Analysing Failure Modes for Maintenance Strategies Development at South Tripoli Gas Turbine Power Plant

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***Abstract*— The reliable operation of power plants is essential for the continuity of modern societies. The South Tripoli Power Plant in Libya plays a crucial role within the national power grid. However, it faces significant challenges, including frequent operational failures, aging infrastructure, and ineffective maintenance practices, all of which compromise its reliability and escalate operational costs. This research is motivated by the urgent need to improve maintenance strategies in accordance with documented failure patterns, thereby establishing a comprehensive framework for effective maintenance planning. To address these challenges, a maintenance optimization framework has been developed that integrates Failure Modes, Effects, and Criticality Analysis (FMECA) with Fuzzy Logic techniques to enhance decision making processes regarding maintenance. Furthermore, a fuzzy FMECA framework has been designed to categorize maintenance strategies, thereby facilitating data driven maintenance planning. The contributions of this research are aimed at improving plant reliability, reducing the incidence of unplanned outages, and ensuring the sustainable performance of energy infrastructure.**

Keywords—Failure Modes, FMECA, Fuzzy Logic, Maintenance Strategy, Gas Turbine, Power Plant

I. INTRODUCTION

Reliable operation of power plants is essential for sustaining modern societies, as electricity is a fundamental driver of industrial production, communication, healthcare, and economic development. In Libya, the South Tripoli Power Plant serves as a critical component of the national power network; however, it faces numerous challenges such as frequent failures, aging infrastructure, and inefficient maintenance practices. These issues not only compromise the plant's reliability but also lead to increased operational costs [1]. Therefore, it becomes imperative to address these challenges through innovative maintenance strategies.

This research is motivated by the necessity to determine the most effective maintenance regime for the identified failure modes while also establishing a structured, empirical, and transparent process for maintenance planning at the South Tripoli Power Plant. With the ultimate goal of enhancing the plant's reliability and operational efficiency, the proposed framework will serve as a critical tool for maintenance managers in streamlining maintenance strategies and ensuring sustained performance.

The evolution of maintenance strategies within power plants has garnered significant attention in recent years. Traditionally, maintenance practices have revolved around two main approaches: corrective maintenance and preventive maintenance. Corrective maintenance, characterized by reactive repairs after failures occur, often leads to extensive downtimes and greater costs [2]. Conversely, preventive maintenance relies on scheduled interventions to mitigate the risk of unexpected breakdowns [3]. Despite its benefits, traditional preventive maintenance can result in unnecessary maintenance tasks if not optimized effectively [4].

In recent decades, condition-based maintenance (CBM) and predictive maintenance (PdM) methods have gained prominence. CBM involves monitoring the actual condition of equipment through sensors and real-time data analytics, transitioning maintenance actions only when specific parameters indicate deterioration [5]. This proactive approach allows for the timely detection of issues before they escalate into failures. Similarly, PdM predicts the remaining useful life of equipment components through analytical models and machine learning techniques, further enhancing the decision-making process in maintenance management [6].

Failure Modes, Effects, and Criticality Analysis (FMECA) has been widely adopted for systematically identifying and evaluating potential failure modes and their impacts on system performance [7]. By prioritizing maintenance actions based on risk assessments, FMECA enables maintenance managers to focus on critical areas requiring immediate attention [8].

However, traditional FMECA approaches often struggle with the inherent uncertainty and subjectivity associated with expert judgments and failure data [9]. This limitation has prompted the integration of Fuzzy Logic in maintenance strategy formulation. Utilizing fuzzy set theory allows for more nuanced assessments of uncertainties in variables such as occurrence, severity, and detection. The use of fuzzy inference systems (FIS) provides a robust framework to handle these uncertainties, improving the accuracy and reliability of risk assessments [10]. Recent studies have demonstrated that incorporating fuzzy logic into maintenance analytics leads to better prioritization of maintenance actions, ultimately enhancing the operational reliability of complex industrial systems [11].

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The literature underscores the evolving landscape of maintenance strategies in power plants, highlighting the need for robust methodologies that integrate advanced analytical tools like FMECA and fuzzy logic [12]. By exploring these concepts, this research aims to develop a comprehensive maintenance optimization framework that addresses the challenges faced by the South Tripoli Power Plant and contributes to the broader discourse on effective maintenance management in energy infrastructure.

To improve power-plant operational efficiency, this study develops a maintenance-optimization framework that combines Failure Modes, Effects, and Criticality Analysis (FMECA) with fuzzy logic. The hybrid approach is designed to support maintenance decisions under uncertainty—a common condition in complex industrial systems. The work centers on a thorough assessment of current maintenance practices at the South Tripoli Power Plant, using operational data and expert judgments to identify and rank likely failure modes.

Discusses the evolution of maintenance strategies from corrective to preventive and condition-based maintenance. Explains the traditional FMECA approach, its limitations, and the need for fuzzy logic integration for better risk assessment.

II. METHODOLOGY

The methodology adopted in this research integrates Failure Mode, Effects, and Criticality Analysis (FMECA) with Fuzzy Theory to optimize maintenance strategies at the South Tripoli Power Plant. This approach addresses the challenges associated with traditional maintenance practices and aims to enhance decision-making processes under uncertainty.

A. *Phases of the Methodology*

This initial phase involves a thorough evaluation of the existing maintenance regime at the South Tripoli Power Plant. A systematic review of historical maintenance records and performance data specific to the turbine systems is performed. Additionally, qualitative insights are gathered through structured interviews with key stakeholders, including maintenance personnel and management staff.

Following the diagnostic assessment, FMECA is applied to identify and categorize potential failure modes within the power plant's systems, as seen in Fig. 1 [13]. A detailed questionnaire is developed to assess the occurrence, severity, and detection of each identified failure mode through expert evaluations. The data collected are analyzed to calculate the Risk Priority Number (RPN) and Criticality Number (CN) for each failure mode, enabling prioritization based on risk assessment [14].

