where,

The value of the RF function is denoted as S_i

Failures that belong to G^- almost have no impact on the effectiveness of the manufacturing process. Therefore, these failures are not considered by the FMEA team.

Step 7. The rank of failures that have the greatest importance is determined by considering all RFs simultaneously and is calculated based on the value S_i. Based on the obtained ranking results, the FMEA team can determine the sequence of actions that should be taken to increase the reliability of the manufacturing process. Figure 1 presents a brief graphical representation of the proposed model.

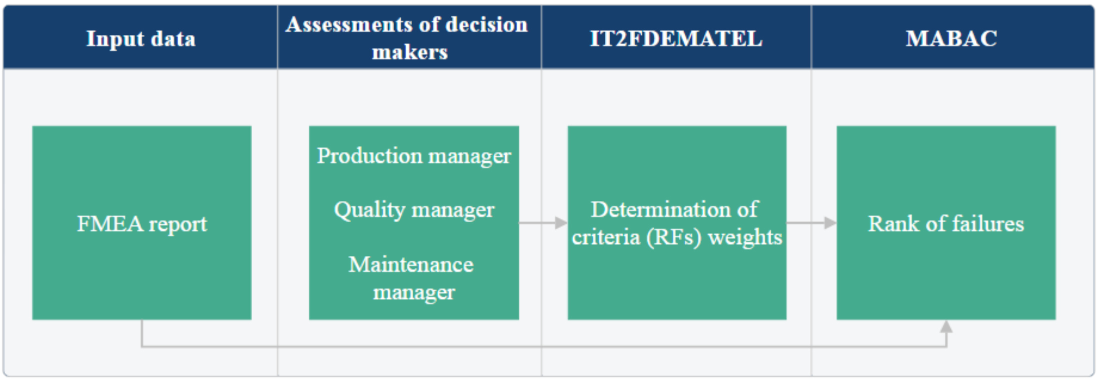

Figure 1. The proposed model

Figure 1 provides a concise graphical representation of the proposed model, highlighting its key components. The diagram illustrates the input data, including the FMEA report and DMs' assessments, as well as the weighting process using IT2FDEMATEL and the ranking approach based on MABAC method.

3 Case Study

The proposed model was tested using real-life data from an automotive company located in the Republic of Serbia, which is part of the global automotive supply chain. According to the size criterion, the company is classified as a small and medium enterprise (SME) with a predominantly mechanized technological level. The IATF16949 [1] standard has been introduced and is applied in the considered enterprise.

The necessary data on the relative internal impact of RFs were obtained through questionnaires specifically constructed for this study. Members of the FMEA team independently assessed the internal impact of the RFs defined in the conventional FMEA. They could express their evaluations using five linguistic statements included in the questionnaire. This questionnaire was sent via email to the FMEA team.

The values of the RFs were taken from the FMEA report.

3.1 An Application of the Proposed IT2FDEMATEL

The procedure of the proposed algorithm is shown below.

According to the proposed algorithm (Step 1), the fuzzy matrix of the relative internal impact of RFs is constructed at the level of each member of the FMEA team:

$$\begin{array}{ccc} \text{Production manager} & \text{Quality manager} & \text{Maintenance manager} \\ \begin{bmatrix} 0 & W2 & W4 \\ W4 & 0 & W1 \\ W3 & W5 & 0 \end{bmatrix} & \begin{bmatrix} 0 & W4 & W3 \\ W3 & 0 & W2 \\ W2 & W4 & 0 \end{bmatrix} & \begin{bmatrix} 0 & W4 & W5 \\ W4 & 0 & W1 \\ W1 & W4 & 0 \end{bmatrix} \end{array}$$

