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GREY RELATIONAL ANALYSIS IN FMEA FOR GAS TURBINE RISK PRIORITIZATION

By

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ABSTRACT

This study proposed risk prioritization of gas turbine power plant using Grey relational analysis (GRA) approach. Firstly, Failure Mode and Effects Analysis (FMEA) was applied for the risk analysis of the system. The risk priority in the FMEA was determined using risk priority numbers (RPNs) that can be obtained by evaluating three factors: occurrence (O), severity (S), and detection (D). It was observed that the conventional FMEA based on crisp RPN is not robust enough in risk priority ranking of the failure modes. To overcome this short-coming we employed Grey relational analysis (GRA) to calculate the grey relation coefficient. The GRA method produced the following results for the first five failure modes: FM1 = 0.4337, FM2 = 0.5215, FM3 = 0.5699, FM4 = 0.5307, and FM5 = 0.6565. Unlike traditional FMEA which produced identical RPN values of 54 for FM3 and FM6, GRA distinguished these as 0.5699 and 0.5314 respectively. This result shows that the GRA method was able to resolve the drawback observed in the traditional FMEA approach. The feasibility of GRA in FMEA was verified by using it to deal with failure risk evaluation of the compressor subsystem of a gas turbine power plant.

Keywords: Severity, Occurrence, GRA, FMEA, Risk analysis, Gas Turbine.

1. Introduction

Electricity is considered as the backbone of any industrialized nation. Today, power industries are facing challenges in ensuring uninterrupted electricity supply. As power demand continues to rise globally, utilities and plant operators are challenged to minimize unplanned outages, optimize asset

utilization, and maintain high levels of safety and compliance. The reliability and efficiency of modern power systems are essential in sustaining economic growth, social well-being, and technological development.

Risk assessment practices are central to ensuring that critical components such as turbines, transformers, circuit breakers, and compressors operate efficiently and safely. A plant consists of several generating units which work together to meet the electric load demand of customers. This study is focused on gas turbine power plant; which is a type of fossil power plant. It comprises of three basic components: the compressor, Combustion chamber and the turbine (Sanyaolu et al, 2023). Power plants are expected to operate with high reliability and availability so as to curtail the often-high operation and maintenance cost experienced by power plant operators.According to Rausand and Vatn, (1998) risk can be defined as the product of probability of system failure and the consequences of the failure happening. There are several techniques developed to perform risk assessment or prioritization. These include; Failure Mode and Effect Analysis (FMEA), Root Cause Analysis (RCA), Hazard and Operability Analysis (HAZOP), checklist analysis, and Fault Tree Analysis (FTA) (Charles et al, 2025). The quality of a risk analysis output depends on the aspects of data sources, human factor, tools and methods used, and capability and experience of the analyst.

In performing risk assessment, the reliability-centered maintenance (RCM) framework utilizes Failure Mode and Effects Analysis (FMEA) in prioritizing the risk of failure modes of a system. Here, risk is represented in the form of a Risk Priority Number (RPN) which is computed by the product of the severity rating (S), occurrence probability (O), and the detection rating (D) for all failure modes of the system. Consequently, many authors have criticized FMEA because of some limitations such as; inability to consider other significant factors such as: economic cost, production loss, environmental impact, and the use of only accurate data to enact expert opinions. But in most practical cases, the information may be a fuzzy estimate (Zammori and Gabbrielli, 2012 and Liu et al., 2011). According to Liu et al. (2013), the techniques proposed to overcome the FMEA drawbacks can be grouped into five key categories, namely: MCDM, artificial intelligence (AI), mathematical programming (MP), hybrid approaches, and others. Fundamentally, each of the above techniques uses a different approach of implementation for coping with the deficiencies associated with the FMEA.

To the best knowledge of researchers, no study on risk analysis of gas turbine compressor sub system in Nigeria exists in indexed literature. Therefore, the aim of this study is to develop an enhanced methodology based on the integration of FMEA and GRA approach for the assessment of the level of risk of a gas turbine equipment.

The objectives of the study are to:

- develop a framework for the ranking of failure modes of a gas turbine equipment using traditional FMEA.
- develop a framework for the ranking of failure modes of a gas turbine equipment using artificial neural network method.

2. Literature Review

The traditional FMEA has some limitations just like every other risk assessment tool however many alternative variations and methods have been advocated in the literature in order to overcome some of these challenges. The application of the GRA methodology can be utilised in risk analysis of power systems as has been reported in the literature. Panchal and Kumar, (2017a) presented an integrated framework for the risk analysis of a compressor house unit (CHU) in a medium size coal-fired thermal power plant. Firstly, they performed FMEA where the various components of the considered system were prioritized based on the RPN score. Then fuzzy FMEA and GRA were utilised to overcome the limitation of the traditional FMEA method. In fuzzy FMEA, a fuzzy decision support system (FDSS) was developed to compute the FRPN scores and the ranking of various components of the considered system was done. Further, to make an intelligent decision making of risky components of the considered system GRA was done using the same linguistic terms which were defined for the fuzzy FMEA approach and the ranking results were compared with those of FMEA and fuzzy FMEA results.

