International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

Enhanced Condition Monitoring of Gearboxes Using Fuzzy Comprehensive Evaluation and Group Decision-Making: A Case Study

M. Ramamohana Rao[1], Ravindra Andukuri[2], M.R.S. Satyanarayana[3]

[1,2,3]Department of Mechanical Engineering, GITAM Deemed to be University, Visakhapatnam, INDIA

Abstract

In this study, we introduce a novel methodology for the condition monitoring of gearboxes by integrating fuzzy comprehensive evaluation and group decision-making. Traditional risk assessment methods often suffer from subjective biases and uncertainties inherent in expert evaluations. Our approach mitigates these limitations by aggregating expert opinions using fuzzy membership functions and assigning weights based on the similarity of individual evaluations to the group consensus. This converts qualitative judgments into quantitative measures, resulting in more precise and objective Risk Priority Numbers (RPNs). We validate the efficacy of our methodology through a case study involving a gearbox. The primary failure modes identified include gear tooth wear, misalignment, bearing failure, lubrication failure, and thermal overload. Our results indicate a significant improvement in condition monitoring accuracy, with calculated fuzzy RPN values closely aligning with historical data and expert feedback. Comparative analysis highlights the advantages of our methodology over conventional RPN calculations, particularly in reducing subjective biases and enhancing the reliability of risk assessments. Our findings demonstrate that this methodology can be effectively applied in various industrial settings, establishing a robust framework for mechanical system condition monitoring. Future research should explore integrating advanced data analytics and machine learning techniques to enhance the methodology's accuracy and efficiency.

Keywords: Condition Monitoring, Gearbox, Risk Priority Number (RPN), Expert Evaluation, Mechanical Systems, Group decision making.

Introduction

Modern mechanical systems' efficiency and safety depend on their components' reliability and the reduction of risks related to component failures. Essential in many industrial contexts, gearboxes can fail in several ways, including due to lubrication problems, gear tooth wear, misalignment, and bearing failure. If these failures are not properly monitored and addressed, they can cause substantial downtime and increase maintenance costs [1-3]. There has been a heavy reliance on time-honored risk assessment techniques like Failure Mode and Effects Analysis (FMEA) to pinpoint probable points of failure and the havoc they could wreak on system performance [4]. Traditional risk assessment relies on the risk priority number (RPN) technique, which multiplies occurrence, severity, and detection scores. The conventional RPN approach falls short when dealing with expert evaluations, which are inherently fraught with uncertainty and subjective judgments [5, 6].

Improved risk assessment methods have been developed through recent developments in fuzzy logic and multi-criteria decision-making (MCDM) techniques [7, 8]. These methods incorporate numerical and linguistic information to capture the complexities of expert opinions better. These cutting-edge approaches were only possible with fuzzy set theory, which allows for the modeling of imprecise and uncertain data [9]. By incorporating fuzzy logic into FMEA, a more accurate and trustworthy risk assessment can be achieved (Fuzzy FMEA) [10–14]. This is because fuzzy numbers can represent occurrence, detection, and severity scores.

One way to make risk assessments more solid is to use group decision-making and combine the views of experts. To efficiently aggregate expert opinions and weigh the importance of various criteria, techniques like the Best and Worst Method (BWM) and the Analytic Hierarchy Process (AHP) have been used [15–17]. Hybrid models, which offer a thorough risk assessment and decision-making framework, have been developed by combining these approaches with fuzzy logic [18, 19].

Research into advanced diagnostic and prognostic methods has focused on improving the capacity to detect faults and predict when gearboxes will fail within the framework of condition monitoring. Several methods have been developed to accurately detect and categorize gearbox faults, including acoustic emission, vibration analysis, and machine learning algorithms [20–23]. When used with Fuzzy FMEA, these techniques offer a potent instrument for evaluating and reducing hazards connected to gearbox breakdowns [24–27].

The purpose of this research is to lay out a solid approach to condition monitoring through the use of fuzzy comprehensive evaluation and group decision-making. The proposed methodology incorporates expert feedback and considers uncertainties to improve the accuracy and reliability of risk evaluations. Its promising use in a case study suggests it could be widely used in other industrial settings where accurate risk assessment is vital for guaranteeing safety and reliability [28-30].

2. Methodology

The proposed methodology for enhancing the monitoring of gearboxes integrates group decision-making with fuzzy comprehensive evaluation. This approach minimizes subjective biases and improves the precision and reliability of risk assessments. The methodology includes several critical steps: identifying and assessing experts, consolidating expert opinions, performing a fuzzy comprehensive evaluation, calculating Risk Priority Numbers (RPNs), and validating the approach through a case study.

2.1 Expert Evaluation and Group Decision-Making

2.1.1 Expert Selection and Evaluation

Initially, a panel of experts is selected based on their experience and expertise in gearbox operations and maintenance. Each expert is responsible for assessing potential failure modes of the gearbox and assigning interval scores for severity (S), occurrence probability (O), and detection difficulty (D). These scores reflect the subjective judgments and inherent uncertainties of each expert. Severity represents the potential impact of each failure mode on the system, considering factors such as economic losses, operational downtimes, and safety hazards. Severity scores are presented as intervals to depict the range of possible consequences. Occurrence probability indicates the likelihood of a failure mode occurring within the system, considering factors such as historical failure data and operational conditions. The occurrence probability is represented as an interval to account for uncertainties in predicting failure events. Detection difficulty denotes the challenge of identifying a failure mode before it leads to significant consequences, based on the effectiveness of current monitoring methods. Detection difficulty scores are presented as intervals to illustrate the varying degrees of uncertainty associated with detection capabilities.

