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A Hybrid FMEA-ROC-CoCoSo Approach for Improved Risk Assessment and Reduced Complexity in Failure Mode Prioritization

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Abstract: This paper proposes a novel hybrid model that integrates failure mode and effects analysis (FMEA), Rank Order Centroid (ROC), and Combined Compromise Solution (CoCoSo) to improve risk assessment and prioritization of failure modes. A case study in the healthcare sector will be conducted to validate the effectiveness of the proposed model. ROC is used to assign weights to the FMEA criteria (severity, occurrence, and detectability). CoCoSo is then applied to create a robust ranking of failure modes by considering multiple criteria simultaneously. The results of the case study show that the hybrid FMEA-ROC-CoCoSo model improves the accuracy and objectivity of risk prioritization. It effectively identifies critical failure modes, outperforming traditional FMEA. The hybrid approach not only improves risk management decision making, leading to better mitigation strategies and higher system reliability, but also reduces the complexity typically found in FMEA hybrid models. This model provides a more comprehensive risk assessment tool suitable for application in different industries.

Keywords: hybrid FMEA; ROC; CoCoSo; risk assessment; failure mode prioritization

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1. Introduction

Risk assessment plays an important role in managing complex systems, especially in industries such as manufacturing, healthcare, and transportation. Identifying, evaluating, and prioritizing risks is critical to improving safety, ensuring system performance, and minimizing errors. One of the most commonly used risk assessment methods is failure mode and effects analysis (FMEA). FMEA systematically identifies potential failures in systems, processes, or products and evaluates their impact based on three factors: severity, occurrence, and detectability [1–3].

However, the traditional FMEA has several limitations. It relies heavily on the risk priority number (RPN), which is calculated by multiplying the severity, occurrence, and detectability values. This approach assumes that these three factors are equally important, which is not always the case. In addition, FMEA often struggles with the subjectivity of expert judgment, which leads to inconsistent results. It also does not take into account the interdependencies between failure modes, which can complicate risk prioritization in complex systems [4–6].

To overcome these limitations, researchers have explored various improvements and alternative methods. One approach is the use of multi-criteria decision making (MCDM) techniques, which enable a more comprehensive risk analysis by considering multiple criteria simultaneously. Techniques such as the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), VlseKriterijumska Optimizacija I Kompromisno

Resenje (VIKOR), and Gray Relational Analysis (GRA) have been incorporated into FMEA to improve the accuracy and reliability of risk assessment. TOPSIS ranks alternatives based on their distance to an ideal solution, providing a more structured approach to prioritizing risks. However, it is insensitive to the weighting of the criteria and cannot fully capture the complexity of the interactions of failure modes. VIKOR, which focuses on finding a compromise solution between conflicting criteria, improves the balance in risk prioritization but can still cause problems in systems with strong dependencies. GRA addresses uncertainty in risk assessment, especially with incomplete information, but can also fail in environments with complex risk interactions [7–9].

Despite the improvements offered by these multi-criteria decision-making methods (MCDMs), challenges remain in overcoming the subjectivity and complexity of risk assessments. One of the main problems with traditional FMEA (Failure Modes and Effects Analysis) is its simplistic approach to weighting the three key factors: severity, occurrence, and detectability. In the traditional FMEA method, these factors are treated as equally important, and the Risk Priority Number (RPN) is calculated by simply multiplying the scores for each factor. This assumes that all failure modes and associated risks can be accurately assessed with the same weighting for each factor, which is rarely the case in real-life scenarios [10–12].

In practice, some risks are determined more by their severity (e.g., catastrophic failures with serious consequences), while others are influenced more by their detectability (e.g., hidden problems that are difficult to detect before they cause problems). In some contexts, where frequent failures, even of low severity, can significantly disrupt operations, the occurrence of failures could be the deciding factor. Therefore, equal weighting in traditional FMEA oversimplifies the complexity of risk assessment and leads to an inaccurate prioritization of risks. This can lead to certain risks being under- or overestimated, reducing the overall effectiveness of the risk management process [13].

Subjectivity is another important issue in FMEA, as expert judgments are often used to assign points for severity, occurrence, and detectability. These assessments can vary from expert to expert, leading to contradictory assessments. The lack of a structured method for dealing with these subjective inputs leads to further uncertainty, which can distort the prioritization of risks. In addition, traditional FMEA does not take into account the interrelationships between failure modes or the influence of multiple factors interacting with each other, making the assessment of risks in modern, interconnected systems even more complex [14].

To overcome these challenges, hybrid approaches have been developed that combine FMEA with advanced decision-making methods. By integrating techniques with MCDM methods, these hybrid models can address the problem of equal weighting in traditional FMEA. For example, AHP allows decision makers to assign a different weighting to each factor depending on its relative importance to ensure that the most critical aspects of the risk are adequately addressed. This improves the accuracy of risk assessments as it more realistically reflects the true impact of each failure mode [15].

In addition, hybrid approaches help to mitigate the subjectivity problem by introducing more structured and systematic procedures for evaluating expert judgment. Methods such as AHP allow decision makers to make pairwise comparisons, reducing biases and inconsistencies in evaluation. These hybrid models provide a more nuanced, flexible framework for prioritizing risks that takes into account both the relative importance of the different criteria and the interactions between them. This ultimately leads to more reliable and effective risk prioritization in complex systems [16]. The integration of FMEA and MCDM increases complexity, especially when the number of failure modes or criteria increases. Mastering this complexity often requires advanced software tools and a deep understanding of both methods. As a result, the practical applicability of the model can be limited, making it difficult for users without specialized training to effectively apply and interpret the results.

