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Neutrosophic Failure Mode and Effect Analysis—Elimination and Choice Translating Reality Method for Prioritizing Failure Modes

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Abstract: Operations managers and engineers in the automotive industry confront the key challenge in ensuring the reliability of the manufacturing process. To accurately classify failure modes, this study proposed a novel Multi-Criteria Decision-Making (MCDM) model integrated with Single-Valued Neutrosophic Sets (SVNSs) for operations management to prioritize actions in eliminating failure modes that had the greatest impact on the concerned reliability. The identification and evaluation of failure modes were grounded in the conventional Failure Mode and Effect Analysis (FMEA), while the relative importance of risk factors (RFs) was expressed through predefined linguistic terms modelled with the SVNSs. The assessment of these risk factors was formulated as a fuzzy group decision-making problem and the fuzzy weight vector was derived from the Order Weighted Averaging (OWA) operator. Failure rankings were conducted through a modified version of the Elimination and Choice Translating Reality (ELECTRE) method; being tested and validated with real-world data from an automotive company, the proposed FMEA-ELECTRE model could inspire stakeholders in various industries to explore this scientific contribution further.

Keywords: Automotive industry; SVNSs; FMEA; OWA operator; ELECTRE

1 Introduction

In the automotive industry, substantial income is generated to exert significant influence in nearly all the economic sectors of the country where the considered company operates and connects with others. To achieve competitive advantages in the uncertain global market in the long term, manufacturers in the automotive industry have to ensure high reliability of the manufacturing process. In practice, for the identification and elimination of failure modes occurring in the manufacturing process, the most commonly used method is Failure Mode and Effect Analysis (FMEA) [1, 2], which is prescribed by the International Automotive Task Force (IATF) 16949 standard [3]. In the conventional FMEA, the identified failure modes are evaluated with respect to three risk factors (RFs): the severity, the occurrence of failure realization, and the difficulty of failure detection. The values of these RFs are assessed by the FMEA team with a standard measurement scale defined as the interval between ten and ten. The rank of failure modes is determined on the basis of Risk Priority Number (RPN), calculated using the prescribed mathematical formulation. In the relevant literature, many authors have discussed the disadvantages of the conventional FMEA [4, 5].

Numerous studies in the literature have proposed approaches that combine the FMEA, Multi-Criteria Decision-Making methods (MCDM) [6], and fuzzy sets theory [7–9] in order to overcome the shortcomings of the conventional FMEA method. In addition to classical fuzzy numbers and type-2 fuzzy numbers, one of the approaches for modeling uncertainty is the application of the Intuitionistic Fuzzy Sets (IFSs) [10, 11]. The literature contains numerous concepts inspired by the IFSs. For instance, Smarandache [12, 13] proposed the neutrosophic sets (NSs), which include three functions: independent indeterminacy-membership inspired by the IFSs, i.e., decision makers (DMs) use truth membership $T(x)$, indeterminacy-membership $I(x)$, and falsity membership $F(x)$ to express the judgments on a given object. It should be emphasised that these three functions in the NSs are completely independent. In Wang et al. [14], various properties of the single-valued neutrosophic sets (SVNSs) were discussed and the sets were presented as a specific case of the NSs. It can be stated that the SVNSs are a very useful tool for characterizing evaluation information by the DMs regarding alternatives under indeterminate or inconsistent conditions. In this paper, the relative importance of the RFs was modelled using the SVNSs [15].

In this research, the authors assumed that the assessment of the relative importance of RFs should be formulated as a fuzzy group decision-making problem by analogy [8, 16, 17]. Having applied in this study, the aggregation of assessments into a single evaluation was performed by the Single-Valued Neutrosophic Weighted Averaging Operator (SVNWAO) as follows [18].

The ranking of failure modes was obtained by using a modified Elimination and Choice Translating Reality (French: ÉLimination Et Choix Traduisant la REalité; ELECTRE) [19] combined with the SVNSs. In the literature, studies proposing ELECTRE with SVNSs could be found [20], similar to this research. Tooranloo et al. [20] proposed a modification of ELECTRE which consists of: (i) modeling the relative importance of criteria and their values by the SVNSs; (ii) determining criteria weights and the fuzzy decision matrix as a fuzzy group decision-making problem; (iii) determining criteria weights based on fuzzy algebra rules [18]; applying crispification of the SVNSs following the procedures proposed by Biswas et al. [21]; (iv) constructing the aggregated fuzzy decision matrix with the neutrosophic weighted averaging operator; (v) proposing a procedure for determining the concordance and discordance sets; and (vi) calculating the values of the discordance matrix by applying the procedures proposed in the conventional ELECTRE and using normalized Euclidean distance [22].

Saini et al. [23] described the values of all existing uncertainties by Pythagorean Neutrosophic Fuzzy Sets (PNFS). The aggregated values of the fuzzy decision matrix were given by the Pythagorean Neutrosophic Weighted Aggregation Operator (PNWAO) in this paper. The normalization of the PNFS was performed according to the proposed procedure and the determination of the concordance set was carried out in accordance with the prescribed procedures. The discordance matrix was defined based on the procedures developed in conventional ELECTRE in combination with Euclidean distance [24].

The motivation for this research stems from the absence of studies integrating the FMEA, the ELECTRE, and the SVNSs. Assigning the same weight to the RFs, one of the shortcomings of the FMEA analysis [5], could be eliminated by the proposed model. Another shortcoming of the FMEA, is that the DMs could not easily express values using precise numbers. This paper overcame this issue by employing the SVNSs and the prioritization of failure modes was performed with the proposed ELECTRE with the SVNSs. Thus, the identified research gap was addressed in this study.

The broader objectives of this research could be summarized as follows: a) modeling existing uncertainties in the relative importance of the RFs using the SVNSs; b) stating the relative importance of the RFs as a fuzzy group decision-making problem and determining the RF weights by the Order Weighted Averaging (OWA) extended with the SVNSs; c) determining failure classes using the proposed SVNS-ELECTRE method; and d) defining management actions aimed at eliminating failure modes that have the greatest impact on the reliability of the manufacturing process, thereby improving its efficiency.

The paper is further organized as follows: Section 2 presents the basic definitions of the SVNSs. Section 3 describes the proposed methodology. A case study and results based on real-life data are provided in Section 4. The conclusions are presented in the final section.