2.1.2 Aggregation of Expert Opinions

The diverse opinions of numerous experts are aggregated through group decision-making. The weights assigned to each expert's opinion are determined by comparing the similarity and difference between the group average and individual expert evaluations. This method ensures that experts whose assessments closely align with the group consensus are given greater weights, thereby reducing the impact of outlier opinions. The aggregation process involves several steps: First, the group average is used to compare the evaluations of all experts for each failure mode. Statistical measures, such as cosine similarity or other appropriate metrics, are employed to assess the degree of similarity between the group average and each expert's evaluation. Additionally, the discrepancy between the group average and each expert's assessment is calculated. Weights are then assigned to each expert's evaluation based on the calculated similarity and difference. Experts whose evaluations closely align with the group consensus receive higher weights, while those whose evaluations significantly deviate from the group average receive lower weights. The comprehensive evaluation for each potential failure mode is formed by aggregating the weighted evaluations. This involves integrating the interval scores for detection difficulty, occurrence probability, and severity, considering the assigned weights.

2.2 Fuzzy Comprehensive Evaluation

2.2.1 Fuzzy Membership Functions

The combined expert evaluations are transformed into fuzzy membership functions. These functions convert qualitative assessments into quantitative measurements, allowing for the inherent uncertainty in expert judgments. The membership functions indicate the extent to which each failure mode belongs to a different risk level. For example, a triangular or trapezoidal fuzzy membership function could be defined as follows:

$$\mu_S(x) = \left\{ \begin{matrix} 0 & if\ x \leq a \\ \dfrac{x-a}{b-a} & if\ a < x \leq b \\ 1 & if\ b < x < c \\ \dfrac{d-x}{d-c} & if\ c \leq x < d \\ 0 & if\ x \geq d \end{matrix} \right\}$$

The parameters a, b, c, and d determine the form of the membership function for detection, severity, and occurrence, respectively, in this function. Each risk factor has a range of potential values, and these parameters reflect that. Expert evaluations inform their selection. Expert evaluations' uncertainties and variabilities can be more realistically and flexibly represented with fuzzy membership functions. The methodology can better evaluate the risks of each failure mode by translating qualitative judgments into quantitative fuzzy values, laying a solid groundwork for further analysis and decision-making.

2.2.2 Construction of Evaluation Matrix

The membership functions are employed to generate a fuzzy evaluation matrix. This matrix integrates the weighted expert opinions, thoroughly assessing each failure mode. The factors that are considered are severity, occurrence probability, and detection difficulty, each represented by its respective membership function.

The evaluation matrix R for each failure mode is organized as follows:

$$R = \begin{bmatrix} \mu_{S1} & \mu_{O1} & \mu_{D1} \\ \mu_{S2} & \mu_{O2} & \mu_{D2} \\ \vdots & \vdots & \vdots \\ \mu_{Sn} & \mu_{On} & \mu_{Dn} \end{bmatrix}$$

In the $i-th$ expert's matrix, the fuzzy membership values for severity, occurrence, and detection are denoted by μ_{Si}, μ_{Oi}, and μ_{Di}. Each row represents the fuzzy evaluations that a single expert has provided for a specific failure mode. The matrix structure makes it possible to consolidate a variety of expert opinions into a unified framework, which in turn facilitates a comprehensive and robust examination of the potential risks. The evaluation matrix guarantees that the final risk assessment accurately and reliably captures the variations and uncertainties that are inherent in expert judgments by integrating the weighted expert opinions through the fuzzy membership functions.

2.2.3 Fuzzy Logic and Aggregation

Evaluations from the fuzzy matrix are combined using fuzzy logic. The membership values are aggregated using fuzzy operators in this step, which produces a composite risk score for each failure mode. The fuzzy comprehensive evaluation guarantees that the final risk scores are robust and effectively account for the uncertainties in expert judgments.

A number of steps are involved in the aggregation process:

a) Fuzzification: This involves the conversion of the input data (aggregated expert evaluations) into fuzzy membership values by utilizing the defined membership functions. Qualitative expert judgments are converted into quantitative fuzzy values that can be mathematically adjusted in this step.

b) Fuzzy Operators of Application: Fuzzy operators are employed to combine the fuzzified values from the evaluation matrix. One typical operator is the fuzzy weighted average, which aggregates the membership values by taking into account the weights assigned to each expert's evaluation. The formula for the fuzzy weighted average is as follows:

$$\mu_{aggregated} = \frac{\sum_{i=1}^{n} w_i \cdot \mu_i}{\sum_{i=1}^{n} w_i}$$

where w_i is the weight assigned to the $i-th$ expert's evaluation, and μ_i is the fuzzy membership value for each factor (severity, occurrence, and detection).

c) Defuzzification: A composite risk score for each failure mode is obtained by returning the fuzzy output to a crisp value. The centroid or the mean of maximum are the most common methods to accomplish this. Crisp values are computed using the centroid method:

$$x^* = \frac{\int x \cdot \mu(x)\, dx}{\int \mu(x)\, dx}$$

The result of this process is a single, definitive risk score indicative of the inherent uncertainties in the judgments of the expert evaluations that have been aggregated.

Implementing these procedures, the methodology converts qualitative expert evaluations into precise quantitative risk scores. This guarantees that the final risk assessments are comprehensive, robust, and accurate in capturing the collective expertise and uncertainties prevalent in the situation.

2.3 Determination of Risk Priority Number (RPN)

2.3.1 Calculation of RPN

The aggregated fuzzy evaluations determine each failure mode's Risk Priority Number (RPN). The RPN is traditionally calculated by multiplying the severity (S), occurrence (O), and detection (D) scores.

Nevertheless, this methodology modifies the conventional RPN formula to include fuzzy membership values, thereby enabling a more precise and nuanced risk assessment:

$$RPN_f = \mu_{Sf} \times \mu_{Of} \times \mu_{Df}$$

The aggregated fuzzy membership values for severity, occurrence, and detection are designated as μ_{Sf}, μ_{Of} and μ_{Df}, respectively, in this formula. From the fuzzy comprehensive evaluation process, which incorporates the diverse expert opinions and accounts for the inherent uncertainties in their judgments, these values are derived.

