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Risk Mitigation of Air Knocker Using Fuzzy FMEA-AHP: A Case Study

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Abstract: This research is driven by the necessity for effective and high-quality maintenance systems capable of fulfilling rigorous equipment maintenance standards. The purpose of this study was to identify potential failures in an air knocker, evaluate the risk of failure through the Fuzzy FMEA approach, and optimize decision-making using the AHP method. This study was based on theories related to maintenance, Fuzzy FMEA, and AHP. The research methodologies employed comprised a literature review, data analysis, and the application of Expert Choice software to compute weights and ratings according to pertinent criteria. The results showed that the integration of Fuzzy FMEA and AHP methods was effective in identifying potential failures, evaluating risks more accurately, and prioritizing optimal corrective actions in the maintenance system. This study suggests that the integration of Fuzzy FMEA and AHP methods can improve risk management and decision-making in maintenance systems. This strategy assists organizations in mitigating the risk of failure, enhancing efficiency, and more effectively addressing process requirements. This methodology enables a more comprehensive examination of risk variables and the efficient management of uncertainties, as well as the decision-making process for assessing the risks associated with air knocker operations.

Keywords: AHP, Fuzzy FMEA, potential failures, decision making.

Introduction

Air knockers are mechanical devices employed across multiple industries, particularly in scenarios involving the movement of materials or those that exhibit slow or challenging flow characteristics. Its purpose is to address the issues of accumulation, aggregation, or obstruction of materials in flow systems, including pipelines, hoppers, and conveyors. Air knockers operate by intermittently or abruptly expelling high-pressure air into the material's surface, effectively disaggregating clumps and promoting a more uniform flow. However, like other industrial machinery, the utilization of air knockers may pose risks of damage and operational interruption.

Operational facility issues that disrupt or halt production can be classified into three categories: human, machines, and methods factors. These three factors mutually influence each other. The crucial factor among the requirements above is the performance of the production machine. The air knocker experienced sudden damage due to a lack of maintenance, product quality, and productivity. Consequently, it is crucial to execute efficient risk-mitigation strategies to reduce the possibility of air knocker damage and guarantee sustainable operation.

The problem of air knockers in the context of risk assessment and failure mode analysis can be effectively addressed by integrating Fuzzy Failure Mode and Effect Analysis (FMEA) with the Analytic Hierarchy Process (AHP). This integration facilitates a comprehensive evaluation of the risk factors associated with the air knocker system by employing fuzzy logic to mitigate uncertainties and inconsistencies in the assessment process. The research by Wang *et al.* [1] indicated that the risk assessment process could be enhanced by systematically including various criteria and expert opinions via a combination of Fuzzy FMEA and AHP [2].

Fuzzy FMEA and AHP are the two methodologies utilized for risk management. Fuzzy FMEA is an enhanced iteration of traditional FMEA that employs fuzzy logic to address ambiguity and imprecision in the evaluation of risks. This concept was initially introduced by Wang *et al.* [1] and has since been utilized in other research investigations, including those conducted by Roghanian & Mojibian [3] and Ilangkumaran *et al.* [4]. AHP is a technique used for making decisions that involve multiple criteria. This was developed by Saaty [5]. It assigns priority and arranges options based on their relative importance within a hierarchical structure.

Fuzzy FMEA and AHP provide a solid foundation for complex decision-making, especially in uncertain and subjective circumstances. Fuzzy FMEA and AHP are preferred over regular methods, as explained in this work. The recent literature supports the benefits of this combined approach. Fuzzy FMEA can address uncertainty in risk assessment. Traditional FMEA uses precise severity, occurrence, and detection ratings, potentially oversimplifying complex circumstances. Fuzzy logic can represent these ratings as fuzzy sets to accommodate ambiguity and imprecision [6], [7]. This is significant as expert opinions in healthcare and engineering differ markedly due to individual experiences and perspectives [8]. Fuzzy FMEA uses fuzzy logic to understand potential failure mechanisms better and improve risk ratings. Fuzzy FMEA and AHP improve decision-making by combining qualitative and quantitative evaluations. AHP's systematic approach simplifies complex decision concerns, making it easy to evaluate numerous criteria and options [6], [9]. Fuzzy FMEA assists organizations in risk prioritization by assessing the probability of failure and its consequences.

A recent study proved that this hybrid methodology improves supply chain management and quality risk assessments. The combination of Fuzzy FMEA and AHP results in a more comprehensive and precise approach to risk management than classic FMEA methodologies [10], [11]. Fuzzy FMEA and AHP facilitate flexible decision-making. Fuzzy logic enables membership functions and rules to adjust to evolving data and expert insight, making it suitable for dynamic conditions [12]. AHP enables decision-makers to adjust criteria weights and preferences in response to new information, enhancing its adaptability. Adaptability is crucial for risk management in fast-changing industries, such as healthcare [8]. This integration allows for a more comprehensive assessment of risk factors by incorporating fuzzy logic to resolve uncertainties and inconsistencies in the evaluation process [13]. This makes decision-making relevant and efficient [6]. Researchers have effectively overcome the limits of traditional FMEA methodologies and improved the risk assessment process by including the Fuzzy AHP. These methodologies can also be tailored to an organization's needs, enabling the risk assessment framework to adhere to industry standards. Recent research has shown that the hybrid technique is effective in many areas, making it relevant to modern decision-making.

In an automotive case study of Altubaishe & Desai [6], the usefulness of the hybrid AHP-PROMETHEE-based FMEA method was demonstrated. Research by Yeganeh *et al.* [14], Basuki *et al.* [15], and Purba *et al.* [16] have shown that combining the Fuzzy AHP with FMEA can significantly improve risk prioritization and decision-making procedures. The application of fuzzy methodologies, such as the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), in conjunction with the Fuzzy AHP, has proven highly successful in addressing the limitations of the traditional FMEA methods [17], [18]. Ilyasu et al [19] showed that a hybrid Fuzzy AHP and TOPSIS model could estimate quality risk in several fields. The integrated approach outlined in the paper Sagnak *et al.* [20] offers a comprehensive framework for risk assessment. It considers many criteria and expert opinions systematically, resulting in a more reliable and resilient evaluation.

Rahmatin *et al.* [21] employed Fuzzy FMEA and ANP (Analytic Network Process) to assess marketing risks in the potato chip industry. The research utilized Fuzzy FMEA to identify and evaluate risks, followed by the ANP method to establish the primary strategy for risk mitigation. The results indicated that the integration of Fuzzy FMEA and ANP yielded enhanced risk management outcomes compared with traditional FMEA. In a separate study, the fuzzy FMEA-AHP methodology enhanced the efficiency of the logistics system [22], [23], [24], [25]. The study employed Fuzzy FMEA to address uncertainty in risk assessment and AHP to determine the priority and ranking of the detected failure modes.