The integration of fuzzy logic, illustrated in Fig. 2, enhances the traditional FMECA by addressing uncertainties in the assessment process. Four scenarios are outlined to compute fuzzy RPN using different membership functions triangular, trapezoidal, and Gaussian. Each model's performance is compared statistically to determine the most accurate representation of expert evaluations. This step aims to capture the imprecision inherent in expert judgments when assessing failure parameters.

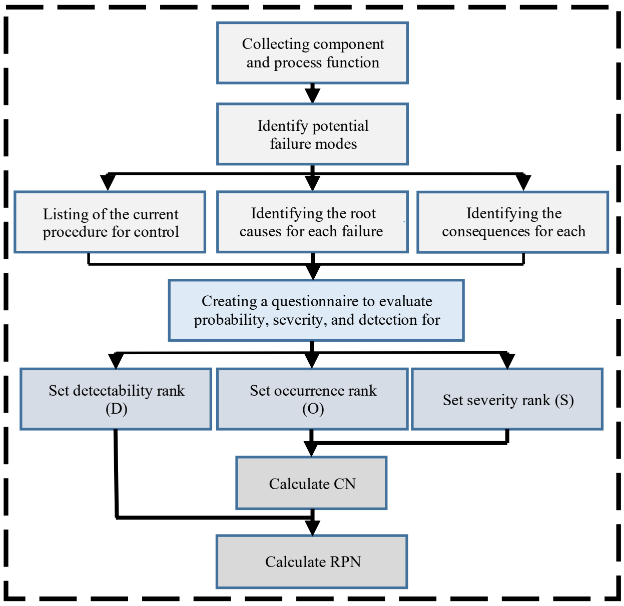

Fig. 1: The flowchart for the FMECA process

In the final phase, tailored maintenance strategies are assigned based on the calculated RPN and CN values. A structured set of fuzzy IF-THEN rules is established to facilitate the selection of appropriate maintenance actions corrective, preventive, or condition-based based on the criticality of each failure mode. The Mamdani fuzzy inference system is employed to analyse the interactions between the RPN and CN inputs, providing systematic recommendations for maintenance actions [15].

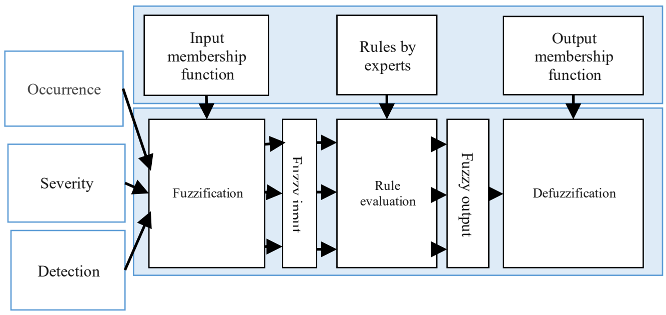

Fig. 2: The several phases of the Fuzzy Inference System (FIS)

B. *Data Collection*

Data collection for this study involves both primary and secondary sources. Original data is collected through interviews and surveys conducted among maintenance personnel and plant management. Structured interviews elicit insights into current maintenance practices and challenges, while surveys quantify these perspectives using FMECA-scale questions. The secondary Data was historical data, including maintenance management system records, work order histories, failure reports, and equipment manuals, are reviewed to gather comprehensive insights into the operational context and past performance of the turbine systems, as shown in Fig 3.

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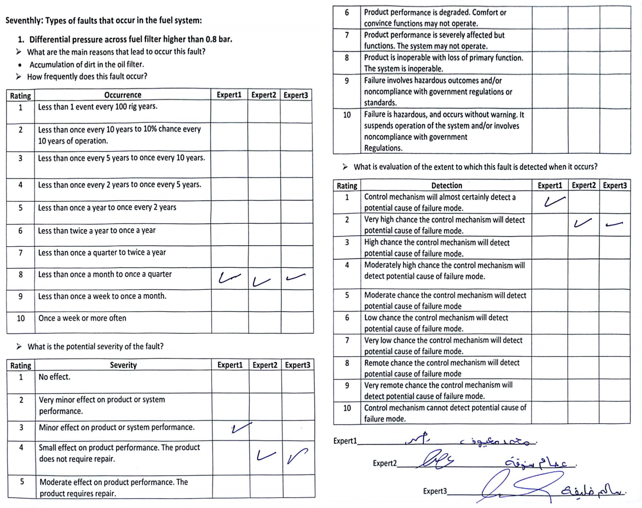

Seventhly: Types of faults that occur in the fuel system:

1. **Differential pressure across fuel filter higher than 0.8 bar.**

➢ What are the main reasons that lead to occur this fault?

• Accumulation of dirt in the oil filter.

➢ How frequently does this fault occur?

Rating	Occurrence	Expert1	Expert2	Expert3
1	Less than 1 event every 100 rig years.			
2	Less than once every 10 years to 10% chance every 10 years of operation.			
3	Less than once every 5 years to once every 10 years.			
4	Less than once every 2 years to once every 5 years.			
5	Less than once a year to once every 2 years			
6	Less than twice a year to once a year			
7	Less than once a quarter to twice a year			
8	Less than once a month to once a quarter	✓	✓	✓
9	Less than once a week to once a month.			
10	Once a week or more often			

➢ What is the potential severity of the fault?

Rating	Severity	Expert1	Expert2	Expert3
1	No effect.			
2	Very minor effect on product or system performance.			
3	Minor effect on product or system performance.	✓		
4	Small effect on product performance. The product does not require repair.		✓	✓
5	Moderate effect on product performance. The product requires repair.			
6	Product performance is degraded. Comfort or convince functions may not operate.			
7	Product performance is severely affected but functions. The system may not operate.			
8	Product is inoperable with loss of primary function. The system is inoperable.			
9	Failure involves hazardous outcomes and/or noncompliance with government regulations or standards.			
10	Failure is hazardous, and occurs without warning. It suspends operation of the system and/or involves noncompliance with government Regulations.			

