A Comparative Study of K-Means Clustering and a Novel Ranking Algorithm for Risk Priority Number Analysis in FMECA

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Abstract

Failure mode, effects, and criticality analysis (FMECA) has become a fundamental tool for identifying critical failure modes and prioritizing maintenance activities. As part of the analysis, the risk priority number (RPN), a numeric assessment of the risk, has received much attention as it is computed using severity (S), occurrence (O), and detectability (D), which serve as the main criteria for criticality analysis in many practical FMECA cases. In this paper, we assemble and present a dataset containing RPN evaluations from 20 real-world cases. We then apply K-Means clustering to classify failure modes with different criticality levels and propose a novel ranking algorithm that prioritizes mitigation actions based on specific criteria for each failure mode. Our experimental results suggest that both clustering and ranking methods can provide prioritization for critical failure modes under given assumptions, while our novel ranking algorithm can adapt to general scenarios and provide more accurate prioritization that can help develop effective maintenance strategies to minimize failure risk and optimize maintenance costs.

1. Introduction

The details of failure mode, effects, and criticality analysis (FMECA) were first documented as MIL-STD-1629 (1949) and then revised in MIL-STD-1629A (1980) by United States Department of Defense, including the procedures of conducting failure mode and effects analysis (FMEA) and the qualitative and quantitative approaches for criticality analysis (CA). Since then, FMECA was used by the United States National Aeronautics and Space Administration (NASA) in the aeronautic industry to evaluate aircraft safety such as for the MSFC Saturn 5 Vehicle (Dill, Brown, Curtis, Herrmann, & Trampus, 1963). In recent decades, it has also been widely adopted by various industries (Bouti & Kadi, 1994).

Different applications of FMEA may require different procedures, for instance, IEEE Std C57.125-2015 (Revision of IEEE Std C57.125-1991) (2015) for FMEA was used on power transformers (Singh, Singh, & Singh, 2019), while criticality number and risk priority number (RPN) are commonly used for CA across different fields. RPN introduces severity (S), occurrence (O), and detectability (D) to calculate criticality among failure modes, providing prioritization for taking preventative actions. Despite its drawbacks, RPN has been widely applied in various industries till recent years (Mohanty et al., 2021; Catelani et al., 2021; Zhai et al., 2021), making it important to derive reliable insights from existing RPN evaluations.

Previous research has focused on classifying failure modes based on RPN results for action planning. Failure modes can be classified directly into *Acceptable*, *Tolerable*, and *Unacceptable* based on RPN values (Yssaad, Khiat, & Chaker, 2012; Saraswati, Marie, & Witonohadi, 2014). Alternatively, Fuzzy Adaptive Resonance Theory (Fuzzy ART) has been used to categorize failure modes into priority classes based on criterion scores (Keskin & Özkan, 2009) , with K-Means clustering also used for criticality level classification (Bezerra et al., 2020). On the other hand, researchers have used ranking methods to prioritize failure modes for decision-making. One approach is to improve the RPN, such as with weighted RPN (Tanjung et al., 2019) or fuzzy measure and integral (Liu, Deng, & Jiang, 2017). Other studies have introduced new indices like the Maintainability Criticality Index (MCI) with Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and Preference Section Index (PSI) to optimize maintenance planning (Pancholi & Bhatt, 2017). The Overall Failure Index (OFI) ranks corrective actions based on RPN (Khorshidi, Gunawan, & Ibrahim, 2016). While most studies rank failure modes, it's important to consider that certain failure modes may have significant impact on a specific criterion, even if their assessment at the failure mode level is non-significant.

According to the relevant work, it is noticed that both classification and ranking methods have been studied and applied for bringing values from RPN evaluations. It is worthwhile to study and validate how they can provide reliable practices under different scenarios. In this paper, a dataset collected from various RPN-based evaluation results is introduced. The dataset was then used for clustering and ranking experiments to assess the effectiveness and feasibility of both algorithms.

The remainder of the paper is organized as follows. Section 2 introduces the methods along with relevant validation indices we used for clustering and ranking tests. The experimental results are presented in Section 3, while the conclusion is given in Section 4.

