Optimizing Risk Assessment in Industrial Systems: A Decision-Support Framework Using Fuzzy and Grey Relational Analysis

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Abstract: Dependability plays a crucial role in determining the performance success of a system, focusing on understanding the factors contributing to system failures. The Failure Mode and Effects Analysis (FMEA) method, a traditional safety technique widely utilized across various safety-critical sectors, employs the Risk Priority Number (RPN) to gauge criticality and prioritize failure modes. However, it faces limitations, particularly in scenarios with ambiguous or uncertain information. Therefore, this study introduces a fuzzy criticality assessment approach to evaluate system failure modes, offering an alternative prioritization to the conventional method. Furthermore, a novel hybrid method is proposed, merging the Grey Relational Analysis (GRA) and Fuzzy Analytic Hierarchy Process. This hybrid approach addresses the shortcomings related to the absence of established inference rules, relying heavily on experience, and assigns weights to three equally significant parameters: severity, detection, and frequency, a departure from the traditional method. Through a real gas turbine system case study, this approach demonstrates promising outcomes in risk assessment and prioritizing failure modes, effectively handling various forms of ambiguity, uncertainty, and diverse expert judgments.

Keywords: FMEA, RPN, risk assessment, Fuzzy AHP, Grey relational analysis.

1. INTRODUCTION

Failure mode and effect analysis (FMEA) is vastly employed as an analytical methodology for recognizing, ranking, and reducing different failures modes. For such failure mode, three criticality factors: severity (S), non-detection (ND), and frequency (F) are assessed, and a risk priority number (RPN) is computed by multiplying these factors to evaluate the risk value(Ammar Chakhrit et al.).

Moreover, it demonstrates in different of applications that the FMEA still has many flaws. First, different integration of severity, detection, and frequency factors can provide an equal RPN value. While, the risk assessment for the different criticality can be wildly different. Second, in the calculation of the risk priority number, the potential importance of criticality parameters is not considered. Other disadvantage of the traditional FMEA methodology is the specific assessment of criticality factors concerning each failure mode. Nevertheless, because of restricted data and time pressure, criticality factors cannot correctly evaluating and the risk assessment process can be imprecise or uncertain (Bougofa, Bouafia, & Bellaouar, 2020; Bougofa et al., 2021; Liu, Liu, & Lin, 2013).

To solve the flaws, several ameliorated FMEA method was suggested by different works. (Ilangkumaran, Shanmugam, Sakthivel, & Visagavel, 2014) suggested a risk assessment model based on analytic hierarchy method to assess the risk level of important failures in the paper industry. For the criticality assessment of risk in a 2- dimensional ambiguous linguistic context, (Liu, You, & You, 2014) utilized the interval 2-tuple hybrid weighted distance (ITHWD) measure; then (Liu, Hu, Wang, & Sun, 2018) employed the alternative queuing approach in order to classify the criticality of the different failure modes. (Certa, Enea, Galante, & La Fata, 2017) gave an ELECTRE TRI-based approach to find risk level group of failure modes based on criticality factors. However, they still show some shortcomings due to the complication and ambiguity of the conventional technique. For this case, many researchers have utilized fuzzy system to resolve the issues mentioned above (Zadeh, Klir, & Yuan, 1996).(Wang, Chin, Poon, & Yang, 2009) utilized the criticality parameters as fuzzy values for risk assessment and ranking of failure modes in FMEA. (Liu, Liu, & Liu, 2013) arranged and ranked the risk evaluation approach in FMEA to represent the links between risk parameters and riskiness. More recently, a novel integrated decision-making model that combined the fuzzy analytic hierarchy process and grey relation analysis method were suggested by (Ammar Chakhrit & Chennoufi, 2021a). They provided an alternative ranking for failure modes which reduce the shortcoming of insufficient constructed inference rules, which require a lot of experience.

In light of the research problem previously mentioned, the originality and innovations of this research is based to reduce the ambiguity and minimize the judgments uncertainty, for that a novel hybridized approach that integrates the GRA method and fuzzy AHP method may resolve this issue. This model provides an alternative ranking for the criticality and enables reducing the flaws regarding the deficiency of constructed inference rules that requires a lot of experience, and give the weightage for the different factors, which are estimated to be equally important in the conventional FMEA technique.