To address this challenge and improve the weighting process in the FMEA approach, we propose a novel hybrid FMEA-ROC-CoCoSo model. This model aims to overcome the limitations of traditional FMEA, especially in assigning appropriate weights to the most important risk factors: severity, occurrence, and detectability.

By incorporating the Rank Order Centroid (ROC) to more accurately assign weights based on relative importance and the Combined Compromise Solution (CoCoSo) to effectively rank and prioritize failure modes, this hybrid approach improves the robustness and precision of risk assessments. The proposed model improves the consistency and accuracy of risk prioritization and provides a more reliable framework for decision making in complex systems. The results of this study will demonstrate how the hybrid FMEA-ROC-CoCoSo model outperforms traditional methods and provides a valuable tool for industries requiring advanced risk management strategies.

2. Background Research

In this section, a comprehensive literature review is presented, focusing on several studies that have proposed hybrid models to address the problem of relative weighting between FMEA risk variables and their different levels of complexity. This topic is particularly relevant as the industry tends to favor simpler, more user-friendly models and often disregards more complex solutions despite their greater potential for robust problem-solving capabilities.

Failure mode and effects analysis (FMEA) is widely used in industry to identify, evaluate, and prioritize failure modes in systems and processes with the aim of reducing risk and improving reliability. Traditional FMEA methods, while simple and effective in many cases, struggle with uncertainty, subjectivity, and complex system dependencies. Hybrid models that integrate techniques such as fuzzy logic, artificial intelligence (AI), and Bayesian networks have evolved to overcome these limitations. Despite their potential, the implementation of hybrid FMEA models poses significant challenges to the industry, ranging from technical difficulties to organizational barriers.

Traditional FMEA uses three key factors—severity (S), occurrence (O), and detection (D)—to calculate the risk priority number (RPN), which helps prioritize failure modes based on risk. While effective, this approach suffers from subjectivity in the assignment of S, O, and D values and a lack of sensitivity to uncertainties inherent in complex systems [17]. The traditional RPN calculation does not fully capture the dependencies between failure modes and does not provide a method to account for uncertainties in expert judgment. Furthermore, the linear multiplication of S, O, and D can lead to misleading risk priorities, highlighting the need for more sophisticated approaches [18].

Hybrid FMEA models integrate various methods to overcome the limitations of traditional FMEA. These include fuzzy logic, which addresses the subjectivity and uncertainty of FMEA assessments, and machine learning techniques, which use historical data to predict failure modes more accurately. Fuzzy logic allows FMEA to incorporate linguistic terms such as "low", "medium", and "high" and convert them into fuzzy numbers to better handle the inherent ambiguity in risk assessments [19]. This approach refines the RPN calculation and provides a more nuanced understanding of risk in uncertain environments. Bayesian networks are probabilistic models that dynamically update risk predictions based on new data, allowing the industry to continuously refine its failure mode predictions. This method is especially useful for complex systems where failure modes are interdependent [20]. Neural networks and AI-based models improve FMEA by learning from historical failure data and improving prediction accuracy. Na´amnh et al., for example, developed an FMEA model based on neural networks that adapts to changes in system behavior and thus represents a dynamic tool for risk management [21].

The hybridization of FMEA increases its complexity but significantly improves its usefulness for modern, data-driven industrial applications. However, this complexity also brings with it numerous implementation challenges [22].

Implementing hybrid FMEA models requires sophisticated technical expertise, particularly in dealing with advanced methods such as fuzzy logic, Bayesian networks, and AI. These techniques require specialized knowledge that is not available in many industries [23]. For example, fuzzy FMEA involves the construction of membership functions and fuzzy inference systems, which require a deep understanding of fuzzy set theory [20]. Hybrid FMEA models rely heavily on data, particularly historical failure data and system performance metrics. In industries where such data are unavailable or incomplete, it becomes difficult to train machine learning models or construct Bayesian networks [20]. In addition, the quality of the data can have a significant impact on the accuracy of the model, making data management a critical issue [24]. Fuzzy logic, Bayesian methods, and machine learning algorithms are computationally intensive and require advanced hardware and software infrastructure. For example, Bayesian networks can become computationally intensive as the complexity of the system increases [25].

The integration of hybrid FMEA models into existing industrial systems represents a further technical hurdle. Most industries have implemented quality management systems based on traditional FMEA methods. Switching to hybrid models may require a significant reconfiguration of these systems as well as new software tools that can handle fuzzy logic or AI [26]. In addition to the technical challenges, organizational and cultural barriers often hinder the introduction of hybrid FMEA models. Successful implementation requires a change in mindset and practice, which can be difficult to achieve in entrenched organizational cultures [27].

Many industries lack the necessary expertise to implement and maintain hybrid FMEA models. Specialists in fuzzy logic, AI, and Bayesian analysis are required to design, implement, and interpret the results of these models. Without proper training and education, the complexity of hybrid FMEA can overwhelm employees and lead to improper implementation [27]. Employees who are accustomed to traditional FMEA methods may resist the introduction of hybrid models, especially if they perceive them to be too complex or unnecessary. Organizational inertia can slow down the transition and lead to partial or incorrect implementations [28]. Implementing hybrid FMEA models requires significant investment in training programs to ensure that employees know how to use these advanced tools effectively. Industry is often reluctant to allocate resources for training, especially when the perceived benefits of hybrid FMEA are not immediately clear [27].

One of the main barriers to the adoption of hybrid FMEA models is cost. Traditional FMEA is relatively inexpensive to implement, whereas hybrid models require investment in specialized software, hardware, and expertise. In addition, the maintenance of hybrid systems, which involves continuous data collection and model updating, adds to ongoing operational costs [29].