➢ What is evaluation of the extent to which this fault is detected when it occurs?

Rating	Detection	Expert1	Expert2	Expert3
1	Control mechanism will almost certainly detect a potential cause of failure mode.	✓		
2	Very high chance the control mechanism will detect potential cause of failure mode.		✓	✓
3	High chance the control mechanism will detect potential cause of failure mode.			
4	Moderately high chance the control mechanism will detect potential cause of failure mode.			
5	Moderate chance the control mechanism will detect potential cause of failure mode			
6	Low chance the control mechanism will detect potential cause of failure mode.			
7	Very low chance the control mechanism will detect potential cause of failure mode.			
8	Remote chance the control mechanism will detect potential cause of failure mode			
9	Very remote chance the control mechanism will detect potential cause of failure mode.			
10	Control mechanism cannot detect potential cause of failure mode.			

Expert1__________

Expert2__________

Expert3__________

Fig. 3: Interviews Original data

C. *Statistical and Fuzzy Analysis*

To analyse the fuzzy RPN values resulting from the various membership function models, statistical measures such as standard deviation and coefficient of variation are employed [16]. This comparative analysis aims to identify the model that best represents the expert evaluations, ensuring a robust basis for decision-making in the maintenance strategy selection.

Expert opinion aggregation is achieved through a consensus-based method, where evaluations from multiple experts are integrated to minimize bias [17]. The output from the fuzzy logic analysis informs the final Risk Priority Number and Criticality Number, which guide the assignment of optimal maintenance strategies.

The methodology embraces a systematic and empirical approach, establishing a reliable framework for evaluating and prioritizing failure modes in the South Tripoli Power Plant. By integrating FMECA with fuzzy logic.

III. RESULTS

This study presents the results of implementing the proposed maintenance-optimization framework. Findings show that the integrated FMECA–fuzzy logic approach improves maintenance decision-making and more effectively prioritizes corrective and preventive actions based on the identified failure modes.

A. *Traditional FMECA Findings*

Initial assessments revealed a range of 41 different failure modes associated with critical components of the power plant. Each failure mode was evaluated based on three parameters: occurrence (O), severity (S), and detection (D) as seen in Fig. 4. Expert evaluations yielded corresponding Risk Priority Numbers (RPN) and Criticality Numbers (CN), providing a quantifiable basis for prioritizing maintenance actions.

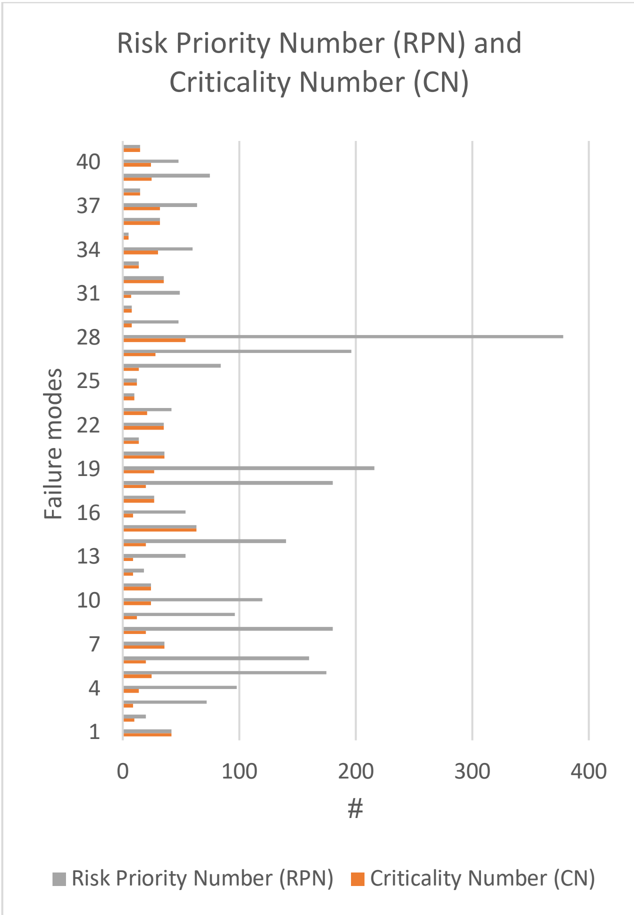

Fig. 4: The Risk Priority Number (RPN) Vs Criticality Number (CN)

The findings indicated several high-priority failure modes, particularly those associated with critical systems such as the compressor and turbine. For instance, failure modes reflecting high occurrences and severity, such as compressor blade vibrations and high exhaust temperatures, were identified as key areas requiring immediate maintenance intervention.

These results provide a clear representation of the most pressing issues facing the plant, underscoring the importance of transitioning from a reactive to a proactive maintenance strategy.

