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Hybrid RPI-MCDM Approach for FMEA: A Case Study on Belt Conveyor in Bir El Ater Mine, Algeria

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ABSTRACT

Failure Modes and Effects Analysis (FMEA) is a widely-used technique for enhancing dependability by ranking failure modes according to their Risk Priority Number (RPN). However, RPN has limitations, such as non-injectivity, non-surjectivity, and difficulties in weighing risk variables. The Risk Prioritization Index (RPI) model offers an alternative, addressing some of these limitations and providing user-friendly prioritization of failure modes. This study proposes an integrated risk assessment model that combines the RPI model with Multiple Criteria Decision-Making (MCDM) methods, specifically the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). The first approach uses entropy, average weight, and scenarios to estimate the impact of risk variables and identify key elements. The second approach combines rankings of failure modes from five RPI models using the integrated MCDM-TOPSIS method. The proposed methods are applied to a case study of a belt conveyor system in a mining company in Bir El Ater, Algeria, demonstrating their effectiveness and dependability.

1. INTRODUCTION

Failure Mode and Effects Analysis (FMEA) is a structured technique used to identify potential failure modes, their impacts, causes, and associated risks in processes, products, or services. By systematically locating possible failure points and assessing risks, organizations can prioritize areas for improvement. FMEA involves the identification, analysis, and prioritization of risks that may lead to failures. It helps determine the causes of potential failures, their potential impacts, and the likelihood of occurrence. Subsequently, FMEA guides decision-making regarding necessary actions to address the identified risks [1-3].

FMEA promotes an interdisciplinary approach and assists in identifying design risks and potential issues related to processes or products. It enables the identification of risk areas and the development of preventive measures. The benefits of FMEA extend to the manufacturing process, as it allows for the recognition of potential issues and the formulation of plans to mitigate or eliminate risks.

In the field of product design, engineering, and activity planning, FMEA is commonly used to identify and analyze potential failure modes. The traditional FMEA evaluates each failure mode based on its Severity, Occurrence, and Detectability using rating scales. The Risk Priority Number (RPN), calculated using Eq. (1), is a widely adopted approach to rank failure modes based on their criticality within a given risk scenario.

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

Typically, the most critical failure modes with the highest RPN ratings are used to identify areas that require redesign or intervention [4, 5]. A plan of action and recommendations for management or improvement are then proposed. Engineers iteratively reassess the failure modes to guide them toward more reliable design solutions. Despite its widespread use, FMEA has well-known limitations, primarily related to the non-injective and non-surjective nature of the RPN function [6].

The prioritization of failure modes in FMEA can be uncertain due to the possibility of multiple failure modes receiving the same RPN rating, despite different Severity, Occurrence, and Detectability ratios. Additionally, certain RPN ratings, which range from 1 to 1000 in the conventional method, may never be achieved. The non-surjective nature of the RPN function arises from its non-injective behavior [4].

Several studies have emphasized the importance of considering the relative importance of risk variables in FMEA, as their significance can vary depending on the risk scenario and application field [7, 8]. However, the traditional RPN approach cannot accommodate scenarios where Occurrence is more critical than Severity or where Detectability is the most significant risk factor. The relative importance between the three variables remains fixed regardless of the situation [9, 10]. Furthermore, accurately assessing these risk variables can be challenging for FMEA teams. Current field data may not be suitable for determining risk variables using the RPN method, the team may lack the required expertise for quantitative or qualitative analysis, and field data may not be available to rank all risk factors. Additionally, different FMEA teams may generate different risk prioritizations even when using the qualitative method to rate risk variables, highlighting the limitations of the FMEA framework related to team experience and the team-dependent nature of the qualitative approach [11].

Numerous research studies have attempted to overcome the limitations of the standard RPN and have proposed alternative approaches to enhance the FMEA technique [12]. Liu [13] presented examples of how uncertainty theories and multi-criteria decision-making can improve conventional FMEA procedures. Wang et al. [14] introduced an FMEA model that prioritizes failure modes in the presence of uncertainty, ambiguity, and insufficient information. Zhao et al. [15] suggested a method to address subjective evaluations among FMEA team members. Liu et al. [16] presented a novel FMEA model that employs various techniques for risk prioritization. However, these alternative approaches require further research to address challenges associated with weighting risk variables.

In this study, we propose utilizing the modified Risk Priority Index (RPI) technique as a straightforward yet reasonable risk prioritization model for FMEA. The modified RPI technique aims to overcome the limitations of the standard RPN while preserving its simplicity. It addresses the non-injectivity and non-surjectivity problems and allows for distinct risk factors with varying relative importance. By offering a reliable and user-friendly tool for reliability analysis and prioritizing failure modes, the modified RPI technique contributes to the advancement of engineered systems design [17].

Overall, this introduction provides background information on the FMEA technique, highlights its limitations, and discusses various alternative approaches. It is organized to enhance coherence and readability, condensing the text by eliminating redundancies and focusing on relevant information. The citations have been formatted consistently and according to the journal's guidelines. Towards the end of the introduction, a brief summary of the main research gap and the specific contribution of the proposed method is provided to emphasize the novelty and relevance of the study [17].

2. METHODOLOGIES

The model's architectural layout for evaluating the risk of a belt conveyor is depicted in Figure 1. The suggested model comprises three stages. The first stage involves identifying the failure modes and risk variables. Risk factors such as S, O, and D are developed as criteria in the FMEA. Engineers generally evaluate risks linked to possible failures or damages when conducting a risk assessment process. Input from professionals with expertise and training is sought to identify potential risks [18].