A more detailed representation of the risk factors is facilitated by this approach, which employs fuzzy membership values in place of single-point estimates. The fuzzy RPN (RPN_f) that results reflects the variability and uncertainty in the expert evaluations, resulting in a more precise and dependable risk prioritization. This modification improves the conventional RPN calculation by offering a thorough evaluation that more accurately reflects the intricacies and subtleties of each failure mode..

2.3.2 Comparative Analysis

Comparisons are made between the RPN values obtained through the proposed methodology and those derived from conventional RPN methods. This comparative analysis emphasizes the enhancements in reliability and accuracy that were accomplished by integrating fuzzy comprehensive evaluation and group decision-making. The proposed methodology's efficacy is evaluated by calculating the discrepancy between the traditional and fuzzy RPN values. This distinction is denoted as:

$$\Delta RPN = RPN_{traditional} - RPN_f$$

Where $RPN_{traditional}$ denotes the Risk Priority Number determined through the conventional approach (multiplying single-point estimates of severity, occurrence, and detection), and RPN_f denotes the Risk Priority Number obtained following the fuzzy comprehensive evaluation.

This analysis illustrates the potential of fuzzy logic and expert consensus to produce a more precise and nuanced risk assessment by contrasting these values. The fuzzy RPN method's ΔRPN value indicates whether it identifies risks that the traditional method may overlook or underestimate. This comparison highlights the advantages of the proposed approach in capturing the complexities and uncertainties inherent in expert evaluations, resulting in more reliable and effective risk management decisions.

3. Case Study Application: Gearbox

The proposed methodology was implemented on a gearbox, a critical mechanical component extensively employed in various industrial systems. Gearboxes are indispensable for the transmission of power and the regulation of rotational speeds and torques, rendering their dependability essential for the overall performance of the system. Established failure modes and historical data are readily accessible for analysis, as the chosen gearbox (as shown in Fig 1) is well-documented. The effectiveness of the proposed methodology can be validated on the basis of this comprehensive documentation and historical data. A comprehensive array of potential issues that the methodology can address is presented by the gearbox's common failure modes, including misalignment, gear tooth wear, bearing failure, lubrication failure, and thermal overload. By employing the methodology on this well-documented component, the investigation guarantees that the findings are pertinent and applicable to actual industrial scenarios. The credibility of the findings is further increased by using historical data for validation, demonstrating the practical applicability and reliability of the proposed approach in accurately assessing and prioritizing risks in mechanical systems.

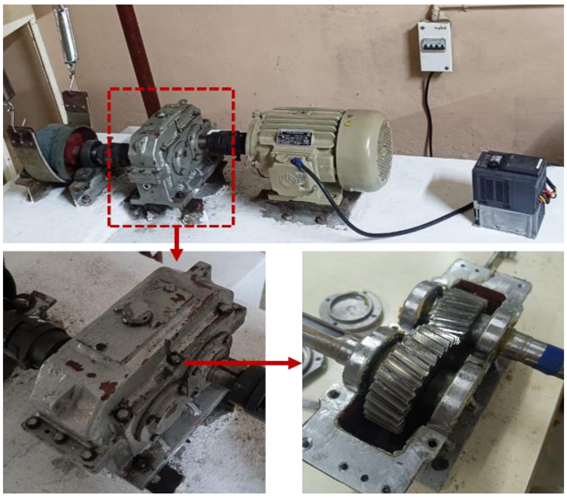

Fig.1. Helical Gearbox Assembly

3.1 Implementation and Analysis

The combined group decision-making and fuzzy comprehensive evaluation approach is used to evaluate the failure modes of the gearbox, which is how the condition monitoring methodology is implemented. As part of this rollout, specialists will evaluate possible failure modes and give interval ratings based on severity, frequency, and detection difficulty. To determine the RPN_f for each failure mode, these scores are combined and utilized in fuzzy membership functions.

After obtaining the fuzzy RPN values, the data is carefully examined to find places where the gearbox's condition monitoring system lacks or could improve. The main goal of this analysis is to find the most important failure modes that could affect the gearbox's operation. Prioritizing these failure modes allows maintenance to be more targeted in preventing system failures by fixing possible issues before they happen.

Thanks to the methodology's thorough analysis, we can see exactly where our current monitoring system is falling short and how to fix it. By zeroing in on the most critical threats, this method improves the gearbox's overall performance and reliability by allocating resources efficiently. Better, more trustworthy risk management decisions result from this process's incorporation of group decision-making and fuzzy comprehensive evaluation, which guarantee fair, thorough assessments and represent the panel's combined knowledge.

3.2 Failure Modes of Gearbox

The methodology considers various main failure modes of gearboxes to offer a thorough evaluation. To understand the gearbox's overall health and operational reliability, it is crucial to understand these failure modes. Each possible failure mode of the gearbox, along with a short description and its possible effect on the gearbox's operation, is summarized in the following table:

Table 1. Failure modes of Gearbox.

Code	Failure Mode	Description	Potential Impact
F1	Gear Tooth Wear	Wear of the gear teeth due to friction and inadequate lubrication	Gradual deterioration of gear teeth, leading to reduced efficiency

F2	Misalignment	Misalignment of gears causing uneven load distribution and increased stress	Increased wear and potential failure of gears
F3	Bearing Failure	Failure of bearings due to fatigue, inadequate lubrication, or contamination	Impact on smooth operation, leading to increased vibration and noise
F4	Lubrication Failure	Insufficient or degraded lubrication leading to increased friction and wear	Significant performance degradation and increased wear
F5	Thermal Overload	Overheating of the gearbox due to excessive load or inadequate cooling	Compromised structural integrity and potential failure
F6	Pitting and Spalling	Surface fatigue leading to the removal of material from gear teeth	Reduced efficiency and potential for gear failure
F7	Scuffing	Severe wear caused by metal-to-metal contact under high load conditions	Significant damage to gear surfaces and increased wear
F8	Corrosion	Chemical attack on gear materials due to exposure to corrosive environments	Material degradation and potential failure
F9	Gear Cracking	Cracks in the gear teeth caused by fatigue or excessive loading	Compromised structural integrity and risk of catastrophic failure
F10	Shaft Deflection	Bending or deflection of the gearbox shaft leading to misalignment and uneven wear	Increased wear and potential propagation of other failure modes

The table1 above offers a concise and organized summary of the primary failure modes assessed during the gearbox evaluation. The gradual deterioration of gear teeth is frequently the result of friction and inadequate lubrication, which is a primary failure mode. Uneven load distribution and increased stress can result from gear misalignment, exacerbating wear and potential failure. The smooth operation of the gearbox can be impacted by bearing failure, which can be caused by fatigue, inadequate lubrication, or contamination.