The aggregated matrix of the relative internal impact of RFs (Step 2 of the proposed algorithm) is given as follows:

$$\begin{bmatrix} 0 & \begin{array}{c}((4.51, 6.42, 8.212; 1),\\ (5.72, 6.42, 7.71; 0.75))\end{array} & \begin{array}{c}((4.74, 6.76, 8.22; 1),\\ (5.31, 6.76, 7.83; 0.75))\end{array} \\ \begin{array}{c}((4.51, 6.42, 8.22; 1),\\ (5.73, 6.42, 7.71; 0.75))\end{array} & 0 & \begin{array}{c}((0.99, 1.25, 3; 1),\\ (1.12, 1.25, 2.45; 0.75))\end{array} \\ \begin{array}{c}((1.29, 1.88, 4.04; 1),\\ (1.54, 1.88, 3.42; 0.75))\end{array} & \begin{array}{c}((6.44, 7.94, 9; 1),\\ (6.93, 7.94, 8.67; 0.75))\end{array} & 0 \end{bmatrix}$$

Let's determine the index $\tilde{\tilde{\theta}}$ (Step 3 of the proposed Algorithm):

$$\tilde{\tilde{\theta}} = \max \left\{ \begin{array}{c} \frac{1}{((9.24, 13.18, 16.44; 1), (11.03, 13.18, 15.55; 0.75))}, \\ \frac{1}{((10.94, 14.13617.22; 1), (12.65, 14.36, 16.38; 0.75))} \end{array} \right\}$$

$$\tilde{\tilde{\theta}} = ((0.06, 0.08, 0.11; 1), (0.06, 0.08, 0.09; 0.75))$$

According to the proposed algorithm (Step 4), the direct relation matrix, $\tilde{D}$ is determined:

$$\begin{bmatrix} 0 & \begin{array}{c}((0.27, 0.49, 089; 1),\\(0.37, 0.49, 0.70; 0.75))\end{array} & \begin{array}{c}((0.29, 0.51, 0.89; 1),\\(0.34, 0.51, 0.71; 0.75))\end{array} \\ \begin{array}{c}((0.27, 0.49, 0.89; 1),\\(0.37, 0.49, 0.70; 0.75))\end{array} & 0 & \begin{array}{c}((0.06, 0.09, 0.32; 1),\\(0.07, 0.09, 0.22; 0.75))\end{array} \\ \begin{array}{c}((0.09, 0.14, 0.44; 1),\\(0.10, 0.14, 0.31; 0.75))\end{array} & \begin{array}{c}((0.39, 0.60, 0.97; 1),\\(0.44, 0.60, 0.79; 0.75))\end{array} & 0 \end{bmatrix}$$

The procedure for determining the total relation matrix (Step 5 of the proposed Algorithm) is shown below. The phase matrix $\tilde{\tilde{A}}$ is calculated, as follows:

$$\begin{bmatrix} \begin{array}{c}((1, 1, 1; 1),\\(1, 1, 1; 1))\end{array} & \begin{array}{c}((0.11, 0.51, 0.72; 1),\\(0.30, 0.51, 0.63; 0.75))\end{array} & \begin{array}{c}((0.11, 0.49, 0.71; 1),\\(0.29, 0.49, 0.66; 0.75))\end{array} \\ \begin{array}{c}((0.11, 0.51, 0.72; 1),\\(0.30, 0.51, 0.63; 0.75))\end{array} & \begin{array}{c}((1, 1, 1; 1),\\(1, 1, 1; 1))\end{array} & \begin{array}{c}((0.68, 0.91, 0.94; 1),\\(0.78, 0.91, 0.93; 0.75))\end{array} \\ \begin{array}{c}((0.56, 0.86, 0.92; 1),\\(0.69, 0.86, 0.90; 0.75))\end{array} & \begin{array}{c}((0.03, 0.40, 0.61; 1),\\(0.21, 0.40, 0.56; 0.75))\end{array} & \begin{array}{c}((1, 1, 1; 1),\\(1, 1, 1; 1))\end{array} \end{bmatrix}$$

The calculation of the values of the adjugate matrix is illustrated in the following example:

$$A_{11} = d\left(\tilde{\tilde{a}}_{22} \cdot \tilde{\tilde{a}}_{33}, \tilde{\tilde{a}}_{23} \cdot \tilde{\tilde{a}}_{32}\right) =$$
$$d((1, 1, 1; 1), (1, 1, 1; 1)), ((0.43, 0.64, 0.96; 1), (0.48, 0.64, 0.84; 0.75)) = 0.62$$