2.1 Identifying the weights that appear to have an impact

The relative importance of criteria is determined using their weights in the assessment scheme [19, 20]. In this study, two methods, namely the Entropy Method and Mean Weight (MW), are used to assign weights. Additionally, weights are assumed for proposed scenarios.

2.1.1 Entropy method

In a given scenario where a decision matrix involves a significant amount of data for a range of potential materials, the entropy method is utilized to allocate weights to the criteria. The entropy method functions based on a predetermined decision matrix. As per the information theory's principle, the level of uncertainty conveyed by a discrete probability distribution is proportional to the width of the distribution, where a wider distribution indicates higher uncertainty than a more concentrated one [21, 22]. The entropy approach utilizes the data for each criterion to determine its relative importance. The entropy of the set of normalized results for the j^{th} criterion is calculated as follows:

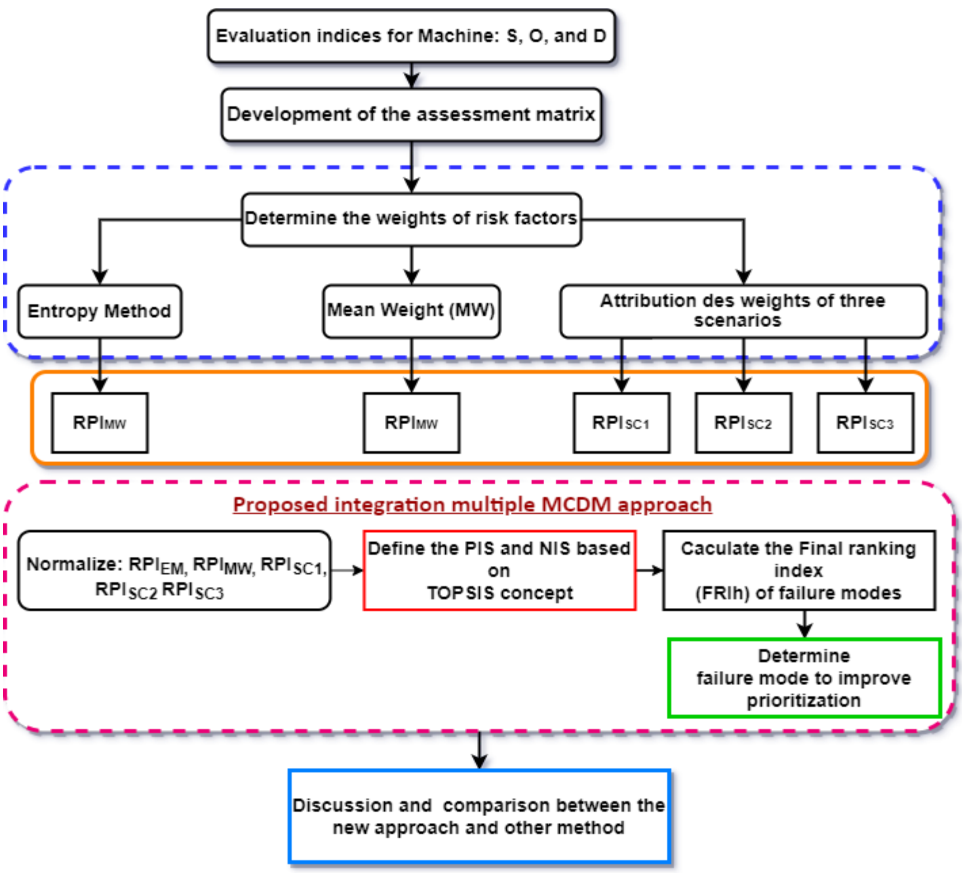

Figure 1. The proposed RPI-MCDM-based FMEA model

$$E_j = -\frac{\left[\sum_{i=1}^{m} P_{ij} ln(P_{ij})\right]}{\ln(m)} \quad (2)$$

j=1, 2…, n and i=1, 2…, m

The P_{ij} is provided by the normalized decision matrix and is:

$$E_j = -P_{ij} = \frac{r_{ij}}{\sum_i^m r_{ij}} \quad (3)$$

where, r_{ij} is an element of the decision matrix, E_j as the information entropy value for j[th] criteria. Hence, the criteria weights, w_j is obtained using the following expression:

$$\mathrm{W_j} = \frac{1-E_j}{\sum(1-E_j)}\ ; j = 1,2,\ldots,n \quad (4)$$

where, (1− E_j) is the degree of divers' i[th] of the information involved in the outcomes of the j[th] criterion.

2.1.2 Mean Weight (MW)

The mean weight is a commonly used approach when there is a lack of input or insufficient information from the decision maker to make a decision [23]. It assumes that all criteria are equally important, and this can be calculated using Eq. (5).

$$W_J = \frac{1}{n} \quad (5)$$

where, n is the number of criteria.

2.2 Using the RPI method to obtain the rankings of the failure modes

In the RPI (risk priority index function) model [18], two functions are utilized to give priority to failure modes: the first is the risk isosurface function [RI], which prioritizes failure modes based on the importance of risk variables; the second is the risk priority index function [RPI], which considers the relative weight of variables to prioritize failure modes. The RI function is easy to use and understand, and often sufficient for prioritizing failure modes. However, if there is a need to account for varying relative weights of risk factors, the RPI function should be used, which requires following a set of specified actions.

The phases for the RPI model may be summed up as follows:

Step 1: The following equation may be used to calculate RI while taking into account that the order of significance of A > B > C is more logical:

$$RI(A,B,C)_{A>B>C} = (1-A).\propto^2 + B\propto + C - \propto \quad (6)$$

where, A, B, C, α ∈ N.