The gearbox's performance is significantly impacted by lubrication failure, which occurs when the lubrication is insufficient or degraded, resulting in increased friction and wear. The gearbox's structural integrity is compromised due to thermal overload, which is caused by overheating due to excessive load or inadequate cooling. Pitting and spalling are surface fatigue mechanisms that induce material removal from gear teeth, resulting in decreased efficiency and the potential for failure. Scuffing, which results from severe metal-to-metal contact under high load conditions, causes wear and damage to gear surfaces. Corrosion is the chemical attack on gear materials that results from exposure to corrosive environments, which can result in material degradation and potential failure. The structural integrity of the gearbox is compromised by gear cracking, which is a consequence of fatigue or excessive loading and is characterized by cracks in the gear teeth. Lastly, shaft deflection results from the gearbox shaft's bending or deflection, which can result in misalignment and uneven wear. This can further propagate other failure modes.

The methodology guarantees a comprehensive and detailed assessment of the gearbox's condition by taking into account these ten major failure modes: gear tooth wear, misalignment, bearing failure, lubrication failure, thermal overload, pitting and spalling, scuffing, corrosion, gear cracking, and shaft deflection. This comprehensive approach facilitates the identification and prioritization of critical issues, thereby enhancing the reliability of the gearbox and enabling targeted maintenance.

3.3 Implementation and Analysis

A panel of experts is chosen to assess the gearbox's failure modes. Assessments of the severity, occurrence, and detection difficulty of each failure mode are provided by each expert. The resulting assessments are then aggregated using fuzzy membership functions to account for the inherent uncertainties and variations in expert judgments. We employ aggregated fuzzy evaluations to determine each failure mode's Risk Priority Number (RPN). Results are summarized in the subsequent table:

Table 2: Fuzzy Membership Values and Calculated RPN for Gearbox Failure Modes

	Severity (S_f)	Occurrence (O_f)	Detection (D_f)
F1	0.80	0.70	0.60
F2	0.75	0.65	0.55
F3	0.85	0.60	0.50
F4	0.70	0.75	0.55
F5	0.65	0.60	0.65
F6	0.75	0.55	0.60
F7	0.70	0.65	0.50
F8	0.65	0.60	0.55
F9	0.80	0.50	0.60
F10	0.70	0.55	0.60

Table 2 presents a comprehensive overview of the fuzzy membership values for severity (μ_{Sf}), occurrence (μ_{Of}), and detection μ_{Df}) for each failure mode. The fuzzy membership values indicate the extent to which each failure mode is associated with various risk levels, as determined by the combined evaluations of experts.

3.4 Calculation of Traditional RPN for Gearbox

a) Ranges of severity, occurrence, and detection scores

In the context of Failure Mode and Effects Analysis (FMEA), expert judgment or historical data is often used to assign scores for severity, occurrence, and detection to the Gearbox. These scores are typically on a scale from 1 to 10.

The table3 provides a comprehensive evaluation of failure modes by assigning a range of scores for severity, occurrence, and detection based on expert judgment or historical data. The scores typically range from 1 to 10, with higher scores indicating greater severity, higher frequency, or lower detectability.

Table 3. Ranges for severity, occurrence, and detection scores based on expert judgment or historical data

Score	Severity (S)	Occurrence (O)	Detection (D)
1	No effect	Highly unlikely	Almost certain to detect
2-3	Minor effect	Rare	High likelihood of detection
4-5	Moderate effect	Occasional	Moderate likelihood of detection
6-7	Significant effect	Frequent	Low likelihood of detection
8-9	Major effect	Very frequent	Very low likelihood of detection

10	Catastrophic effect	Almost certain	Almost impossible to detect

For severity, a score of 1 indicates no effect, while scores of 2 to 3 represent a minor effect. Moderate effects are scored between 4 and 5, significant effects between 6 and 7, and major effects between 8 and 9. A score of 10 signifies a catastrophic effect.
For occurrence, a score of 1 means the failure is highly unlikely, while scores of 2 to 3 indicate it is rare. An occasional failure is scored between 4 and 5, frequent occurrences between 6 and 7, and very frequent occurrences between 8 and 9. A score of 10 suggests the failure is almost certain to occur.
For detection, a score of 1 implies the failure is almost certain to be detected, while scores of 2 to 3 indicate a high likelihood of detection. Moderate likelihood of detection is scored between 4 and 5, low likelihood between 6 and 7, and very low likelihood between 8 and 9. A score of 10 indicates it is almost impossible to detect the failure.

b) Traditional RPN

The table4 provides a comprehensive evaluation of failure modes for a gearbox, detailing the traditional RPN (Risk Priority Number) calculation. Each failure mode is assigned scores for severity (S), occurrence (O), and detection (D) based on expert judgment or historical data. The traditional RPN is calculated by multiplying these three scores.