In a similar manner, the values of the other elements of the adjugate matrix are calculated, so that:

$$adjA = \begin{bmatrix} 0.62 & -0.28 & 0.04 \\ -0.24 & 0.63 & -0.62 \\ 0.61 & -0.04 & 0.63 \end{bmatrix}$$

The value of the determinant of matrix $\tilde{\tilde{A}}$ is calculated in a similar way as the values of the adjugated matrix, so that:

$$|\tilde{\tilde{A}}| = 0.54$$

The inverse matrix is:

$$A^{-1} = \frac{adj\tilde{\tilde{A}}}{|\tilde{\tilde{A}}|} = \begin{bmatrix} 1.14 & -0.52 & 0.07 \\ -0.45 & 1.16 & -1.14 \\ 1.13 & -0.07 & 1.16 \end{bmatrix}$$

The fuzzy matrix $\tilde{\tilde{D}}$ is transformed into matrix D by applying the defuzzification procedure [29]:

$$defuzz\tilde{\tilde{D}} = \begin{bmatrix} 0 & 0.47 & 0.48 \\ 0.47 & 0 & 0.13 \\ 0.18 & 0.56 & 0 \end{bmatrix}$$

The total relation matrix T is:

$$T = \begin{bmatrix} 0.33 & 0.51 & 0.02 \\ 0.68 & -0.25 & 0.18 \\ -0.05 & 0.61 & -0.62 \end{bmatrix}$$

Determining the weight of RFs is illustrated for RF k=1:

$$S_1 = 0.33 + 0.51 + 0.02 = 0.86$$
$$C_1 = 0.33 + 0.68 - 0.05 = 0.96$$
$$W_1 = \sqrt{(0.86 + 0.96)^2 + (0.86 - 0.96)^2} = 1.80$$

In a similar manner, the weights of the other RFs are calculated, so that:

$$W_2 = 1.50$$
$$W_3 = 0.60$$

The normalized weights vector (Step 7 of the proposed Algorithm) is:

$$[0.46, \quad 0.38, \quad 0.16]$$

3.2 An Application of the Proposed MABAC

The decision matrix (Step 1 of the proposed Algorithm) is constructed according to the FMEA report and is presented in Table 1.

Table 1. The decision matrix

Phase 7-Laser Cut							
No.	**Potential Failure Mode**	**Potential Effect of Failure**	$k = 1$	**Potential Causes**	$k = 2$	**Prevention**	$k = 3$
$i = 1$	mixed parts in the box	operator lost time	3	human error	3	train operator	4
$i = 2$	parts wet	corrosion, scrap parts	7	containers wet	2	usage of containers that have not been exposed to weather condition	3
$i = 3$	torch not heated	decreased mechanical characteristic of material can cause failure of entire assembly	9	operator from previous operation did mistake	1	train operator	4
$i = 4$	deformed parts in the box	scrap parts	8	parts deformed during transport	1	train logistic operator	3
$i = 5$	arm not welded	scrap parts	9	op 05 operator mistake	2	train operators	4
$i = 6$	improper weld dimension	scrap parts, bad laser cut	9	op 05 weld parameter bad	2	regular parameter check on op 05	4
$i = 7$	bad cut parts	scrap parts, bad (impossible) welding down the flow	9	bad positioning of the parts; bad laser program bad tools; bad centering bad laser trajectory	3	regularly check positioning of the parts	3
$i = 8$	load cut torch on tool	laser failure	7	operator error	2	train operator	2
$i = 9$	torch longer than nominal	process cannot start, lost time	4	supplier mistake	1	inform supplier	3
$i = 10$	bad inputs	laser failure	7	operator mistake	3	train operator	4