Hybrid FMEA models produce complex results that can be difficult for non-experts to interpret. For example, fuzzy FMEA results are not as easy to interpret as the RPN in traditional FMEA and often require in-depth knowledge of fuzzy logic to interpret the risk assessment results. This complexity in interpretation can hinder decision-making processes as managers may not fully understand or trust the results generated by the hybrid models. As a result, decision makers may resort to traditional, simpler methods, even if hybrid FMEA models provide better accuracy and precision [30].

Scaling hybrid FMEA models to large industrial systems can be difficult. For example, constructing Bayesian networks for highly complex systems involves modeling numerous dependencies, which can lead to overly complicated and computationally intensive models [24]. It can be difficult for industries to maintain these models over time, particularly as system configurations change. Instead of implementing hybrid FMEA models for the entire system, companies can start with an incremental implementation and focus on high-risk areas or subsystems where hybrid methods will bring the most benefit. This allows for a smoother transition and reduces resistance to change as employees can gradually familiarize themselves with the new techniques [31]. Collaboration with academic institutions can help industries overcome the technical and organizational barriers to adopting hybrid

FMEA models. Research institutions often have the necessary expertise to develop and test new methods, and joint projects can give industries access to cutting-edge tools and techniques [27]. The development of user-friendly software tools can significantly reduce the complexity of implementing hybrid FMEA models. These tools can hide the underlying complexity of methods such as fuzzy logic or Bayesian networks and provide intuitive interfaces that offer actionable insights to decision makers [32]. In addition, automating data collection and model update processes can reduce the operational burden of maintaining hybrid FMEA models. This can be achieved by integrating hybrid FMEA tools with industrial Internet of Things (IoT) systems that continuously collect and analyze data in real time [33].

Hybrid FMEA models offer a significant improvement over traditional FMEA by removing limitations such as subjectivity, uncertainty, and lack of adaptability in complex systems. However, their implementation in industry remains a challenge due to technical, organizational, and financial barriers. Overcoming these challenges requires a combination of gradual implementation, collaboration with experts, and the development of user-friendly tools. As the industry evolves and introduces more complex systems, hybrid FMEA models will play an increasingly important role in ensuring reliability and risk management. However, the success of these models depends on the industry's ability to overcome the complexity of implementation and effectively integrate them into their existing processes.

3. The Proposed FMEA Model

In this section, we propose a new hybrid FMEA model, FMEA-ROC-CoCoSo, which not only improves the accuracy and robustness of risk prioritization, but is also characterized by its ease of use, which can facilitate its acceptance in the industry. The implementation of hybrid models, such as the use of fuzzy logic or neural networks, often requires advanced technical knowledge and high computing power, which is an obstacle for many organizations [34]. However, by integrating techniques such as Rank Order Centroid (ROC) and Combined Compromise Solution (CoCoSo), the new model simplifies the assignment of weights and prioritization of failure modes.

The ROC provides a simple and objective method for calculating weights and removes subjectivity in the weighting of severity, occurrence, and detection criteria. CoCoSo, in turn, allows different trade-off solutions to be combined without the need for complex mathematical operations, providing a clearer and easier-to-understand risk assessment.

This simplification makes the model more accessible and requires less training and technical infrastructure. Therefore, it has a greater potential to be accepted and implemented by industries that want to improve their risk analysis without investing in overly complex models. The fact that the model is more intuitive and less dependent on experts in specific areas of data analysis or advanced mathematics also increases its feasibility and makes it a practical and efficient option for companies looking to modernize their risk management.

3.1. Failure Modes and Effects Analysis

Failure modes and effects analysis is a systematic method for identifying potential failures in a system, product, or process. It assesses the risks based on three key factors: severity, occurrence, and detection, each of which is rated on a scale of 1 to 10:

- Severity (S): measures the impact of the failure, with 10 being the highest level.
- Occurrence (O): Indicates how likely it is that the failure will occur, with 10 being very likely.
- Detection (D): Indicates how easily the failure can be detected before it occurs, where 10 means it is least likely to be detected.

These values are multiplied to calculate the risk priority number (RPN), where a higher RPN means a higher risk:

$$RPN = S \cdot O \cdot D \tag{1}$$

In this proposal, the RPN is replaced by a hybrid combination of the Rank Order Centroid (ROC) method and the Combined Compromise Solution (CoCoSo) method, which aim to improve risk assessment by removing the limitations of the RPN, such as the equal weighting of all factors.

3.2. Rank Order Centroid

The Rank Order Centroid (ROC) method was introduced to assign weights in decision scenarios based on ranking criteria [35]. It provides a simple and effective way to determine the relative importance of factors by calculating weights from their ranks. This method is particularly useful in multi-criteria decision making as it avoids assuming equal weights for all criteria and instead assigns higher weights to the more important factors. The ROC method calculates the weighting for each criterion using the following formula:

$$w_j = \frac{1}{n} \sum_{k=j}^{n} \frac{1}{k} \tag{2}$$

where w_j is the weight for the criterion ranked j, n is the total number of criteria, and k runs from j to n.

The values obtained from Equation (2) will be used in Equations (6) and (7) with the aim of assigning different weights to the decision variables. This ensures that in a given risk scenario, the risk variables (severity, occurrence, and detectability) can be assigned different weights, allowing for greater flexibility in reflecting the specific characteristics of each scenario. Such an approach enables the assignment of weights to the FMEA risk variables and addresses a commonly identified limitation of FMEA, namely, its inability to assign varying weights to risk variables.

This approach balances simplicity with practicality, making it easier to apply in situations where subjective judgment is needed to rank criteria.