Table 4. Traditional RPN Calculation for Gearbox Failure Modes

Failure Mode	Severity (S)	Occurrence (O)	Detection (D)	Traditional RPN (S × O × D)
F1	7	5	1	35.00
F2	9	3	1	27.00
F3	5	5	1	25.50
F4	9	2	1	29.00
F5	4	6	1	26.00
F6	5	5	1	25.00
F7	5	5	1	23.00
F8	5	4	1	22.00
F9	7	3.5	1	24.50
F10	7	3.35	1	23.50

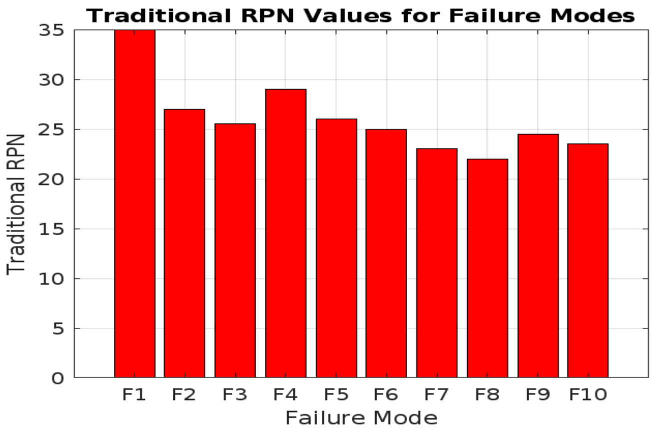

Fig. 2. Traditional RPN values for Failure modes

According to Fig 2., the traditional RPN calculation is performed as follows:
Severity (S) reflects the potential impact of a failure mode. A higher score indicates a more severe impact. For instance, a severity score of 7 for F1 indicates a significant effect. Occurrence (O) represents how frequently a failure mode is expected to occur. A higher score indicates a higher frequency. For example, F1 has an occurrence score of 5, suggesting occasional failures. Detection (D) measures the likelihood of detecting a failure before it causes harm. A lower score indicates a higher likelihood of detection. For instance, F1 has a detection score of 1, meaning it is almost certain to be detected.
For F1, with a severity score of 7, occurrence score of 5, and detection score of 1, the traditional RPN is 35.00. This indicates a significant effect that occurs occasionally and is almost certain to be detected. F2 has a severity score of 9, occurrence score of 3, and detection score of 1, resulting in a traditional RPN of 27.00. This suggests a major effect that occurs rarely and is almost certain to be detected. F3, with scores of 5 for severity, 5 for occurrence, and 1 for detection, results in a traditional RPN of 25.50. This indicates a moderate effect that occurs occasionally and is almost certain to be detected. F4 has a severity score of 9, occurrence score of 2, and detection score of 1, leading to a traditional RPN of 29.00. This suggests a major effect that occurs rarely and is almost certain to be detected. F5, with scores of 4 for severity, 6 for occurrence, and 1 for detection, has a traditional RPN of 26.00. This indicates a moderate effect that occurs frequently and is almost certain to be detected. Similar calculations are performed for the remaining failure modes, each showing the impact, frequency, and detectability, leading to their respective traditional RPN values.

4. Results and Discussion

The suggested approach for monitoring the condition of gearboxes, which combines fuzzy comprehensive evaluation and group decision-making, was verified through a case study. This section provides an overview of the study's findings and examines the enhancements made regarding accuracy and reliability in the risk assessments.

4.1 Calculation of Fuzzy RPN Values

The fuzzy membership values for severity (S), occurrence (O), and detection (D) were combined by considering the weighted expert opinions. The collected values were subsequently utilized to compute the RPN_f for every failure mode. The aggregation process entailed consolidating the various expert evaluations into a unified set of fuzzy membership values that precisely represent the overall assessment of each failure mode. The fuzzy RPN values were computed by multiplying the combined membership values for severity, occurrence, and detection for each failure mode. The findings are succinctly illustrated in fig 3.

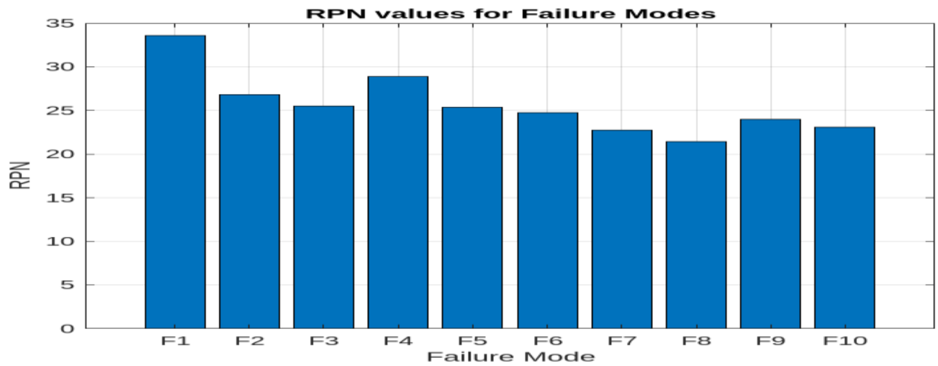

Fig. 3. Fuzzy RPN values for Failure modes

The fig.3 illustrated that, the wear of the gear tooth is assigned a severity score of 0.80, an occurrence score of 0.70, and a detection difficulty score of 0.60. These scores combine to give a RPN of 33.60. The elevated RPN signifies that gear tooth wear is a crucial failure mode that necessitates immediate attention in the condition monitoring system. Furthermore, additional failure modes such as misalignment, bearing failure, and lubrication failure are emphasized according to their corresponding RPN values.

Utilizing fuzzy membership values in the calculation of the RPN allows for a more refined and precise evaluation of risk, considering the intricacies and uncertainties that are inherent in expert opinions. This methodology guarantees that the most crucial failure modes are efficiently recognized and ranked in order of importance, allowing for focused maintenance interventions to enhance the dependability and efficiency of the gearbox. By prioritizing the failure modes with the highest RPN values, the condition monitoring system can be fine-tuned to proactively prevent potential problems and reduce operational disruptions to a minimum.

4.2 Validation of Results

The validity and dependability of the risk assessments are ensured by comparing the results obtained from the suggested methodology with historical data and expert feedback. This validation process entails comparing the RPN_f values obtained from the proposed methodology with the conventional RPN values computed using historical data.