Phase 7-Laser Cut							
No.	**Potential Failure Mode**	**Potential Effect of Failure**	$k = 1$	**Potential Causes**	$k = 2$	**Prevention**	$k = 3$
$i = 11$	torch shorter than nominal	bad dimension and cut, scrap parts, problems down the flow	8	supplier mistake	2	inform supplier, train operator	3
$i = 12$	non marked parts where produced (table a, table b)	problems in assembling down the flow, scrap part	7	operator mistake	2	train operator	3
$i = 13$	Mixed arm where produced	problems in assembling down the flow, scrap part	7	operator mistake	2	train operator	3
$i = 14$	mixed arm (gr/dx)	impossible to load op 10 , operator lost time	5	operator mistake	2	train operator	3

Phase 8-CO_2 Welding							
No.	**Potential Failure Mode**	**Potential Effect of Failure**	$k = 1$	**Potential Causes**	$k = 2$	**Prevention**	$k = 3$
$i = 15$	oiled parts	bad welds - scraped parts	9	supplier mistake	2	check every part before loading and inform supplier	4
$i = 16$	deformed parts	impossible or partial closing of the clamps/ impossible start production parts	7	deformed part during material handling	2	training to the logistic operator	3
				deformed part during operation	1	check robot program	3
				supplier send deformed part	2	inform supplier	3
$i = 17$	miss one part	impossible start production parts	7	forget to carry on the part on the assembly jig	1	electronic check of presence of the part	2
$i = 18$	wrong load parts	impossible start production parts	7	wrong position of the parts on the assembly jig	2	presence of mechanical mistake	1
$i = 19$	wrong position of the parts	impossible or partial closing of the clamps / impossible start production parts	6	geometric repeatability of the parts missing	5	check of limit of the clamps	1
			6	not enough reference points	1	check and approval assembly jis project	1

Phase 8-CO_2 Welding							
No.	**Potential Failure Mode**	**Potential Effect of Failure**	$k = 1$	**Potential Causes**	$k = 2$	**Prevention**	$k = 3$
$i = 20$	lack of imprinted code	cannot start next operation	6	program failure	2	check program	4
$i = 21$	miss welding	seal parts no guaranteed	9	wrong program	2	approval first sample	3
$i = 22$	pore welding	seal parts no guaranteed	9	not good position components	3	self-check 100%	3
$i = 23$	wrong position welding	seal parts no guaranteed	9	wrong robot route	2	check robot program	3
$i = 24$	insufficient welding seal	seal parts no guaranteed	9	wrong parameters	1	check parameters and qualification process	3
$i = 25$	weld with many holes	scrapped part	9	lack of weld gas	2	regular check of gas level	3
$i = 26$	dimension welding	seal parts no guaranteed	9	wrong program	2	check robot program	3
$i = 27$	bad connection between welding arm and torch	scrapped part	9	bad positioning of robot and tool on op20	3	regular check robot positioning	3
$i = 28$	miss welding	seal parts no guaranteed	9	wrong program	2	approval first sample	3
$i = 29$	pore welding	parts no guaranteed	9	not good position components	3	self-check 100%	3
$i = 30$	wrong position welding	seal parts no guaranteed	9	wrong robot route	2	check robot program	3
$i = 31$	insufficient welding seal	seal parts no guaranteed	9	wrong parameters	1	check parameters and qualification process	3
$i = 32$	weld with many holes	scrapped part	9	lack of weld gas	2	regular check of gas level	3
$i = 33$	dimension welding	seal parts no guaranteed	9	wrong program	2	check robot program	3
$i = 34$	oiled parts	bad welds - scraped parts	9	supplier mistake	2	check every part before loading and inform supplier	3
$i = 35$	deformed parts	impossible or partial closing of the clamps / impossible start production parts	7	deformed part during material handling	2	training to the logistic operator	1
$i = 36$	miss one part	impossible start production parts	7	forget to carry on the part on the assembly jig	1	electronic check of presence of the part	2