2 Basic Definitions of the SVNSs

Neutrosophic sets originated from neutrosophy, a new branch of philosophy that reflects the origin, nature, and scope of neutralities, as well as their interactions with different ideational spectra [12, 13]. Modelling uncertainty and imprecision in real-world problems is based on the application of the SVNSs, which are a special case of the NS. The following sections provide some basic definitions, operations, and properties related to the SVNSs [14].

Definition 1. Let X be the universe of discourse, with a generic element $x \in X$. Then, neutrosophic set A in X is defined as follows: $A = \{x \mid x \in X\}$, where $T(x)$, $I(x)$ and $F(x)$ are the truth-membership function, the indeterminacy membership function, and the falsity-membership function, respectively. These functions are defined as $T(x), I(x), F(x) : X \to [0, 1]$ and $0 \leq T(x) + I(x) + F(x) \leq 3$ [12, 13].

The set $I(x)$ may represent not only indeterminacy but also vagueness, uncertainty, imprecision, error, contradiction, undefinedness, unknown, incompleteness, redundancy, and similar concepts [25]. To capture vague information more precisely, the indeterminacy-membership degree can be decomposed into subcomponents such as contradiction, uncertainty, and unknown [12].

Definition 2. Let X be the universe of discourse. The Single Valued Neutrosophic Set A over X is an object having the form: $A = \{x \mid x \in X\}$, $T(x)$, $I(x)$ and $F(x)$, where are the truth membership function, the intermediacy-membership function and the falsity-membership function, respectively, $T(x), I(x), F(x) : X \to [0, 1]$ and $0 \leq T(x) + I(x) + F(x) \leq 3$ [14]. A Single Valued Neutrosophic Set is represented by an ordered triplet $\langle T(x), I(x), F(x) \rangle$.

Definition 3. Let us two SVNSs, $\tilde{A} = \langle T_{\tilde{A}}(x), I_{\tilde{A}}(x), F_{\tilde{A}}(x)\rangle$ and $\tilde{B} = \langle T_{\tilde{B}}(x), I_{\tilde{B}}(x), F_{\tilde{B}}(x)\rangle$. The following set of operations as given [14]:

- $\tilde{A} \subseteq \tilde{B}$ if and only if $T_{\tilde{A}}(x) \leq T_{\tilde{B}}(x),\ I_{\tilde{A}}(x) \geq I_{\tilde{B}}(x),\ F_{\tilde{A}}(x) \geq F_{\tilde{B}}(x)$ for all $x \in X$.
- $\tilde{A} = \tilde{B}$ if and only if $\tilde{A} \subseteq \tilde{B}$ and $\tilde{B} \subseteq \tilde{A}$ for all $x \in X$.

$$\tilde{A}^c = \langle T_{\tilde{A}}(x), 1 - I_{\tilde{A}}(x), F_{\tilde{A}}(x)\rangle \tag{1}$$

$$\tilde{A} \cup \tilde{B} = \langle \max\left(T_{\tilde{A}}(x), T_{\tilde{B}}(x)\right), \min\left(I_{\tilde{A}}(x), I_{\tilde{B}}(x)\right), \min\left(F_{\tilde{A}}(x), F_{\tilde{B}}(x)\right)\rangle \tag{2}$$

$$\tilde{A} \cap \tilde{B} = \langle \min\left(T_{\tilde{A}}(x), T_{\tilde{B}}(x)\right), \max\left(I_{\tilde{A}}(x), I_{\tilde{B}}(x)\right), \max\left(F_{\tilde{A}}(x), F_{\tilde{B}}(x)\right)\rangle \tag{3}$$

Definition 4. Let us two SVNSs, $\tilde{A} = \langle T_{\tilde{A}}(x), I_{\tilde{A}}(x), F_{\tilde{A}}(x)\rangle$ and $\tilde{B} = \langle T_{\tilde{B}}(x), I_{\tilde{B}}(x), F_{\tilde{B}}(x)\rangle$. The following set of operations as given [17]:

$$\tilde{A} + \tilde{B} = \langle T_{\tilde{A}}(x) + T_{\tilde{B}}(x) - T_{\tilde{A}}(x) \cdot T_{\tilde{B}}(x), I_{\tilde{A}}(x) \cdot I_{\tilde{B}}(x), F_{\tilde{A}}(x) \cdot F_{\tilde{B}}(x)\rangle \tag{4}$$

$$\tilde{A} \cdot \tilde{B} = \langle T_{\tilde{A}}(x) \cdot T_{\tilde{B}}(x), I_{\tilde{A}}(x) + I_{\tilde{B}}(x) - I_{\tilde{A}}(x) \cdot I_{\tilde{B}}(x), F_{\tilde{A}}(x) + F_{\tilde{B}}(x) - F_{\tilde{A}}(x) \cdot F_{\tilde{B}}(x)\rangle \tag{5}$$

$$\lambda \cdot \tilde{A} = \left\langle 1 - \left(1 - T_{\tilde{A}}(x)\right)^{\lambda}, \left(I_{\tilde{A}}(x)\right)^{\lambda}, \left(F_{\tilde{A}}(x)\right)^{\lambda} \right\rangle \tag{6}$$

$$(\tilde{A})^{\lambda} = \left\langle \left(T_{\tilde{A}}(x)\right)^{\lambda}, 1 - \left(1 - I_{\tilde{A}}(x)\right)^{\lambda}, 1 - \left(1 - F_{\tilde{A}}(x)\right)^{\lambda} \right\rangle \tag{7}$$

Definition 5. Let us two SVNSs, $\tilde{A} = \langle T_{\tilde{A}}(x_i), I_{\tilde{A}}(x_i), F_{\tilde{A}}(x_i)\rangle$ and $\tilde{B} = \langle T_{\tilde{B}}(x_i), I_{\tilde{B}}(x_i), F_{\tilde{B}}(x_i)\rangle$. Hamming distances between the SVNSs is given by [22]:

$$d = \frac{1}{3} \cdot \sum_{i=1,\ldots,n} \left|T_{\tilde{A}}(x_i) - T_{\tilde{B}}(x_i)\right| + \left|I_{\tilde{A}}(x_i) - I_{\tilde{B}}(x_i)\right| + \left|F_{\tilde{A}}(x_i) - F_{\tilde{B}}(x_i)\right| \tag{8}$$

Definition 6. Let us Single Valued Neutrosophic Set $\tilde{A} = \langle T_{\tilde{A}}(x_i), I_{\tilde{A}}(x_i), F_{\tilde{A}}(x_i)\rangle$. The representative scalar of Single Valued Neutrosophic Set $\tilde{A}$, A is given by [18]:

$$A = \frac{T_{\tilde{A}}(x_i) + I_{\tilde{A}}(x_i) - F_{\tilde{A}}(x_i) + 1}{3} \tag{9}$$

3 Methodology

The proposed model, which integrated the FMEA framework, the ELECTRE, and the SVNSs for failure estimation and classification, is shown in Figure 1.