As an illustration, consider a risk scenario where risk factors are evaluated using a 10-point scale and prioritized in the order of S > O > D. In this case, the RI function can be expressed using Eq. (3).

$$RI(S,O,D)_{S>O>D} = (1-S).10^2 + O.10 + D - 10 \quad (7)$$

Step 2: Assign the risk factors weights based on accepted expert reasoning to get a global failure mode risk value.

$$\delta_A = \frac{RI(A,B,C)_{A>B>C_{Rank}} + RI(A,B,C)_{A>C>B_{Rank}}}{2} \quad (8)$$

$$\delta_B = \frac{RI(A,B,C)_{B>A>C_{Rank}} + RI(A,B,C)_{B>C>A_{Rank}}}{2} \quad (9)$$

$$\delta_C = \frac{RI(A,B,C)_{C>A>B_{Rank}} + RI(A,B,C)_{C>B>A_{Rank}}}{2} \quad (10)$$

The delta risk drivers, denoted as δ_A, δ_B, and δ_C, are calculated based on the delta values of the risk factors, δ_S, δ_O, and δ_D. For example, if Severity, Occurrence, and Detectability are used as risk factors, then the delta values for these factors would be used to calculate the delta risk drivers.

$$RPI = w_A\,\delta_A + w_B\,\delta_B + w_C\,\delta_C \quad (11)$$

The following equation gives the failure mode RPI for the significance order $w_S > w_O > w_D$:

$$RPI = w_S\,\delta_S + w_O\,\delta_O + w_D\,\delta_D \quad (12)$$

Step 3: Verification of $w_A - w_B$ by flowing inequality:

$$w_S - w_O > \frac{1}{\varepsilon^2} - \frac{1}{\varepsilon^3} \quad (13)$$

Formula (13) guarantees that the user's ranking of importance is preserved. For this to happen, there must be a difference of more than 0.009 percentage points between the highest and middle weights. Although this value is very small, it is crucial to maintain the user's desired ranking and has no practical use in real-world applications.

Step 4: Eq. (14) gives the RPI's final form:

$$RPI = \left(\frac{w_A\varepsilon^3 + 1}{\varepsilon^3}\right)\delta_A + \left(\frac{w_B\varepsilon^2 + 1}{\varepsilon^2}\right)\delta_B + w_C\,\delta_C \quad (14)$$

2.3 Hybrid RPI-MCDM based FMEA model

Various strategies can lead to different outcomes when sorting options for assessment or selection. It is uncommon for all alternative ranks to be the same across all ranking techniques, making decision-making more complex. Hybrid MCDM approaches, such as those mentioned in references [24-28], have been explored to address this issue.

This research employs a modified RPI approach with three alternative weighting strategies to rank failures. However, to calculate the ultimate utility degree for each option, an appropriate integration approach is necessary. The suggested integrated model can assist risk managers in making better-informed decisions regarding the prioritization of failure types. It emphasizes the necessity for them to combine multiple MCDM techniques to achieve a comprehensive result.

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The TOPSIS method, proposed by Hwang and Yoon [30], is a widely used MCDM technique due to its simplicity and programmability. It determines the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution [31]. This research employs a modified RPI approach with three alternative weighting strategies to rank failures. However, to calculate the ultimate utility degree for each option, an appropriate integration approach is necessary. The suggested integrated model can assist risk managers in making better-informed decisions regarding the prioritization of failure types. It emphasizes the necessity for them to combine multiple MCDM techniques, such as TOPSIS, to achieve a comprehensive result.

The comprehensive procedures for multiple integrated MCDM approaches, based on the TOPSIS idea, are utilized to combine evaluation scores and can be obtained as follows:

Step 1: The scores of the failure modes are transformed into an index that ranges from 0 to 1.

The ranking indexes of RPI_{EM}, RPI_{MW}, $VRPIsc_1$, RPI_{sc2}, RPI_{sc3} are transformed by:

a. Create a Normalized Matrix.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{m} x_{ij}^2}} \tag{15}$$

b. Determine the weighted Normalized Matrix.

$$V_{ij} = r_{ij} \times W_j \tag{16}$$

where, W_j the weights of criteria and given by entropy method.

Step 2: Calculate (z+ and z- values, which represent the maximum and minimum scores for each column).

Get the highest and lowest scores (z+ and z-) for each method for each failure mode.

$$Z^+ = \underbrace{max}_{n}\{RPI_{EM}, RPI_{MW}, RPI_{SC1}, RPI_{SC2}, RPI_{SC3}\} = \{Z_1^+, Z_2^+, Z_3^+, Z_{4,}^+, Z_5^-\} \tag{17}$$

$$Z^- = \underbrace{max}_{n}\{RPI_{EM}, RPI_{MW}, RPI_{SC1}, RPI_{SC2}, RPI_{SC3}\} = \{Z_1^-, Z_2^-, Z_3^-, Z_4^-, Z_5^-\} \tag{18}$$

Step 3: Find the difference or distance between each failure mode and both the maximum and minimum scores, represented by z+ and z-.