Moreover, the integration of Fuzzy AHP with FMEA has been applied across various sectors, including software projects, supply chains, and construction. This application has demonstrated the adaptability and efficiency of this approach in various scenarios [10], [11], [17], [23], [26], [27], [28]. Researchers have successfully developed advanced risk assessment models by combining the advantages of the Fuzzy AHP and FMEA. These models account for uncertainties, effectively prioritize risks, and facilitate decision-making processes [29], [30].

The fundamental difference between traditional FMEA and Fuzzy FMEA resides in their methodologies for addressing uncertainty and imprecision in risk assessment. Traditional FMEA employs quantitative methodology to evaluate risks. This involves assigning numerical values to the Severity, Occurrence, and Detection (SOD) ratings and then calculating the Risk Priority Number (RPN) as the product of these ratings [31]. This strategy is appropriate for circumstances in which risks are well-defined and can be measured.

In contrast, Fuzzy FMEA uses fuzzy logic to manage uncertainty and imprecision during risk assessment efficiently. The use of language terminology enables a more adaptive and detailed evaluation of risks because it can incorporate descriptions of the severity, occurrence, and detection of each failure mode [14], [32]. Each language variable was characterized by five linguistic terms: very low (VL), low (L), fair (F), high (H), and Very High (V). This approach is best suited to situations when the risks are not clearly defined or measured or where expert knowledge and judgment are required in the risk assessment process [33].

The Fuzzy FMEA methodology employed a triangle fuzzy number (a, b, c) to construct the membership functions. In this case, x represents the specified rating, and u(x) signifies the level of membership, which is the value of the membership function. This enables a more intricate and refined evaluation of risks, as it may encompass the uncertainty and imprecision inherent in the risk evaluation process.

The integration of Fuzzy FMEA with AHP offers an advantageous approach for enhancing risk assessment and decision-making processes. This is accomplished by providing a comprehensive and precise evaluation of risk factors across different domains. In addition, the application of fuzzy methods, such as fuzzy AHP and fuzzy weighted geometric mean, can greatly enhance the evaluation of risks and decision-making procedures associated with the air knocker system [13]. These approaches provide a robust and complete framework for risk prioritization and decision-making in air knocker operations.

Furthermore, the integration of Fuzzy FMEA with AHP provides novel risk assessment models that address the limitations of traditional FMEA methodologies and provide more accurate risk evaluations [27], [34], [35], [36]. Researchers can enhance the management of hazards related to air knocker systems by utilizing fuzzy multiple-criteria decision-making techniques, including fuzzy cognitive mapping and fuzzy multiple-criteria decision-making.

In summary, the combination of Fuzzy FMEA and AHP techniques presents a potential solution for dealing with air knockers. This approach facilitates a comprehensive examination of risk variables and uncertainty management, hence enhancing the decision-making process in evaluating hazards linked to air knocker activities.

Methods

The systematic integration of Fuzzy FMEA and the AHP enhances risk assessment and prioritization across many applications. Fuzzy FMEA and AHP processes are outlined below. Fuzzy FMEA begun by identifying the system or process failure modes. A team of specialists provided thoughts based on their experience and knowledge of the system during brainstorming sessions [20]. The subsequent phase involved documenting the failure modes for analysis. After identifying each failure mode, the system impacts of each were analyzed. This entailed understanding how each failure affected the system's performance, safety, and reliability. The causes of each failure mode should be identified to improve risk management [37].

Traditional FMEA evaluates failure modes based on severity, occurrence, and detection. Fuzzy logic enables experts to express their assessments using linguistic terms (e.g., low, medium, and high) instead of numerical values. This captures the subjectivity and ambiguity of expert judgments. Membership functions converted prior language assessments into fuzzy numbers. This conversion aggregates expert viewpoints and makes failure mode risks more nuanced [23], [38]. The RPN was determined by the Equation 1.

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

The fuzzy severity (S), occurrence (O), and detection (D) values determined the Fuzzy FMEA RPN. This produced a fuzzy RPN (F-RPN) that reflected the evaluation of uncertainty. Following the computation of the F-RPNs, the failure modes were ranked according to risk. This priority helps uncover failure modes that require quick attention and correction [23], [37]. The AHP then weighed S, O, and D based on their importance. A pairwise comparison of criteria enables decision-makers to express preferences and judgments systematically. The AHP procedure consists of several steps: (1) Experts' pairwise comparison criteria to determine importance.

(2) Pairwise comparison results were utilized to generate each criterion's weights using the AHP methodology.
(3) A consistency ratio was established to ensure consistent evaluations through pairwise comparisons.

The weights from AHP were used to compute the F-RPNs to represent the importance of each criterion. Incorporating subjective severity, occurrence, and detection into risk evaluation strengthens the risk prioritization process [39]. Based on the prioritized risks, action plans were developed to mitigate or eliminate the identified risks. This may involve the implementation of corrective actions, redesigning processes, or enhancing monitoring systems to reduce the likelihood of failure. It is essential to continuously monitor the effectiveness of the implemented actions and periodically review Fuzzy FMEA and AHP processes. This ensures that risk assessment remains relevant and effective for managing potential failures over time [37], [39].

Risk variables were arranged according to the relevant operational scope of the machine maintenance system. These characteristics were derived from interviews and field research, and categorized as internal failures, external failures, and human failures, with the specifications shown in Table 1. Table 1 illustrates three variables with indicators, each of which has several sub-indicators. Table 2 displays the sub-indicators for each equipment failure indicator.

Table 1. Risk mitigation

Operational Risk		
No.	**Variable**	**Indicator**
1	Equipment Failure	Adjustments that do not comply with standards. Lifetime
2	Human Failure	Maintenance errors Oil contamination occurs
3	Method Failure	Wrong operating mode Long operating time

The Table 1 shows that there are three variables with indicators, each of which consists of several sub-indicators. Table 2 shows the sub-indicators of each equipment failure indicator.

Table 2. Failure table

	Tools failure
A.	Adjustments that do not comply with standards.
1	Adjusting the main pump is not carried out by the vendor
B.	Lifetime
1	Hour meter exceeds maintenance schedule
	Human Failure
A.	Maintenance errors
1	The mechanic did not carry out a daily check on the unit resulting in an external leak in the hydraulic system
B.	Misuse of oil
1	Oil specifications do not use ISO VG 68
C.	Oil contamination occurs
1	Oil mixed with water
	Method Failure
A.	Incorrect operation mode
1	Operators use H mode in unit use
B.	Long operating time
1	Hour meter exceeds maintenance schedule

These data were obtained through interviews and field studies on the overall production process during the air knocker treatment process. These stages were used to evaluate manufacturing, inventory control, output monitoring, and consumer feedback. Corporate management and staff were interviewed to understand how maintenance management affects efficiency and productivity. After the interviews, a brief overview was provided to form a questionnaire. Specialists received this questionnaire to assess threats. AHP was used to create the questionnaire. Firm employees completed the questionnaire based on their position, knowledge, and tenure. The company employed diverse researchers for this project. The identification of hazards was the next step in improving a company's maintenance system problem-solving. This inquiry sought to understand past and contemporary events, data, and circumstances. The next stage was a thorough analysis of all data collected in the previous stage. In this activity, relevant data was sorted and selected.