Phase 8-CO_2 Welding							
No.	**Potential Failure Mode**	**Potential Effect of Failure**	$k = 1$	**Potential Causes**	$k = 2$	**Prevention**	$k = 3$
$i = 37$	wrong load parts	impossible start production parts	8	wrong position of the parts on the assembly jig	2	presence of mechanical mistake	1
$i = 38$	wrong position of the parts	impossible or partial closing of the clamps / impossible start production parts	6	geometric repeatability of the parts missing	5	check of limit of the clamps	1
$i = 39$	miss welding	seal parts no guaranteed	9	wrong program	2	approval first sample	3
$i = 40$	pore welding	seal parts no guaranteed	9	not good position components	3	self-check 100%	3
$i = 50$	dimension welding	seal parts no guaranteed	9	wrong program	2	check robot program	3
$i = 51$	oiled parts	bad welds - scraped parts	9	supplier mistake	2	check every part before loading and inform supplier	3
$i = 52$	deformed parts	impossible or partial closing of the clamps / impossible start production parts	7	deformed part during material handling	2	training to the logistic operator	2
$i = 53$	migs one part	impossible start production parts	7	forget to carry on the part on the assembly jig	1	electronic check of presence of the part	2
$i = 54$	wrong load parts	impossible start production parts	8	wrong position of the parts on the assembly jig	2	presence of mechanical mistake	2
$i = 55$	wrong position of the parts	impossible or partial closing of the clamps / impossible start production parts	6	geometric repeatability of the parts missing	5	check of limit of the clamps	1
$i = 56$	miss welding	seal parts no guaranteed	9	wrong program	2	approval first sample	3
$i = 57$	pore welding	seal parts no guaranteed	9	not good position components	3	self-check 100%	1
$i = 58$	wrong position welding	seal parts no guaranteed	9	wrong robot route	2	check robot program	3
$i = 59$	insufficient welding seal	seal parts no guaranteed	9	wrong parameters	1	check parameters and qualification process	3

Phase 8-CO_2 Welding							
No.	**Potential Failure Mode**	**Potential Effect of Failure**	$k = 1$	**Potential Causes**	$k = 2$	**Prevention**	$k = 3$
$i = 60$	weld with many holes	scrapped part	8	lack of weld gas	2	regular check of gas level	3
$i = 61$	dimension welding	seal parts no guaranteed	8	wrong program	2	check robot program	3

Table 2. The weighted normalized decision matrix

	$k = 1$	$k = 2$	$k = 3$		$k = 1$	$k = 2$	$k = 3$
$i = 1$	0.575	0.656	0.872	$i = 32$	0.953	0.569	0.835
$i = 2$	0.849	0.569	0.835	$i = 33$	0.953	0.569	0.835
$i = 3$	0.953	0.463	0.872	$i = 34$	0.953	0.569	0.835
$i = 4$	0.902	0.463	0.835	$i = 35$	0.953	0.569	0.708
$i = 5$	0.953	0.569	0.872	$i = 36$	0.849	0.463	0.786
$i = 6$	0.953	0.569	0.872	$i = 37$	0.902	0.569	0.708
$i = 7$	0.953	0.656	0.835	$i = 38$	0.791	0.785	0.708
$i = 8$	0.849	0.569	0.786	$i = 39$	0.953	0.569	0.835
$i = 9$	0.656	0.463	0.835	$i = 40$	0.953	0.656	0.835
$i = 10$	0.849	0.656	0.872	$i = 41$	0.953	0.569	0.835
$i = 11$	0.902	0.569	0.835	$i = 42$	0.953	0.463	0.835
$i = 12$	0.849	0.569	0.835	$i = 43$	0.953	0.569	0.835
$i = 13$	0.849	0.569	0.835	$i = 44$	0.953	0.569	0.835
$i = 14$	0.727	0.569	0.835	$i = 45$	0.953	0.569	0.835
$i = 15$	0.953	0.569	0.872	$i = 46$	0.953	0.656	0.835
$i = 16$	0.849	0.569	0.835	$i = 47$	0.953	0.569	0.835
$i = 17$	0.849	0.463	0.786	$i = 48$	0.953	0.463	0.835
$i = 18$	0.849	0.569	0.708	$i = 49$	0.953	0.569	0.835
$i = 19$	0.791	0.785	0.708	$i = 50$	0.953	0.569	0.835
$i = 20$	0.791	0.569	0.872	$i = 51$	0.953	0.569	0.835
$i = 21$	0.953	0.569	0.835	$i = 52$	0.849	0.569	0.786
$i = 22$	0.953	0.656	0.835	$i = 53$	0.849	0.463	0.786
$i = 23$	0.953	0.569	0.835	$i = 54$	0.902	0.569	0.786
$i = 24$	0.953	0.463	0.835	$i = 55$	0.791	0.785	0.708
$i = 25$	0.953	0.569	0.835	$i = 56$	0.953	0.569	0.835
$i = 26$	0.953	0.569	0.835	$i = 57$	0.953	0.656	0.708
$i = 27$	0.953	0.656	0.835	$i = 58$	0.953	0.569	0.835
$i = 28$	0.953	0.569	0.835	$i = 59$	0.953	0.463	0.835
$i = 29$	0.953	0.656	0.835	$i = 60$	0.902	0.569	0.835
$i = 30$	0.953	0.569	0.835	$i = 61$	0.902	0.569	0.835
$i = 31$	0.953	0.463	0.835				