It is possible to determine the distance between each failure mode and both the positive ideal solution (PIS) and negative ideal solution (NIS), which are represented by z+ and z-, respectively.

$$\alpha_n^+ = \sqrt{\begin{array}{c}(RPI_{EM} - Z_1^+)^2 + (RPI_{MW} - Z_2^+)^{2^2} \\ +(RPI_{SC1} - Z_3^+) \\ +(RPI_{SC2} - Z_4^+)^2 + (RPI_{SC3} - Z_5^+)^2\end{array}} \tag{19}$$

$$\alpha_n^- = \sqrt{\begin{array}{c}(RPI_{EM} - Z_1^-)^2 + (RPI_{MW} - Z_2^-)^{2^2} \\ +(RPI_{SC1} - Z_3^-) \\ +(RPI_{SC2} - Z_4^-)^2 + (RPI_{SC3} - Z_5^-)^2\end{array}} \tag{20}$$

$n = 1,2, \dots, m$

Step 4: Create the final ranking index.

The Final Ranking Index (FRIn) is utilized as a reliable metric to establish the benchmark for the ultimate ranking [23]. In our proposed model, we employ the separation distance between the positive ideal solution and the negative ideal solution for MCDM approaches to calculate the ranking index, which is expressed as follows:

$$FRI_n = \left(\frac{\alpha_n^-}{\sum_{n=1}^{m} \alpha_n^-}\right) - \left(\frac{\alpha_n^+}{\sum_{n=1}^{m} \alpha_n^+}\right) \tag{21}$$

where: $-1 \leq FRI_n \leq 1$.

3. CASE STUDY

The current research was carried out at the open pit phosphate mine operated by Bir El Ater company in southeast Algeria. The ore is transferred from the loading hopper via the conveyor belt (Figure 2). The conveyor belt's statistical data has shown how successful the new hybrid FMEA model that has been developed is.

Figure 2. Belt Conveyor in Bir El Ater Mine, Algeria

The study analyzed three years of breakdown statistics for functional belt conveyors and identified 20 unique failure modes. Table 1 lists the corresponding Fi failure mechanisms for each failure mode. Table 2 presents linguistic terminology and values for S, O, and D. However, Table 3 shows that the failure modes F9 and F13, F2 and F18, F1 and F5, and F8 and F14 occupy the same rank position, highlighting a common limitation of using RPN to identify failure scenarios. The study's analysis also identifies the three most critical failure modes as F4, F3, and F9. A comparison of the values assigned to the risk variables for these three modes with their RPN rank reveals that the decrease in detectability score affected the classification of F9, despite high S and O values for the first two faults. These findings demonstrate how the conventional FMEA approach can impact the relative weighting of each risk indicator in an uncontrollable manner (See Table 4).

As a result, RPIMw, RPIENW, and RPIsc1 correspondingly prioritize the failure modes as F4, F9, and FM13. Table 5 shows that different RPI approaches produce different rankings for the failure types. This is a difficulty. It might be dangerous and biased to solve and evaluate a reality of the situation using only one approach. It is obvious that a complete answer cannot be found by applying one evaluation method.

Table 1. FMEA machine of belt conveyer

	Fmea Machine – Analysis of Failure Modes, Their Effects and Their Criticality System: Belt Conveyer						Failure Number
	Element	**Function**	**Failure Mode**	**Causes of Failure**	**Effect of Failure**	**Detection**	
Electric Motor	**Fan**	Keep the Motor temperature down	Blocked fan	Corrosion -Physical damage. -Foreign material build up -Bad maintenance -Aging	Overheating and lead to expensive repair.	Auditory	F1
	Bearing	Reduce friction of the rotating shaft. Rotation guidance	Destruction of engine components	-Lack of lubrication -Improper lubrication or grease -Improper mounting -Shaft misalignment	Overload & overheat. Shaft damage. High repair cost	Monitor vibration monthly	F2
	Stator Defect	-Create a magnetic field -Carry current -Retain armature	-Eccentricity -Broken winding insulation -Thermal stress	-Lack of maintenance -Wear -Aging -Lack of maintenance. -Shaft voltages due to asymmetric electrical circuits	Motor inefficiency, high cost to repair	Use vibration analyse & infrared thermograph analysis.	F3
	Rotor Defect	The moving part of the motor	-Eccentric rotor -Broken rotor bar -Voltages surge -Overheat	-Thermal stress -Imbalance -Assembly problem -Overloading or heavy starts maintenance -Aging	Bearing damage motor Rebuild high repair cost	Use vibration analysis to detect rotor defect	F4
	External Faults Mechanical	Misalignment	Coupling & shaft Transmit the movement	- Movement abnormal and vibration and destruction of bearing	Bad type material. -Bad maintenance -improper installation -improper manufact -corrosion	Equipment shutdown to avoid bearing damage and expensive repairs	F5
Reducer and its Components	**The Reservoir**	Keep enough oil	-Lack of oil in the tank	Insufficient oil level	Bad drum training	Vibration and abnormal heating of reducers	F6
	Bevel Pinion with Helical Teeth	Transmit a rotational movement	Degradation of teeth by breaking	▪ Fatigue ▪ Defective quenching ▪ Bad load distribution	Noise and vibration	Analysis Vibratory	F7
	Pinion Toothed Helical	Transmit a rotational movement	Flaking	insufficient thickness of the treated layer (poor surface hardening)	Vibration	Analysis Vibratory	F8
			Seizure	Lubrication conditions, the quality of the lubricant, its pollution or the efficiency of the cooling system - poor lubrication	Noise and Vibration and increased temperature at the bearings	Analysis Vibration and thermal analysis	F9
	Pinion Shaft	transmission of motion	The shear failure	- Fatigue failure of the shaft	Reducer stop	visual	F10
	Spherical Roller Bearing	Provides rotational guidance	Deformation plastic	- preload overstress -non-compliance with assembly and handling instructions	Shaft drive fault	Analysis Vibratory	F11
	Rolling With Conical Rollers	Provides rotational guidance	Bearing seizure or fatigue	Poor shaft guidance	-Reduced bearing life. - Deterioration of the drive system	Analysis Vibratory	F12
	Rolling Spherical on Rollers	Provides rotational guidance	The rupture of the outer ring	-Misalignment -Strange body entered - Unsuitable tools	Vibration	Analysis Vibratory	F13
	Shaft	Transmission of motion	Bad transmission	Shaft twist -Misalignmentof the shaft	Vibration and rapid deterioration of the drive system.	Analysis Vibratory	F14
	Keyway	Make the connection between the shaft and the coupling	Matting	Misalignment of tha shaft	Shaft drive fault	Vibration Coupling noise	F15