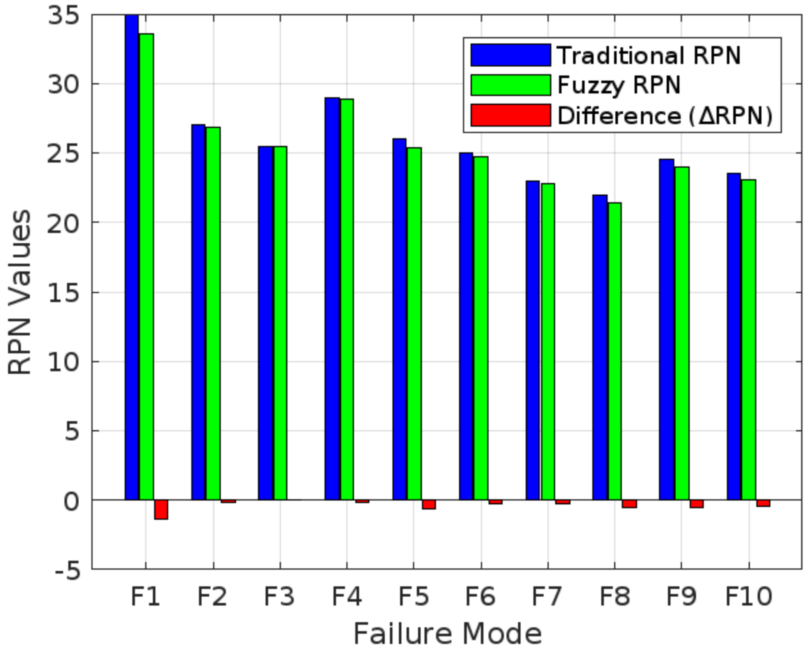

Fig. 4. Comparison of Traditional and Fuzzy RPN values for Failure modes.

The fig 4 depicts, compares the conventional RPN values obtained from historical data and the fuzzy RPN values computed using the suggested methodology. The information includes the difference (ΔRPN) between the traditional and fuzzy RPN values. As an illustration, the gear tooth wear has a historical RPN of 35.00 and a fuzzy RPN of 33.60, leading to a difference of -1.40. The negative disparity suggests a small decrease in the perceived risk when employing the fuzzy methodology, which considers expert uncertainty and offers a more detailed evaluation.

The comparison demonstrates that the fuzzy RPN values closely align with the historical RPN values, exhibiting only minor discrepancies. The disparities emphasize the modifications implemented by the

fuzzy logic approach to more precisely represent the levels of risk based on combined expert opinions. For example, the RPN for misalignment decreases marginally from 27.00 to 26.81. At the same time, the RPN for bearing failure remains constant at 25.50, suggesting that the methodologies used for assessing these failure modes are consistent.
The validation verifies that the proposed methodology effectively detects failure modes and offers dependable risk assessments. Combining fuzzy logic and group decision-making makes the condition monitoring system more resilient as it incorporates expert opinions and considers uncertainties. The methodology is highly valuable for industrial applications as it provides a more comprehensive and accurate risk assessment, facilitating better maintenance planning and decision-making.
The accuracy and reliability of the risk assessments are ensured by validating the results obtained from the proposed methodology against historical data and expert feedback. This validation process entails comparing the RPN_f values obtained from the proposed method with the conventional RPN values computed using historical data.

4.4 Correlation Between Traditional RPN and Fuzzy RPN: Validation Through Expert Feedback
The scatter plot (fig 5) illustrates the correlation between Traditional RPN (Risk Priority Number) values and Fuzzy RPN values for various failure modes. Each blue dot represents a failure mode, with its position determined by the traditional RPN value on the x-axis and the corresponding fuzzy RPN value on the y-axis. The red line represents the linear regression fit, indicating the relationship between the two sets of RPN values.

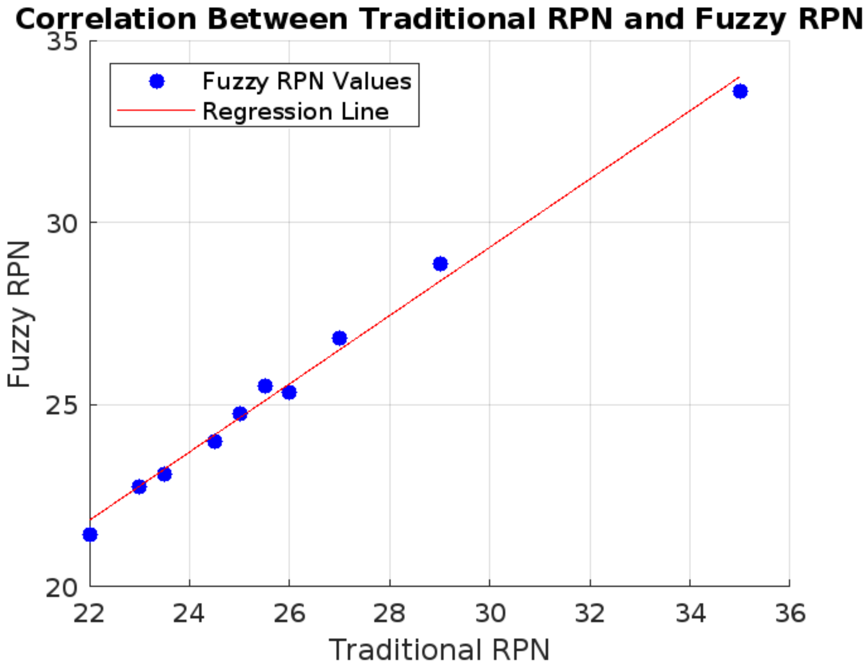

Fig. 5. Correlation between Traditional and Fuzzy RPN

The scatter plot shows a strong positive correlation between the traditional RPN values and the fuzzy RPN values. This is evident from the linear alignment of the data points along the regression line, suggesting that as the traditional RPN increases, the fuzzy RPN also increases. The red regression line highlights the overall trend and confirms the strong linear relationship between the traditional and fuzzy RPN values.