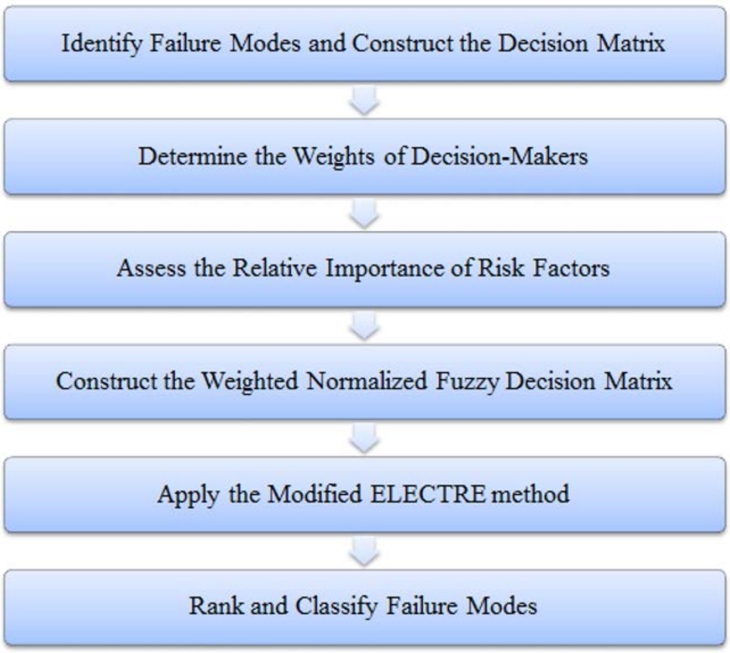

Figure 1. The proposed model

A detailed explanation of the proposed methodology was provided in the following sections. All steps were thoroughly explained and supported by appropriate formulas and rules. Figure 1 presents a simplified and general overview of the proposed model.

3.1 Identified Failure Modes

Generally, the identified failure modes can be represented by a set of indices $\{1, \ldots, i, \ldots, I\}$, where I presents the total number of failure modes, and the index of each failure is denoted as $i,\ i = 1, \ldots, I$.

In this research, the failure modes identified in the FMEA report of the logistics inspection and labeling process of the considered automotive company are taken into account. These failure modes include: material damage $(i = 1)$, presence of deformations $(i = 2)$, presence of oxide $(i = 3)$, presence of sharp edges $(i = 4)$, excessive burrs in slots or holes $(i = 5)$, dimensional deviation $(i = 6)$, incorrect part orientation $(i = 7)$, surface scratches $(i = 8)$, lack of deburring $(i = 9)$, incorrect welding position $(i = 10)$, weld splatter presence $(i = 11)$, incomplete welds $(i = 12)$, overheating during welding $(i = 13)$, part misalignment before welding $(i = 14)$, insufficient penetration in weld $(i = 15)$, missing component $(i = 16)$, wrong component assembled $(i = 17)$, oil or grease contamination $(i = 18)$, crack formation $(i = 19)$, wrong hole diameter $(i = 20)$, excessive part thickness variation $(i = 21)$, wrong label or marking $(i = 22)$ and incorrect threading $(i = 23)$.

3.2 Considered Risk Factors

The set of the RFs used to evaluate the failure modes can be represented by a set of indices $\{1, \ldots, k, \ldots, K\}$. The total number of the RFs is denoted as K, and each risk factor (RF) is indexed by $k,\ k = 1, \ldots, K$, as in this research. In the conventional FMEA, three RFs were defined: severity $(k = 1)$, occurrence $(k = 2)$, and detection capability $(k = 3)$. These RFs were also used in this study.

3.3 Decision Makers (DMs) and Evaluation Approaches

For the purpose of this research, data obtained from the FMEA report prepared by the FMEA team were used. The assessment of the importance of the RFs was conducted by surveying three DMs: the FMEA facilitator $(e = 1)$, the production manager $(e = 2)$, and the quality manager $(e = 3)$ from the considered company.

In the relevant literature, many papers proposed linguistic rating systems that included various measurement scales [7–9]. In this research, the relative importance of RFs could be adequately assessed using a three-point scale. These predefined linguistic expressions were modeled by the SVNSs:

- Low importance $(L1)$: $\langle 0.05, 0.75, 0.9\rangle$
- Medium importance $(L2)$: $\langle 0.5, 0.4, 0.45\rangle$
- High importance $(L3)$: $\langle 0.95, 0.3, 0.15\rangle$

The domain values of these SVNSs were defined on the real line within the interval from zero to one. A value of zero or one indicates that the relative importance of the RFs is the smallest or largest, respectively.

3.4 Proposed Algorithm

In practice, the DMs do not have equal importance. In this case, the assessment was conducted by the company's CEO and two members of the FMEA team. In this way, the reputation, knowledge, and experience of the DMs were taken into account in the decision-making process.

Considering this fact, it is assumed that the determination of DM weights should be formulated as a fuzzy group decision-making problem. The relative importance of each DM is described by a predefined linguistic expression, which is modelled by the SVNSs. The weights of the DMs, Ψ_e, are determined using the procedures proposed by Biswas et al. [16]:

$$\Psi_e = \frac{1 - \sqrt{(1 - T_e(x))^2 + (I_e(x))^2 + (F_e(x))^2}}{\sum\limits_{e=1,\ldots,E} \left(1 - \sqrt{\frac{(1-T_e(x))^2 + (I_e(x))^2 + (F_e(x))^2}{3}}\right)} \tag{10}$$

The aggregation of DMs' assessments into a single evaluation of weights of RFs, $\tilde{\omega}_k,\ k = 1, \ldots, K$ is determined by the SVNWAO [16]:

$$\tilde{\omega}_k = \left\langle \left(1 - \prod_{e=1,\ldots,E} \left(1 - T_k^e(x)\right)^{\Psi_e}\right), \prod_{e=1,\ldots,E} \left(I_k^e\right)^{\Psi_e}, \prod_{e=1,\ldots,E} \left(F_k^e\right)^{\Psi_e} \right\rangle \tag{11}$$