Das et al. (2024) introduced a framework combining fuzzy AHP and VIKOR to rank various risks in the nuclear power industry. The approach aims to reduce mishaps and minimise recovery time and costs by identifying and prioritising risks based on expert assessments of severity, occurrence, and detection. The Fuzzy AHP-VIKOR approach was employed to calculate the weight of each performance criterion and the ranking of each risk or hazard. Panchal and Kumar, (2016) suggested an integrated framework for behaviour analysis in a process plant. Their technique incorporates quantitative and qualitative analysis. To improve the system's availability and maintainability characteristics, a detailed qualitative analysis was performed utilising RCA and FMEA to highlight

the numerous failure causes. Limitations of traditional FMEA in risk ranking of risky/critical components were overcome by employing a Fuzzy Decision-Making System (FDMS) and GRA. The ranking results obtained were compared with results obtained from the use of FMEA ranking only for better decision-making of risky components. The framework was employed to carry out the behavioural analysis of a real Water Treatment Plant (WTP) of a coal-fired thermal power plant in North India. Alrifaey et al. (2019) proposed identification and prioritisation of risk factors in an electrical generator based on the hybrid FMEA framework. Their research integrates ANP with FMEA and DEMATEL to identify and prioritise risk factors in electrical generators, enhancing the traditional FMEA approach by considering interrelationships among failure modes. The hybrid framework of FMEA was conducted in a hazardous environment at a power generation unit in an oil and gas plant located in Yemen.

Panchal and Srivastava, (2018) applied fuzzy integrated MCDM framework for qualitative analysis of the compressed natural gas dispensing system. A total of 43 risks were identified and seven were assessed as critical to the system. The regulator malfunction of the metering skid, internal leakage of the compressor, motherboard failure of the dispenser, internal pipe leakage and air filter choking of priority panel and plug leakage of cascade have been identified as a critical risk in their study. In their study, they performed an integrated approach of FMEA, fuzzy FMEA and fuzzy GRA respectively. Panchal and Kumar, (2017b) developed qualitative and quantitative approaches based integrated framework for studying the behaviour of a real industrial system. Further, for improving the system's availability, qualitative analysis was performed using the root cause analysis (RCA) approach and the failure causes listed under the RCA approach were used to carry the system's FMEA. The limitations of FMEA in risk ranking were nullified by using fuzzy FMEA and GRA approaches and the ranking results obtained were compared with FMEA approach-based results. They implemented their framework on a coal handling system in a coal-fired thermal power plant located in North India.

Feili et al. (2013) demonstrated the application of FMEA approach for risk analysis in geothermal power plant. Under this analysis five major parts of the geothermal power plant were studied and on the basis of results corrective measures have been suggested to system analyst/maintenance personnel for improving the system reliability. Maleki and Saadat (2013) proposed a novel method for FMEA which makes use of AHP and the REMBRANDT system. The proposed approach was applied on the hydraulic gear pump system and the raking results were compared for better decision making. Guimarães and Lapa (2004) have presented

the application of fuzzy FMEA approach for the criticality evaluation of various components of PWR chemical and volume control system of a nuclear power plant. Guimarães and Lapa (2007) have implemented fuzzy inference system for risk analysis in the production of nuclear energy. Wang et al. (2009) have done risk analysis using fuzzy weighted geometric mean in FMEA. Tay and Lim (2006) developed a novel method for the simplification of fuzzy FMEA by reducing the number of rules. Further, fuzzy RPN models have been developed by them and the performance of these models were evaluated in a semiconductor manufacturing plant (Tay and Lim, 2010). Braglia et al. (2003) presented the application of fuzzy TOPSIS approach in FMEA. Dhal et al. (2011) proposed a novel grey relation technique-based fuzzy MCDM approach for the effective selection of flexible manufacturing system. Sharma et al. (2007b) have presented an integrated approach for the qualitative behaviour of the paper plant. The qualitative behaviour of the paper plant has been done using knowledge base approach namely fuzzy FMEA and GRA approach. The ranking results so obtained were compared with the FMEA ranking results. The qualitative results so obtained were highly useful for the system's analyst in designing a suitable maintenance policy for the considered system. Further quantitative analysis has been done using fuzzy λ-τ approach. Ilangkumaran et al. (2014) have developed an integrated model for assigning the risk priorities/ranking of risky components in a paper industry. The integrated model was based on traditional FMEA and fuzzy AHP approach. FMEA approach was used to compute the RPN score for various subsystem of the considered system and fuzzy AHP was used to compute the relative weights of the decision factors. On the basis of RPN score and relative weights the ranking results were compared for advanced decision making of risky components.