2. FUZZY RISK EVALUATION MODEL

As being the FMEA method has considerable shortcomings in the calculation process and risk interpretation for these reasons a fuzzy risk evaluation based approach is given in section 2. The notion of fuzzy sets that was developed by Zadeh is the foundation for the fuzzy risk assessment model(Ammar Chakhrit et al., 2023; Ammar Chakhrit & Chennoufi, 2021c). It gives a more reliable to assess risk related with various failure modes (Ammar Chakhrit & Chennoufi, 2021b; Chennoufi & Chakhrit, 2023; Far, Mirzaei, Katrini, Haghshenas, & Sayahi, 2018), where the different factors utilized in the conventional technique will be fuzzified by using a proper membership function that employs knowledge rules IF - THEN that come from expert opinion, where the relation is represented as:

$$criticality = frequency \times severity \times detection \qquad (1)$$

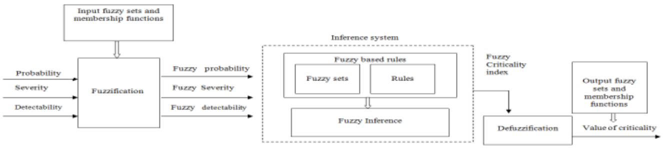

Figure1. Fuzzy risk model

3. PROPOSED APPROACH

A new model that integrates the GRA approach and fuzzy AHP is proposed to resolve flaws of the traditional technique. The proposed model can be acquired by the subsequent phases.

3.1. Recognizing comparative series

The comparative series is a data set that contains values for the relevant components. The comparison series, which includes the three factors mentioned above, is as follows:

$$r_i(m) = (r_i(1), r_i(2), r_i(3), \ldots\ldots r_i(m)) \in R, \ldots i = 1,2,3,\ldots n \qquad (2)$$

Where m denotes the risk parameters number and n is the failure modes number. r_i (m) represents the m^{th} parameters of r_i and the n comparative series is given as follows:

$$r = \begin{bmatrix} r_1 \\ r_2 \\ . \\ . \\ r_n \end{bmatrix} \begin{bmatrix} r_1(1) & r_1(2) & \ldots & r_i(m) \\ r_2(1) & r_2(2) & \ldots & r_2(m) \\ . & & & \\ . & & & \\ r_n(1) & r_n(2) & \ldots & r_n(m) \end{bmatrix} \qquad (3)$$

3.2. Standard series specification

Finding the degree of relation is the goal of recognizing the standard series; it displays the ideal level of all deciding elements. The standard series are as follows:

$$r_0(m) = (r_0(1), r_0(2), \ldots, r_0(m)) = (1,1,\ldots.,1) \qquad (4)$$

3.3. Comparative and standard Series differences

$$\Delta_{0i}(m) = \begin{bmatrix} \Delta_{01}(1) & \Delta_{01}(2) & \ldots & \Delta_{01}(m) \\ \Delta_{02}(1) & \Delta_{02}(2) & \ldots & \Delta_{02}(m) \\ . & & & \\ . & & & \\ \Delta_{0n}(1) & \Delta_{0n}(2) & \ldots & \Delta_{0n}(m) \end{bmatrix} \qquad (5)$$

Where $r_0(m)$ is the standard series, $r_i(m)$ is the comparative series, and $\Delta_{0i}(m) = |r_0(m) - r_i(m)|$

3.4. the Grey Relationship Coefficient

The standard series is examined with three risk variables. The following formula is used to calculate the grey relationship coefficient for frequency, non-detection, and severity factors:

$$\gamma(r_0(m), r_i(m)) = \frac{\Delta_{\min} + \zeta\Delta_{\max}}{\Delta_{0i}(m) + \zeta\Delta_{\max}} \qquad (6)$$

ζ Is a predetermined coefficient with a typical value of 0.5.