The algorithm of the proposed SVNS-ELECTRE method was executed through the following steps:

Step 1. Define the decision matrix:

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

It should be noted that the values of the decision matrix are taken from the FMEA report. These values are crisp.
Step 2. Construct the normalized decision matrix:

$$[r_{ik}]_{I\times K} \tag{13}$$

$$r_{ik} = \frac{x_{ik}}{\sum\limits_{i=1,\dots,I} x_{ik}} \tag{14}$$

Step 3. Construct the weighted normalized fuzzy decision matrix:

$$[\tilde{z}_{ik}]_{I\times K} \tag{15}$$

$$\tilde{z}_{ik} = \tilde{\omega}_k \cdot x_{ik} \tag{16}$$

Step 4. Construct the concordance set, $\mathcal{S}_{ik}$, and discordance set, $\mathcal{NS}_{ik}$, according to the rules defined in the conventional ELECTRE:

$$\begin{array}{ll} \operatorname{defuzz}(\tilde{z}_{ik}) \geq \operatorname{defuzz}(\tilde{z}_{i'k}) \rightarrow & k \in \mathcal{S}_{ii'} \\ \operatorname{defuzz}(\tilde{z}_{ik}) < \operatorname{defuzz}(\tilde{z}_{i'k}) \rightarrow & k \in \mathcal{NS}_{ii'} \end{array} \tag{17}$$

Step 5. Determine the concordance matrix according to the conventional ELECTRE procedure combined with fuzzy algebra rules:

$$[c_{ii'}]_{I\times I} \tag{18}$$

$$c_{ii'} = \operatorname{defuzz}\left(\sum_{k=1,\dots K',} \tilde{\omega}_k\right) k \in S_{ii'} \tag{19}$$

$$\gamma = \frac{1}{I\cdot(I-1)} \cdot \sum_{i=1,\dots,I} \sum_{i'=1,\dots,I} c_{ii'} \tag{20}$$

Step 6. Construct the discordance matrix:

$$[n_{ii'}]_{I\times I} \tag{21}$$

$$n_{ii'} = \frac{\max\limits_{k\in \mathrm{NS}_{ii'}} d(\tilde{z}_{ik}, \tilde{z}_{i'k})}{\max\limits_{k=1,\dots,K} d(\tilde{z}_{ik}, \tilde{z}_{ik'})} \tag{22}$$

Here, $d(\tilde{z}_{ik}, \tilde{z}_{ik'})$ denotes the Hamming distance [22].
The discordance threshold is:

$$\eta = \frac{1}{I\cdot(I-1)} \cdot \sum_{i=1,\dots,I} \sum_{i'=1,\dots,I} n_{ii'} \tag{23}$$

Step 7. Construct the concordance dominance matrix:

$$[m_{ii'}]_{I\times I} \tag{24}$$

$$m_{ii'} = \begin{cases} 1 & c_{ii'} \geq \gamma \wedge n_{ii'} < \eta \\ 0 & c_{ii'} < \gamma \vee n_{ii'} > \eta \end{cases} \tag{25}$$

Step 8. Failure classes were determined based on the concordance dominance matrix. The priority of management initiatives was defined according to the obtained results.

4 Results

The developed model was tested using data obtained from the business process of a manufacturing company engaged in the production of metal components within the automotive supply chain. The identified failure modes being considered in this study were detected in the phase of material reception services, referred to as logistic inspection and labeling, in the business process,. The relative importance of the RFs was assessed by applying the interview method.

4.1 Determination of Risk Factor Weights

The relative importance of the DMs was described using predefined linguistic expressions. The weight of the first DM, based on the evaluations $L2$, $L3$ and $L1$, is:

$$\Psi_1 = \frac{1-\sqrt{\frac{(1-0.5)^2+(0.4)^2+(0.45)^2}{3}}}{1-\sqrt{\frac{(1-0.1)^2+(0.75)^2+(0.9)^2}{3}}+1-\sqrt{\frac{(1-0.5)^2+(0.4)^2+(0.45)^2}{3}}+1-\sqrt{\frac{(1-0.05)^2+(0.2)^2+(0.05)^2}{3}}} = 0.35$$

In a similar manner, the weights of the remaining two DMs were calculated, so that: $\Psi_2 = 0.56$; $\Psi_3 = 0.08$. It should be noted that these DM weights were obtained solely for the considered case study. The assessment of the relative importance of the RFs is presented in Table 1.

Table 1. The assessed relative importance of the RFs

e	$k=1$	$k=2$	$k=3$
$e=1$	$L3$	$L2$	$L2$
$e=2$	$L2$	$L2$	$L2$
$e=3$	$L3$	$L3$	$L1$

The weight value of the third criterion was obtained by applying the SVNWAO [16]:

$$\tilde{\omega}_1 = \langle 0.82, 0.30, 0.26\rangle \quad \tilde{\omega}_2 = \langle 0.58, 0.39, 0.42\rangle \quad \tilde{\omega}_3 = \langle 0.47, 0.43, 0.48\rangle$$

Table 2. The decision matrix

i	$k=1$	$k=2$	$k=3$	i	$k=1$	$k=3$	$k=3$
$i=1$	8	4	3	$i=13$	8	1	2
$i=2$	7	4	4	$i=14$	8	2	3
$i=3$	6	5	4	$i=15$	9	1	2
$i=4$	5	3	6	$i=16$	10	2	4
$i=5$	6	3	5	$i=17$	9	2	5
$i=6$	8	4	6	$i=18$	6	3	4
$i=7$	7	3	2	$i=19$	9	3	4
$i=8$	4	5	3	$i=20$	8	3	5
$i=9$	5	4	5	$i=21$	7	3	5
$i=10$	9	1	2	$i=22$	5	2	3
$i=11$	7	2	3	$i=23$	8	2	6
$i=12$	9	1	2				