Zhang and Chu (2011) exhibit the application of a novel fuzzy FMEA approach for the precise risk prioritisation of horizontal directional drilling machine. Chen et al. (2014) proposed FMEA and fuzzy fault tree-based structured framework for the risk analysis and the proposed framework was applied on the selected semi industrial combustor system for assessing its risky components. Hoseynabadi et al. (2010) employed FMEA approach for studying the reliability of wind turbine system where a proprietary software reliability analysis tool plays an important role for assessing the considered system reliability. Abdelgawad and Fayek (2011) presented the use of fuzzy FMEA and fuzzy AHP approach for the risk analysis in a construction company. Fuzzy FMEA was used to prioritise the various risks associated with in the construction industry and the limitations of fuzzy FMEA approach in risk ranking were overcome by implementing the fuzzy AHP approach. The classification of the various approaches is given in Table 1.

Thus, on the basis of literature reviewed, it has been reported that the hybrid FMEA + GRA approach has been not applied for the risk analysis of a gas turbine compressor. To fill this gap in extant literature, the authors in this paper, have presented the application of the hybrid FMEA + GRA approach for the risk analysis of the system under investigation.

Table1: Classification of Approaches

Approach Category	Approach	Literature
Mathematical programming	Fuzzy DEA	Garcia et al (2005), Chang and Sun (2009), Chin et al (2009)
Artificial Intelligence	Fuzzy rule-based system	Bowles and Peláez (1995), Puente et al (2002), Pillay and Wang (2003), Yang et al (2008), Gargama and Chaturvedi (2011)
	Fuzzy ART	Keskin and Ozkan (2009)
	Fuzzy cognitive map (FCM)	Peláez and Bowles (1996)
hybrid MCDM approach	Fuzzy AHP	Ilangkumaran et al. (2014), Abdelgawad and Fayek (2010), Braglia et al. (2003), Maleki and Saadat (2013)

3. Methods and Approach

This section presents the methods and approaches employed for risk analysis and prioritization. It specifically introduces the FMEA and GRA techniques.

3.1 Failure Mode and Effect Analysis (FMEA)

Failure Mode and Effect Analysis (FMEA) was developed in the 1960s, where it proved to be highly effective in the military and aviation sectors. It is widely recognized as a key analytical tool for identifying, classifying, and eliminating potential or existing failures, thereby supporting risk management decisions aimed at improving system reliability and safety (Shi et al, 2019).

In contemporary practice, FMEA is extensively used in the power sector to prioritize the risks associated with failure modes in machinery systems and equipment, particularly before selecting maintenance strategies within the Reliability-Centered Maintenance (RCM) framework. The

approach involves identifying all possible failure modes within a system, analyzing their root causes, evaluating their impacts, and developing corrective actions for process improvement. FMEA relies on the Risk Priority Number (RPN) for risk evaluation (Zhang and Chu, 2011).

The RPN is calculated as the product of three risk factors: the probability of occurrence (O), the severity of the consequences (S), and the likelihood of detecting the failure before it occurs (D). The RPN value ranges from 1 to 1,000 and is expressed by equation (1):

$$RPN = O \times S \times D \quad (1)$$

Components with higher RPN values are considered more critical compared to those with lower values (Abdelgawad and Fayek, 2011).

Some key drawbacks or limitations of the FMEA approach in risk ranking are outlined below:

- The RPN value, calculated using different combinations of probability of occurrence (O), severity (S), and probability of non-detection (D) for various components of a system, may yield identical scores. However, the underlying risk implications of these combinations can differ significantly, potentially leading to misleading conclusions for maintenance engineers (Panchal and Kumar, 2017a).
- The three risk factors O, S, and D are assumed to have equal importance and are assigned equal weights. In practical applications, this assumption may not hold true, which can reduce the accuracy of the risk assessment results (Jiang, et al., 2018).

To overcome the limitations of the conventional FMEA method highlighted above, this study proposes the application of Grey Relational Analysis (GRA) approach for prioritizing critical or high-risk components within the system under consideration.