Drum	Train the Band	Presence of flat spots or cracks Lining wear	Absence of friction coating Presence of foreign bodies between the belt and the drum	Déport bande Usure bande Tape speed reduction Tape offset	Visual inspection	Presence of flat spots or cracks Lining wear	F16
		Bad connection with the key	Usure rainure ou clavette	Beat	Visual inspection	Bad connection with the key	F17
Bands		Receive the product and transport it	Rupture (take off)	Tape too offset.	Production shutdown	Visual inspection	F18
			Tension insuffisant	Defective tensioning system: belt too long, significant expansion	Dragline: reduced speed	Visual inspection	F19
Roller Convoyer		Center and guide the tape	Blocking	Defective bearing: presence of foreign bodies high friction	Belt wear: flat on the rollers	Visual inspection	F20

Table 2. Linguistic terms and values for S, O, D

Linguistic Terms			Score
Severity (S)	**Occurrence (O)**	**Detection (D)**	
Very dangerous (VH)	Failure is practically inevitable (FI)	Absolute uncertainty (AU)	10
Hazardous (H)	Very high (VH)	Very remote (VR)	9
Extreme (E)	Repeated failures	Remote (R)	8
Major (MA)	High (H)	Very low (RL)	7
Significant (S)	Moderately high (MH)	Low (L)	6
Moderate (MO)	Moderate (M)	Moderate (M)	5
Low (L)	Relatively low (RL)	Moderately high (MH)	4
Minor (MI)	Low (L)	High (H)	3
Very minor (VM)	Remote (R)	Very high (VH)	2
None (N) Almost	Nearly impossible (NI)	certain (AC)	1

Table 3. The conventional FMEA ranking

Modes	S	O	D	RPN	Priority
F1	3	7	6	126	12
F2	3	8	9	216	7
F3	5	7	10	350	2
F4	7	7	10	490	1
F5	2	7	9	126	12
F6	3	3	8	72	19
F7	6	9	3	162	10
F8	4	10	3	120	15
F9	10	10	3	300	3
F10	6	10	3	180	9
F11	3	10	3	90	18
F12	10	9	3	270	6
F13	6	10	5	300	3
F14	3	10	4	120	15
F15	6	3	3	54	20
F16	3	6	7	126	12
F17	6	3	8	144	11
F18	6	6	6	216	7
F19	8	6	6	288	5
F20	3	6	6	108	17

In the RPIMw model, the ranking of failure modes is as follows for the top 3 positions: F4 (7-7-10) > F9 (10-10-3) > F13 (6-10-5). This indicates that the failure mode with a Severity score of (S=7), an Occurrence score of (O=7), and the highest Detectability score of (D=10) is considered the most crucial failure mode.

The RPIENW model determined that the top three critical failure modes were F4 (7-7-10), F9 (10-10-3), and F13 (6-10-5).

The weight (Table 4) is estimated with, we use two methods: Entropy Method, and Mean Weight (MW). Moreover, assuming weights with a proposed scenario.

Table 4. Different estimated weights

Entropy Method	0.38857	0.230255	0.381175
Mean Weight Method	0.3333	0.3333	0.3333
Scenario 1	0.5	0.2	0.3
Scenario 2	0.2	0.5	0.3
Scenario 3	0.2	0.3	0.5

Table 5. Rankings of the failure modes generated using various RPI methods

RPI_{EM}	RPI_{MW}	SC1	SC2	SC3	RANK
F4	F4	F4	F9	F4	1
F9	F9	F9	F13	F3	2
F13	F13	F13	F4	F2	3
F3	F3	F19	F10	F13	4
F19	F12	F12	F2	F9	5
F12	F10	F3	F3	F19	6
F2	F2	F17	F14	F17	7
F17	F19	F10	F12	F5	8
F10	F17	F18	F8	F10	9
F18	F14	F2	F19	F14	10
F14	F18	F7	F7	F12	11
F7	F8	F8	F5	F18	12
F5	F7	F14	F11	F16	13
F8	F5	F16	F17	F1	14
F16	F1	F1	F18	F6	15
F1	F16	F5	F1	F8	16
F6	F11	F6	F16	F7	17
F11	F6	F15	F6	F20	18
F20	F20	F11	F20	F11	19
F15	F15	F20	F15	F15	20

The RPIsc1 model ranks the failure modes and the top 3 positions are as follows: F4 (7-7-10) > F9 (10-10-3) > F13 (6-10-5).

The RPIsc2 model ranks the failure modes in the following order for the top 3 positions: F9 (10-10-3) > F13 (6-10-5) > F4 (7-7-10).

The RPIsc3 model ranks the failure modes in the following order for the top three positions: F4 (7-7-10) > F3 (5-7-10) > F2 (3-8-9).