Fuzzy Failure Mode Effect Analysis (FMEA)

The process of fuzzy FMEA started with the fuzzification process by changing risk factors into severity, occurrence, and detection into fuzzy ones. The identified risks were evaluated using three parameters in accordance with the Fuzzy FMEA concept approach, namely the Fuzzy FMEA input, which includes the value of the level of impact/severity (S), the level of occurrence (O), and the level of detection (D). The rating scale for S, O, and D was composed of input variables with a range of 1-10, which were categorized into five linguistic levels. Additionally, fuzzy values were included for each category, as illustrated in Table 3.

Table 3. Linguistic tables and fuzzy numbers on severity, occurrence and detection

Fuzzy Numbers			Category
Severity	Occurrence	Detection	
1,2,3,4	1,2,3	1,2,3,4	Very Low
3,4,5	2,3,4,5	3,4,5	Low
4,5,6	4,5,6,7	4,5,6	Fair
5,6,7	6,7,8,9	5,6,7	High
6,7,10,10	8,9,10,10	6,7,10,10	Very High

Source: Wang *et al.*. [1]

Table 3 shows the categories and fuzzy values that were used in the fuzzification process. In order to generate membership levels for each input, the membership functions were employed to convert the three inputs into fuzzy form. After the membership level of each input was obtained, fuzzy computing and defuzzification were carried out to get a single value (crisp). A centroid, which was a singular value of the output variable calculated by determining the center of gravity of the variable in the form of a fuzzy membership function, was employed in this study as a defuzzification method.

The risk assessment in this method employed the Fuzzy Logic Toolbox within MATLAB, a suite of tools utilized for fuzzy system design. This tool is also applicable for creating or modifying a Fuzzy Inference System (FIS) in MATLAB. Defuzzification converted the fuzzy output from fuzzy inference into a single precise value for decision-making. This stage facilitates the prioritization and management of risks by transforming subjective assessments into objective metrics. The defuzzification process can substantially influence the outcomes and determinations of the FMEA. Expert Choice utilized fuzzy logic to prioritize and assess options for decision-making. The Expert Choice data entry procedure comprised the subsequent steps. The first step was identifying the decision criteria and options. Cost, duration, and quality may be considered when selecting a project [40].

Expert Choice evaluated criteria and alternatives using pairwise comparisons. Users evaluated items on a scale from one to nine to express their preferences. This technique is necessary to determine imprecise weights for each criterion [41]. This tool allows users to express their preferences in a fuzzy language, accommodating uncertainty in decision-making. Using fuzzy weights to compare pairings, the detailed ratings for each alternative were calculated. After creating the fuzzy inference system in MATLAB, input data and fuzzy rules were used to derive the outputs. MATLAB applied rules to the incoming data to perform fuzzy inference. A fuzzy set indicating the output category membership was frequently the result [42]. Defuzzification converted the fuzzy output to a precise value. Castellano asserts that the centroid approach is often employed to ascertain the center of gravity of the fuzzy output set [43]. A representative value may be utilized for decision-making with this technique. This result could then be evaluated within the program to determine the probability of malfunction. Following these steps to obtain Expert Choice results, the software calculated fuzzy weights for each criterion and alternative using pairwise comparison data. This synthesis clarifies the relative importance of each factor in decision-making [44]. Expert Choice utilized fuzzy weights to rank alternatives, facilitating optimal decision-making for stakeholders. The ranking shows integrated preferences and facilitates informed decisions [45].

The fuzzification process in FMEA involved converting the input data into a fuzzy form to describe the uncertainty or ambiguity associated with the input values. In this process, values such as severity, occurrence, and detection were translated into a fuzzy membership function that reflects the membership level of each value in a predetermined fuzzy set. This enables the use of fuzzy logic to acknowledge uncertainty in risk assessment and enables adaptive and flexible decision-making based on the level of uncertainty. Figure 1 illustrates the fuzzification process for severity, occurrence, and detection.

The subsequent step involved assessing the "If-Then" fuzzy rules to determine the inference outcomes from the fuzzification process, comprising 125 distinct rules utilized for calculating the Centroid in the defuzzification process. It would produce crisp values and calculate Fuzzy RPN values. The fuzzy rules "If-Then" are delineated in Table 4.