2. METHODOLOGY

This section begins by introducing the adopted clustering method, as well as the validation indices, and subsequently presents the proposed ranking method to establish priorities for taking actions at the criterion level.

2.1. Clustering Methods

The RPN is one of the most widely used methods for calculating criticality in FMECA. It is defined as $RPN = S \times O \times D$, where Severity ($S$), occurrence ($O$), and detection ($D$) are the three criteria used to evaluate each failure mode. By considering these criteria as features, classification or clustering can be performed to identify patterns for categorizing criticality levels. In this paper, we employ K-Means to assess the performance of clustering.

2.1.1. K-Means

K-Means is a widely used clustering method. Its earliest contribution dating back to Steinhaus (1957). The development of the K-Means family of methods has been studied by Pérez-Ortega et al. (2019). The ultimate objective of K-Means is to obtain a set of clusters as,

$$\arg\min_{\mathbf{X}} \sum_{i=1}^{k} \sum_{\mathbf{x} \in \mathbb{X}_i} \|\mathbf{x} - \mathbf{c}_i\|^2, \tag{1}$$

where $\mathbf{X} = \{\mathbb{X}_1, \mathbb{X}_2, ..., \mathbb{X}_k\}$ denote the k clusters partitioned from all samples $\mathbf{x}$ and $\mathbf{c}_i$ is the i^{th} cluster.

The algorithms can be defined as two iterative steps: (1) Assign the samples to the nearest clusters by comparing the distances to the clustering centers; (2) Update the clustering centers by taking the mean of the updated clusters. The algorithm will cease when all the clusters remain no change after some number of iterations.

2.1.2. Validity Indices

A successful clustering should demonstrate clear separation among clusters, while also maintaining compactness within each cluster. In this paper, we utilize the Davies-Bouldin (DB) index for evaluating the clustering performance, which can be calculated as follows (Davies & Bouldin, 1979):

$$DB_k = \frac{1}{k} \sum_{i,j=1}^{k} \max_{j \neq i} \frac{S_i + S_j}{M_{i,j}}, \tag{2}$$

where S_i is the within cluster distance of cluster i and $M_{i,j}$ is the distance between clusters i and j.

2.2. Proposed Ranking Method

Direct usage of RPN values is the simplest way to rank failure modes, considering the combined impact of all three criteria. However, this method can be problematic if, for example, a failure mode has a high severity rating (e.g., 9 on a scale of 1 to 10) but low occurrence and detection ratings (e.g., 1 for both), resulting in a low RPN value compared to others with average ratings for all three criteria. Moreover, the conventional ranking by RPN is done at the failure mode level, while mitigation actions following FMECA are typically aimed at a single criterion at a time. Therefore, the conventional ranking by RPN may underestimate failure modes without considering criteria that require more urgent action.

To address these limitations, we propose a novel ranking method in this paper to provide priority for mitigation actions directly at the criterion level. This method enables us to avoid the risk of underestimating failure modes with exceptional criteria that require more urgent attention.

2.2.1. Risk Priority Ranking (RPR)

The proposed RPR algorithm is summarized in Algorithm 1. With a given evaluation matrix **E**, there are evaluated **S**, **O**, and **D** as three columns, along with an identifier assigned to each failure mode, which is the corresponding row index in **E** with a total of N_m rows. Before ranking, the score matrix **C** is initialized with the same dimension as **E** and the original RPN is calculated and stored in **R**, while a copy of **E** is recorded as $\mathbf{E}^{\dagger}$, used for ranking steps.