3.3. Combined Compromise Solution

The Combined Compromise Solution (CoCoSo) method, introduced by Yazdani et al. in 2019 [36], is a multi-criteria decision-making (MCDM) approach that integrates the Simple Additive Weighting (SAW) and Weighted Product Model (WPM) techniques to provide a compromised ranking of alternatives. The method addresses the limitations of traditional MCDM methods by combining additive and multiplicative strategies, resulting in a more robust and balanced decision-making process. The CoCoSo method starts with constructing a decision matrix, where alternatives are evaluated against multiple criteria, classified as either benefit (where higher values are preferred) or non-benefit (where lower values are preferred). The data are normalized to ensure comparability, scaling benefit criteria upwards and non-benefit criteria downwards. It then aggregates normalized values by combining the SAW and WPM techniques, applying k-values to adjust the influence of additive and multiplicative strategies or to emphasize specific criteria. This hybrid approach results in a comprehensive score for each alternative, enabling their ranking and supporting more effective and objective decision-making.

As previously outlined, the CoCoSo method begins with the construction of the initial decision matrix:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}; \quad i = 1, 2, \ldots, m; \quad j = 1, 2, \ldots, n \tag{3}$$

The decision matrix $X = \left(x_{ij}\right)_{m \times n}$ establishes a relationship between decision variables, represented by the index j (with its maximum value denoted as n), and the alternatives, represented by the index i (with its maximum value denoted as m), i.e., $i = 1, 2, \ldots m$ and $j = 1, 2, \ldots, n$.

The next step is normalizing the initial decision matrix, where for benefit criteria we apply the following expression, Equation (4):

$$r_{ij} = \frac{x_{ij} - \min\limits_{i}\left(x_{ij}\right)}{\max\limits_{i}\left(x_{ij}\right) - \min\limits_{i}\left(x_{ij}\right)}; \quad i = 1,\, 2,\, \ldots,\, m; \quad j = 1,\, 2,\, \ldots,\, n \tag{4}$$

For cost criteria, we apply the following, Equation (5).

$$r_{ij} = \frac{\max\limits_{i}\left(x_{ij}\right) - x_{ij}}{\max\limits_{i}\left(x_{ij}\right) - \min\limits_{i}\left(x_{ij}\right)}; \quad i = 1,\, 2,\, \ldots,\, m; \quad j = 1,\, 2,\, \ldots,\, n \tag{5}$$

The next step is to calculate the sum of the weighted comparability matrix, Equation (6):

$$S_i = \sum_{j=i}^{n} \left(w_j \cdot r_{ij}\right) \tag{6}$$

and the power of the weighted comparability matrix, Equation (7):

$$P_i = \sum_{j=i}^{n} \left(r_{ij}\right)^{wj} \tag{7}$$

The next step is to calculate the relative weights of the alternatives using the following aggregation equations. Equations (8)–(10).

$$k_{ia} = \frac{P_i + S_i}{\sum\limits_{i=1}^{m} \left(P_i + S_i\right)} \tag{8}$$

$$k_{ib} = \frac{S_i}{\min\limits_{i}(S_i)} + \frac{P_i}{\min\limits_{i}(P_i)} \tag{9}$$

$$k_{ic} = \frac{\lambda S_i + (1-\lambda) P_i}{\lambda \max\limits_{i} S_i + (1-\lambda) \max\limits_{i} P_i} \tag{10}$$

The final step is to rank the alternatives according to their k-values, as indicated in Equation (11), with higher values leading to better rankings.

$$k_i = \left(k_{ia} \cdot k_{ib} \cdot k_{ic}\right)^{\frac{1}{3}} + \frac{1}{3}\left(k_{ia} + k_{ib} + k_{ic}\right) \tag{11}$$

Based on the calculated compromise ratios, the alternatives are ranked, providing a more balanced and flexible evaluation compared to traditional methods such as TOPSIS or VIKOR. The CoCoSo method addresses the problem of rank reversals and allows for a more accurate assessment of alternatives, especially in situations where there are conflicting or complex criteria.

In the proposed model, we consider the prioritization of failure modes as a multi-criteria decision problem. The decision criteria are the FMEA risk variables: severity, occurrence, and detectability. To ensure a balanced assessment depending on the risk scenario, the weights for these criteria are determined using the Rank Order Centroid (ROC) method. These weighted criteria are then used to prioritize the failure modes based on their risk assessment. By combining the assigned weights and the multi-criteria CoCoSo decision method, we create a more robust and systematic approach to ranking the failure modes and ensure that each failure type is evaluated according to the significance of the risks associated with it.

Figure 1 shows a clear and practical seven-step process for applying the hybrid FMEA model to prioritize failure modes. The process starts by evaluating the decision matrix scores (FMEA scores) and assigning weights to each criterion using the Rank Order Centroid (ROC) method. Next, the scores are normalized, and a weighted comparability matrix is created to highlight relationships between failure modes. The matrix's power is then calculated to focus on the most important relationships, and the relative weights of the alternatives are determined. Finally, the failure modes are ranked by importance, helping organizations focus on the most critical risks.