Table 3. The weighted normalized fuzzy decision matrix

i	$k=1$	$k=2$	$k=3$
$i=1$	$\langle 0.082, 0.942, 0.935\rangle$	$\langle 0.054, 0.942, 0.946\rangle$	$\langle 0.021, 0.972, 0.975\rangle$
$i=2$	$\langle 0.069, 0.951, 0.945\rangle$	$\langle 0.054, 0.942, 0.946\rangle$	$\langle 0.028, 0.962, 0.967\rangle$
$i=3$	$\langle 0.060, 0.958, 0.953\rangle$	$\langle 0.067, 0.928, 0.933\rangle$	$\langle 0.028, 0.962, 0.967\rangle$
$i=4$	$\langle 0.060, 0.958, 0.953\rangle$	$\langle 0.040, 0.956, 0.959\rangle$	$\langle 0.042, 0.944, 0.951\rangle$
$i=5$	$\langle 0.060, 0.958, 0.953\rangle$	$\langle 0.040, 0.956, 0.959\rangle$	$\langle 0.035, 0.953, 0.959\rangle$
$i=6$	$\langle 0.082, 0.942, 0.935\rangle$	$\langle 0.054, 0.942, 0.946\rangle$	$\langle 0.042, 0.944, 0.951\rangle$
$i=7$	$\langle 0.050, 0.965, 0.961\rangle$	$\langle 0.040, 0.956, 0.959\rangle$	$\langle 0.014, 0.981, 0.983\rangle$
$i=8$	$\langle 0.040, 0.972, 0.968\rangle$	$\langle 0.067, 0.928, 0.933\rangle$	$\langle 0.021, 0.972, 0.975\rangle$
$i=9$	$\langle 0.050, 0.965, 0.961\rangle$	$\langle 0.054, 0.942, 0.946\rangle$	$\langle 0.035, 0.953, 0.959\rangle$
$i=10$	$\langle 0.088, 0.938, 0.930\rangle$	$\langle 0.014, 0.985, 0.986\rangle$	$\langle 0.014, 0.981, 0.983\rangle$
$i=11$	$\langle 0.069, 0.951, 0.945\rangle$	$\langle 0.027, 0.971, 0.973\rangle$	$\langle 0.021, 0.972, 0.975\rangle$
$i=12$	$\langle 0.088, 0.938, 0.930\rangle$	$\langle 0.014, 0.985, 0.986\rangle$	$\langle 0.014, 0.981, 0.983\rangle$
$i=13$	$\langle 0.082, 0.942, 0.935\rangle$	$\langle 0.014, 0.985, 0.986\rangle$	$\langle 0.014, 0.981, 0.983\rangle$
$i=14$	$\langle 0.082, 0.942, 0.935\rangle$	$\langle 0.027, 0.971, 0.973\rangle$	$\langle 0.021, 0.972, 0.975\rangle$
$i=15$	$\langle 0.088, 0.938, 0.930\rangle$	$\langle 0.014, 0.985, 0.986\rangle$	$\langle 0.014, 0.981, 0.983\rangle$
$i=16$	$\langle 0.097, 0.931, 0.923\rangle$	$\langle 0.027, 0.971, 0.973\rangle$	$\langle 0.028, 0.962, 0.967\rangle$
$i=17$	$\langle 0.088, 0.938, 0.930\rangle$	$\langle 0.027, 0.971, 0.973\rangle$	$\langle 0.035, 0.953, 0.959\rangle$
$i=18$	$\langle 0.060, 0.958, 0.953\rangle$	$\langle 0.040, 0.956, 0.959\rangle$	$\langle 0.028, 0.962, 0.967\rangle$
$i=19$	$\langle 0.088, 0.938, 0.930\rangle$	$\langle 0.040, 0.956, 0.959\rangle$	$\langle 0.028, 0.962, 0.967\rangle$
$i=20$	$\langle 0.082, 0.942, 0.935\rangle$	$\langle 0.040, 0.956, 0.959\rangle$	$\langle 0.035, 0.953, 0.959\rangle$
$i=21$	$\langle 0.069, 0.951, 0.945\rangle$	$\langle 0.040, 0.956, 0.959\rangle$	$\langle 0.035, 0.953, 0.959\rangle$
$i=22$	$\langle 0.050, 0.965, 0.961\rangle$	$\langle 0.027, 0.971, 0.973\rangle$	$\langle 0.021, 0.972, 0.975\rangle$
$i=23$	$\langle 0.082, 0.942, 0.935\rangle$	$\langle 0.027, 0.971, 0.973\rangle$	$\langle 0.042, 0.944, 0.951\rangle$

4.2 Application of the SVNS-ELECTRE

The decision matrix, described in Step 1 of the proposed algorithm, was constructed based on the FMEA report of the considered automotive company, as presented in Table 2.

By applying the proposed algorithm from Step 2 to Step 3, the weighted normalized fuzzy decision matrix is constructed and presented in Table 3.

After determining the concordance and discordance sets (not presented here due to space limitations), the concordance matrix in Table 4 and the discordance matrix in Table 5 were obtained, in accordance with Steps 4 to 6 of the proposed algorithm.

Table 4. The concordance matrix

	$i=1$	$i=2$	$i=3$	$i=4$	$i=5$	$i=6$	$i=7$	$i=8$	$i=9$	$i=10$	$i=11$	$i=12$
$i=1$	–	0.643	0.620	0.643	0.643	0.643	0.643	0.620	0.653	0.582	0.653	0.582
$i=2$	0.582	–	0.653	0.643	0.643	0.517	0.653	0.636	0.643	0.473	0.653	0.582
$i=3$	0.582	0.473	–	0.643	0.643	0.517	0.582	0.653	0.653	0.636	0.636	0.636
$i=4$	0.473	0.473	0.473	–	0.582	0.473	0.582	0.636	0.653	0.473	0.473	0.473
$i=5$	0.473	0.473	0.636	0.636	–	0	0.582	0.636	0.636	0.582	0.582	0.582
$i=6$	0.653	0.653	0.636	0.653	0.653	–	0.653	0.636	0.653	0.582	0.653	0.582
$i=7$	0.517	0.620	0.620	0.643	0.643	0	–	0.620	0.620	0.582	0.643	0.582
$i=8$	0.582	0.517	0.517	0.517	0.517	0.517	0.582	–	0.582	0.517	0.582	0.582
$i=9$	0.582	0.582	0	0.643	0.636	0.517	0.582	0.620	–	0.653	0.653	0.653
$i=10$	0.620	0.643	0.620	0.643	0.620	0.620	0.636	0.636	0	–	0.620	0.653
$i=11$	0.473	0.620	0.620	0.582	0.620	0	0.636	0.636	0	0.582	–	0.473
$i=12$	0.620	0.620	0.620	0.643	0.620	0.620	0.636	0.620	0	0.653	0.643	–
$i=13$	0.620	0.620	0.620	0.643	0.620	0.620	0.636	0.620	0	0.582	0.643	0.582
$i=14$	0.636	0.620	0.620	0.643	0.620	0.620	0.636	0.636	0	0.582	0.653	0.582
$i=15$	0.620	0.620	0.620	0.643	0.620	0.620	0.636	0.620	0	0.653	0.653	0.653
$i=16$	0.636	0.636	0.636	0.643	0.620	0.620	0.636	0.636	0	0.653	0.653	0.653
$i=17$	0.636	0.636	0.636	0.643	0.636	0.620	0.636	0.636	0.473	0.653	0.653	0.653
$i=18$	0.473	0.473	0.636	0.643	0.643	0	0.582	0.636	0	0.653	0.582	0.582
$i=19$	0.636	0.636	0.636	0.643	0.643	0.620	0.653	0.636	0	0.653	0.653	0.653
$i=20$	0.636	0.636	0.636	0.643	0.653	0.620	0.653	0.636	0.473	0.653	0.653	0.582
$i=21$	0.473	0.636	0.636	0.643	0.653	0	0.653	0.636	0.473	0.653	0.653	0.582
$i=22$	0.636	0	0	0.643	0	0	0.473	0.636	0.620	0.653	0.582	0.582
$i=23$	0.636	0.636	0.636	0.653	0.636	0.636	0.636	0.636	0.473	0.653	0.653	0.582