During the first step of iterations, the dynamic RPN $\mathbf{R}^{\dagger}$ is calculated first using updated $\mathbf{E}^{\dagger}$. Then the failure mode with the largest RPN in $\mathbf{R}^{\dagger}$ at the current iteration is located, whose identifier denoted as u, and at the same time, the criterion with the largest score is selected, denoted as v = 1 or 2 or 3. If for any step there are multiple choices, we set the priority for reference as *max* (RPN) $\rightarrow$ *max* (S) $\rightarrow$ *max* (O) $\rightarrow$ *max* (D) $\rightarrow$ *min* (u) $\rightarrow$ *min* (v), to ensure a unique answer. After locating the pair $[u, v]$ at iteration n, the corresponding cell in $\mathbf{C}$, i.e., $\mathbf{C}[u, v]$, is rewarded with score $f(n)$, where $f(n)$ is defined as scoring function and solely dependent on the number of iteration n. After updating the score matrix $\mathbf{C}$, the cell in the dynamic evaluation matrix, i.e., $\mathbf{E}^{\dagger}[u, v]$, is updated by a minus of δ, which is to simulate the impacts of mitigation actions. Then the next iteration will start with the same steps as described above.

The iterations stop when the minimum possible score is reached, meaning the highest value in the updated evaluation matrix $\mathbf{E}^{\dagger}$ is no longer greater than the minimum score. This yields the updated score matrix $\mathbf{C}$. The algorithm then selects the criterion with the highest score iteratively and adds it to the final priority ranking list $\mathbb{L}$. The corresponding cell in $\mathbf{C}$ for the selected criterion is set to 0, excluded from the next iteration. This creates a ranking list for mitigation priority at the criterion level. The scoring function used is crucial and several have been explored to see how they affect the results.

2.2.2. Scoring Function

The scoring function used in **Algorithm 1** is dependent on the number of iterations. To accurately set the function's domain, it's crucial to determine the total number of iterations needed to complete the RPR process. The formula to calculate the total number of iterations, denoted as $\hat{N}$, is as follows:

$$\hat{N} = \sum_{m}\sum_{n}\lceil \frac{\mathbf{E}\,[m, n] - \mu_L^{(m,n)}}{\Delta^{(m,n)}} \rceil, \tag{3}$$

where $\mathbf{E}$ is the evaluation matrix. $\mu_L^{(m,n)}$ and $\Delta^{(m,n)}$ are respectively the minimal possible rating and the step size for decreasing the scores during ranking corresponding to each failure mode m and its certain criterion n. Then the following scoring functions are defined and tested,

$$f_1(i) = N(1 - \frac{i}{N})^2, \tag{4}$$

$$f_2(i) = N - i, \tag{5}$$

$$f_3(i) = N\sqrt{1 - \frac{i}{N}}, \tag{6}$$

where $i = 1, 2, ...$ corresponding to the number of iterations. If $N \geq \hat{N}$, all criterion larger than 1 will have scores in the end, otherwise the selected criterion after a certain iterations will no longer obtain scores before completing the ranking.

Algorithm 1 Risk Priority Ranking (RPR) Algorithm

Input: evaluation matrix $\mathbf{E} = \left[e_{i,j}\right]_{N_m \times 3} = [\mathbf{S}\ \mathbf{O}\ \mathbf{D}]$
Output: priority ranking list $\mathbb{L}$