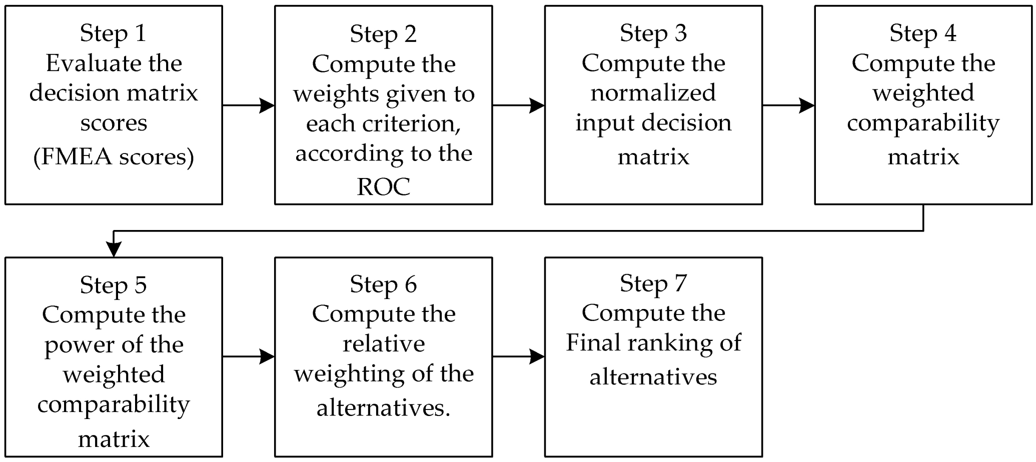

Figure 1. Flowchart of the proposed model illustrating the calculation sequence for prioritizing failure modes.

4. An Illustrative Example

To analyze the performance of the proposed model, we refer to the case study of Lu et al. (2013), who used failure mode and effects analysis (FMEA) to improve safety in the blood transfusion process [37]. The analysis spans the entire process—from blood collection to transfusion—focusing on critical stages such as patient identification, blood collection, and matching. By pinpointing possible "failure modes" at each stage, such as mislabeling samples or mismatching blood types, the study aims to prevent errors and failures.

A multidisciplinary team conducted the FMEA to ensure risks were evaluated from various perspectives. Each failure mode was rated based on its severity (impact on patient safety), likelihood of occurrence, and detectability. Table 1 summarizes the 19 failure modes identified in the case study and the scores assigned by the team for each FMEA variable. The table also includes the calculation of the RPN for each failure mode.

This case study has been used in various articles as a means of validating models such as the fuzzy VIKOR model and the ITHWD model [38]. For this reason, we consider it acceptable to use the same case study to compare the performance of the proposed model with the performance of the original RPN model, the fuzzy VIKOR model, and the ITHWD model. In the paper that introduced the ITHWD model [38], only 11 out of the 19 failure modes from the original case study were considered. Table 2 presents these 11 selected failure modes, with numbering consistent with Table 1. In addition to listing the failure modes, Table 2 also displays the rankings generated by the original RPN, the fuzzy VIKOR model, and the ITHWD model. The performance of the proposed model is then compared with these results.

Table 1. Description of the failure modes considered in the study by Lu et al. [37], assessment of the risk variables, and the respective RPNs.

FM	Failure Mode Description	S	O	D	RPN	Rank
1	Insufficient and/or incorrect clinical information on request form	7	6	3	126	5
2	Blood plasma abuse	6	6	5	180	4
3	Insufficient preoperative assessment of the blood product requirement	7	5	7	245	1
4	Blood group verification incomplete	7	5	3	105	
5	No etiology detection samples before blood transfusion	8	7	1	56	
6	Non-cancellation of ordering special blood components	7	3	1	21	
7	Sample for type and cross drawn from the wrong patient or incorrectly labeled	10	1	2	20	
8	Insufficient/unclear information on the sample label	7	2	2	28	
9	Delivery of blood sample and/or request form delayed	5	3	6	90	
10	Inaccurate cross-matching	10	1	6	60	
11	Incorrect blood components issued	10	1	8	80	
12	Quality checks not performed on blood products	8	2	5	80	
13	Blood components for different patients issued at the same time	8	1	3	24	
14	Blood product delivered to the wrong department	10	1	2	20	
15	Failure to perform pretransfusion checks	10	1	2	20	
16	Preparation time before infusion > 30 min	8	6	5	240	2
17	Transfusion cannot be completed within the appropriate time	7	4	4	112	
18	Blood transfusion reaction occurs during the transfusion process	8	4	7	224	3
19	Bags of blood products are improperly disposed of	7	4	4	112	

Table 2. Failure modes considered in Liu et al.'s study and their respective rankings according to RPN, fuzzy VIKOR, and ITHWD.

FM	S	O	D	RPN	Ranking RPN	Ranking Fuzzy VIKOR	Ranking ITHWD
1	7	6	3	126	5	4	4
2	6	6	5	180	4	7	6
3	7	5	7	245	1	2	1
4	7	5	3	105	8	8	10
9	5	3	6	90	9	11	11
11	10	1	8	80	10	1	3
12	8	2	5	80	10	6	9
16	8	6	5	240	2	5	5
17	7	4	4	112	6	10	7
18	8	4	7	224	3	3	2
19	7	4	4	112	6	9	8

5. Results

The following text sets out the four main considerations that are essential for an effective application of the proposed methodology:

1. The first step involves considering FMEA scores as decision-making criteria, followed by determining their respective weights based on their order of importance within

the risk scenario context. These relative weights are calculated using the Rank Order Centroid (ROC) method. Since the CoCoSo method does not provide a specific methodology for assigning criteria weights, the ROC method emerges as the most suitable option due to its simplicity and effectiveness, as it assigns weights solely based on the established order of importance. This approach proves highly practical in FMEA, especially when compared to more complex alternatives such as the AHP method, which adds significant complexity without proportional improvements in results.