The application of RPI with 5 different weight conditions for the prioritization of failure modes resulted in inconsistencies, mainly due to changes in the order of significance that need to be established to reflect the intended risk scenario. The subsequent sections aim to illustrate and explain the implementation of the proposed risk prioritization approach in this study.

In this study, a reliable method was proposed by combining multiple MCDM values to obtain the final results. Table 6 shows the ultimate ranking of failure modes, which was evaluated using Eqs. (1)-(21). The results reveal that F4 is the most critical failure mode, followed by F9 and F13.

Table 6. Results of the proposed integrated ranking method

Modes F.	α_n-	α_n+	FRI_n	Rank
F1	0.037926	0.071719	0.03147	15
F2	0.072872	0.03708	-0.03179	5
F3	0.078768	0.029649	-0.04392	4
F4	0.105819	0.00322	-0.09254	1
F5	0.043692	0.068921	0.023705	14
F6	0.026142	0.08359	0.052978	17
F7	0.045255	0.063251	0.0171	12
F8	0.04624	0.064528	0.017381	13
F9	0.096567	0.015069	-0.07334	2
F10	0.069489	0.039934	-0.02613	8
F11	0.028451	0.085908	0.053018	18
F12	0.071007	0.037886	-0.02937	7
F13	0.089423	0.021093	-0.06137	3
F14	0.0539	0.05876	0.005186	11
F15	0.003893	0.105439	0.093069	20
F16	0.036888	0.072408	0.033038	16
F17	0.0609	0.047235	-0.01169	9
F18	0.053396	0.054092	0.001364	10
F19	0.07183	0.036473	-0.03141	6
F20	0.01571	0.095452	0.073257	19

4. RESULTS AND DISCUSSION

The proposed model is appropriate for the practical implementation of risk analysis and management. In the absence of any observed failure modes, expert judgment is relied upon to assess potential hazards. Based on evaluations of severity, likelihood of occurrence, and detectability, the top five fault modes are identified as F4>F9>F13>F3>F2, with significant attention given to noise-related problems such as the rotor fault (F4), seizing of pinion toothed Helical (F9), and rolling spherical on rollers (F13) which provide rotational guidance. The driving system has several critical flaws, including bearing damage, noise and vibration, and elevated bearing temperatures, which are the primary causes.

The RPI-MCDM based FMEA model proposed is a trustworthy source of information that can assist experts and decision makers in comprehending the severity of risk associated with failure modes. Among the identified failure modes, F4, F9, F13, and FM3 are considered high-risk and demand immediate attention from risk managers for developing improvement strategies. F19, F12, F10, F17, and F18 belong to a lower risk category and can be prioritized for enhancement if adequate financial resources are available.

This research proposes a more rigorous approach to determine the risk ranking of different failure types, which is an improvement over the traditional methods that relied on a single approach. The new method overcomes the issues of objectivity and subjectivity and results in a more suitable classification of risk. Figure 3 illustrates the rankings generated by the suggested approach and five other methods. The novel model identifies F4, F9, and F13 as the three critical failure modes, which differs from the outcomes of other models.

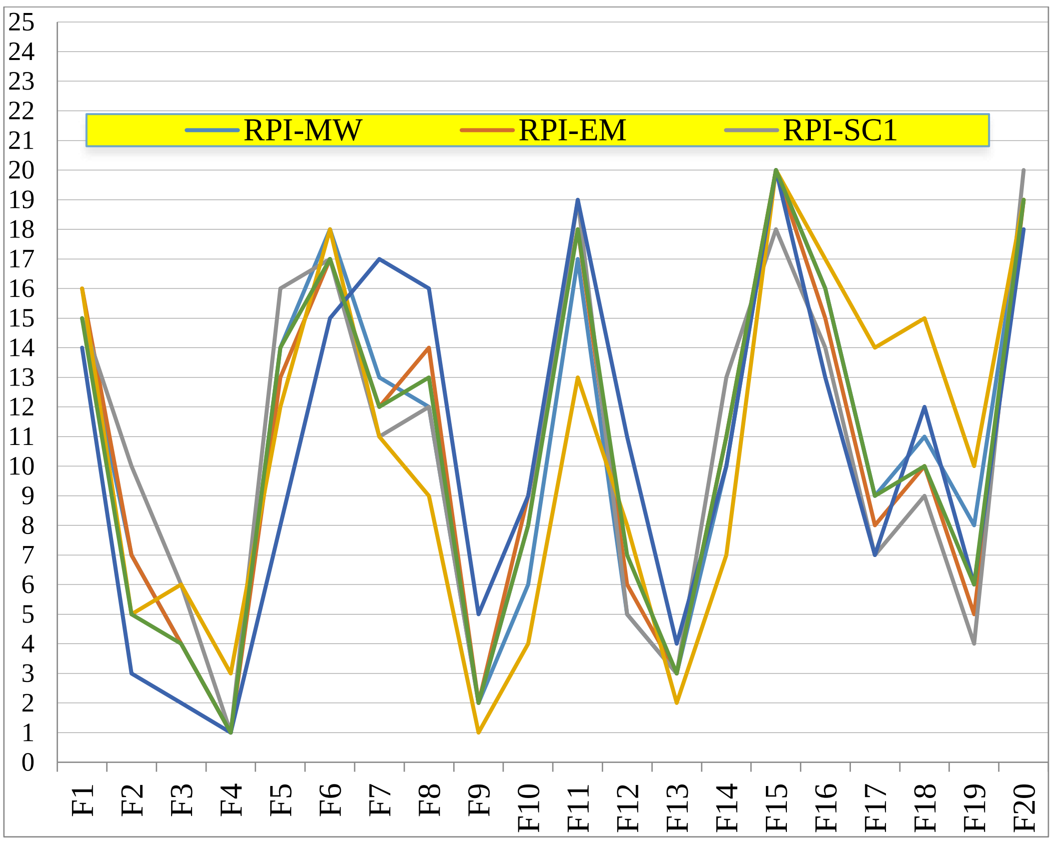

Figure 3. Failure mode ranking obtained using different methods

The suggested method is deemed more dependable than using a single approach to rate risks since it considers multiple factors. Although a few integrated methods have been developed, combining them all can provide a more comprehensive and practical usability ranking.