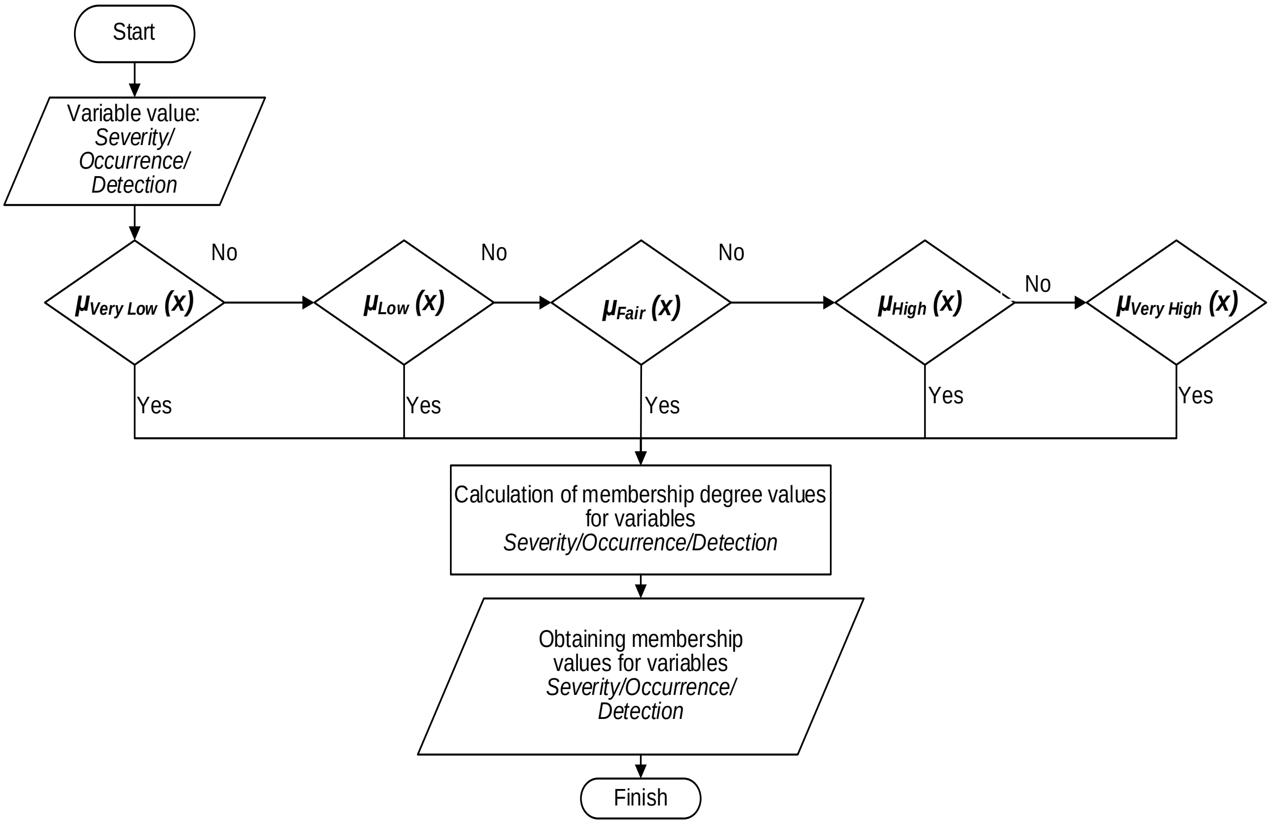

Figure 1. Fuzzification process for severity, occurrence and detection

Table 4. Fuzzy RPNRule

Rule	If			Fuzzy RPN
	Severity (S)	**Occurrence (O)**	**Detection (D)**	
1	Very Low	Very Low	Very High	Very Low
2	Very Low	Low	Very High	Low
3	Very Low	Fair	Very High	Low
4	Very Low	High	Very High	Low
5	Very Low	Very High	Very High	Low
6	Very Low	Very Low	High	Low
7	Very Low	Low	High	Low
8	Very Low	Fair	High	Low
9	Very Low	High	High	Low
10	Very Low	Very High	High	Low
⋮	⋮	⋮	⋮	⋮
⋮	⋮	⋮	⋮	⋮
⋮	⋮	⋮	⋮	⋮
125	Very High	Very High	Very Low	Very High

After the fuzzy inference process, the next step in the FMEA analysis was the defuzzification process. Defuzzification is the process of converting a fuzzy output derived from the fuzzy inference stage into a singular exact value suitable for decision-making. This phase is crucial as it transforms subjective assessments into objective metrics, facilitating the prioritization and management of risks. The selection of the defuzzification method can significantly influence the results and subsequent assessment of the FMEA process.

***Analytical Hierarchy Process* (AHP)**

The Analytical Hierarchy Process (AHP) method has been proven to be an effective tool for complex decision-making. This study utilized the Expert Choice application, a widely recognized tool for implementing the AHP approach. The Expert Choice program was utilized to ascertain the weight of each criterion regarding severity, occurrence, and detection within the FMEA approach, with the objective of integrating these two methodologies. The interview results indicate that the following factors and alternatives need to be considered, and alternatives are suggested for risk mitigation (Table 5).

Table 5. Risk mitigation proposals

	Factor
1	Equipment failure
2	Human failure
3	Method failure
	Alternative
1	Adjust according to standards
2	Operation lifetime
3	Use the right oil
4	Correct operating mode

In Table 5, there are criteria for the proposed risk mitigation and possible alternatives. The weight of each criterion was calculated based on the questionnaire that provided to decision-makers at the company.

Fuzzy FMEA enhances traditional FMEA by incorporating fuzzy logic, which mitigates the intrinsic ambiguity and subjectivity in risk assessments. This method enables a more sophisticated assessment of failure modes by employing fuzzy sets to represent expert judgments and uncertainties in the risk variables. Resende *et al.* [46] emphasizes that the integration of fuzzy logic into FMEA does not compromise its core principles; rather, it enhances the methodology by mitigating its limitations, particularly in sectors like aeronautics, where precision is vital. Fuzzy FMEA can be improved by AHP to analyze the reasons for failures in logistics systems, particularly during crises like the COVID-19 pandemic [23]. This integration facilitates a systematic assessment of the weights of risk indicators, which is crucial for effectively prioritizing issues.

The AHP technique enhances Fuzzy FMEA by offering a systematic framework for decision-making that integrates various criteria. It allows the ranking of risks by considering both qualitative and quantitative evaluations. For instance, Ilyasu *et al.* [19] demonstrated the use of a hybrid Fuzzy FMEA model that combines AHP and TOPSIS to analyze quality risks. This integration allows for a thorough evaluation of potential quality problems in pharmaceutical items. The AHP component facilitates the systematic prioritization of failure modes found using Fuzzy FMEA, ensuring that the most critical risks are handled as a priority.

Furthermore, the integration of various techniques provides a comprehensive perspective on risk management. Fuzzy FMEA incorporates the imprecise nature of expert opinions, whereas AHP offers a well-defined structure for decision-making. The collaboration of fuzzy logic and AHP in building project risk analysis was clearly demonstrated in research conducted by Cuadros *et al.* [47]. Cuadros emphasized the significance of considering risk correlations and the subjective nature of expert opinions.

The integration of Fuzzy FMEA and AHP methods was aimed at improving risk analysis and decision-making in maintenance management. The fuzzy FMEA-AHP method combines two methods: Fuzzy FMEA and AHP. The fuzzy FMEA method was used to identify and analyze potential failures in a system by considering data uncertainty or ambiguity [23]. The AHP method was used to determine the relative weight of the relevant criteria in decision-making.

Results and Discussions

Fuzzy FMEA utilized fuzzy logic to handle ambiguity and lack of precision in expert assessments regarding the severity, occurrence, and detection of failure modes. Experts can utilize fuzzy sets to articulate their ideas using language variables, which are subsequently transformed into numerical values using membership functions. This approach enables a more sophisticated comprehension of risk factors, in contrast to the precise values employed in traditional FMEA [38], [48]. For example, the fuzzy set theory can be used to combine multiple expert opinions to produce a more dependable risk assessment. Simultaneously, the AHP can be employed to determine the importance of these assessments, thereby improving the reliability of the risk priority numbers (RPNs) obtained from FMEA [48].

The AHP component of this integration was used to rank the detected risks based on their relative significance. AHP enables decision-makers to systematically compare various failure modes by assigning rankings based on several factors, such as cost, safety, and operational impact [8]. Prioritization is essential, as it guides the decision-making process in which hazards are handled as a priority. An illustration of the application of fuzzy AHP is to show its ability to simulate worst-case scenarios in risk assessments. This enables the full evaluation of potential repercussions, as demonstrated by Chang *et al.* [49]. In addition, the combination of AHP and Fuzzy FMEA enables the inclusion of both subjective expert judgments and objective data, resulting in improved consistency and reliability of risk assessment outcomes [50]. The severity, occurrence, and detection assessment results in FMEA. Traditional FMEA was calculated to determine the RPN (Table 6). The ranking was established from the lowest to the greatest RPN value of all main operational risk indicators for equipment maintenance at the organization (Table 7). The fuzzy input visualization of severity, occurrence, and detection are presented in Figure 2 and Figure 3.