2. According to the FMEA framework and variable definitions, severity and occurrence are considered beneficial variables because higher scores indicate greater criticality of the failure mode, aligning with the goal of identifying the most critical failure modes. In contrast, detectability is treated as a non-beneficial variable because higher scores imply reduced detectability, increasing overall risk. This classification reflects an inverse relationship with risk reduction. This assignment to the FMEA variables represents a hybridization of two methods: the FMEA framework through its risk variables and the CoCoSo model through its cost–benefit criteria. By combining these approaches, the proposed methodology leverages the strengths of both frameworks, enabling more accurate and effective failure mode prioritization within the FMEA process.
3. Classifying detectability as a non-beneficial variable requires adjusting its assigned values across various failure modes. In the FMEA evaluation, detectability is rated on an inverse scale: greater detectability corresponds to the lowest value on a 1-to-10 scale (i.e., 1), while lower detectability receives the highest value (i.e., 10). This inverse relationship follows the RPN calculation principle, where higher detectability leads to lower RPN values, reducing perceived risk. However, in the CoCoSo method, all evaluation scales must align under the same paradigm, distinguishing criteria as either beneficial or non-beneficial. To ensure compatibility, the detectability values in Table 2 are updated using the transformation: D(new) = 10 − D(old). This step is crucial, as the lack of this adjustment would compromise the accuracy of failure mode prioritization. Moreover, this adjustment is essential for the correct hybridization of the two methods, ensuring consistent application across all cost-type variables considered in an extended FMEA approach. This includes not only the traditional FMEA variables—severity (S), occurrence (O), and detectability (D)—but also any additional cost-related variables introduced in future evaluations.
4. Therefore, the most critical failure mode is the one with the highest contributions in the variables of severity and occurrence and the lowest contribution in the detectability variable. This principle will determine the ordering of failure modes in the CoCoSo ranking, from the most critical (first in rank) to the least critical (last position in the rank).

Table 3 shows the decision matrix described in Equation (3), with the detectability variable values already adjusted as explained in the previous section.

The next step is to evaluate the weights given to each criterion. According to the ROC method, it starts by establishing the order of importance; for this case, we use the typical order of importance where S is more important that occurrence, and occurrence is more important than detectability, meaning that S > O > D. In the flow, the weights for the FMEA variables are calculated.

$$w_s = \frac{1}{3}\left(\frac{1}{1} + \frac{1}{2} + \frac{1}{3}\right) = 0.61 \tag{12}$$

$$w_o = \frac{1}{3}\left(\frac{1}{2} + \frac{1}{3}\right) = 0.28 \tag{13}$$

$$w_D = \frac{1}{3}\left(\frac{1}{3}\right) = 0.11 \tag{14}$$

The next step is to normalize the input matrix using Equations (4) and (5), depending on the type of criterion: beneficial or non-beneficial. Table 4 presents the normalized decision matrix for this case study.

Table 3. Case study decision matrix with D scores modified in line with the CoCoSo method.

	Beneficial	*Beneficial*	*non-Beneficial*
FM	**S**	**O**	**D**
3	7	5	3
16	8	6	5
18	8	4	3
2	6	6	5
1	7	6	7
17	7	4	6
19	7	4	6
4	7	5	7
9	5	3	4
11	10	1	2
12	8	2	5

Table 4. Normalized input decision matrix.

FM	S	O	D
3	0.4	0.8	0.8
16	0.6	1	0.4
18	0.6	0.6	0.8
2	0.2	1	0.4
1	0.4	1	0
17	0.4	0.6	0.2
19	0.4	0.6	0.2
4	0.4	0.8	0
9	0	0.4	0.6
11	1	0	1
12	0.6	0.2	0.4

The next two steps are to obtain the weighted matrix (Table 5) using Equation (6) and the power weight of comparability matrix (Table 6) using Equation (7).

The next step is to calculate the relative weights of the alternatives using the aggregation equations: Equations (8)–(10) for ka, kb, and kc. Table 7 summarizes the results obtained for each failure mode.

The final step is to calculate the ranking of the alternatives using Equation (11). Table 8 summarizes the results for the k of the individual alternatives. Table 9 summarizes the previous results obtained in the work of Liu et al. and the results obtained with the proposed method.

Table 5. Weighted comparability matrix.

FM	S	O	D	Si
3	0.24	0.22	0.09	0.56
16	0.37	0.28	0.04	0.69
18	0.37	0.17	0.09	0.62
2	0.12	0.28	0.04	0.44
1	0.24	0.28	0.00	0.52
17	0.24	0.17	0.02	0.43
19	0.24	0.17	0.02	0.43
4	0.24	0.22	0.00	0.47
9	0.00	0.11	0.07	0.18
11	0.61	0.00	0.11	0.72
12	0.37	0.06	0.04	0.47

Table 6. Power of the weighted comparability matrix.

FM	S	O	D	Pi
3	0.42	0.66	0.76	1.85
16	0.54	0.70	0.71	1.95
18	0.54	0.61	0.76	1.91
2	0.28	0.70	0.71	1.68
1	0.42	0.70	0.00	1.12
17	0.42	0.61	0.66	1.69
19	0.42	0.61	0.66	1.69
4	0.42	0.66	0.00	1.08
9	0.00	0.54	0.74	1.28
11	0.74	0.00	0.78	1.52
12	0.54	0.45	0.71	1.70

Table 7. Relative weighting of the alternatives.

FM	Ka	kb	kc
3	2.40	4.83	0.898577
16	2.64	5.68	0.987525
18	2.54	5.27	0.949089
2	2.13	4.06	0.796917
1	1.65	3.98	0.615862
17	2.12	4.00	0.79308
19	2.12	4.00	0.79308
4	1.55	3.63	0.579312
9	1.46	2.19	0.546813
11	2.25	5.47	0.840452
12	2.16	4.19	0.809837

Table 8. Final ranking of alternatives.