In Figure 2, as an illustrative example, the 'torch not heated' failure (i=3) is shown, which affects the mechanical characteristics of the material and can cause the failure of the entire assembly.

By applying the proposed Algorithm (Step 2 to Step 3 of the proposed Algorithm), the weighted normalized decision matrix is constructed and presented in Table 2.

Matrix V (Step 4 of the proposed Algorithm) is presented in Table 3.

The column matrix is calculated using the geometric mean (Step 5 of the proposed Algorithm):

$$[1.36, \quad 0.92, \quad 0.97]$$

By applying the proposed Algorithm (Step 6 to Step 7), the set of failures belonging to G^+ was determined. These failures have a significant impact on reducing the effectiveness of the manufacturing process.

Based on the obtained results, it can be clearly concluded that 28 failures belong to G^-, which constitutes 46% of the total number of identified failures in the FMEA report. These failures have almost no impact on the effectiveness of the manufacturing process, so the FMEA team does not need to allocate resources for their elimination.

(a)

(b)

Figure 2. Realization of failure (i=3)

In accordance with the rules defined in the conventional MABAC, the failures that belong to G^+ can be divided into two groups in this research. The first group of failures, presented in Table 4, has the greatest impact on the effectiveness of the manufacturing process. The order of implementing the corresponding management activities corresponds to the obtained rank.

If the FMEA team has a sufficient budget, they can take appropriate measures to eliminate failures that have a medium impact on the effectiveness of the manufacturing process. The order of implementing these activities corresponds to the obtained rank, as presented in Table 5.

The following section provides explanations and a discussion of the obtained results.

3.3 Discussion

By using the proposed methodology, all identified failures in the manufacturing process of the considered automotive company are classified into two groups with respect to the RFs defined in conventional FMEA and their weights. The first group includes failures with the greatest importance for the effectiveness and reliability of the manufacturing process, which in turn impacts the overall business performance of the company. The FMEA team can address failures in the second group if there is sufficient budget available.

The obtained results can be compared with IT2FMADM integrated into the FMEA framework [2, 13, 26, 36]. The proposed models allow for ranking all identified failures. This way, priorities for addressing failures and the sequence of management actions required for their elimination are determined. The main drawback of these models is that the FMEA team cannot precisely determine how many failures need to be eliminated.

In the enhanced FMEA [37], identified failures are classified into three groups. Failures with a high impact are given equal priority, and the order of elimination within this group is based on the subjective assessment of the FMEA team. Compared to the enhanced FMEA [26, 37], the proposed model is superior as it precisely determines the priority of failures in the first group.