Table 6. Failure mode and effect analysis and severity, occurrence, detection assessment

Types of Failure	Possible Effect	S	Possible Modes	O	Executed Controls	D	RPN	Ranking
Adjusting the main pump is not carried out by the vendor	Production cessation	7	Not coordinating with related departments	6	Ensure that the main pump adjustment is carried out by the vendor according to the applicable contract	6	252	1
Hour meter exceeds maintenance schedule	Damage to the tool	6	Delays in the production process	4	Regular monitoring of tools.	8	192	4
The instrument does not carry out a daily check on the unit resulting in an internal leak in the hydraulic system	Decreased product quality	5	Employees do not comply with SOPs	7	Provide adequate training to employees	5	175	5
Oil specifications do not use ISO VG 68	Products that do not meet customer specifications	7	Employees do not properly understand specifications and quality standards	3	Clarify specifications and quality standards to employees.	8	168	6
Oil mixed with water	Product defects that hinder production	9	Errors in following the production flow	6	Regular monitoring of production processes	4	216	2
Operators use H mode in unit use	Equipment damage	6	Inaccuracy of unit usage	5	Improved the accuracy of using unit mode	7	210	3
Hour meter exceeds maintenance schedule	Equipment damage	9	Equipment damage	2	Carry out monitoring according to schedule	6	108	7

Then, the ranking was ranged made from the lowest to the highest RPN value of all the main indicators of operational risk indicators for equipment maintenance at the company (Table 7).

Table 7. The rankingRanking was based on the highest RPN values.

Indicator	RPN	Ranking
Adjusting the main pump is not carried out by the vendor	252	1
Oil mixed with water	216	2
Operators use H mode in unit use	210	3
Hour meter exceeds maintenance schedule	192	4
The instrument does not carry out a daily check on the unit resulting in an external leak in the hydraulic system	189	5
Oil specifications do not use ISO VG 68	180	6
Hour meter exceeds maintenance schedule	175	7

The fuzzy input visualization of Severity, Occurrence, and Detection are as Figure 2 and 3.

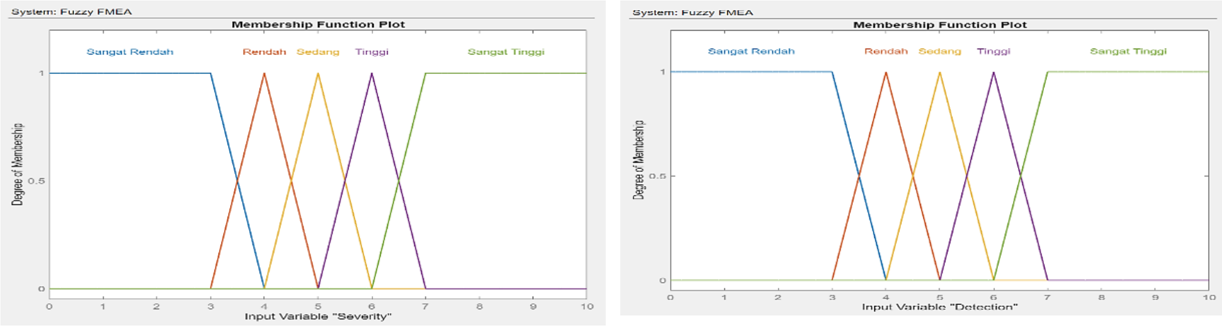

Figure 2. Fuzzy severity variable and fuzzy detection variable inputs

Based on the image in Figure 2, the fuzzy values for each category can be obtained as follows:

Very Low : 1, 2, 3, 4
Low : 3, 4, 5
Medium : 4, 5, 6
High : 5, 6, 7
Very High : 6, 7, 8, 9 10

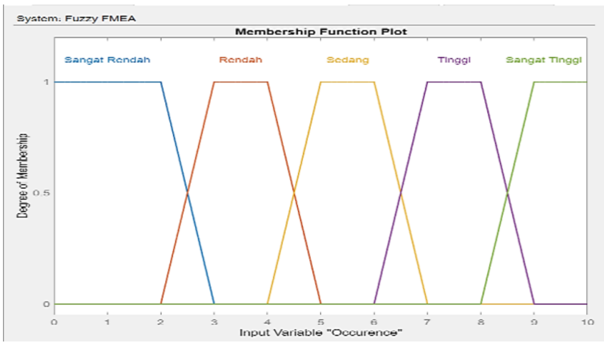

Figure 3. Fuzzy occurrence variable input

Based on the image in Figure 3, the fuzzy values for each category can be obtained as follows:

Very Low : 1, 2, 3
Low : 3, 4, 5, 6
Medium : 4, 5, 6, 7
High : 5, 6, 7, 8
Very High : 8, 9 10

From the results of the above equations, the degree of membership of each indicator wasis obtained as follows:

Table 8. Membership degree values from fuzzification results

μ (*S*)	μ (*O*)	μ (*D*)
0,50	1	1,00
1,00	1	0,50
0,25	1	1,00
1,00	1	1,00
0,75	1	0,25
1,00	1	1,00
0,25	1	0,50

Inferring fuzzy-logic relationships from Mamdani inferences involved using fuzzy rules consisting of IF and THEN statements. These rules depend on predefined variables and values that were subsequently used to constrain the required rules. Defuzzification is the process of converting the fuzzified input, represented as a fuzzy set derived from the aggregation of fuzzy IF-THEN rules, into numerical values inside a fuzzy set. This study employed the Centroid or Center of Gravity (COG) approach. The solution was obtained by considering the center point of the fuzzy area, which was represented by the middle value of the fuzzy set. Figure 4 illustrates the membership function of the FRPN output. The FRPN findings were derived from the data presented in Figure 4, and a ranking was conducted from the highest to the lowest FRPN value (Table 9).

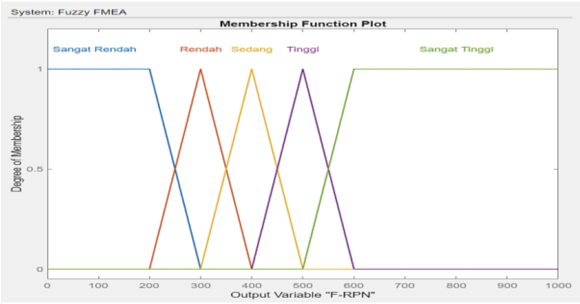

Figure 4. Fuzzy RPN variable outputs

Based on the image in Figure 4, the fuzzy values for each category can be obtained as follows:
Very Low : 100, 200, 300
Low : 200, 300, 400
Medium : 300, 400, 500
High : 400, 500, 600
Very High : 500, 600, 700, 800, 900, 1000

Based on the above data, the FRPN results were obtained, and ranking was carried out from the highest to the lowest value on the FRPN (Table 9).