FM	k	Rank
3	4.894953	4
16	5.556488	1
18	5.25047	2
2	4.230755	6
1	3.670658	9
17	4.189717	7
19	4.189717	7
4	3.398767	10
9	2.602686	11
11	5.030212	3
12	4.333838	5

Table 9. Final ranking comparison.

FM	S	O	D	RPN	Rank	Rank	Rank	Ranking
					RPN	Fuzzy VIKOR	ITHWD	Cocoso S > O > D
3	7	5	7	245	1	2	1	4
16	8	6	5	240	2	5	5	1
18	8	4	7	224	3	3	2	2
2	6	6	5	180	4	7	6	6
1	7	6	3	126	5	4	4	9
17	7	4	4	112	6	10	7	7
19	7	4	4	112	6	9	8	7
4	7	5	3	105	8	8	10	10
9	5	3	6	90	9	11	11	11
11	10	1	8	80	10	1	3	3
12	8	2	5	80	10	6	9	5

6. Discussion

In fact, the application of the proposed hybrid model proved to be quite simple and fast. Compared to the four models presented in Table 9, only the traditional RPN method was slightly easier and faster to apply. However, it is important to emphasize that the FMEA ROC-CoCoSo model was specifically designed to combine ease of use with a more robust and comprehensive analysis, making it particularly suitable for complex industrial contexts. This has achieved one of the main objectives that motivated the development of this hybrid model: to create a practical and efficient tool for industrial environments where quick and easy implementation is required without compromising the accuracy of the results. Validation through practical application confirms the suitability of the model for efficiently solving industrial problems, further increasing its usefulness in production and risk management scenarios. Regarding the performance of the model, we can observe the following:

1. *Classification of failure modes:* comparing the results obtained with the proposed model for failure modes 11 and 12, we note that the model can assign different classifications to these failure modes, unlike the traditional RPN method which assigns the same classification to them. This limitation of the traditional RPN is also overcome by

the other three methods presented in Table 9. In addition, the critical failure modes identified by the proposed model are consistent with the expectations from the case study, especially failure modes 16 and 18, which are ranked first and second, respectively. These failure modes have the highest degree of criticality, which confirms that the model is able to prioritize the risks in accordance with the real operational hazards. The ranking is consistent with the weighting of the severity, occurrence, and detectability variables, which were considered most important for this industrial context. This correspondence between the results of the model and the expected prioritization strengthens the reliability and robustness of the FMEA ROC-CoCoSo model, as it accurately reflects the critical failure modes and ensures that the most severe risks are identified and effectively addressed. Furthermore, this result demonstrates the model's ability to produce a clear and actionable risk hierarchy, which is essential for decision making in an industrial environment. By classifying failure modes in a way that is consistent with practical expectations and operational reality, the model provides a level of reliability and precision that is critical for preventing system failures and optimizing risk mitigation strategies.

2. *Sensitivity to the weighting of FMEA variables:* The proposed model shows a good sensitivity in the assignment of weights for each FMEA variable. The ranking determined with the ROC-CoCoSo model clearly reflects the weighting of each variable, in the order S > O > D (severity > occurrence > detectability). This order was chosen because it is appropriate for the case study under investigation, in which severity and probability of occurrence have a greater weight than detectability. It is important that the order of importance is determined according to the scenario under investigation. A comparison of failure modes 3 and 16 shows that both the traditional RPN and ITHWD models rank failure mode 3 first and identify it as the most critical. Failure mode 16, however, has higher severity and occurrence values, indicating greater criticality. The reason that failure mode 3 is identified as more critical in these models is the fact that the detectability variable for failure mode 3 is two points higher than for failure mode 16. However, this variable is the one with the lowest weight in the analyzed scenario. Thus, both the RPN and ITHWD models show low sensitivity to the relative contribution of each variable when their respective weights are considered. In contrast, the proposed model (FMEA ROC-CoCoSo) is more sensitive and assigns the first place in the ranking to failure mode 16, which is consistent with its higher criticality. This sensitivity can also be easily observed in the proposed model for other failure modes, namely, failure modes 18 and 11.
3. *Coherence between input and output:* Another important point to emphasize is the coherence of the proposed model between the input (classifications assigned to FMEA variables) and the output (ranking of failure modes). For example, failure modes 17 and 19 have the same classifications in the severity, occurrence, and detectability variables, i.e., S = 7, O = 4, and D = 4. As the classifications in the FMEA variables are identical, one would expect them to occupy the same position in the ranking. However, in the fuzzy VIKOR and ITHWD models, the rankings of these two failure modes are different. In the fuzzy VIKOR model, failure mode 17 is in 10th place, while failure mode 19 is in 9th place. In the ITHWD model, failure mode 17 is ranked 7th and failure mode 19 is ranked 8th. This discrepancy in the rankings is not correct, as the values assigned to the FMEA variables are the same for both failure modes. Analyzing the performance of the proposed model in this regard shows that the model has adequate coherence between input and output, as expected. The model assigns the same rank position to failure types 17 and 19, which correctly reflects the identical classifications of the FMEA variables. This coherence can also be observed in the RPN model, which leads to the same result.

The hybrid FMEA-ROC-CoCoSo model is characterized by its combination of simplicity, analytical robustness, and sensitivity to FMEA variables. Practical application shows that the model is capable of producing coherent and accurate rankings, taking into account the weighting of each variable according to the industrial context under study. The model's ease of implementation also makes it an effective tool for risk management in industries where accuracy and rapid application of results are crucial. Its ability to overcome the limitations of traditional models such as RPN and its consistency in classifying failure modes with identical values make it a valuable choice for efficiently solving industrial problems tailored to the specifics of each case.