3.2 GRA Method

Grey Relational Analysis (GRA) is one of the subheadings of Grey Theory which was developed by Julong Deng in 1982. The grey system which is between the white system and the black system, means where information is partially known, expresses poor, incomplete and uncertain information. While black system represents the lack of information, white represents the full of information. GRA a useful tool used for solving multicriteria decision making problems under incomplete information. The principle of ranking is based on the level of similarity between the reference alternative and each comparison alternative (Kuo and Liang 2011). It also offers a

measure to examine the relationship between qualitative and quantitative series. The steps taken in implementing the GRA framework is stated as follows:

Step 1: Identification of Comparative Series

Comparative series also known as information series. It contains values of likelihood of occurrence, detection and severity. Comparative series applied to FMEA is shown as the following;

$$X_i(k) = [X_i(1) \;\; X_i(2) \;\; X_i(3)]$$

$$k = 1, 2 \; or \; 3 \; (number \; of \; risk \; factors)$$

$$i = 1, 2, 3, \ldots. \; n \; (n \; is \; the \; number \; of \; failure \; modes)$$

Here k has the values of 1, 2 and 3; meaning $X_1(1),\ X_1(2),\ X_1(3)$ are the scores of likelihoods of occurrence, detectability and severity of the first failure mode, respectively. If all series are comparative series, the n information series can be defined as following matrix in which n is the number of failure modes;

$$X_i(k) = \; [X_1(k)\, X_2(k) \; \cdots \; X_n(k) \;\;]$$
$$= [\, X_1(1)\, X_1(2) \quad \ldots \quad X_1(3)\, X_2(1)\, X_2(2) \ldots \quad X_2(3)\, . \; \ldots . X_n(1)\, X_n(2) \quad \ldots \quad X_n(3)\,] \qquad (2)$$

Step 2: Identification of Standard Series

An objective series called as the standard series can be expressed as the following;

Series notation $X_0(k) = \; \{X_0(1), X_0(2), X_0(3)\}$

Matrix notation $X_0(k) = [X_0(1) \;\; X_0(2) \;\; X_0(3)]$

In FMEA the smallest score represents the smallest risk. Thus, the standard series should be the lowest score of likelihood of occurrence, detectability and severity factors which is shown as the following;

$$X_0(k) = \; \{X_0(1), X_0(2), X_0(3)\} = \{1\, , 1, 1\}$$

Matrix notation is:

$$X_0(k) = [1 \;\; 1 \;\; 1] \qquad (3)$$

The purpose of defining standard series is to determine the degree of relation (Chu, et al.., 2007). As the degree of relation goes higher the score comes closer to the desired value.

Step 3: Estimating the Difference Between Comparative and Standard Series

To find the degree of grey relationship, the difference between the scores of risk factors and scores of standard series must be calculated. The result of this calculation is expressed as the matrix equation below.

$\Delta_i(k) = [\Delta_{01}(k)\ \Delta_{02}(k)\ \cdots\ \Delta_{0n}(k)\ ]$
$= [\ \Delta_{01}(1)\ \Delta_{01}(2)\ \ \ldots\ \ \Delta_{01}(3)\ \Delta_{02}(1)\ \Delta_{02}(2)\ \ \ldots\ \ \Delta_{02}(3)\ .\ \ \ldots\ \ \ldots$

Here, i =1, 2, 3,…..n (n is the number of failure modes)

$\Delta_i(k)$ is calculated as follows:

$$\Delta_{01}(k) = |X_0(k) - X_i(k)|$$

Step 4: Estimation of Grey Relationship Coefficient

To estimate the grey relationship coefficient, three risk factors of the failure modes are compared with the standard series. The correlation coefficient is calculated using the following equation;

$$\gamma[X_0(k), X_i(k)] = \frac{\Delta_{min} + \zeta\Delta_{max}}{\Delta_i(k) + \zeta\Delta_{max}} \qquad (5)$$

Where,

$X_0(k)$; standard series

$X_i(k)$; comparative series

i=1,2,3…n (n is the number of failure modes)

k=1,2 or 3 (number of risk factors)

$$\Delta_{min} = minimum\ value\ of\ all\ \Delta_i(k)$$
$$\Delta_{max} = maximum\ value\ of\ all\ \Delta_i(k)$$

and ζ is an identifier coefficient which only affects the relative value of risk without changing the priority and is assumed to be 0.5.

Step 5: Determining the Degree of Relation

Degree of relation denotes the relationship between the potential causes and the optimal values of the decision factors. In order to find the degree of relation, first the relative weight of the risk factors is decided. The relative weights will be used in the following formulation

$$\tau_i(k) = \beta_k \sum_{k=1}^{3} \Delta_i(k) \quad (6)$$

i=1,2,3…n (n is the number of failure modes)

k=1,2 or 3 (number of risk factors)

β_k is the weighting coefficient of risk factors and $\sum_{k=1}^{3} \beta_k = 1$

If all factors are equally important stated formula can be changed as follows;

$$\tau_i(k) = \frac{1}{3} \sum_{k=1}^{3} \Delta_i(k) \quad (7)$$

The weighting coefficient (β_k) can be computed either on the basis of expert feedback or assumed directly. In this work, Wang's scale (Wang et al., 2007) has been used for generating the fuzzy comparison matrix for three risk factors. The Wang's scale used for matrix generation is shown in Table 2.