Table 6 compares the outcomes of the proposed method with two MCDM models, where F4 is the top-priority failure mode in all models. While VIKOR considers F3 as the second-highest priority failure mode, EDAS and the proposed model suggest FM9 as the second priority. The discrepancy is due to the similarity in severity levels of the two failure modes resulting in equivalent weightage being assigned to severity and detection. The relative severity of various failure modes could be lost if only the final rankings are considered. The results were shared with the experts of the case company who confirmed the proposed method's practicality compared to other methods.

The suggested model is capable of analyzing the influence relationships of risk parameters and prioritizing failure modes using the RPI-MCDM hybrid method. This approach overcomes the limitations of traditional FMEA methods.

5. CONCLUSION AND FUTURE RESEARCH

Since the 1950s, FMEA has been developed as a technology to identify possible faults before they occur. However, traditional FMEA approaches have limitations in producing comprehensive and acceptable analytical results. This study proposes an evaluation model, which classifies failure modes of systems and machines, in order to enhance failure modes in the mining industry. A belt conveyor is used as a reference case, as it is a crucial continuous conveying equipment in the mining industry. The study finds that vibration, temperature, wear, and lack of tightness of equipment are the factors that cause the most critical failure modes. Different risk ranking methods have varying concepts and calculation procedures, thus multiple methods can ensure more stable and objective analysis results. The proposed methodology is feasible and can be applied to various classification domains.

The proposed model provides several contributions and conclusions, including:

• The use of ENTROPY to determine dominant weights and consider interaction among evaluation factors.

• The ability to overcome the limitations of FMEA by using RPI models with different scenarios and weights.

• The proposed method integrates multiple MCDM approaches, utilizing TOPSIS to define the PIS and NIS, and calculates the Final Ranking Index (FRIn) of failure modes.

• To enhance the quality of maintenance, identifying the most critical failure mode is essential. Although the proposed model has demonstrated improved results compared to prior methods, it still has some limitations.

The current approach for evaluating possible failure modes relies on expert interviews and historical machine data, and incorporating up-to-date data can improve the objectivity of the analysis. Additionally, expanding the RPI model with more variables and exploring other MCDM techniques can enhance the analysis further. Fuzzy set theory or fuzzy-MCDM can be used to account for data quality during the evaluation process. These improvements can lead to more accurate and reliable results in future studies.

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REFERENCES

[1] Military, U.S. (1949). Procedure for performing a failure mode effect and criticality analysis. United States military procedure MIL-P-1629.

[2] Bejan, A. (2015). Constructal thermodynamics. Constructal Law & Second Law Conference, Parma, pp. S1-S8.

[3] Reiling, J.G., Knutzen, B.L., Stoecklein, M. (2003). FMEA-the cure for medical errors. Quality Progress, 36(8): 67-71.

[4] Lukas, L. (2014). Risk mapping for mobile communication. In 2014 International Conference on Mathematics and Computers in Sciences and in Industry, Varna, Bulgaria, pp. 1-5. https://doi.org/10.1109/MCSI.2014.59

[5] Teng, S.H., Ho, S.Y. (1996). Failure mode and effects analysis: An integrated approach for product design and process control. International Journal of Quality & Reliability Management, 13(5): 8-26. https://doi.org/10.1108/02656719610118151

[6] Chang, D.S., Paul Sun, K.L. (2009). Applying DEA to enhance assessment capability of FMEA. International Journal of Quality & Reliability Management, 26(6): 629-643. https://doi.org/10.1108/02656710910966165

[7] de Almada GarciaI, P.A., Leal Junior, I.C., Oliveira, M.A. (2013). A weight restricted DEA model for FMEA risk prioritization. Production, 23(3): 500-507. https://doi.org/10.1590/S0103-65132012005000092

[8] Zhang, Z., Chu, X. (2011). Risk prioritization in failure mode and effects analysis under uncertainty. Expert Systems with Applications, 38(1): 206-214. https://doi.org/10.1016/j.eswa.2010.06.046

[9] Chin, K.S., Wang, Y.M., Poon, G.K.K., Yang, J.B. (2009). Failure mode and effects analysis by data envelopment analysis. Decision Support Systems, 48(1): 246-256. https://doi.org/10.1016/j.dss.2009.08.005

[10] Abdelgawad, M., Fayek, A.R. (2010). Risk management in the construction industry using combined fuzzy FMEA and fuzzy AHP. Journal of Construction Engineering and Management, 136(9): 1028-1036. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000210

[11] Yang, J., Huang, H.Z., He, L.P., Zhu, S.P., Wen, D. (2011). Risk evaluation in failure mode and effects analysis of aircraft turbine rotor blades using Dempster–Shafer evidence theory under uncertainty. Engineering Failure Analysis, 18(8): 2084-2092. https://doi.org/10.1016/j.engfailanal.2011.06.014

[12] Witcher, M.F. (2014). Failure mode and effect analysis (FMEA) as a quality by design (QbD) tool for managing biopharmaceutical product development and manufacturing risks. Bioprocessing Journal, 13(3).