The closeness of the data points to the regression line indicates the consistency and reliability of the fuzzy RPN values in representing the risk levels.
The slight differences between the traditional RPN values and the fuzzy RPN values, as seen by the spread of the data points around the regression line, represent the enhancements made by the fuzzy comprehensive evaluation method. These adjustments provide a more nuanced and accurate risk assessment by incorporating expert judgments and accounting for uncertainties. The correlation between the traditional and fuzzy RPN values, as shown in the scatter plot, validates the effectiveness of the fuzzy comprehensive evaluation method. The strong alignment with historical RPN data suggests that the proposed methodology can accurately predict and prioritize failure risks, aligning well with industry standards and practical assessments.
The feedback from experts, which aligns with the observations from the scatter plot, confirms that the fuzzy RPN values offer a more precise representation of the risks associated with each failure mode. Experts noted that the fuzzy RPN values consider uncertainties and variations in their judgments, resulting in a more accurate and dependable risk assessment. The scatter plot and the accompanying regression analysis demonstrate that the fuzzy comprehensive evaluation method enhances the traditional RPN calculations. By incorporating expert feedback and considering uncertainties, the fuzzy RPN values provide a more reliable and detailed risk assessment. This validation through correlation with historical data and expert feedback underscores the practical usability and precision of the proposed methodology in real-life industrial applications.

4.5 Discussion

Incorporating fuzzy logic and group decision-making greatly improves the condition-monitoring process by addressing the inherent limitations of traditional RPN calculations. Conventional approaches frequently need to accurately represent the complete spectrum of expert opinions, especially when accounting for the uncertainties and variations in their evaluations. The proposed methodology utilizes fuzzy logic to convert qualitative judgments into quantitative measures, resulting in a more nuanced and precise risk assessment. This approach guarantees that the variability and uncertainty in expert opinions are adequately depicted, resulting in risk assessments that are more dependable and resilient.
The gearbox case study unequivocally illustrates this methodology's pragmatic applicability and efficacy in an industrial setting. Utilizing the fuzzy comprehensive evaluation method and group decision-making enables a more intricate and precise determination of crucial failure modes. By increasing precision, maintenance efforts can be prioritized more effectively, resulting in reduced downtime and improved gearbox reliability.
The findings from the case study indicate that the proposed methodology is efficient for gearboxes and can be extended to various mechanical components and industrial systems. The adaptability of the fuzzy logic approach allows it to be applied to diverse equipment and operational contexts, making it a versatile tool for condition monitoring in various industries.
Moreover, the study emphasizes the possibility of future research expanding the utilization of this methodology. By incorporating sophisticated data analytics and machine learning techniques, the accuracy and efficiency of the condition monitoring process can be significantly improved. These technologies facilitate the efficient analysis of extensive datasets, enabling the identification of patterns and trends that may not be discernible through conventional analysis methods. Additionally, they offer predictive insights that can enhance maintenance planning and operational decision-making.

5. Conclusion

This study introduces a strong methodology for monitoring the condition of gearboxes. It combines group decision-making and fuzzy comprehensive evaluation to improve the accuracy and dependability of risk assessments. This approach significantly enhances the identification and prioritization of failure modes by overcoming the limitations of traditional RPN calculations.

The proposed methodology entails selecting a group of experts to assess the potential failure modes of the gearbox. These experts will assign interval scores to evaluate these failure modes' severity, occurrence, and detection. The scores are consolidated using fuzzy membership functions and then integrated through fuzzy logic to compute the RPN_f. The case study findings indicate that the fuzzy RPN values are superior in accuracy and reliability compared to traditional RPN values. This allows for a more precise evaluation of the risks associated with each failure mode.

The key findings indicate that the proposed methodology has been validated for accuracy, as the RPN_f values closely match historical data and expert feedback. The methodology minimizes subjective bias by integrating group decision-making and allocating weights based on expert similarity. This leads to a more equitable and unbiased assessment. Another notable discovery is the practical applicability of the methodology, which can be adapted to different industrial contexts. This provides a strong framework for monitoring the condition of mechanical systems.

The suggested approach presents numerous tangible ramifications for industrial implementations. Accurate identification and prioritization of failure modes enable improved maintenance strategies, resulting in more targeted maintenance actions, reduced downtime, and increased reliability of gearboxes. Integrating fuzzy logic and expert consensus supports enhanced decision-making by providing a comprehensive and objective risk assessment, aiding maintenance planning and risk management. The versatility of the methodology concerning different mechanical components and industrial systems renders it a highly adaptable tool for condition monitoring in diverse industries.

Future research should prioritize expanding the utilization of this methodology to encompass other crucial mechanical components and industrial systems. Incorporating advanced data analytics and machine learning techniques into the fuzzy comprehensive evaluation can improve the accuracy and efficiency of condition monitoring systems. Longitudinal studies could be implemented to assess the enduring advantages and efficacy of the methodology in practical industrial settings.

Although the proposed methodology presents notable enhancements compared to conventional risk assessment methods, it does have some limitations. The dependence on expert evaluations introduces an inherent subjectivity, although this is lessened by the collective decision-making process. The efficacy of the methodology is contingent upon the calibre and accessibility of historical data for validation. Subsequent investigations should focus on overcoming these constraints and enhancing the method.

References:

1. Anand, A., Haq, M. I. U., Vohra, K., Raina, A., & Wani, M. F. (2017). Role of green tribology in sustainability of mechanical systems: a state of the art survey. Materials Today: Proceedings, 4(2), 3659-3665.
2. Jordan, J. M., Blockmans, B., & Desmet, W. (2023). A linear formulation for misaligned helical gear contact analysis using analytical contact stiffnesses. *Mechanism and Machine Theory*, *187*, 105373.
3. Liu, H., Liu, H., Zhu, C., & Tang, J. (2020). Study on gear contact fatigue failure competition mechanism considering tooth wear evolution. *Tribology International*, *147*, 106277.