3.5. the Degree of relation determination

Equation 7 is used to estimate the relative value of each criticality factor if they are all of equal importance.

$$\tau_i(m) = \frac{1}{n}\sum_{m=1}^{n}\Delta_i(m) \qquad (7)$$

If the risk factors have various importance:

$$\tau_i(m) = \sum_{m=1}^{n}\Delta_i(m)\beta(m)..and\sum_{m=1}^{n}\beta(m) = 1 \qquad (8)$$

3.5.1. Fuzzy analytic hierarchy method

Saaty developed the fuzzy analytic hierarchy. It is an excellent method for resolving decision-making issues. The Fuzzy AHP technique is shown below:

Step 1: As shown in equation 9 , a pair-wise comparison matrix is created. The expert is asked to express linguistic terms in pair-wise comparisons across all criteria using triangular fuzzy numbers utilizing expert questionnaires.

$$A = \begin{bmatrix} (111) & j_{12}h_{12}k_{12} & j_{1n}h_{1n}k_{1n} \\ j_{21}h_{21}k_{21} & (111) & j_{2n}h_{2n}k_{2n} \\ j_{n1}h_{n1}k_{n1} & j_{n2}h_{n2}k_{n2} & (111) \end{bmatrix} \qquad (9)$$

A_{ij} is a fuzzy number (j, h, and k) for reciprocal $A^{-1} = (j,h,k)^{-1} = (\frac{1}{k}, \frac{1}{h}, \frac{1}{j})$

Step 2: Compute the fuzzy geometric mean for each criterion

Step 3: The fuzzy weights are calculated using normalization. To determine the fuzzy weight of the ith criterion, apply the following equation:

$$w_i = r_i \otimes (r1 \oplus r2 \oplus ... \oplus rn)^{-1} \quad (10)$$

3.6. Criticality Ranking

The failure modes are prioritized according to how closely they are related to each other. Priority is given to the failure modes with the lowest degree of grey relation

4. CASE STUDY

The system selected for this study is a gas turbine system, In Algeria, the spread of these systems are clearly seen. It is a combustion engine that can transform natural gas into mechanical energy(A Chakhrit et al., 2022). After that, a generator powered by this energy produces electricity. This system is shown in figure 2:

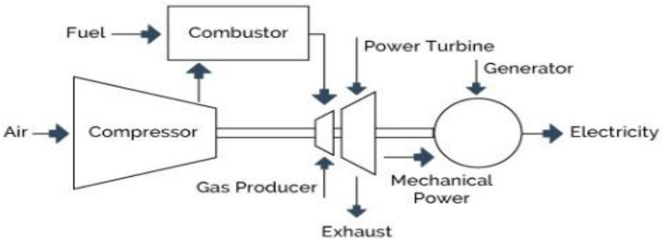

Figure2. Gas turbine design

4.1. Proposed approach

FMEA data is employed in this part, and the grey relation method is used with different situations (risk factors with various and similar weights). The FAHP method is called to determine the risk parameters weights based on expert opinion.

The first step is to construct comparative series regarding to the various parameters by the matrix as follows.

$$\begin{bmatrix} r_1(1) & r_1(2) & r_1(3) \\ r_2(1) & r_2(2) & r_2(3) \\ & & \\ r_8(1) & r_8(2) & r_8(3) \\ & & \\ r_{14}(1) & r_{14}(2) & r_{14}(3) \\ r_{15}(1) & r_{15}(2) & r_{15}(3) \end{bmatrix} = \begin{bmatrix} 2 & 10 & 6 \\ 2 & 5 & 3 \\ & & \\ 5 & 6 & 6 \\ & & \\ 8 & 9 & 7 \\ 7 & 9 & 6 \end{bmatrix} \quad (11)$$

The difference between the standard and comparative series is given by Equation 5, which is shown in the matrix below.