Table 2: Wang's scale for matrix generation

Uncertain judgment	Fuzzy scale
Approximately important	½, 1, 2
Approximately X time more important[a]	X−1, X, X+1
Approximately X time less important	1/X+1, 1/X, 1/X−1
Between Y and Z time more important[b]	Y, Y+Z/2, Z
Between Y and Z time less important	1/Z, 2/Y+Z, 1/Y

Notes: [a](X = 2, 3, ... 9) and [b](Y, Z = 1, 2, ... 9, Y < Z)

Step 6: Ranking the priority of risk

The ranking of component is done based on the degree of relation obtained. As the degree of relation is closer to 1, it means the failure mode is closer to the optimal value. The failure mode which has the lowest degree of relation is usually the first one to be improved upon. Therefore, the lower degree of relation represents the higher risk priority.

3.3 Fuzzy synthetic extent analysis method (For computing weighting coefficients)

This section presents fuzzy synthetic extent analysis method (Chang, 1992; Chan et al., 2008) for computing the weighting coefficients. The Chang's extent analysis on Fuzzy AHP is based on degree of possibilities of each criterion. The steps involved in Chang extent analysis method are as follows:

Step 1: fuzzy synthetic extent calculation

Let $X = \{x_1, x_2 \ldots x_n\}$ is a set of an object and $U = \{u_1, u_2 \ldots u_m\}$ is the goal set. Then according to Chang's extent analysis approach (Chang, 1992; Chan et al., 2008), each object is taken as extent analysis for each goal is performed respectively. Mathematically, the fuzzy synthetic extent value M_i (for I = 1, 2, 3) is represented by the equation (8)

$$M_i \sum_{J=1}^{m} A^j g_i \div \left[\sum_{i=1}^{n} \sum_{j=1}^{m} A^j g_i \right] \quad (8)$$

Where $A^1 g_i, A^1 g_i, \ldots\ldots A^m g_i, i = 1, 2, 3, \ldots$ n are the value of extent analysis of i^{th} object for a goal and $A^J g_i \rightarrow$ TFNs.

Where;

$j = 1, 2, 3 \ldots m$ for criteria

$i = 1, 2, 3 \ldots n$ for alternatives.

Step 2: comparison of fuzzy values

To estimates the set of weights value under each criterion, principle of comparison has been used and greatest/least fuzzy number is searched (Chan et al., 2008; Wang et al. 2007). Let M_1 and M_2 are the convex fuzzy numbers represented by (l_1, m_1, u_1) and (l_2, m_2, u_2) respectively. The degree of possibility (V) of $M_1 \geq M_2$ is defined by (Chan and Kumar, 2005) as;

$$V = (M_1 \geq M_2) = Sup\ x \geq y\ [min \mu_{M1}(x), \mu_{M2}(y)] \quad (9)$$

Where; *sup* represents supremum (i.e., the least upper bound of a set)

If $m_1 \geq m_2$ and $\mu_{M1}(x) = \mu_{M2}(y)$ then $V(M_1 \geq M_2) = 1$

To compare M_1 and M_2, we need both the values of $V(M_1 \geq M_2)$ and $V(M_2 \geq M_1)$

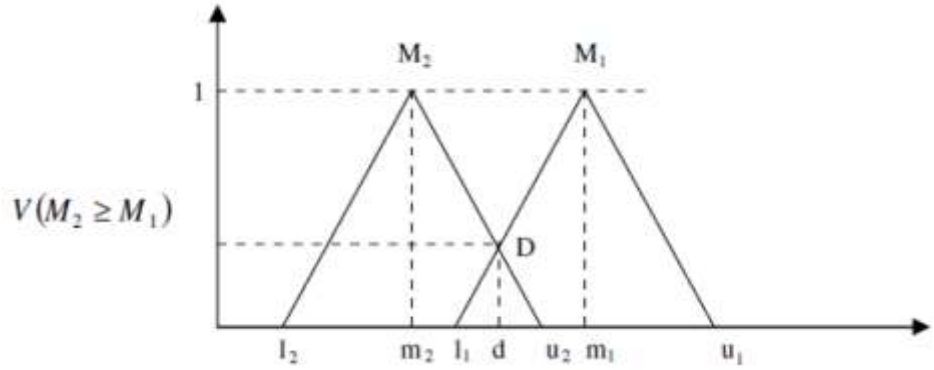


Figure 1. The definition of the degree of possibility of V ($M_2 \geq M_1$)

The values V ($M_2 \geq M_1$) is shown in Figure 1 and is represented by the point *D*. Mathematically is given by;

$$V(M_2 \geq M_1) = hgt(M_1 \cap M_2) = \mu_{M2}(d) \quad (10)$$

In equation (10) *d* is the ordinate of *D* (an intersection point of μM_1 and μM_2) and is computed as:

$$V(M_2 \geq M_1) = hgt(M_1 \cap M_2) = \mu_{M2}(d) = \frac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)} = D \quad (11)$$