initialize score matrix $\mathbf{C} = 0_{N_m,3}$.
let $\mathbf{R}_{i,1} \leftarrow \mathbf{E}_{i,1} \cdot \mathbf{E}_{i,2} \cdot \mathbf{E}_{i,3}$, where $1 \leq i \leq N_m$.
let $\mathbf{E}^{\dagger} \leftarrow \mathbf{E}$, and $n \leftarrow 0$.
while there exist x and y such that $\mathbf{E}^{\dagger}_{x,y} > \mu_L$ **do**
  let $\mathbf{R}^{\dagger}_{i,1} \leftarrow \mathbf{E}^{\dagger}_{i,1} \cdot \mathbf{E}^{\dagger}_{i,2} \cdot \mathbf{E}^{\dagger}_{i,3}$, where $1 \leq i \leq N_m$.
  let $\mathbb{X} \leftarrow \arg\max_x \mathbf{R}^{\dagger}_{x,1}$.
  for $j \leftarrow 1$ to 3 **do**
    let $\mathbb{X} \leftarrow \arg\max_{x \in \mathbb{X}} \mathbf{E}^{\dagger}_{x,j}$
  end for
  let $u \leftarrow min(\mathbb{X})$, $v \leftarrow min(\arg\max_x \mathbf{E}^{\dagger}_{u,x})$.
  if $\mathbf{E}^{\dagger}_{u,v} \leq \mu_{min}$ **then**
    break
  else
    let $\mathbf{E}^{\dagger}_{u,v} \leftarrow \mathbf{E}^{\dagger}_{u,v} - \Delta$.
    let $\mathbf{C}_{u,v} \leftarrow \mathbf{C}_{u,v} + f(n++)$.
  end if
end while
while there exist x and y such that $\mathbf{C}_{x,y} > 0$ **do**
  let $\mathbb{Z} \leftarrow \arg\max_{(x,y)} \mathbf{C}_{x,y}$.
  let $\mathbb{Z} \leftarrow \arg\max_{(x,y) \in \arg\max_{(x,y)\in\mathbb{Z}} \mathbf{R}_{x,1}} \mathbf{E}_{x,y}$.
  let $(p, q) \leftarrow \arg\min_{(x,y) \in \arg\min_{(x,y)\in\mathbb{Z}} y} x$.
  let $\mathbf{C}_{p,q} \leftarrow 0$.
  append triplet [i (*priority rank*), p (*failure mode*), q (*criterion index*)] to priority ranking list $\mathbb{L}$.
end while
return the priority ranking list $\mathbb{L}$.

3. Experiment

3.1. Data Collection & Preparation

The RPN evaluation results were collected from 20 prior work with 338 instances in total (Keskin & Özkan, 2009; Singh et al., 2019; Khorshidi et al., 2016; Catelani et al., 2021; Zhai et al., 2021; Catelani et al., 2011; Yssaad et al., 2012; Khalil et al., 2014; Saraswati et al., 2014; El-Dogdog et al., 2016; Silva et al., 2020; Bezerra et al., 2020; Scriboni, 2020; Royer et al., 2020; Pancholi & Bhatt, 2017; Dumnić et al., 2020; Nursanti et al., 2018; Ciani et al., 2019; Tanjung et al., 2019; Mohanty et al., 2021). Each instance is identified by a specific failure mode. We then have the severity scores $\mathbf{S}$ = $[S_1^{(1)}, S_2^{(1)}, ..., S_j^{(i)}, ..., S_{N_m}^{(N_r)}]^T$, where i = 1, 2, ..., N_r refers to the reference with N_r the total number of references collected, and j = 1, 2, ..., N_m refers to the failure mode with N_m the total number of failure modes in all N_r references. The N_m can be computed with $N_m = \sum_{i=1}^{N_r} N_m^{(i)}$, where $N_m^{(i)}$ is the number of failure modes in reference i. The same formats were also defined for the occurrence scores $\mathbf{O}$ and detection scores $\mathbf{D}$.

As in different evaluation the range of scoring for S, O, and D could be different, the results collected were firstly normalized for both clustering and ranking purposes. We define the nomarlized $\tilde{\mathbf{S}}$ = $[\tilde{S}_1^{(1)}, \tilde{S}_2^{(1)}, ..., \tilde{S}_j^{(i)}, ..., \tilde{S}_{N_m}^{(N_r)}]^T$, where $\tilde{S}_j^{(i)}$

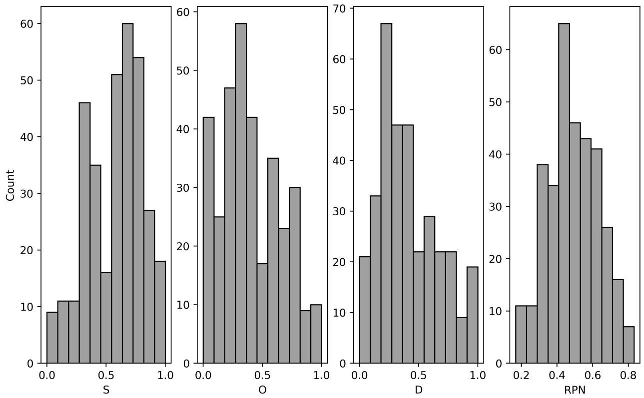

Figure 1. Histogram of $\tilde{S}$, $\tilde{O}$, $\tilde{D}$, and $R\tilde{P}N$ in the data set.