$$\begin{bmatrix} \Delta_{01}(1) & \Delta_{01}(2) & \Delta_{01}(3) \\ \Delta_{02}(1) & \Delta_{02}(2) & \Delta_{02}(3) \\ . & . & . \\ . & . & . \\ \Delta_{08}(1) & \Delta_{08}(2) & \Delta_{08}(3) \\ . & . & . \\ \Delta_{014}(1) & \Delta_{014}(2) & \Delta_{014}(3) \\ \Delta_{015}(1) & \Delta_{015}(2) & \Delta_{015}(3) \end{bmatrix} = \begin{bmatrix} 1 & 9 & 5 \\ 1 & 4 & 2 \\ . & . & . \\ . & . & . \\ 4 & 5 & 5 \\ . & . & . \\ 7 & 8 & 6 \\ 6 & 8 & 5 \end{bmatrix} \quad (12)$$

As described previously, the grey relation coefficient is derived by equation 6.

$$\begin{bmatrix} \gamma_{01}(1) & \gamma_{01}(2) & \gamma_{01}(3) \\ \gamma_{02}(1) & \gamma_{02}(2) & \gamma_{02}(3) \\ . & . & . \\ . & . & . \\ \gamma_{08}(1) & \gamma_{08}(2) & \gamma_{08}(3) \\ . & . & . \\ \gamma_{014}(1) & \gamma_{014}(2) & \gamma_{014}(3) \\ \gamma_{015}(1) & \gamma_{015}(2) & \gamma_{015}(3) \end{bmatrix} = \begin{bmatrix} 1 & 0.4 & 0.58 \\ 1 & 0.64 & 0.85 \\ . & . & . \\ . & . & . \\ 0.64 & 0.58 & 0.58 \\ . & . & . \\ 0.48 & 0.44 & 0.52 \\ 0.52 & 0.44 & 0.58 \end{bmatrix} \quad (13)$$

If all risk factors have similar weights, equation 7 is used to compute the relation degree. For instance; the first failure mode is deduced as;

$$\tau_i(k) = \frac{1}{3}(\gamma_{01}(1) + \gamma_{01}(2) + \gamma_{01}(3)) = \frac{1}{3}(1 + 0.4 + 0.58) = 0.66$$

The second situation where the parameters with various weights; the fuzzy AHP technique is used to assign weights to the risk factors. The significance of the risk parameters has been compared by experts to triangular fuzzy values. The overall results are presented in table 1.

5. CASE STUDY

Table 2 represents the findings of the different approach for gas turbine system. As given in the Table 2 that the prioritization of failures mode obtained from the traditional FMEA is classified as FM14, FM15 FM12, FM10, FM8, FM13, (FM9, FM1), FM11, FM4, (FM5, FM3), FM7, FM6, FM2, respectively. However, after utilizing the fuzzy model provided a novel ranking for the criticality. For example, in the traditional methodology, FM13 was classified in the sixth rank. While, it ranked at the third classification in the fuzzy proposed model. Simultaneously, in both the methods, FM14 was the most critical mode.

By comparing the traditional finding of the fuzzy model with FMEA method, the flaws combined with conventional FMEA can evidently shown; the most significant flaw of the conventional methodology is that the various combinations of the different factors give an equal RPN value; however, the risk interpretations can be different, for instance, FM3and FM5 have an equal risk priority number of 60, while the risk outcome cannot exactly be the same, but the proposed fuzzy model differs in those. The second shortcoming of the traditional methodology disregards the importance between the different parameters. The three inputs are suggested to be equally important, but in actual implementations, the inputs' relative relevance is still present; for instance, the failure mode 13 with a moderate frequency, low detection, and very high severity (6, 3, 9) with a lower risk priority number of 162 than one with all factors moderate as the failure mode 8 with risk priority number of 180; on the contrary with the fuzzy model can distinctly observed that FM13 has a higher value than FM8with values 0.572, 0.457, and hence will be given more attention for preventive and corrective actions. Concerning the suggested grey analysis model, there has been an observed variation in the ranking order with the previous approach. For example, FM14, FM15 have higher priority in all model (the most significant modes of failure). While, the failure mode 13 has lower priority in the suggested model and a higher classification in other models. The important cause is explicated by different risk assessment models and prioritization processes utilized in each approach.