	$i=13$	$i=14$	$i=15$	$i=16$	$i=17$	$i=18$	$i=19$	$i=20$	$i=21$	$i=22$	$i=23$
$i=1$	0.653	0.653	0.582	0.517	0.517	0.643	0.517	0.643	0.643	0.582	0.643
$i=2$	0.582	0.582	0.582	0.582	0.517	0.653	0.582	0.517	0.643	0.653	0.517
$i=3$	0.636	0.636	0.636	0.636	0.643	0.636	0.636	0.517	0.517	0.653	0.517
$i=4$	0.473	0.473	0.473	0.473	0.473	0.582	0.582	0.582	0.582	0.643	0.473
$i=5$	0.582	0.582	0.582	0.582	0.582	0.653	0.582	0.582	0.582	0.653	0.517
$i=6$	0.653	0.653	0.582	0.582	0.582	0.653	0.582	0.653	0.653	0.653	0.653
$i=7$	0.582	0.517	0.582	0.517	0.517	0.643	0.517	0.517	0.643	0.643	0.517
$i=8$	0.582	0.582	0.582	0.517	0.517	0.517	0.517	0.517	0.517	0.582	0.517
$i=9$	0.653	0.653	0.653	0.653	0.653	0.653	0.653	0.653	0.653	0.653	0.643
$i=10$	0.653	0.620	0.653	0	0.620	0	0.620	0	0	0	0
$i=11$	0.473	0.582	0	0.517	0.517	0.620	0	0	0.620	0.653	0.517
$i=12$	0.653	0.620	0.653	0	0.620	0.620	0.620	0.620	0.620	0.620	0.620
$i=13$	–	0.620	0.582	0	0	0.620	0	0.620	0.620	0.620	0.620
$i=14$	0.653	–	0.582	0.517	0.517	0.620	0	0.620	0.620	0.653	0.643
$i=15$	0.653	0.620	–	0	0.620	0.620	0.620	0.620	0.620	0.620	0.620
$i=16$	0.653	0.653	0.653	–	0.643	0.636	0.636	0.620	0.620	0.653	0.643
$i=17$	0.653	0.653	0.653	0.582	–	0.620	0.620	0.636	0.636	0.653	0.643
$i=18$	0.582	0.582	0.582	0.582	0.582	–	0.582	0.517	0.517	0.636	0
$i=19$	0.653	0.653	0.653	0.582	0.653	0.653	–	0.643	0.643	0.653	0.643
$i=20$	0.653	0.653	0.582	0.582	0.582	0.582	0.582	–	0.653	0.653	0.643
$i=21$	0.582	0.582	0.582	0.582	0.582	0.653	0.582	0.582	–	0.653	0.517
$i=22$	0.582	0.582	0.582	0.517	0.517	0.517	0	0	0	–	0.517
$i=23$	0.653	0.653	0.582	0.582	0.582	0.653	0.473	0.636	0.636	0.653	–

Table 5. The discordance matrix

	$i=1$	$i=2$	$i=3$	$i=4$	$i=5$	$i=6$	$i=7$	$i=8$	$i=9$	$i=10$	$i=11$	$i=12$
$i=1$	–	0.776	0.711	1	0.872	1	0.296	0.381	0.605	0.122	0	0.122
$i=2$	1	–	0	1	0.584	1	0	0.547	0.490	1	0	0.383
$i=3$	1	1	–	0.593	0.296	1	0.309	0	0	0.436	0.960	0.436
$i=4$	0.769	0.856	1	–	0	1	0.258	1	0	0.846	0.575	0.733
$i=5$	1	1	1	1	–	1	0.342	1	1	0.867	0.490	0.867
$i=6$	0	0	0.711	0	0	–	0	0.380	0	0.122	0	0.122
$i=7$	1	1	1	1	1	1	–	1	1	1	0.490	1
$i=8$	1	1	1	0.904	0.605	1	0.296	–	0.490	0.736	0.593	0.736
$i=9$	1	1	1	1	0.608	1	0	1	–	0	0	0
$i=10$	1	0.398	1	1	1	1	0.854	1	1	–	0.847	0
$i=11$	1	1	1	1	1	1	1	1	1	1	–	1
$i=12$	1	1	1	1	1	1	0.854	1	1	1	0.510	–
$i=13$	1	1	1	1	1	1	1	1	1	1	0.602	1
$i=14$	1	1	1	1	0.873	1	0.519	1	1	0.375	0	0.375
$i=15$	1	1	1	1	1	1	0.854	1	1	1	0	1
$i=16$	1	1	1	0.511	0.447	1	0.353	0.859	1	0	0	0
$i=17$	1	1	1	0.338	0.591	1	0.437	1	1	0	0	0
$i=18$	1	1	1	1	1	1	0.510	1	1	0	0	0.867
$i=19$	1	0.873	1	0.675	0.338	1	0	0.675	1	0	0	0
$i=20$	0.839	1	1	0.428	0	1	0	0.771	1	0	0	0.183
$i=21$	0.840	1	1	1	0	1	0.671	1	1	0	0	0.574
$i=22$	1	1	1	1	1	1	0	1	1	0	0	1
$i=23$	1	1	1	0	0.749	1	0.433	1	1	0	0	0.155