B. *Fuzzy FMECA Model Performance*

The application of fuzzy logic models triangular, trapezoidal, and Gaussian shown in Fig.5, allowed for a more nuanced understanding of the uncertainties associated with expert assessments. Statistical comparisons showed that the Gaussian membership function outperformed the others in terms of data dispersion, evidenced by a lower standard deviation and coefficient of variation as shown in Fig. 6

Through fuzzy aggregation of expert opinions, the research demonstrated a refined calculation of RPN and CN using a Gaussian fuzzy model implemented in MATLAB Simulink seen in Fig. 7. The consensus approach reduced individual biases inherent in expert evaluations and provided

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a more accurate depiction of the risks associated with various failure modes

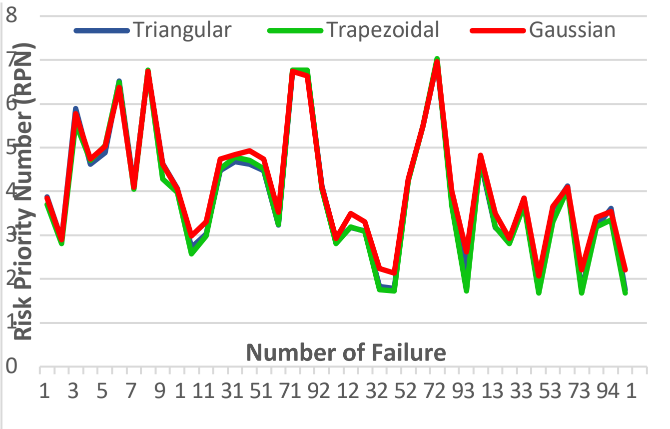

Fig. 5: The three Fuzzy Logic Models triangular, trapezoidal, and Gaussian

The rule base, illustrated in Fig. 8, serves as an expert system that processes the numerical inputs of the Risk Priority Number (RPN) and the Criticality Number (CN) to generate informed and systematic maintenance decisions. This approach ensures a more robust and justified maintenance strategy selection

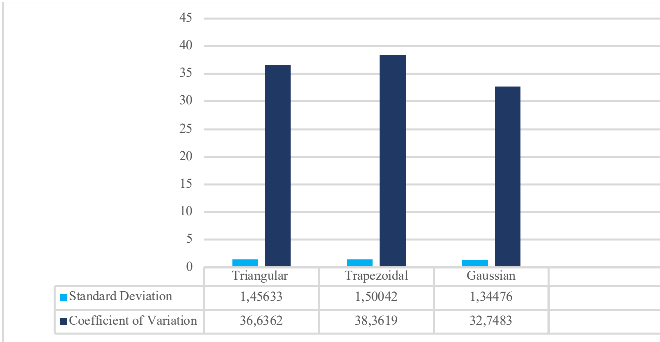

Fig. 6: The statistic parameters of the three Fuzzy Logic Models

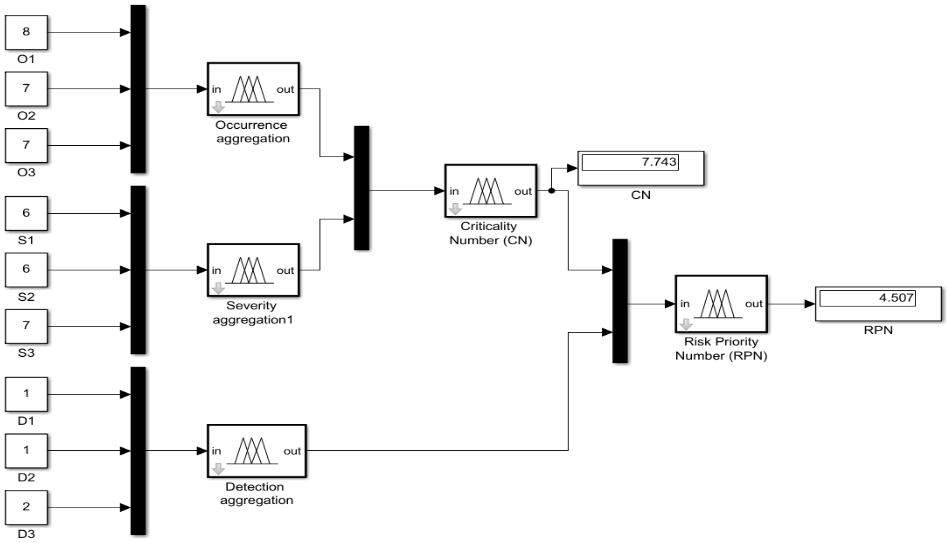

Fig. 7: MATLAB simulation for gathering expert opinions and calculating CN and RPN