Step 3: compute priority weight

The degree of possibility (*V*) for *k* convex fuzzy numbers $M_i \sim M_{i+1} \geq K,\ (i = 1, 2, \ldots . K)$ is defined as (Chang, 1992)

$$V(M \geq M_1, M_2, \ldots . M_k) = V[(M \geq M_1)\ and\ (M \geq M_2)\ and \ldots . and\ (M \geq M_k)] \quad (12)$$

$$= V(M \geq M_i),\ \ i = 1, \qquad 2, \ldots . k \quad (13)$$

Assuming that relative preference of each alternative $[d'(t_i)]$ has relation with the M_i as: $d'(t_i) = V(M_i \geq M_k)$ for $K = 1, 2, \ldots n$; $K \neq i$, where *n* is the number of criteria. Then the weight vector (w') of crisp fuzzy number is estimated by the equation:

$$w' = (d'(t_1), d'(t_2), \ldots . d'(t_n))^T \quad (14)$$

where t_i ($i = 1, 2, \ldots, n$), *n* elements and *T* is the transpose.

Step 4: calculate normalised weight vector

Using normalisation, the normalised weight vector (w) is given as:

$$w = (d(t_1), d(t_2), \ldots . d(t_n))^T \quad (15)$$

4. RESULT AND DISCUSSION

4.1 FMEA result and ranking

The RPN values were computed as the product of occurrence (O), severity (S), and detection (D) for each failure mode using equation (1) and given in Table 3.

Table 3: Expert feedback-based FMEA table for computing RPN scores

S/N	Component	Failure Mode	Effect of Failure	Possible Cause(s)	O	S	D	RPN
FM 1	Compressor Rotor/Shaft	Over-temperature	Reduces turbine serviceability	Dirty compressor rotor	4	10	5	200
FM 2			Excessive expansion of turbine nozzle vanes	Foreign object damage	3	10	2	60
FM 3		Vibration	Vibration pick-ups occur	Loose mounts	3	6	3	54
FM 4			Reduce power generation	Defective bearings	2	7	5	70
FM 5			Illuminator is activated in instrument panel	Faulty vibration indication	4	5	1	20
FM 6		Shaft locked	Damages the blades and the casing	Rubbing of rotor blades with compressor casing	2	9	3	54
FM 7	Compressor Stator	Stall	Increase in temperature	Binding of variable stator vanes	4	7	3	84
FM 8			Gas turbine operates with low efficiency	Ice formation on engine inlet	2	6	1	12
FM 9			Gas turbine shutdown	Blades of air compressor damaged	3	9	4	108
FM 10	Casing	Seal leakage	Causes lack of required energy production to rotate turbine blades	Air leakage	2	4	4	32

In Table 3, the Delphi method was employed in collecting and analysing opinions of experts until a consensus is reached. In this study consensus is reached in the second round. The parameters presented in Table 3 for computing the FMEA RPN scores of the various components in the considered sub-system are defined as follows:

- **Probability of occurrence of failure (O):** This is evaluated based on the mean time between failures (MTBF). The required data are obtained from the company's maintenance logbook and verified by maintenance experts.
- **Severity of failure (S):** This reflects the impact of a specific failure on overall system performance. Data related to the mean time to repair (MTTR) are essential in determining the severity score, which may be classified as very low, low, moderate, high, or very high.
- **Probability of non-detection (D):** This represents the likelihood that a failure or its cause will not be detected. It depends on factors such as the operator's ability to visually identify faults, periodic inspection routines, and the effectiveness of automatic control, alarm, or sensor systems.

From **Table 3**, the classical RPN ranking identifies FM 1 as the most critical failure mode with an RPN score of 200, followed by FM 9 with a score of 108 and FM 7 with a score of 84. However, it is observed that FM 3 and FM 6 share an identical RPN value of 54, despite having different risk characteristics, which may lead to misleading interpretations. Additionally, as previously discussed, this approach is limited by its assumption of equal weighting for O, S, and D.

4.2 Grey relation analysis (GRA) result

The Grey Relational Analysis was applied for the computation of the degree of relation for the various components of the considered compressor sub- system. The same FMEA data in Table 2 that was used for the traditional RPN has been analysed in the Grey Relational Analysis method. The weights of the risk factors were obtained by the fuzzy AHP method according to expert judgments.