	$i=13$	$i=14$	$i=15$	$i=16$	$i=17$	$i=18$	$i=19$	$i=20$	$i=21$	$i=22$	$i=23$
$i=1$	0	0	0.122	0.458	0.590	0.446	0.608	1	1	0.972	0.877
$i=2$	0.383	0.386	0.383	0.841	0.567	0	1	0.781	0.584	0	0.578
$i=3$	0.344	0.456	0.436	0.763	0.195	0	0.852	0.693	0.296	0	0.693
$i=4$	0.846	0.769	0.733	1	1	0	1	1	1	0.575	1
$i=5$	0.684	1	0.867	1	1	0	1	1	1	0	1
$i=6$	0	0	0.122	0.458	0.181	0	0	0	0	0	0
$i=7$	0.988	1	1	1	1	1	1	1	1	0.571	1
$i=8$	0.644	0.854	0.736	1	0.976	0.605	1	1	0.901	0.195	0.854
$i=9$	0	0	0	0	0	0	0	0	0	0	0.289
$i=10$	0	1	0	1	1	1	1	1	1	1	1
$i=11$	1	1	1	1	1	1	1	1	1	1	1
$i=12$	0	1	0	1	1	1	1	1	1	0.417	1
$i=13$	–	1	1	1	1	1	1	1	1	0.493	1
$i=14$	0	–	0.360	1	1	0.749	1	1	1	0	1
$i=15$	0	1	–	1	1	1	1	1	1	0.416	1
$i=16$	0	0	0	–	1	0.447	1	1	0.343	0	1
$i=17$	0	0	0	0.962	–	0.591	1	1	0.892	0	0.571
$i=18$	0.684	1	0.867	1	1	–	1	1	1	1	1
$i=19$	0	0	0	0.550	0	0	–	1	0.511	0	1
$i=20$	0	0	0.183	0.905	0	0	0	–	0	0	0.579
$i=21$	0.392	0.653	0.573	1	1	0	1	1	–	0	0.787
$i=22$	1	1	1	1	1	0.595	1	1	1	–	1
$i=23$	0	0	0.155	0.794	1	0	0.875	1	1	0	–

Let us calculate the average value:

$$\gamma = \frac{1}{23 \cdot (23-1)} \cdot 283.251 = 0.560$$

$$\eta = \frac{1}{23 \cdot (23-1)} \cdot 335.998 = 0.664$$

By using the proposed algorithm in Step 7, the concordance dominance matrix in Table 6 was constructed.

Table 6. The concordance dominance matrix

	$i=1$	$i=2$	$i=3$	$i=4$	$i=5$	$i=6$	$i=7$	$i=8$	$i=9$	$i=10$	$i=11$	$i=12$
$i=1$	–	0	0	0	0	0	1	1	1	1	1	0
$i=2$	0	–	1	0	1	0	1	1	1	0	1	1
$i=3$	0	0	–	1	1	0	1	1	1	1	0	1
$i=4$	0	0	0	–	1	0	1	0	1	0	0	0
$i=5$	0	0	0	0	–	0	1	0	0	0	1	0
$i=6$	0	0	0	0	0	–	0	0	0	0	0	0
$i=7$	0	0	0	0	0	0	–	0	0	0	1	0
$i=8$	0	0	0	0	0	0	1	–	1	0	1	0
$i=9$	0	0	0	0	1	0	1	0	–	1	1	1
$i=10$	0	1	0	0	0	0	0	0	0	–	0	1
$i=11$	0	0	0	0	0	0	0	0	0	0	–	0
$i=12$	0	0	0	0	0	0	0	0	0	0	1	–
$i=13$	0	0	0	0	0	0	0	0	0	0	1	0
$i=14$	0	0	0	0	0	0	1	0	0	1	1	1
$i=15$	0	0	0	0	0	0	0	0	0	0	1	0
$i=16$	0	0	0	1	1	0	1	0	0	1	1	1
$i=17$	0	0	0	1	1	0	1	0	0	1	1	1
$i=18$	0	0	0	0	0	0	1	0	0	1	1	0
$i=19$	0	0	0	0	1	0	1	0	0	1	1	1
$i=20$	0	0	0	1	1	0	1	0	0	1	1	1
$i=21$	0	0	0	0	1	0	0	0	0	1	1	1
$i=22$	0	0	0	0	0	0	0	0	0	1	1	0
$i=23$	0	0	0	1	0	0	1	0	0	1	1	1

	$i=13$	$i=14$	$i=15$	$i=16$	$i=17$	$i=18$	$i=19$	$i=20$	$i=21$	$i=22$	$i=23$
$i=1$	1	1	1	0	0	1	0	0	0	0	0
$i=2$	1	1	1	0	0	1	0	0	1	1	0
$i=3$	1	1	1	0	1	1	0	0	0	1	0
$i=4$	0	0	0	0	0	1	0	0	0	1	0
$i=5$	0	0	0	0	0	1	0	0	0	1	0
$i=6$	1	1	1	1	1	1	1	1	1	1	1
$i=7$	0	0	0	0	0	0	0	0	0	1	0
$i=8$	1	0	0	0	0	0	0	0	0	1	0
$i=9$	1	1	1	1	1	1	1	1	1	1	1
$i=10$	1	0	1	0	0	0	0	0	0	0	0
$i=11$	0	0	0	0	0	0	0	0	0	0	0
$i=12$	1	0	1	0	0	0	0	0	0	1	0
$i=13$	–	0	0	0	0	0	0	0	0	1	0
$i=14$	1	–	1	0	0	0	0	0	0	1	0
$i=15$	1	0	–	0	0	0	0	0	0	1	0
$i=16$	1	1	1	–	0	1	0	0	1	1	0
$i=17$	1	1	1	0	–	1	0	0	0	1	1
$i=18$	0	0	0	0	0	–	0	0	0	0	0
$i=19$	1	1	1	1	1	1	–	1	1	1	0
$i=20$	1	1	1	0	1	1	1	–	1	1	1
$i=21$	1	1	1	0	0	1	0	0	–	1	0
$i=22$	0	0	0	0	0	0	0	0	0	–	0
$i=23$	1	1	1	0	0	0	0	0	0	0	–

The classes of the identified failure modes are presented in Table 7 based on Step 8 of the proposed algorithm.