Table 9. Defuzzification results

No Indicator	FRPN	Ranking
1	500	2
2	400	11
3	500	2
4	500	2
5	400	11
6	500	2
7	777	1

After completing the FRPN calculation in Fuzzy FMEA, the next step was to proceed to the AHP calculation to determine the relative weight results useful for making decisions about corrective actions. Table 10 presents the outcomes of the weighting for each S, O, and D value. Following the data processing and surveys utilizing the Expert Choice program for AHP, the weights and priority variables essential for optimizing the maintenance system were acquired. This design reduces the likelihood of damage to the air knockers (Figure 5). Through the application of the AHP method, structured results were found in the form of weight comparisons that revealed the level of importance of factors in risk mitigation, namely equipment failure, with a weight of 0.526; human failure, with a weight of 0.280; and method failure, with a weight of 0.194.

Table 10. S, O, D weighting results

Ws	Wo	Wd
0,413	0,260	0,327
0,351	0,316	0,333
0,350	0,223	0,427
0,375	0,250	0,375
0,359	0,190	0,452
0,378	0,348	0,274
0,449	0,257	0,294

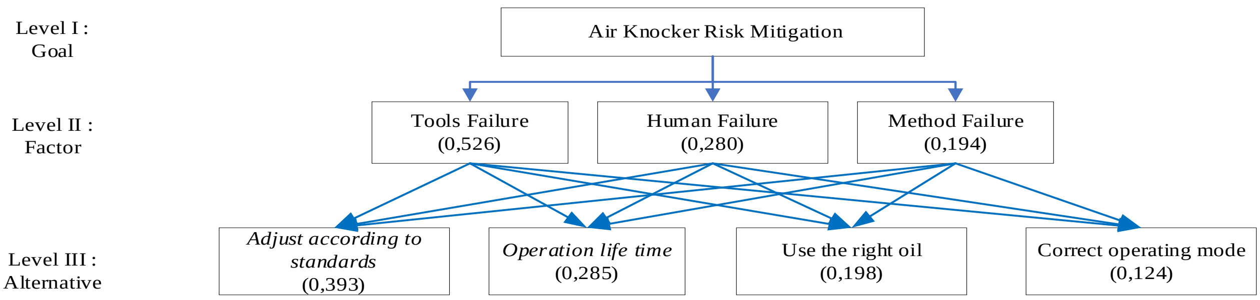

Figure 5. Weighting results on the AHP hierarchy structure

The Integration of Fuzzy FMEA and AHP

This integration of Fuzzy FMEA and AHP produces a Fuzzy Risk Weighted Priority Number (FRWPN) value, namely, the value of the weighting results of severity, occurrence and detection, multiplied by the FRPN value that has been obtained in the previous Fuzzy FMEA processing. The FRWPN formula is presented in Equation 2.

$$FRWPN = W_S \times W_o \times W_d \times FRPN \quad (2)$$

The FRWPN value was also utilized to clarify the priority ranking, highlighting the most significant indicators to prioritize. Table 11 displays the computation results from the FRWPN.

Table 11. FRWPN calculation results

No indicator	FRPN	Ws	Wo	Wd	FRWPN	Ranking
1	500	0,413	0,260	0,327	17,5566	6
3	500	0,351	0,316	0,333	18,4675	2
4	500	0,333	0,313	0,354	18,4485	3
2	777	0,375	0,250	0,375	27,3164	1
6	500	0,316	0,313	0,372	18,3969	4
5	500	0,378	0,348	0,274	18,0215	5
7	500	0,449	0,257	0,294	16,9628	7

Conclusions

Risk identification in maintenance management was accomplished through interviews and direct observations to discover the root cause of potential risks in the air knocker equipment. Seven risk elements were collected and categorized according to the type of failure in the process: equipment failure, human failure, and method failure. Risk management, utilizing the AHP method, yielded structured results in the form of weight comparisons that indicated the significance of factors in risk mitigation: equipment failure with a weight of 0.526, human failure with a weight of 0.280, and method failure with a weight of 0.194. The primary focus of the risk indicators to be addressed was indicator number 2, which pertains to the failure in the oil-water production process; indicator number 3, which involves the operator utilizing the H mode during unit operation; and indicator number 4, which indicates that the hour meter has surpassed the maintenance schedule.

Future research may explore the application of diverse fuzzy scales to describe the degree of uncertainty or ambiguity in risk assessment within Fuzzy FMEA. This approach can provide more detailed and accurate information regarding the potential risk levels. Furthermore, research may investigate the incorporation of alternative optimization methodologies in addition to AHP, including the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Elimination and Choice Expressing the Reality (ELECTRE), or PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluation). This approach provides the opportunity to compare and combine these methods to obtain more comprehensive results.

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References

[1] Y. M. Wang, K. S. Chin, G. K. K. Poon, and J. B. Yang, "Risk evaluation in failure mode and effects analysis using fuzzy weighted geometric mean," *Expert Systems of Applications*, vol. 36, no. 2 PART 1, pp. 1195–1207, Mar. 2009, doi: 10.1016/j.eswa.2007.11.028.

[2] R. Fattahi, R. Tavakkoli-Moghaddam, M. Khalilzadeh, N. Shahsavari-Pour, and R. Soltani, "A novel FMEA model based on fuzzy multiple-criteria decision-making methods for risk assessment," *Journal of Enterprise Information Management*, vol. 33, no. 5, pp. 881–904, 2020, doi: 10.1108/JEIM-09-2019-0282.

[3] E. Roghanian and F. Mojibian, "Using fuzzy FMEA and fuzzy logic in project risk management," *Iran. J. Manag. Stud.*, vol. 8, no. 3, pp. 373–395, 2015, [Online]. Available: http://ijms.ut.ac.ir/

[4] M. Ilangkumaran, P. Shanmugam, G. Sakthivel, and K. Visagavel, "Failure mode and effect analysis using fuzzy analytic hierarchy process," *International Journal of Productivity and Quality Management*, vol. 14, no. 3, pp. 296–313, 2014, doi: 10.1504/IJPQM.2014.064807.