Step 1: Generate comparison series

The first step is to obtain the comparative series; which is an information series related with the occurrence, detectability and severity of all failure modes in **Table 3**. It is shown in the following matrix.

$$\begin{bmatrix} X_1(1) & X_1(2) & X_1(3) & X_2(1) & X_2(2) & X_2(3) & X_3(1) \\ X_3(2) & X_3(3) & X_4(1) & & & & \\ X_4(2) & X_4(3) & X_5(1) & X_5(2) & X_5(3) & X_6(1) & X_6(2) \\ X_6(3) & X_7(1) & X_7(2) & X_7(3) & X_8(1) & X_8(2) & X_8(3) \\ X_9(1) & X_9(2) & X_9(3) & X_{10}(1) & X_{10}(2) & X_{10}(3) & \end{bmatrix}$$

$$= [4\ 10\ 5\ \ 3\ 10\ 2\ \ 3\ \ 6\ 3\ \ 2\ 7\ 5\ \ 4\ 5\ 1\ \ 2\ 9\ 3\ \ 4\ 7\ 3\ \ 2\ 6\ 1\ \ 3\ 6\ 2\ \ 2\ 4\ 4 \quad] \qquad (16)$$

Step 2: Standard series formation

In FMEA the smallest score represents the smallest risk hence, to reduce the potential risk, the values of all risk factors should be as small as possible. Thus, the standard series should be the lowest score of likelihood of occurrence, detectability and severity factors which is defined as;

$$X_0(k) = [X_0(1), X_0(2), X_0(3)] = [1\ , 1, 1] \qquad (17)$$

Step 3: Difference between comparison and standard series

Then, to reveal the degree of fuzzy relation, the difference between values of risk factors and standard series is determined and expressed as the matrix shown below.

$$\begin{bmatrix} \Delta_{01}(1) & \Delta_{01}(2) & \Delta_{01}(3) & \Delta_{02}(1) & \Delta_{02}(2) & \Delta_{02}(3) & \Delta_{03}(1) \\ \Delta_{03}(2) & \Delta_{03}(3) & \Delta_{04}(1) & \Delta_{04}(2) & \Delta_{04}(3) & \Delta_{05}(1) & \\ \Delta_{05}(2) & \Delta_{05}(3) & \Delta_{06}(1) & \Delta_{06}(2) & \Delta_{06}(3) & \Delta_{07}(1) & \Delta_{07}(2) \\ \Delta_{07}(3) & \Delta_{08}(1) & \Delta_{08}(2) & \Delta_{08}(3) & \Delta_{09}(1) & \Delta_{09}(2) & \Delta_{09}(3) \\ \Delta_{10}(1) & \Delta_{10}(2) & \Delta_{10}(3) & & & & \end{bmatrix}$$

$$= [3\ 9\ 4\ \ 2\ 9\ 1\ \ 2\ 5\ 2\ \ 1\ 6\ 4\ \ 3\ 4\ 0\ \ 1\ 8\ 2\ \ 3\ 6\ 2\ \ 1\ 5\ 0\ \ 2\ 5\ 1\ \ 1\ 3\ 3 \quad] \qquad (18)$$

Step 4: Compute grey relationship coefficient

As previously stated, the relational coefficient is calculated with equation (5) which is given by;

$$[X_0(k), X_i(k)] = \frac{\Delta_{min} + \zeta \Delta_{max}}{\Delta_i(k) + \zeta \Delta_{max}}$$

Where $\Delta_{min} = 0$, $\Delta_{max} = 9$ and $\zeta = 0.5$.

$$\begin{bmatrix} \gamma_{01}(1) & \gamma_{01}(2) & \gamma_{01}(3) & \gamma_{02}(1) & \gamma_{02}(2) & \gamma_{02}(3) & \gamma_{03}(1) \\ \gamma_{03}(2) & \gamma_{03}(3) & \gamma_{04}(1) & \gamma_{04}(2) & & & \\ \gamma_{04}(3) & \gamma_{05}(1) & \gamma_{05}(2) & \gamma_{05}(3) & \gamma_{06}(1) & \gamma_{06}(2) & \gamma_{06}(3) \\ \gamma_{07}(1) & \gamma_{07}(2) & \gamma_{07}(3) & \gamma_{08}(1) & \gamma_{08}(2) & \gamma_{08}(3) & \gamma_{09}(1) \\ \gamma_{09}(2) & \gamma_{09}(3) & \gamma_{10}(1) & \gamma_{10}(2) & \gamma_{10}(3) & & \end{bmatrix}$$

$$= \begin{bmatrix} 0.6000 & 0.3333 & 0.5293 & 0.6923 & 0.3333 & 0.8182 & 0.6923 & 0.4737 & 0.6923 \\ 0.8182 & 0.4286 & 0.5294 & 0.6000 & 0.5294 & 1.0000 & 0.8182 & 0.3600 & 0.6923 \\ 0.6000 & 0.4286 & 0.6923 & 0.8182 & 0.4737 & 1.0000 & 0.6923 & 0.3600 & 0.6000 & 0.8182 & 0.6000 & 0.6000 \end{bmatrix}$$

Step 5: Computation of degree of relation

Compute the weighting coefficients (β_k) for risk factors using fuzzy AHP. On the basis of experts feedback a comparison matrix was prepared using Wang's scale (Wang et al., 2007) and the weights for *O, S and D* were computed using fuzzy extent analysis method (Chan et al., 2008) as shown in **Table** 4.