Table 7. The classes of the identified failure modes

Failure Modes	Rank	Failure Modes	Rank
$i=9$	1	$i=23$	8
$i=20$	2	$i=14$	9
$i=19$	3	$i=4$; $i=5$; $i=8$	10
$i=2$; $i=3$	4	$i=10$; $i=12$	11
$i=16$; $i=17$	5	$i=15$; $i=18$	12
$i=6$	6	$i=7$; $i=13$; $i=22$	13
$i=1$; $i=21$	7	$i=11$	14

In the considered case in Table 7, a lack of deburring $(i = 9)$ represents the most critical failure mode. This failure mode, when each RF was examined individually, is moderately to highly critical, but in no case does any RF have an extremely high value. Nevertheless, the surveyed experts from the considered company believe that this failure mode rightfully occupies a high position because if the finishing process is not properly performed, the resulting part is unusable and often poses a hazard to the operator in terms of cuts and punctures during the work process.

Highly ranked failure modes include wrong hole diameter $(i = 20)$ and crack formation $(i = 19)$, thus indicating that inadequate dimensions and cracks in the material cause the greatest damage to the parts.

Failure modes such as incorrect part orientation $(i = 7)$, overheating during welding $(i = 13)$, wrong label or marking $(i = 22)$, and weld splatter presence $(i = 11)$, have a very low impact on part quality and the defect could be reworked. In any case, the FMEA team of the considered enterprise agrees to the obtained ranking of failure modes and confirms the applicability of the proposed model.

To examine the credibility of the obtained results and the robustness of the proposed model, all seven members of the core FMEA team in the considered company, including the FMEA facilitator (leader), rated the following statements based on a scale from one to ten:

- I agree that the top three failure modes in the ranking deserve their positions;
- I agree that the failure modes ranked from 4th to 10th place deserve their positions in the ranking;
- I agree that the failure modes ranked from 11th to 14th place deserve their positions in the ranking.

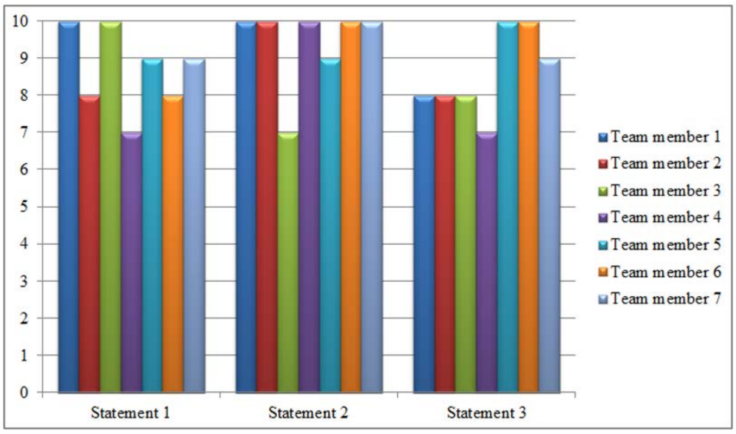

Figure 2. Individual assessments of the FMEA team members regarding the obtained rankings

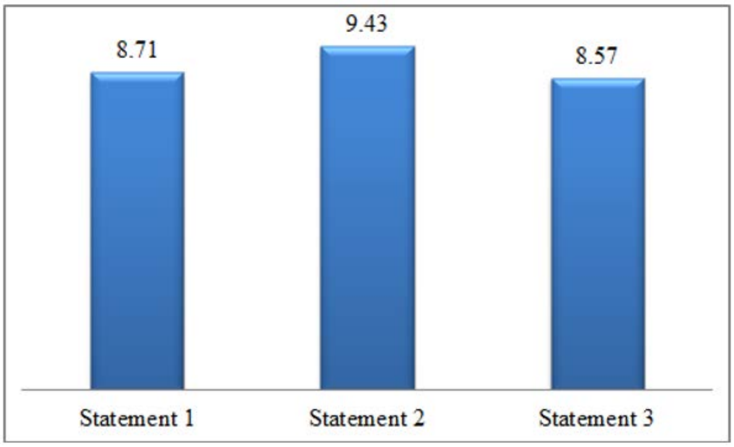

Figure 3. Average scores in agreement with the results of ranking

Individual evaluations are presented in Figure 2 whereas the average scores are shown in Figure 3. A score of one indicated that the FMEA team member did not agree to the given statement at all, while a score of ten indicated total agreement with the statement.

The average scores, representing the agreement of the FMEA team members with the given statements, are 8.71, 9.43, and 8.57, as shown in Figure 3. These values indicated that the FMEA team members agreed to the results obtained through the application of the proposed model. It is therefore considered that the proposed model is robust and sufficiently reliable.

5 Conclusions

This research proposed a practical model aiming to classify and rank failure modes under uncertainties represented by the SVNSs. Based on the obtained results, management initiatives in anticipation of improving the reliability of the manufacturing process could be defined and aptly implemented.

The proposed model was tested and validated using real-life data from an automotive company, where the assessments of DMs were based on their experience as well as empirical data.

The main contributions of this research are:

• Modeling of existing uncertainties using the SVNSs.

• Different weights of the DMs calculated according to the procedures proposed in the relevant literature.

• Relative importance of the RFs formulated as a fuzzy group decision-making problem.

• The weights of the RFs were determined by the Single-Valued Neutrosophic Weighted Averaging Operator, which offers certain advantages compared to other methods, especially practical applications in the industry.

• Construction of the fuzzy decision matrix based on fuzzy algebra rules.

• Determination of the concordance sets following the procedures proposed in this research.

• Construction of the concordance matrix based on a combination of fuzzy algebra rules and the crispification of SVNSs.

• Determination of the discordance matrix based on the procedures proposed in the conventional ELECTRE and the Hamming distance between two SVNSs.

The practical implications of the proposed methodology are oriented towards operations managers, whose responsibility is to prioritize actions to address the identified failure modes. The main advantage of the proposed fuzzy model over existing models that combine the FMEA and the MCDM is the definition of classes of failure modes with the highest importance rather than simply ranking failure modes. This approach defines a set of failure modes to be further analyzed for improvement, with possible extension to different industries.

The limitations of the hybrid model are:

• Subjectivity involved in the process of obtaining the relative importance of criteria and their values;

• Increased computational complexity.

Future research should focus on developing software suitable for mobile devices to implement the proposed model in a user-friendly way.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

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