Table 2 also represented the weightage of the different factors through the grey suggested model. When different weights parameters are utilized, it is clearly shown that is a marked rearranging in the classification for the failure modes, showing their importance. In the case of requests coming from modifications or variations, changing the weights can be a simple way to adjust the strategy. The GRA methodology is called when there are no particular inference rules that require a great deal of experience.

Table1. Fuzzy weights calculation

factors	Frequency	Non-detection	Severity	Fuzzy geometric mean value r_i	Fuzzy weights w_i
Frequency	(1,1,1)	$(\frac{1}{7}, \frac{1}{6}, \frac{1}{5})$	$(\frac{1}{9}, \frac{1}{9}, \frac{1}{8})$	(0.251 0.264 0.292)	0.05
Non-detection	(5,6,7)	(1,1,1)	$(\frac{1}{9}, \frac{1}{8}, \frac{1}{7})$	(0.822 0.908 1)	0.173
Severity	(8,9,9)	(7,8,9)	(1,1,1)	(3.825 4.16 4.32)	0.777

Table2. Ranking of conventional, fuzzy and GRA suggested model

Nº	Failure Mode	Cause	F	S	D	Classical RPN	Ranking	Fuzzy RPN	ranking	GRA with same weights	ranking	GRA with various weight	ranking
1	Vibration	Incorrect signal	2	10	6	120	7	0.457	7	0.660	8	0.461	2
2		bearings not working	2	5	3	30	13	0.20	15	0.831	14	0.622	11
3	Over-temperature	soiled compressor rotor	3	5	4	60	10	0.250	13	0.737	11	0.666	14
4	Stall	changeable stator vanes Binding	3	6	4	72	9	0.274	12	0.718	10	0.619	10
5		Foreign objects degrade	3	4	5	60	10	0.230	14	0.737	11	0.600	9
6	Flame-out	Energy nozzles blockage	4	6	2	48	12	0.358	10	0.771	13	0.660	13
7	Hot spots on flame tube	Uneven flame dispersion around a malfunctioning flame tube.	4	7	2	56	11	0.370	9	0.751	12	0.649	12
8	Vibration	Defective vibration indication	5	6	6	180	5	0.457	6	0.567	3	0.583	8
9		Defective bearings	5	8	3	120	7	0.447	8	0.653	7	0.544	7
10	Over-speed	Excessive fuel flow	6	7	5	210	4	0.5	5	0.580	4	0.544	7
11	No start	particles, water, or air in fuel	2	9	5	90	8	0.308	11	0.693	9	0.500	4

		lines										
12	Stall	irregular fuel pressure	6	8	5	240	3	0.531	4	0.600	5	0.512	5
13	wrong temperature indication	short circuit in thermocouple circuit	6	9	3	162	6	0.572	3	0.620	6	0.516	6
14	Not reaching idle speed	Low electrical power	8	9	7	504	1	0.758	1	0.480	1	0.456	1
15	Defective speed indication	Internal tachometer failure	7	9	6	378	2	0.667	2	0.513	2	0.468	3

6. CONCLUSIONS

The traditional FMEA methodology received different criticism for its shortcomings, especially in the evaluation process and risk priority computation. In this work, a novel risk prioritization approaches to assess the criticality of the different failures in FMEA is proposed.

Compared to the traditional methodology, the advantage of fuzzy model evaluation permits experts to more objectives combining of the different factors by utilizing their experience to reduce the flaws creating in performing of the classical FMEA technique. This study represented the efficiency of the fuzzy criticality approach to control various kind of ambiguities in the failure evaluation technique, such as, fuzziness, incompleteness and vagueness

Fuzzy analytic hierarchy and grey relation analysis approach are utilized in this study to assess and prioritize the failure modes more factual and dynamic. The results can give important outcomes in the decision-making process. The results represent in a real case study of risk ranking of failures modes that the combination of the fuzzy analytic hierarchy and grey relation analysis methods can give a more acceptable risk prioritization order. In addition, the proposed models can be used when the predetermined inference rules are inadequate and require a lot of expertise.