4. Ericson, T. M., & Parker, R. G. (2014). Experimental measurement of the effects of torque on the dynamic behavior and system parameters of planetary gears. *Mechanism and Machine Theory*, *74*, 370-389.
5. Kebabsa, T., Ouelaa, N., Antoni, J., Djamaa, M. C., Khettabi, R., & Djebala, A. (2017). Fault diagnosis through the application of cyclostationarity to signals measured. In *Applied Mechanics, Behavior of Materials, and Engineering Systems: Selected contributions to the 5th Algerian Congress of Mechanics, CAM2015, El-Oued, Algeria, October 25–29* (pp. 251-266). Springer International Publishing.
6. Richard, E., Chang, T. H., & Sutherland, J. W. (1992). *Statistical Quality Design and Control* (pp. 12-15). Upper Saddle River, NJ, USA:: Prentice Hall.
7. Ben-Daya, M., & Duffuaa, S. O. (1995). Maintenance and quality: the missing link. *Journal of quality in maintenance engineering*, *1*(1), 20-26.
8. Zimmermann, H. J. (2011). *Fuzzy set theory—and its applications*. Springer Science & Business Media.
9. Delgado, M., Herrera, F., Herrera-Viedma, E., & Martinez, L. (1998). Combining numerical and linguistic information in group decision making. *Information Sciences*, *107*(1-4), 177-194.
10. Yang, Y. J., Huang, H. Z., Liu, Y., Zhu, S. P., & Peng, W. (2014). Reliability analysis of electrohydraulic servo valve suffering common cause failures. *Eksploatacja i Niezawodność*, *16*(3), 354-359.
11. Chang, K. H. (2009). Evaluate the orderings of risk for failure problems using a more general RPN methodology. *Microelectronics Reliability*, *49*(12), 1586-1596.
12. Chen, K. S., Wang, C. C., Wang, C. H., & Huang, C. F. (2010). Application of RPN analysis to parameter optimization of passive components. *Microelectronics Reliability*, *50*(12), 2012-2019.
13. Bhattacharjee, P., Dey, V., & Mandal, U. K. (2022). Failure Mode and Effects Analysis (FMEA) using interval number based BWM—MCDM approach: Risk Expected Value (REV) method. *Soft Computing*, *26*(22), 12667-12688.
14. Renjith, V. R., Kumar, P. H., & Madhavan, D. (2018). Fuzzy FMECA (failure mode effect and criticality analysis) of LNG storage facility. *Journal of loss prevention in the process industries*, *56*, 537-547.
15. Catelani, M., Ciani, L., Galar, D., & Patrizi, G. (2020). Risk assessment of a wind turbine: A new FMECA-based tool with RPN threshold estimation. *IEEE Access*, *8*, 20181-20190.
16. Chang, K. H., Chang, Y. C., & Tsai, I. T. (2013). Enhancing FMEA assessment by integrating grey relational analysis and the decision-making trial and evaluation laboratory approach. *Engineering Failure Analysis*, *31*, 211-224.
17. Akram, M., & Adeel, A. (2019). Novel TOPSIS method for group decision-making based on hesitant m-polar fuzzy model. *Journal of Intelligent & Fuzzy Systems*, *37*(6), 8077-8096.
18. Meng, F., Li, S., & Tang, J. (2021). A new interval type-2 trapezoid fuzzy multi-attribute group decision-making method and its application to the evaluation of sponge city construction. *Artificial Intelligence Review*, *54*(6), 4063-4096.
19. Wang, L., & Li, N. (2020). Pythagorean fuzzy interaction power Bonferroni mean aggregation operators in multiple attribute decision making. *International Journal of Intelligent Systems*, *35*(1), 150-183.
20. Jamshidi, A., Ait-Kadi, D., Ruiz, A., & Rebaiaia, M. L. (2018). Dynamic risk assessment of complex systems using FCM. *International Journal of Production Research*, *56*(3), 1070-1088.

21. Yan, X., Liu, Y., Jia, M., & Zhu, Y. (2019). A multi-stage hybrid fault diagnosis approach for rolling element bearing under various working conditions. *Ieee Access*, *7*, 138426-138441.
22. Chen, Z., Li, C., & Sanchez, R. V. (2015). Gearbox fault identification and classification with convolutional neural networks. *Shock and Vibration*, *2015*(1), 390134.
23. Sharma, R. K., Kumar, D., & Kumar, P. (2005). Systematic failure mode effect analysis (FMEA) using fuzzy linguistic modelling. *International journal of quality & reliability management*, *22*(9), 986-1004.
24. Asi, O. (2006). Fatigue failure of a helical gear in a gearbox. *Engineering failure analysis*, *13*(7), 1116-1125.
25. Sankar, S., Nataraj, M., & Raja, P. V. (2012). Failure analysis of bearing in wind turbine generator gearbox. *Journal of Information Systems and Communication*, *3*(1), 302.
26. Lamhour, K., & Tizliouine, A. (2019, November). Different failure modes of the horizontal axis wind turbine gearbox. In *2019 7th international renewable and sustainable energy conference (IRSEC)* (pp. 1-8). IEEE.
27. Lei, Y., Lin, J., Zuo, M. J., & He, Z. (2014). Condition monitoring and fault diagnosis of planetary gearboxes: A review. *Measurement*, *48*, 292-305.
28. Mangeli, M., Shahraki, A., & Saljooghi, F. H. (2019). Improvement of risk assessment in the FMEA using nonlinear model, revised fuzzy TOPSIS, and support vector machine. *International journal of industrial ergonomics*, *69*, 209-216.
29. Salameh, J. P., Cauet, S., Etien, E., Sakout, A., & Rambault, L. (2018). Gearbox condition monitoring in wind turbines: A review. *Mechanical Systems and Signal Processing*, *111*, 251-264.
30. Kgatwe, C. K., Madushele, N., Olatunji, O. O., & Adedeji, P. A. (2022, May). A Survey of Fuzzy Logic Systems in Condition Monitoring of Conveyor Gearbox. In *2022 IEEE 13th International Conference on Mechanical and Intelligent Manufacturing Technologies (ICMIMT)* (pp. 240-246). IEEE.