Table 4: Comparison matrix for risk factors (Panchal and Kumar, 2017a)

	O_f	**S**	**O_d**	**Weights**
O_f	(1, 1, 1)	(1/4, 1/3, 1/2)	(1/2, 1, 2)	0.20
S	(2, 3, 4)	(1, 1, 1)	(1, 2, 3)	0.56
O_d	(1/2, 1, 2)	(1/3, 1/2, 1)	(1, 1, 1)	0.24

Therefore, using these weights for the risk factors degree of relation, the first failure mode *FM*1 is calculated using equation (6) as an illustration.

For example; RPN for the first failure mode has been obtained as;

$$\tau_{01}(k) = (\gamma_{01}(1) \times \beta_{k1}) + (\gamma_{01}(2) \times \beta_{k2}) + (\gamma_{01}(3) \times \beta_{k3})$$

$$\tau_{01}(k) = (0.60 \times 0.20) + (0.3333 \times 0.56) + (0.5293 \times 0.24)$$

$$\tau_{01}(k) = 0.4336$$

Similarly, the degrees of coefficient or grey output were computed for other failures modes of the compressor sub-system and ranking of critical components has been done and the result presented in Table 5.

Table 5: Grey RPN output and ranking

Failure Modes	γ_f	γ_s	γ_d	Grey RPN output	Ranking
FM 1	0.60	0.33	0.53	0.4336	1
FM 2	0.69	0.33	0.82	0.5215	3

FM 3	0.69	0.47	0.69	0.5699	7
FM 4	0.82	0.43	0.53	0.5307	5
FM 5	0.60	0.53	1.00	0.6565	9
FM 6	0.82	0.36	0.69	0.5314	6
FM 7	0.60	0.43	0.69	0.5262	4
FM 8	0.82	0.47	1.00	0.6689	10
FM 9	0.69	0.47	0.82	0.4841	2
FM 10	0.82	0.60	0.60	0.6436	8

Table 5 shows that FM1 with the lowest Grey RPN of 0.4337 has been rank first, this is followed by FM9 with Grey RPN of 0.4841, and lastly, FM8 with the highest Grey RPN of 0.6689. From this result it can be observed that GRA approach has been able to solve the problem of duplicity of RPN thereby, producing a better risk priority.

In validating the proposed methodology, the risk analysis of the gas turbine compressor sub-system was solved using TOPSIS technique and the comparative analysis result generated is indicated in Table 4. The comparative analysis results show that the two techniques produce FM1, FM9, and FM2 as the first, second, and third critical failure modes respectively. Also, FM1, FM2, FM3, FM4, FM9, and FM10 have the same ranking in both methods. Therefore, both approaches generated same risk rankings result. The GRA evaluation process is quite simple irrespective of the number of decision criteria used and this will make it more attractive to the maintenance practitioners.

Table 6: Comparative analysis results of TOPSIS and GRA techniques

Failure mode	**O**	**S**	**D**	**TOPSIS (Rank)**	**GRA (Rank)**
FM 1	4	10	5	1.000 (1)	0.4337 (1)
FM 2	3	10	2	0.671 (3)	0.5215 (3)
FM 3	3	6	3	0.391 (7)	0.5699 (7)
FM 4	2	7	5	0.582 (5)	0.5307 (5)
FM 5	4	5	1	0.246 (10)	0.6565 (9)
FM 6	2	9	3	0.656 (4)	0.5314 (6)
FM 7	4	7	3	0.528 (6)	0.5262 (4)
FM 8	2	6	1	0.256 (9)	0.6689 (10)
FM 9	3	9	4	0.780 (2)	0.4841 (2)
FM 10	2	4	4	0.312 (8)	0.6436 (8)

5. CONCLUSION

Risk assessment of power plant should be given adequate importance because of the involvement of huge capital investment involved and the grave consequences of power failure. In this paper, a hybrid FMEA framework based on FMEA and GRA approach was presented to identify, analyse and evaluate the failure modes of a gas turbine equipment. Ten different failure modes were identified from the preliminary FMEA result based on expert opinion, where a criticality assessment was conducted with three inputs such as; severity, occurrence, and detection. The result obtained from the classical FMEA method confirms the shortcomings of the traditional FMEA method such as the production of identical RPN score of 54 for FM3 and FM6 and lack of consideration of the relative importance between risk factors.

Consequently, the GRA method was employed in this study to overcome the limitations of the traditional FMEA method and it eventually resolved the problem of duplicity in RPN score thereby, producing a better risk priority. The GRA methodology, proposed in this research is adequate in producing an acceptable ranking result when compared to more computationally challenging techniques used by previous researchers. This methodology can be applied to other similar machinery with the aim of improving the conventional FMEA technique.

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