REFERENCES

Bougofa, M., Bouafia, A., & Bellaouar, A. (2020). An Integrated Quantitative Bayesian Network in Risk Management for Complex Systems. *International Journal of Performability Engineering*.

Bougofa, M., Taleb-Berrouane, M., Bouafia, A., Baziz, A., Kharzi, R., & Bellaouar, A. (2021). Dynamic availability analysis using dynamic Bayesian and evidential networks. *Process Safety and Environmental Protection, 153*, 486-499.

Certa, A., Enea, M., Galante, G. M., & La Fata, C. M. (2017). ELECTRE TRI-based approach to the failure modes classification on the basis of risk parameters: An alternative to the risk priority number. *Computers & Industrial Engineering, 108*, 100-110.

Chakhrit, A., Bougofa, M., Guetarni, I., Nehal, N., Bouafia, A., Ghazli, F., . . . Chennoufi, M. (2022). *New risk assessment and prioritization failure modes based approach in a gas turbine system.* Paper presented at the IOP Conference Series: Earth and Environmental Science.

Chakhrit, A., Bougofa, M., Guetarni, I. H. M., Bouafia, A., Kharzi, R., Nehal, N., & Chennoufi, M. (2023). A hybrid integrated multi-criteria decision-making approach for risk assessment: a study of automotive parts industry. *International Journal of Quality & Reliability Management*(ahead-of-print).

Chakhrit, A., & Chennoufi, M. (2021a). Failure mode, effects and criticality analysis improvement by using new criticality assessment and prioritization based approach. *Journal of Engineering, Design and Technology*.

Chakhrit, A., & Chennoufi, M. (2021b). Failure mode, effects and criticality analysis improvement by using new criticality assessment and prioritization based approach. *Journal of Engineering, Design and Technology*(ahead-of-print).

Chakhrit, A., & Chennoufi, M. (2021c). Fuzzy multi-criteria approach for criticality assessment and optimization of decision making. *Journal of Intelligent & Fuzzy Systems*(Preprint), 1-16.

Chakhrit, A., Djelamda, I., Bougofa, M., Guetarni, I. H., Bouafia, A., & Chennoufi, M. Integrating fuzzy logic and multi-criteria decision-making in a hybrid FMECA for robust risk prioritization. *Quality and Reliability Engineering International*.

Chennoufi, M., & Chakhrit, A. (2023). An extended FMECA approach using new risk assessment and prioritization based approach. *International Journal of Information Technology*, 1-10.

Far, S. Y., Mirzaei, R., Katrini, M. B., Haghshenas, M., & Sayahi, Z. (2018). Assessment of Health, Safety and Environmental Risks of Zahedan City Gasoline Stations. *Engineering Technology & Applied Science Research, 8*(2), 2689-2692.

Ilangkumaran, M., Shanmugam, P., Sakthivel, G., & Visagavel, K. (2014). Failure mode and effect analysis using fuzzy analytic hierarchy process. *International Journal of Productivity and Quality Management, 14*(3), 296-313.

Liu, H.-C., Hu, Y.-P., Wang, J.-J., & Sun, M. (2018). Failure mode and effects analysis using two-dimensional uncertain linguistic variables and alternative queuing method. *IEEE Transactions on Reliability, 68*(2), 554-565.

Liu, H.-C., Liu, L., & Lin, Q.-L. (2013). Fuzzy failure mode and effects analysis using fuzzy evidential reasoning and belief rule-based methodology. *IEEE Transactions on Reliability, 62*(1), 23-36.

Liu, H.-C., Liu, L., & Liu, N. (2013). Risk evaluation approaches in failure mode and effects analysis: A literature review. *Expert systems with applications, 40*(2), 828-838.

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.

Wang, Y.-M., Chin, K.-S., Poon, G. K. K., & Yang, J.-B. (2009). Risk evaluation in failure mode and effects analysis using fuzzy weighted geometric mean. *Expert systems with applications, 36*(2), 1195-1207.

Zadeh, L. A., Klir, G. J., & Yuan, B. (1996). *Fuzzy sets, fuzzy logic, and fuzzy systems: selected papers* (Vol. 6): World Scientific.