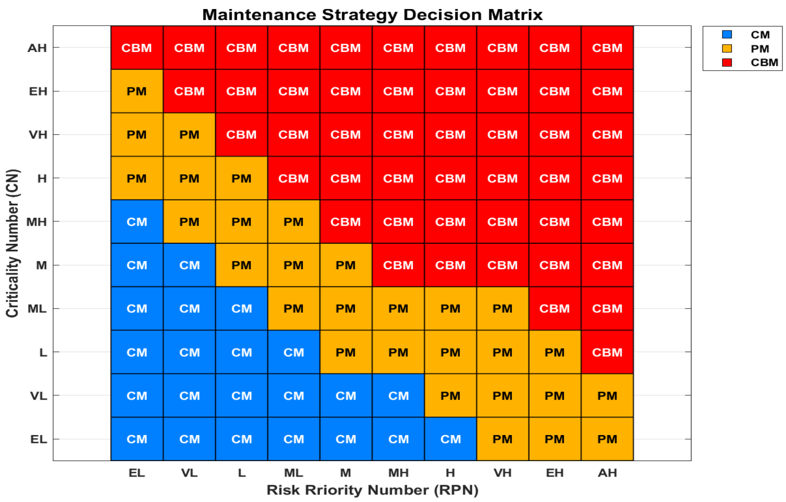

Fig. 8: Rules for selecting maintenance strategies

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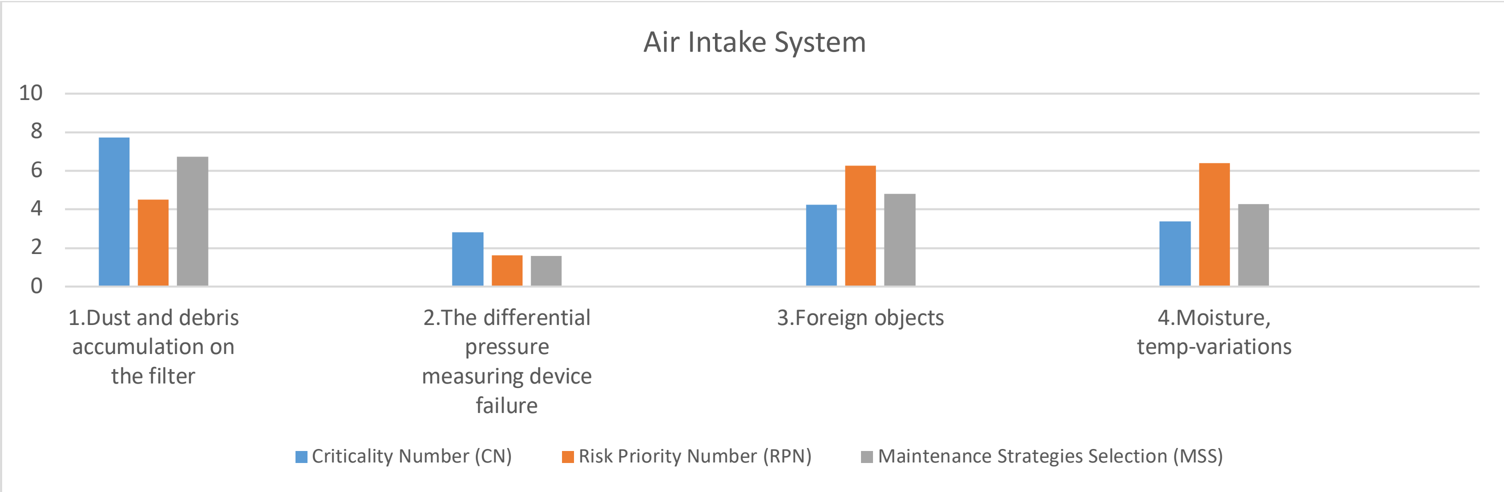