[5] T. L. Saaty, "How to make a decision: The analytic hierarchy process," *European Journal of Operational Research*, vol. 48, no. 1, pp. 9–26, 1990, doi: 10.1016/0377-2217(90)90057-I.
[6] B. Altubaishe and S. Desai, "Multicriteria decision making in supply chain management using FMEA and hybrid AHP-Promethee Algorithms," *Sensors*, vol. 23, no. 8, p. 4041, 2023, doi: 10.3390/s23084041.
[7] A. Febransyah and J. B. Utarja, "A Fuzzy-based decision making approach for product concept selection," *Jurnal Teknik Industri*, vol. 6, no. 1, pp. 25–36, 2005, doi: 10.9744/jti.6.1.25-36.
[8] J. Chang, S. Jang, R. Lalonde, and S. M. Huq, "Fuzzy analytic hierarchy process-based risk priority number for risk assessments of commissioning process of a ring gantry LINAC," *Journal of Applied Clinical Medical Physics*, vol. 23, no. 11, 2022, doi: 10.1002/acm2.13760.
[9] R. Sukwadi, C.-C. Yang, and , Benny, "Integrasi fuzzy AHP-TOPSIS dalam evaluasi kualitas layanan elektronik rumah sakit," *Jurnal Teknik Industri*, vol. 16, no. 1, pp. 25–34, 2014, doi: 10.9744/jti.16.1.25-34.
[10] Ş. ÖZTÜRK and Ç. SOFYALIOĞLU, "Application of grey relational analysis with fuzzy AHP to FMEA method," *Doğuş Üniversitesi Derg.*, vol. 1, no. 13, pp. 114–130, 2012, doi: 10.31671/dogus.2018.119.
[11] A. R. Anugerah, S. A. Ahmad, R. Samin, Z. Samdin, and N. Kamaruddin, "Modified failure mode and effect analysis to mitigate sustainable related risk in the palm oil supply chain," *Advances in Materials and Processing Technology*, vol. 8, no. 2, pp. 2229–2243, 2022, doi: 10.1080/2374068X.2021.1898180.
[12] J. Barraza, "Modeling of fuzzy systems based on the competitive neural network," *Applied Sciences*, vol. 13, no. 24, p. 13091, 2023, doi: 10.3390/app132413091.
[13] B. Erbay and C. Özkan, "Fuzzy FMEA application combined with fuzzy cognitive maps to manage the risks of a software project," *European Journal of Engineering and Formal Sciences*, vol. 2, no. 2, pp. 6–21, 2019, doi: 10.2478/ejef-2018-0007.
[14] A. Yeganeh, M. Younesi Heravi, S. B. Razavian, K. Behzadian, and H. Shariatmadar, "Applying a new systematic fuzzy FMEA technique for risk management in light steel frame systems," *Jou7rnal of Asian Architecture and Building Engineering*, vol. 21, no. 6, pp. 2481–2502, 2022, doi: 10.1080/13467581.2021.1971994.
[15] D. E. Basuki, W. N. Cahyo, D. Handayani, R. A. Apriani, and R. N. Mukarim, "Combined waste assessment model and fuzzy-FMEA in lean six sigma for generating waste reduction strategy: A proposed model," *Jurnal Teknik Industri*, vol. 25, no. 2, pp. 153–168, 2023, doi: 10.9744/jti.25.2.153-168.
[16] L. Purba, I. R. S. Salami, and B. Rahardyan, "Pemilihan metode identifikasi bahaya dan analisis resiko serta penerapannya menggunakan ahp (Analytical Hierarchy Process) di industri manufaktur," *Jurnal Teknik Lingkungan*, vol. 23, no. 1, pp. 22–31, Apr. 2017, doi: 10.5614/j.tl.2017.23.1.3.
[17] P. Zandi, M. Rahmani, M. Khanian, and A. Mosavi, "Agricultural risk management using fuzzy TOPSIS analytical hierarchy process (AHP) and failure mode and effects analysis (FMEA)," *Agriculture*, vol. 10, no. 11, pp. 1–28, 2020, doi: 10.3390/agriculture10110504.
[18] A. Tutuhatunewa, N. E. Maitimu, and L. M. Hukunala, "Integration of SCOR model and AHP to measure the shipyard supply chain performance: A case study," *Jurnal Teknik Industri*, vol. 25, no. 2, pp. 169–178, 2023, doi: 10.9744/jti.25.2.169-178.
[19] S. Ilyasu *et al.*, "Application of hybrid failure mode effect analysis based on fuzzy AHP and fuzzy Topsis in quality risk assessment of fixed-dose artemether-lumefantrine tablets," PREPRINT(Version1) *medRxiv*, Available: https://doi.org/10.1101/2024.01.26.24301832
[20] M. Sagnak, Y. Kazancoglu, Y. D. Ozkan Ozen, and J. A. Garza-Reyes, "Decision-making for risk evaluation: integration of prospect theory with failure modes and effects analysis (FMEA)," *International Journal of Quality and Reliability Management*, vol. 37, no. 6–7, pp. 939–956, 2020, doi: 10.1108/IJQRM-01-2020-0013.
[21] N. Rahmatin, I. Santoso, C. Indriani, S. Rahayu, and S. Widyaningtyas, "Integration of the fuzzy failure mode and effect analysis (fuzzy FMEA) and the Analytical Network Process (ANP) in marketing risk analysis and mitigation," *International Journal of Technology*, vol. 9, no. 4, pp. 809–818, 2018, doi: 10.14716/ijtech.v9i4.2197.
[22] B. Karatop, B. Taşkan, E. Adar, and C. Kubat, "Decision analysis related to the renewable energy investments in Turkey based on a fuzzy AHP-EDAS-Fuzzy FMEA approach," *Computers and Industrial Engineering*, vol. 151, 2021, doi: 10.1016/j.cie.2020.106958.
[23] G. Jin, Q. Meng, and W. Feng, "Optimization of logistics system with fuzzy FMEA-AHP methodology," *Processes*, vol. 10, no. 10, 2022, doi: 10.3390/pr10101973.
[24] M. Bhuvanesh Kumar and R. Parameshwaran, "A comprehensive model to prioritise lean tools for manufacturing industries: A fuzzy FMEA, AHP and QFD-based approach," *International Journal of Services and Operations Management*, vol. 37, no. 2, pp. 170–196, 2020, doi: 10.1504/IJSOM.2020.110337.
[25] R. Septifani, I. Santoso, and B. N. Rodhiyah, "Risk mitigation strategy of rice seed supply chains using fuzzy-FMEA and fuzzy-AHP (Case study: PT. XYZ)," *IOP Conference Series Earth Environmental Science*, vol. 230, no. 1, 2019, doi: 10.1088/1755-1315/230/1/012059.

[26] H. Nguyen, “Fuzzy methods in risk estimation of the ship system failures based on the expert judgments,” *J. Konbin*, vol. 43, no. 1, pp. 393–403, 2017, doi: 10.1515/jok-2017-0058.

[27] R. Septifani, I. Santoso, and Z. Pahlevi, “Analisis risiko produksi frestea menggunakan fuzzy failure mode and effect analysis (Fuzzy FMEA) dan fuzzy analytical hierarchy process (Fuzzy AHP) (Studi kasus di PT. Coca-Cola bottling Indonesia Bandung plant),” *Proc. Natl.*, vol. 2, pp. 13–21, 2018.