Table 3. The matrix V

	$k=1$	$k=2$	$k=3$		$k=1$	$k=2$	$k=3$
$i=1$	1.035	1.006	1.022	$i=32$	1.413	0.919	0.985
$i=2$	1.309	0.919	0.985	$i=33$	1.413	0.919	0.985
$i=3$	1.413	0.764	1.022	$i=34$	1.413	0.919	0.985
$i=4$	1.362	0.764	0.985	$i=35$	1.413	0.919	0.858
$i=5$	1.413	0.919	1.022	$i=36$	1.309	0.813	0.936
$i=6$	1.413	0.919	1.022	$i=37$	1.362	0.919	0.858
$i=7$	1.413	1.006	0.985	$i=38$	1.251	1.135	0.858
$i=8$	1.309	0.919	0.936	$i=39$	1.413	0.919	0.985
$i=9$	1.116	0.813	0.985	$i=40$	1.413	1.006	0.985
$i=10$	1.309	1.006	1.022	$i=41$	1.413	0.919	0.985
$i=11$	1.362	0.919	0.985	$i=42$	1.413	0.813	0.985
$i=12$	1.309	0.919	0.985	$i=43$	1.413	0.919	0.985
$i=13$	1.309	0.919	0.985	$i=44$	1.413	0.919	0.985
$i=14$	1.187	0.919	0.985	$i=45$	1.413	0.919	0.985
$i=15$	1.413	0.919	1.022	$i=46$	1.413	1.006	0.985
$i=16$	1.309	0.919	0.985	$i=47$	1.413	0.919	0.985
$i=17$	1.309	0.813	0.936	$i=48$	1.413	0.813	0.985
$i=18$	1.309	0.919	0.858	$i=49$	1.413	0.919	0.985
$i=19$	1.251	1.135	0.858	$i=50$	1.413	0.919	0.985
$i=20$	1.251	0.919	1.022	$i=51$	1.413	0.919	0.985
$i=21$	1.413	0.919	0.985	$i=52$	1.309	0.919	0.936
$i=22$	1.413	1.006	0.985	$i=53$	1.309	0.813	0.936
$i=23$	1.413	0.919	0.985	$i=54$	1.362	0.919	0.936
$i=24$	1.413	0.813	0.985	$i=55$	1.251	1.135	0.858
$i=25$	1.413	0.919	0.985	$i=56$	1.413	0.919	0.985
$i=26$	1.413	0.919	0.985	$i=57$	1.413	1.006	0.858
$i=27$	1.413	1.006	0.985	$i=58$	1.413	0.919	0.985
$i=28$	1.413	0.919	0.985	$i=59$	1.413	0.813	0.985
$i=29$	1.413	1.006	0.985	$i=60$	1.362	0.919	0.985
$i=30$	1.413	0.919	0.985	$i=61$	1.362	0.919	0.985
$i=31$	1.413	0.813	0.985				

Table 4. Rang of failures which have the most significant impact to effectiveness of manufacturing process

Failures	S_i	Rank	Failures	S_i	Rank
$i=7$	0.154	1-6	$i=46$	0.154	1-6
$i=22$	0.154	1-6	$i=5$	0.104	7-9
$i=27$	0.154	1-6	$i=6$	0.104	7-9
$i=29$	0.154	1-6	$i=15$	0.104	7-9
$i=40$	0.154	1-6			

It should be underlined that the FMEA team must first address the following failures: $(i=7)$, $(i=22)$, $(i=27)$, $(i=29)$, $(i=40)$ and $(i=46)$. Failures that are ranked second and should also be eliminated include: $(i=5)$, $(i=6)$, $(i=15)$.

As emphasized, if the FMEA team has a sufficient budget, they can undertake appropriate management measures to eliminate the failures listed in Table 5.

Based on this analysis, three categories of failures can be distinguished. The first category includes failures with a high impact on the reliability of the manufacturing process, the second encompasses those with a medium (moderate) impact, while the third consists of failures with low or negligible impact. Their distribution is presented in Figure 3.

Failures that belong to the second group have a nearly negligible impact on the effectiveness and reliability of the manufacturing process. Therefore, the FMEA team should not consider them when deciding on the management measures to be taken. This approach simplifies, speeds up, and significantly enhances the decision-making process.