Fig. 9: Cn, RPN & MSS for air intake system failure

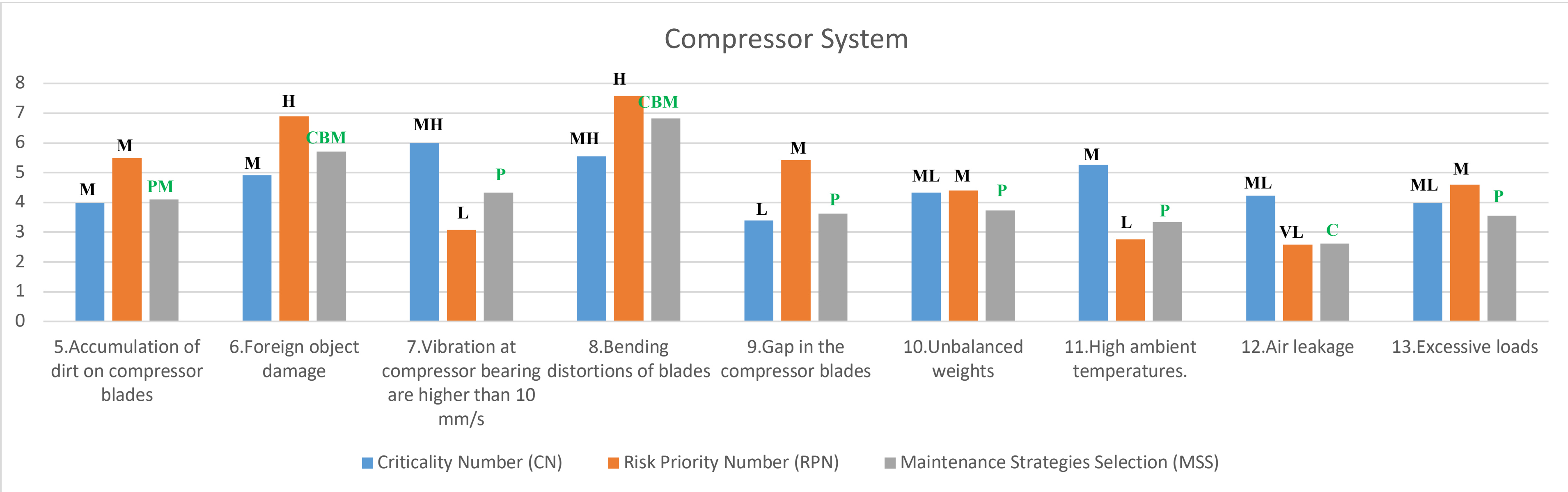

Fig. 10: Cn, RPN & MSS for compressor system failure

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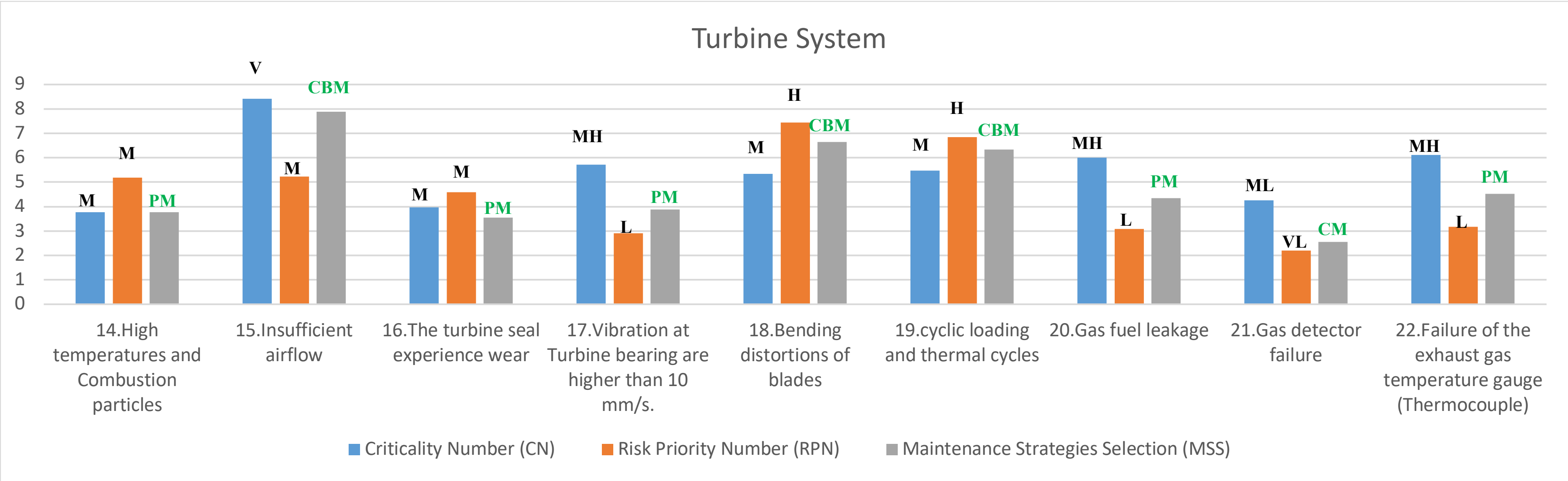