Table 1. Feature Selection for Clustering

	$\tilde{S}$	$\tilde{O}$	$\tilde{D}$	$\tilde{SO}$	$\tilde{SD}$	$\tilde{OD}$	$R\tilde{P}N$
COMB1	√	√	√				
COMB2				√	√	√	
COMB3	√	√	√	√	√	√	
COMB4	√	√	√				√
COMB5				√	√	√	√
COMB6	√	√	√	√	√	√	√

can be computed as,

$$\tilde{S}_j^{(i)} = \frac{S_j^{(i)} - \mu_{Smin}^{(i)}}{\mu_{Smax}^{(i)} - \mu_{Smin}^{(i)}}, \tag{7}$$

where $\mu_{Smax}^{(i)}$ and $\mu_{Smin}^{(i)}$ are the max and min scores for $S_j^{(i)}$ in source i respectively. Then $\tilde{\mathbf{O}}$ with $\mu_{Omax}^{(i)}$ and $\mu_{Omin}^{(i)}$ and $\tilde{\mathbf{D}}$ with $\mu_{Dmax}^{(i)}$ and $\mu_{Dmin}^{(i)}$ can be defined similarly. Then, for clustering purpose, we further introduce four normalized features simply computed with the scores above. The normalized RPN is defined as,

$$R\tilde{P}N_j^{(i)} = \sqrt[3]{\tilde{S}_j^{(i)} \times \tilde{O}_j^{(i)} \times \tilde{D}_j^{(i)}}, \tag{8}$$

which is the squared root of the RPN computed with the traditional way. Furthermore, in order to understand the interactive impacts between the scores, we similarly introduce the following values,

$$\tilde{SO}_j^{(i)} = \sqrt{\tilde{S}_j^{(i)} \times \tilde{O}_j^{(i)}}, \tag{9}$$

$$\tilde{SD}_j^{(i)} = \sqrt{\tilde{S}_j^{(i)} \times \tilde{D}_j^{(i)}}, \tag{10}$$

$$\tilde{OD}_j^{(i)} = \sqrt{\tilde{O}_j^{(i)} \times \tilde{D}_j^{(i)}}, \tag{11}$$

As shown in Fig. 1, S is generally evaluated with a higher score after normalization across different assessments, while the scores for O and D are comparatively lower. The normalized RPN shows an approximately normal distribution within the range of [0.17, 0.87]. The margins at both sides to 0 and 1 respectively indicate that some of the potential values of RPN can rarely be reached.

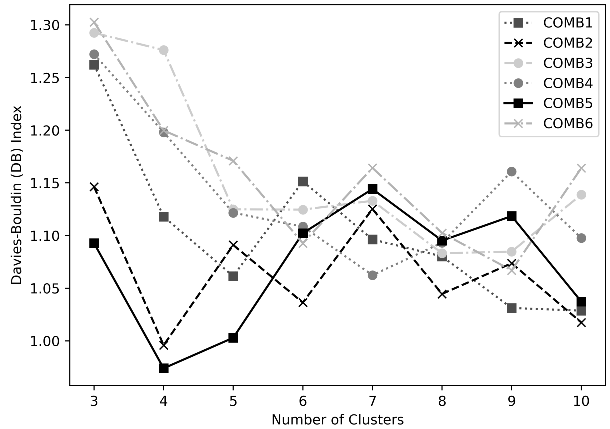

Figure 2. DB index testing results versus number of clusters.

Table 2. K-Means Clusters using *COMB5*

	$\tilde{SO}$	$\tilde{SD}$	$\tilde{OD}$	$R\tilde{P}N$
Cluster 1	0.32	0.34	0.25	0.31
Cluster 2	0.36	0.66	0.32	0.44
Cluster 3	0.56	0.46	0.43	0.49
Cluster 4	0.66	0.67	0.66	0.66

3.2. Clustering Results with K-Means

To assess the effectiveness of features for clustering, different combinations of features are employed and summarized in Table 1. A total of 6 combinations, labeled *COMB1* to *COMB6*, are defined with varying selected features as introduced in Section 3.1.