[28] M. Abdelgawad and A. R. Fayek, “Risk management in the construction industry using combined fuzzy FMEA and Fuzzy AHP,” *Journal of Construction Engineering and Management*, vol. 136, no. 9, pp. 1028–1036, 2010, doi: 10.1061/(asce)co.1943-7862.0000210.

[29] B. Vahdani, M. Salimi, and M. Charkhchian, “A new FMEA method by integrating fuzzy belief structure and TOPSIS to improve risk evaluation process,” *The International Journal of Advanced Manufacturing Technology*, vol. 77, no. 1–4, pp. 357–368, 2015, doi: 10.1007/s00170-014-6466-3.

[30] J. Zhang and Y. Wang, “How to improve the corporate sustainable development?— The importance of the intellectual capital and the role of the investor confidence,” *Sustainability*, vol. 14, no. 7, 2022, doi: 10.3390/su14073749.

[31] W. R. De Magalhães and F. R. Lima, “A model based on FMEA and fuzzy TOPSIS for risk prioritization in industrial processes1,” *Gest. e Prod.*, vol. 28, no. 4, 2021, doi: 10.1590/1806-9649-2020v28e5535.

[32] S. Boral, I. Howard, S. K. Chaturvedi, K. McKee, and V. N. A. Naikan, “An integrated approach for fuzzy failure modes and effects analysis using fuzzy AHP and fuzzy MAIRCA,” *Engineering Failure Analysis*, vol. 108, 2020, doi: 10.1016/j.engfailanal.2019.104195.

[33] N. Chanamool and T. Naenna, “Fuzzy FMEA application to improve decision-making process in an emergency department,” *Applied Soft Computing Journal*, vol. 43, pp. 441–453, 2016, doi: 10.1016/j.asoc. 2016.01.007.

[34] S. Butdee and P. Phuangsalee, “Uncertain risk assessment modelling for bus body manufacturing supply chain using AHP and fuzzy AHP,” *Procedia Manufacturing*, vol. 30, pp. 663–670, 2019, doi: 10.1016/ j.promfg.2019.02.094.

[35] G. Khazaeni, M. Khanzadi, and A. Afshar, “Fuzzy adaptive decision making model for selection balanced risk allocation,” *International Journal of Project Management*, vol. 30, no. 4, pp. 511–522, 2012, doi: 10.1016/j.ijproman.2011.10.003.

[36] A. Calabrese, R. Costa, N. Levialdi, and T. Menichini, “Integrating sustainability into strategic decision-making: A fuzzy AHP method for the selection of relevant sustainability issues,” *Technological Forecasting and Social Change*, vol. 139, pp. 155–168, 2019, doi: 10.1016/j.techfore.2018.11.005.

[37] A. Ghadge, X. Fang, S. Dani, and J. Antony, “Supply chain risk assessment approach for process quality risks,” *International Journal of Quality and Reliability Management*, vol. 34, no. 7, pp. 940–954, 2017, doi: 10.1108/IJQRM-01-2015-0010.

[38] J. Bonato, M. Badurina, and J. Dobrinić, “Parameters assessment of the FMEA method by means of fuzzy logic,” *Journal of Maritime and Transportation Science*, vol. 2, no. Special edition 2, pp. 123–132, 2018, doi: 10.18048/2018-00.123.

[39] M. Karabas *et al.*, “A risk assessment model for supply chains,” *Pressacademia*, vol. 7, no. 1, pp. 122–125, 2018, doi: 10.17261/pressacademia.2018.866.

[40] T. Ramya, A. Kannan, R. S. Balasenthil, and B. A. Bagirathi, “Fuzzy logic modeling for decision making processes using MATLAB,” *Advanced Materials Research*, vol. 984–985, pp. 425–430, 2014, doi: 10.4028/www.scientific.net/amr.984-985.425.

[41] D. K. Grover, “Simulations of various applications of fuzzy logic using the MATLAB,” *International Journal of Computer Applications*, vol. 141, no. 13, pp. 39–45, 2016, doi: 10.5120/ijca2016909746.

[42] A. D. Aghdam, N. J. Dabanloo, F. N. Rahatabad, and K. Maghooli, “Interval type 2 adaptive neuro-fuzzy inference system–based artificial pacemaker design and stability analysis,” *Journal of Long. Term. Effects of Medical Implants*, vol. 34, no. 1, pp. 9–19, Jan. 2024, doi: 10.1615/JLongTermEffMedImplants. 2023044398.

[43] G. Castellano, C. Castiello, V. Pasquadibisceglie, and G. Zaza, “FISDeT: Fuzzy inference system development tool,” *International Journal of Computational Intelligence Systems*, vol. 10, no. 1, p. 13, 2017, doi: 10.2991/ijcis.2017.10.1.2.

[44] C. Hamrouni, A. Alutaybi, and S. Chaoui, “Various antenna structures performance analysis based fuzzy logic functions,” *International Journal of Advanced Computer Science and Applications*, vol. 13, no. 1, 2022, doi: 10.14569/ijacsa.2022.0130109.

[45] E. D. Santis, A. Rizzi, A. Sadeghiany, and F. M. F. Mascioli, “Genetic optimization of a fuzzy control system for energy flow management in micro-grids,” 2013, doi: 10.1109/ifsa-nafips.2013.6608437.

[46] B. A. de Resende, F. G. Dedini, J. J. Eckert, T. F. A. C. Sigahi, J. de S. Pinto, and R. Anholon, “Proposal of a facilitating methodology for fuzzy FMEA implementation with application in process risk analysis in the

aeronautical sector," *International Journal of Quality and Reliability Management*, vol. 41, no. 4, pp. 1063–1088, 2024, doi: 10.1108/IJQRM-07-2023-0237.

[47] A. J. Cuadros, N. A. Cruces-Arévalo, and C. Ortiz, "Quantitative risk analysis for construction projects considering risks correlations and fuzzy logic," *Revista UIS Ingeniarias*, vol. 23, no. 1, Apr. 2024, doi: 10.18273/revuin.v23n1-2024011.

[48] S. Daneshvar, M. Yazdi, and K. A. Adesina, "Fuzzy smart failure modes and effects analysis to improve safety performance of system: Case study of an aircraft landing system," *Quality and Reliability Engineering International*, vol. 36, no. 3, pp. 890–909, 2020, doi: 10.1002/qre.2607.

[49] T. C. Chang and K. S. Chen, "Statistical test of two taguchi six-sigma quality indices to select the supplier with optimal processing quality," *Journal of Testing and Evaluation*, vol. 50, no. 1, 2022, doi: 10.1520/JTE20210016.

[50] H. Li, Y. Guo, F. Li, Y. Cao, L. Wang, and Y. Ma, "Assessment of operation safety risk for south-to-north water diversion project: A fuzzy VIKOR-FMEA approach," *Water Science Technology Water Supply*, vol. 22, no. 4, pp. 3685–3701, 2022, doi: 10.2166/ws.2022.009.