Fig. 11: Cn, RPN & MSS for turbine system failure

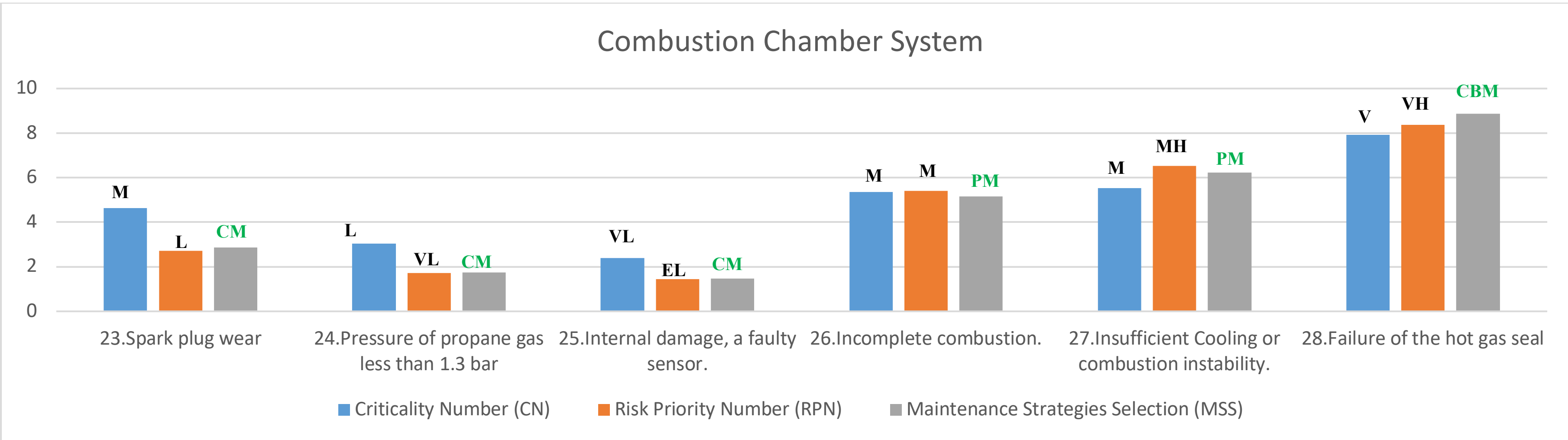

Fig. 12: Cn, RPN & MSS for combustion chamber system failure

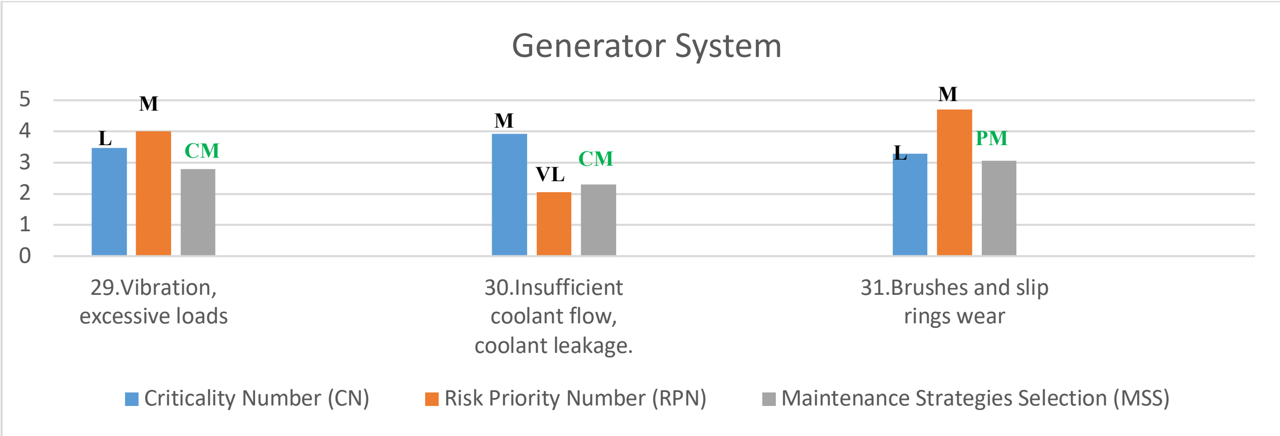

Fig. 13: Cn, RPN & MSS for generator system failure

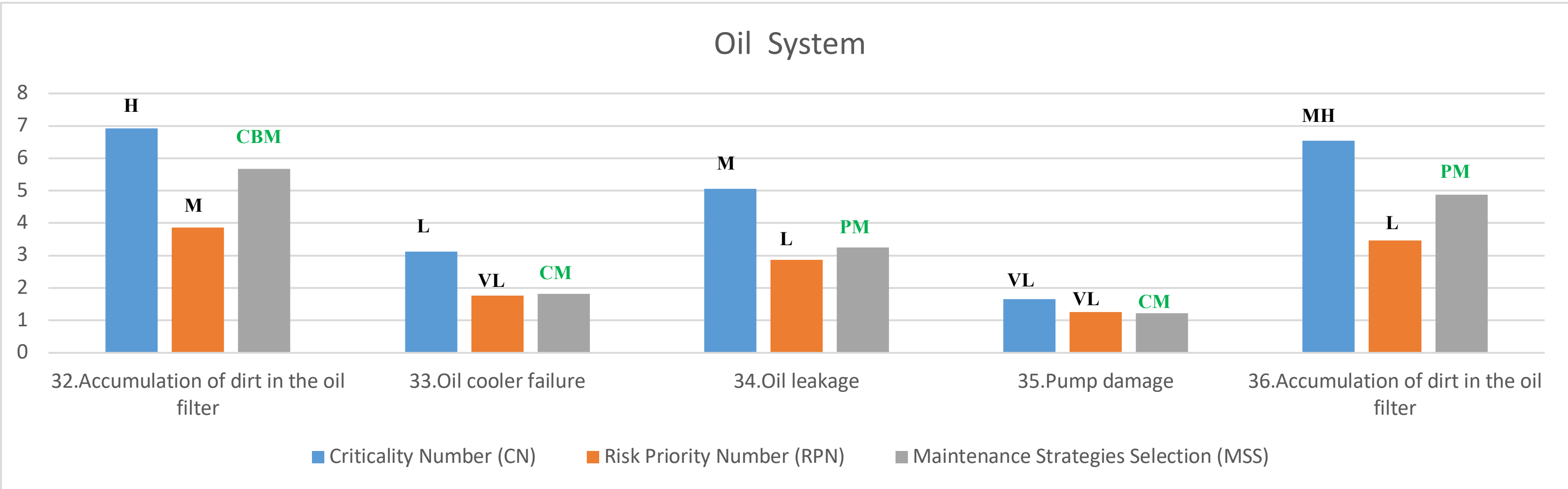

Fig. 14: Cn, RPN & MSS for oil system failure

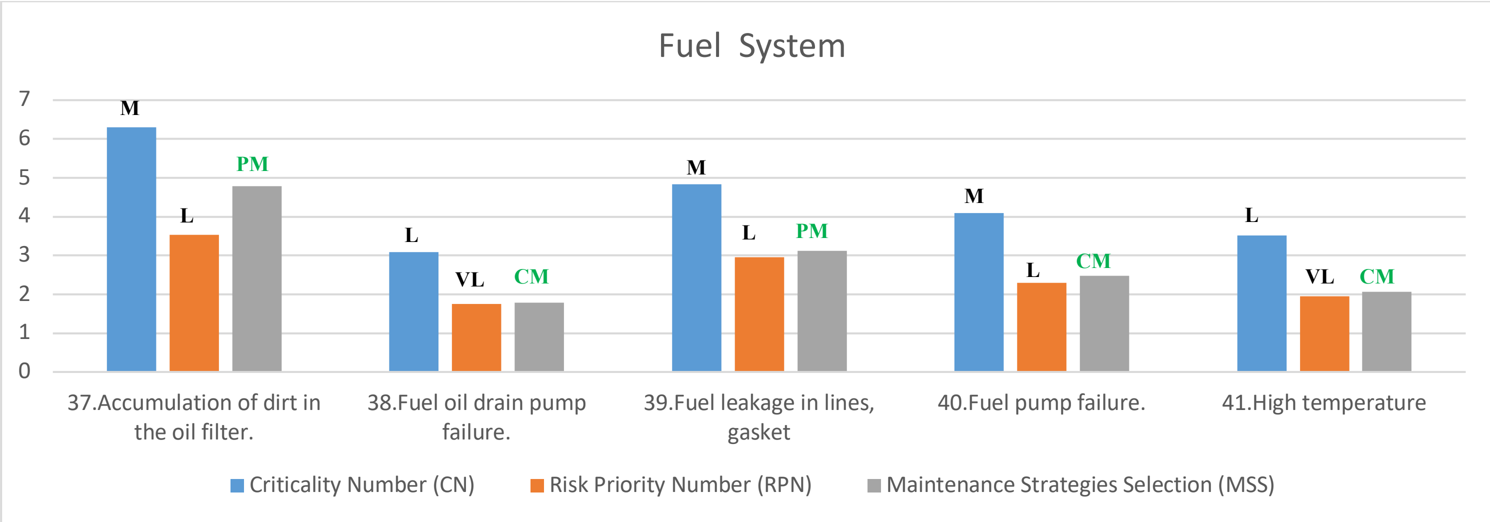

Fig. 15: Cn, RPN & MSS for fuel system failure

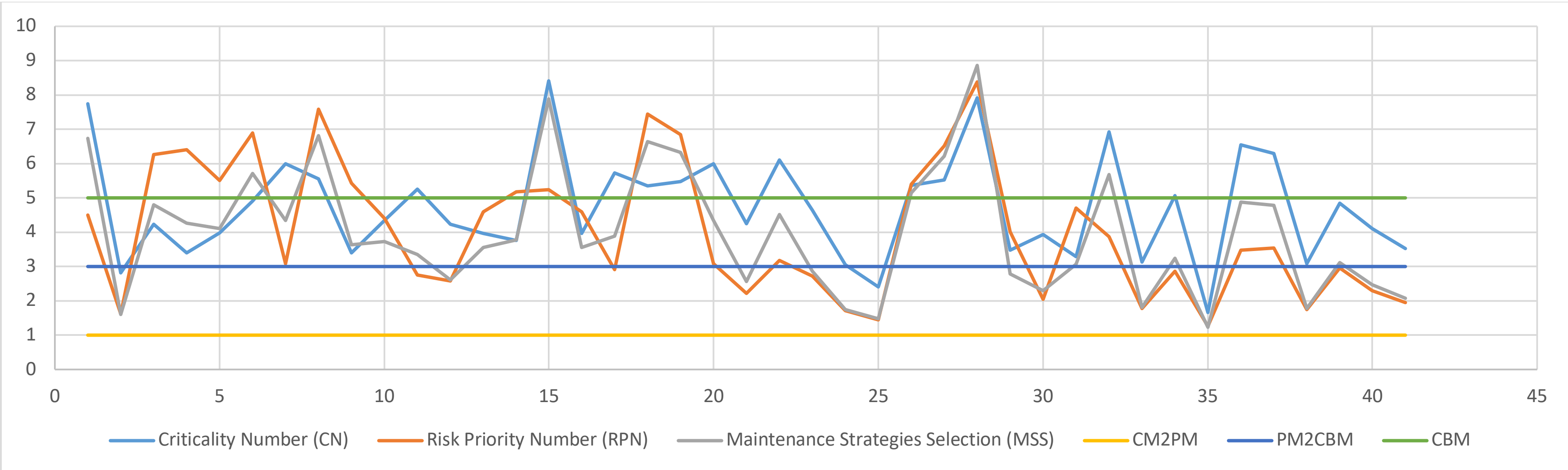

Fig. 16: Cn, RPN & MSS for 41 failure modes

IV. DISCUSSION

A. *Effectiveness of Integrated Approach*

The results indicate that integrating fuzzy logic with traditional FMECA methodologies significantly enhances maintenance planning and decision-making. By accommodating uncertainties in expert evaluations, the fuzzy FMECA model provides a more flexible framework for analyzing risks and prioritizing maintenance actions. The high RPN values assigned to certain failure modes such as compressor vibration and high exhaust temperatures reinforce the critical need for immediate attention to these areas. This confirms existing literature that advocates for prioritizing maintenance efforts based on a systematic assessment of risk factors.

B. *Implications for Maintenance Management*

The findings emphasize the necessity of transitioning to condition-based and predictive maintenance strategies within the South Tripoli Power Plant. By focusing on failure modes that exhibit high severity and occurrence rates, the proposed framework aids maintenance managers in effectively allocating resources and implementing timely interventions, as seen in Fig.s 9-16. Moreover, this research contributes to the existing body of knowledge by demonstrating the practical application of fuzzy logic in maintenance decision-making, particularly in complex industrial environments. It underscores the importance of utilizing advanced analytical tools to enhance operational reliability, reduce unplanned outages, and optimize maintenance costs. The results confirm that the proposed framework not only identifies critical failure modes effectively but also facilitates a structured and data-driven approach to maintenance management. By integrating FMECA with fuzzy logic, the South Tripoli Power Plant can leverage its findings to enhance decision-making processes, ultimately leading to improved reliability and efficiency in operations. Moving forward, the incorporation of real-time monitoring systems and ongoing engagement with expert stakeholders will be crucial for the successful implementation of these findings into the plant's maintenance strategies.

CONCLUSION