K-Means clustering has been evaluated on the dataset with varying numbers of clusters (3 to 10) using the *DB* index. The results in Fig.2 show that *COMB2* and *COMB5* generally achieve better clustering performance, including interactive impacts among $\tilde{SO}$, $\tilde{SD}$, and $\tilde{OD}$. The best result achieved within the range of 3 to 10 clusters is obtained with *COMB5* with 4 clusters. The corresponding cluster centers are summarized in Table 2, and the patterns of the 4 cluster centers align with the previous description of the dataset, where S was generally evaluated with a higher level while O and D with comparatively lower scores.

3.3. Ranking Results with Proposed Methodology

The ranking is performed using RPR with scoring functions f_1, f_2, and f_3. The results are presented in Figure 3 by com-

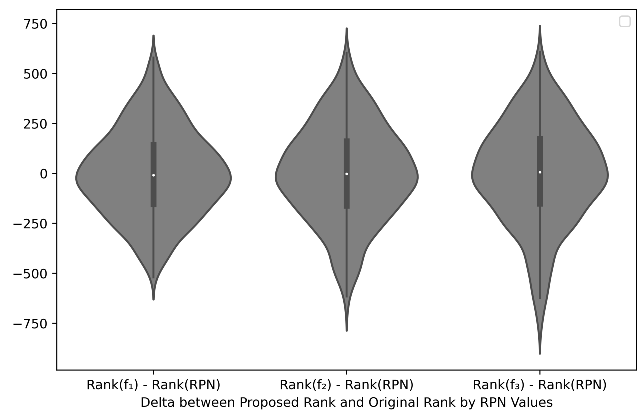

Figure 3. Changes of ranking results from original rank by RPN values to proposed rank, while the Rank(f_1), RPR results using scoring function f_1 shows the smaller variance to 0 and Rank(f_3) shows larger.

Table 3. Ranking Results with Different Scoring Functions

FM	Parameter	Score	RPN	Rank(f_1)	Rank(f_2)	Rank(f_3)
F11	S	7	245	4	4	4
F11	O	7	245	6	6	14
F11	D	5	245	24	25	32
F24	S	8	224	1	1	1
F24	O	7	224	7	9	15
F22	S	7	196	5	5	5
F22	O	7	196	8	10	16
F15	S	8	168	2	2	2
F15	O	7	168	12	12	17
F51	S	7	126	9	7	6

paring the changes from the original rank using RPN values. It can be observed that the ranking results obtained with RPR at the criterion level differ from those obtained by using only RPN as a reference at the failure mode level. Furthermore, the inconsistency with the original rank by RPN increases from f_1 to f_3 as the variance increases.

We adopt the evaluations from (Khorshidi et al., 2016) to test RPR at the criterion-level for a detailed comparison. Table 3 summarizes our findings. We select the top 10 parameters with the highest RPN values as examples, while parameters with a score under 5 are excluded from the table. By comparing the scores of parameters and the corresponding RPN at the failure mode level, we can observe that the ranking results with f_1 are more closely aligned with the RPN. However, the results with f_3 allocate more importance to the values of individual criterion.

4. Conclusion

In this paper, we presented a novel approach for failure mode prioritization based on RPN evaluations. We first collected a dataset of RPN evaluation results and performed a clustering analysis using K-Means. Our results show that with a properly selected combination of features, clustering can effectively classify failure modes with different levels of priority. Then we proposed a ranking method, RPR, that provides a priority ranking list at the criterion level based on the RPN evaluations, without requiring any prior processing. The proposed ranking algorithm allows for balancing the impacts at both the failure mode level and specific criterion level by selecting different scoring functions. Both clustering and ranking methods tested in this paper can provide insights applicable in various industries to prioritize failure modes and optimize maintenance plans. Possible future work includes the implementation of different feature selection and engineering methods, comparison of various clustering and ranking techniques, case studies with more real-world data, and examination of life cycle cost changes with provided maintenance prioritizations. These can further justify the robustness of the proposed methodology.

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