[13] Liu, H.C. (2016). FMEA using uncertainty theories and MCDM methods. In: FMEA Using Uncertainty Theories and MCDM Methods. Springer Singapore. https://doi.org/10.1007/978-981-10-1466-6_2

[14] Wang, L.E., Liu, H.C., Quan, M.Y. (2016). Evaluating the risk of failure modes with a hybrid MCDM model under interval-valued intuitionistic fuzzy environments. Computers & Industrial Engineering, 102: 175-185. https://doi.org/10.1016/j.cie.2016.11.003

[15] Zhao, H., You, J.X., Liu, H.C. (2017). Failure mode and effect analysis using MULTIMOORA method with continuous weighted entropy under interval-valued intuitionistic fuzzy environment. Soft Computing, 21: 5355-5367. https://doi.org/10.1007/s00500-016-2118-x

[16] Liu, H.C., You, J.X., Chen, S., Chen, Y.Z. (2016). An integrated failure mode and effect analysis approach for accurate risk assessment under uncertainty. IIE Transactions, 48(11): 1027-1042. https://doi.org/10.1080/0740817X.2016.1172742

[17] Akbarzade Khorshidi, H., Gunawan, I., Ibrahim, M.Y. (2016). Applying UGF concept to enhance the assessment capability of FMEA. Quality and Reliability Engineering International, 32(3): 1085-1093. https://doi.org/10.1002/qre.1817

[18] Nguyen, T.L., Shu, M.H., Hsu, B.M. (2016). Extended FMEA for sustainable manufacturing: An empirical study in the non-woven fabrics industry. Sustainability, 8(9): 939. https://doi.org/10.3390/su8090939

[19] Anes, V., Henriques, E., Freitas, M., Reis, L. (2018). A new risk prioritization model for failure mode and effects analysis. Quality and Reliability Engineering International, 34(4): 516-528. https://doi.org/10.1002/qre.2269

[20] Zhou, F., Wang, X., Lim, M. K., He, Y., Li, L. (2018). Sustainable recycling partner selection using fuzzy DEMATEL-AEW-FVIKOR: A case study in small-and-medium enterprises (SMEs). Journal of Cleaner Production, 196: 489-504. https://doi.org/10.1016/j.jclepro.2018.05.247

[21] Gören, H.G. (2018). A decision framework for sustainable supplier selection and order allocation with lost sales. Journal of Cleaner Production, 183: 1156-1169. https://doi.org/10.1016/j.jclepro.2018.02.211

[22] Deng, H., Yeh, C., Willis, R.J. (2000). Inter-company comparison using modified TOPSIS with objective weights. Computers & Operations Research, 27(10): 963-973. http://dx.doi.org/10.1016/S0305-0548(99)00069-6

[23] Payton, E., Khubchandani, J., Thompson, A., Price, J.H. (2017). Parents' expectations of high schools in firearm violence prevention. Journal of Community Health, 42: 1118-1126. https://doi.org/10.1007/s10900-017-0360-5

[24] Lo, H.W., Shiue, W., Liou, J.J., Tzeng, G.H. (2020). A hybrid MCDM-based FMEA model for identification of critical failure modes in manufacturing. Soft Computing, 24: 15733-15745. https://doi.org/10.1007/s00500-020-04903-x

[25] Ekmekçioğlu, M., Can Kutlu, A. (2012). A fuzzy hybrid approach for fuzzy process FMEA: An application to a spindle manufacturing process. International Journal of Computational Intelligence Systems, 5(4): 611-626. https://doi.org/10.1080/18756891.2012.718104

[26] Liu, H.C., You, J.X., You, X.Y. (2014). Evaluating the risk of healthcare failure modes using interval 2-tuple hybrid weighted distance measure. Computers & Industrial Engineering, 78: 249-258. https://doi.org/10.1016/j.cie.2014.07.018

[27] Liu, H.C., You, J.X., Ding, X.F., Su, Q. (2015). Improving risk evaluation in FMEA with a hybrid multiple criteria decision making method. International Journal of Quality & Reliability Management, 32(7): 763-782. https://doi.org/10.1108/IJQRM-10-2013-0169

[28] Liu, H.C., You, J.X., Shan, M.M., Shao, L.N. (2015). Failure mode and effects analysis using intuitionistic fuzzy hybrid TOPSIS approach. Soft Computing, 19: 1085-1098. https://doi.org/10.1007/s00500-014-1321-x

[29] Tsai, T.N., Yeh, J.H. (2015). Identification and risk assessment of soldering failure sources using a hybrid failure mode and effect analysis model and a fuzzy inference system. Journal of Intelligent & Fuzzy Systems, 28(6): 2771-2784. https://doi.org/10.3233/IFS-151556

[30] Hwang, C.L., Yoon, K. (1981). Multiple attributes decision making methods and applications. Part of the book series: Lecture Notes in Economics and Mathematical Systems (LNE, volume 186). Springer Berlin, Heidelberg. http://dx.doi.org/10.1007/978-3-642-48318-9

[31] Chen, S.J., Hwang, C.L. (1992). Fuzzy multiple attribute decision making methods and applications. Part of the book series: Lecture Notes in Economics and Mathematical Systems (LNE, volume 375). Springer Berlin, Heidelberg. http://dx.doi.org/10.1007/978-3-642-46768-4