Table 5. Rang of failures which have the impact to effectiveness of manufacturing process

Failures	S_i	**Rank**	**Failures**	S_i	**Rank**
$i = 10$	0.087	10	$i = 43$	0.067	11-29
$i = 21$	0.067	11-29	$i = 44$	0.067	11-29
$i = 23$	0.067	11-29	$i = 45$	0.067	11-29
$i = 25$	0.067	11-29	$i = 47$	0.067	11-29
$i = 26$	0.067	11-29	$i = 49$	0.067	11-29
$i = 28$	0.067	11-29	$i = 50$	0.067	11-29
$i = 30$	0.067	11-29	$i = 51$	0.067	11-29
$i = 32$	0.067	11-29	$i = 56$	0.067	11-29
$i = 33$	0.067	11-29	$i = 57$	0.027	30
$i = 34$	0.067	11-29	$i = 11$	0.016	31-33
$i = 39$	0.067	11-29	$i = 60$	0.016	31-33
$i = 41$	0.067	11-29	$i = 61$	0.016	31-33

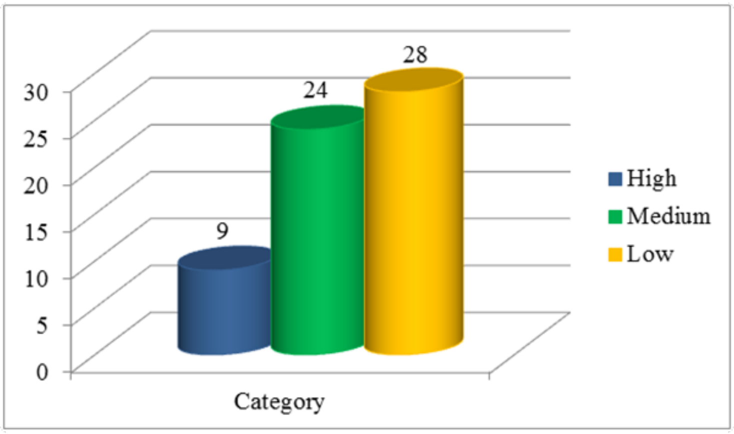

Figure 3. Categories of failures

4 Conclusions

This research proposes a fuzzy two-stage model that integrates IT2FDEMATEL and MABAC. The application of this model is intended to classify and rank failures in a type 2 fuzzy environment and provide a basis for defining management actions aimed at improving manufacturing process reliability.

The proposed model has been tested and verified using failures identified in real automotive companies. The fuzzy rating of the internal impact of RFs is conducted by the DMs based on their experience and literature data.

The main contributions of the presented research are:

(1) Modelling of uncertain internal impacts of RFs is performed using IT2TFNs.

(2) Determination of RF weights is addressed as a fuzzy group decision-making problem.

(3) The weights vector for RFs is determined using the proposed IT2FDEMATEL method.

(4) Failures are classified and ranked using the proposed MABAC method, effectively addressing the limitations associated with traditional approximation methods.

The practical implications of the proposed methodology are aimed at assisting the FMEA team in classifying failures and determining priority actions for addressing the identified issues. This approach helps streamline the decision-making process and enhances the effectiveness of management actions. The methodology identifies which failures need urgent attention, considering the potential costs associated with halting the manufacturing process.

The main advantage of the proposed fuzzy two-stage model over existing models that combine FMEA, type 2 fuzzy sets theory, and MADM is its ability to define the set of failures with the highest importance and prioritize the management measures needed to eliminate them. This approach allows the FMEA team to make decisions based on data obtained in a precise manner, significantly increasing accuracy.

The main limitations of the hybrid model are: (1) the subjectivity in determining the weights of RFs used to evaluate identified failures, and (2) the increased computational complexity compared to the improved FMEA [37]. Future research should focus on developing a software solution to facilitate the user-friendly application of the proposed fuzzy two-stage model.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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