Despite its advantages, the model is not without its limitations. One of the limitations of the proposed method lies specifically in the use of the ROC approach in risk scenarios where the order of importance of risk variables is insufficient to fully characterize their weights. The ROC method assigns relative weights following a fixed proportion derived from a specific formulation (Equation (1)), which may not align with the desired distribution of weights for decision variables in other risk scenarios. Nevertheless, for improving FMEA, the ROC method proves effective and adequately captures the dominance of each variable over the others. This balance ensures that the ROC weighting method remains effective in its application to FMEA. Moreover, its simplicity and ease of use align with the research objectives of enhancing the traditional FMEA method while maintaining its accessibility, a key factor in its longstanding adoption across industries.

Moreover, the current study focuses on a specific industrial case study, which may limit its generalizability to other industries with fundamentally different risk profiles. As the model is based on predefined weightings for FMEA variables, it needs to be carefully adapted and validated for new applications, particularly in industries where the relative importance of severity, occurrence, and detectability can vary widely.

To further refine and extend the applicability of the FMEA-ROC-CoCoSo model, future research should focus on several areas. First, extending the application of the model to a wider range of industries will help to verify its generalizability and adaptability to different operational contexts. Comparative studies comparing the model's performance with other advanced risk assessment methods such as neural networks or machine learning-based models could provide valuable insights into its competitive advantages and limitations.

Secondly, research could investigate dynamic or real-time adjustments to the weighting system that allow for continuous adaptation to changing operating conditions. This could improve the model's responsiveness in environments with rapidly fluctuating risks. Finally, integrating the model into automated systems or software tools that assist in decision making could further simplify its application and improve its accessibility and usability for practitioners.

Innovative Aspects of the Proposed Method

The proposed method introduces several innovative aspects in the prioritization of failure modes within FMEA. First, this study presents for the first time a combination of FMEA, ROC, and the CoCoSo method to improve the prioritization of failure modes. The hypothesis that this integration would lead to improved prioritization was confirmed by the promising results of the study. As far as the authors are aware, this particular combination has never been explored before, which is an important contribution to this topic.

Furthermore, the integration of the ROC method with the CoCoSo model represents a novel approach that has proven to be excellent in differentiating the weighting of FMEA variables. The ability to assign weights based on the order of importance of the FMEA variables proved to be an extremely practical method. This practicality is particularly valuable because it remains effective regardless of the number of FMEA variables involved, ensuring scalability and adaptability for different assessment contexts.

Furthermore, the integration of FMEA variables as decision criteria in the CoCoSo model represents a novel methodological approach that creates a seamless link between risk assessment and multi-criteria decision making.

Another important contribution of this study is the adaptation of the FMEA scores determined for each variable within the CoCoSo method to create the decision matrix. This process cannot be executed directly as it requires an in-depth analysis of the scope of each FMEA variable and an adjustment of their scores according to the benefit–cost paradigm used in the CoCoSo method. The identification of this need and the solution developed for it represent a valuable addition to the methodological contributions of this work.

By introducing these methodological innovations, the proposed approach successfully addresses the key challenges associated with traditional FMEA methods while providing a structured, adaptable, and effective solution for prioritizing failure modes. These contributions emphasize the originality and practical relevance of the study.

7. Conclusions

The hybrid FMEA model ROC-CoCoSo offers a convincing solution to overcome the limitations of traditional failure mode analysis in an industrial context. In this study, the model proved to be both easy to implement and highly effective, particularly when compared to other approaches such as fuzzy VIKOR and ITHWD. While the conventional RPN method is somewhat simpler and faster, the proposed model provides a more sophisticated and robust analysis and is therefore better suited for complex industrial environments where accuracy and depth are critical.

One of the key achievements of the FMEA ROC-CoCoSo model is its ability to maintain consistency between input and output, particularly in cases where identical failure mode classifications should result in identical ratings. This is in contrast to other models, such as fuzzy VIKOR and ITHWD, which show inconsistencies when classifying failure modes with the same FMEA variable values. By accurately reflecting the assigned weights of severity, occurrence, and detectability, the proposed model ensures that the most critical failure modes are correctly prioritized.

In addition, the FMEA ROC-CoCoSo model fills another critical gap in existing methods: its flexibility in adapting to different industrial scenarios by adjusting the weighting of the variables. This allows for customized applications in a range of industries and increases the overall usefulness of the model for risk management and decision making.

The practical implications of this model are significant. The FMEA ROC-CoCoSo model is a tool that strikes a balance between ease of use and analytical depth, allowing industry practitioners to perform more accurate and comprehensive failure mode analysis without sacrificing efficiency. This makes it particularly valuable for industries that face complex risk factors and require accurate prioritization of failure modes to ensure operational safety and reliability.

The proposed FMEA-ROC-CoCoSo model demonstrates significant advantages but also presents limitations. The use of the ROC approach, while simplifying weight calculation, may not fully characterize desired weight distributions in risk scenarios where the order of importance of variables is insufficient. This limitation could affect its applicability in industries with different risk profiles. Despite this, the method effectively enhances FMEA by capturing the dominance of risk variables and maintaining simplicity and ease of use, aligning with the research objectives. Future research should expand its application to diverse industries, compare its performance with advanced risk assessment methods such as neural networks or machine learning models, and investigate dynamic weighting systems to adapt to changing conditions. Integrating the model into automated decision-making tools could further enhance its accessibility and usability for practitioners.

The FMEA ROC-CoCoSo model provides a balanced and adaptable approach to failure mode analysis that combines ease of implementation with advanced analytical capabilities. With further research and development, it has the potential to become a widely used industrial risk management tool that meets the changing needs of modern industry.

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