This research presents a comprehensive analysis of maintenance strategies at the South Tripoli Power Plant, highlighting the integration of Failure Mode, Effects, and Criticality Analysis (FMECA) with fuzzy logic as an innovative approach to enhance maintenance decision-making. The findings demonstrate that traditional maintenance practices often reactive and reliant on fixed schedules fail to adequately address the complexities and uncertainties of modern power plant operations. By employing a data-driven methodology that includes expert evaluations, this research identifies critical failure modes and consequently prioritizes maintenance actions based on risk assessment. Key results reveal 41 failure modes across various plant systems, with specific modes such as compressor vibrations and high exhaust temperatures emerging as high-priority issues warranting immediate intervention. The application of fuzzy models improved the representation of uncertainties associated with expert assessments, facilitating a more nuanced risk analysis. Statistical evaluations confirmed the superiority of the Gaussian fuzzy model in providing consistent and reliable Risk Priority Numbers (RPN) and Criticality Numbers (CN). Moreover, this study underscores the importance of transitioning from traditional maintenance strategies to condition-based and predictive maintenance approaches. By focusing on the critical issues identified, maintenance managers can optimize resource allocation, minimize operational downtimes, and ultimately enhance the reliability and efficiency of power generation. The implications of this research extend beyond the South Tripoli Power Plant, offering valuable insights for power plants facing similar challenges globally. The integration of advanced analytical tools, such as fuzzy logic, into maintenance management practices is essential for achieving operational excellence in complex industrial systems. In conclusion, the proposed framework not only contributes to the theoretical understanding of maintenance optimization but also provides practical solutions for real-world applications. Future research should aim to incorporate real-time data monitoring and expand the methodology to other power plants, further validating and refining the approach. This advancement is crucial for addressing the pressing challenges of reliability and efficiency in energy infrastructure, ultimately supporting the sustainable development of Libya’s power sector.

REFERENCES

[1] B. de Jonge and P. A. Scarf, “A review on maintenance optimization,” *Eur. J. Oper. Res.*, vol. 285, no. 3, pp. 805–824, 2020, doi: 10.1016/j.ejor.2019.09.047.

[2] D. Bumblauskas, D. Gemmill, A. Igou, and J. Anzengruber, *Smart Maintenance Decision Support Systems (SMDSS) based on corporate big data analytics*, vol. 90. Elsevier Ltd, 2017. doi: 10.1016/j.eswa.2017.08.025.

[3] B. S. Dhillon, *Engineering Maintenance*. CRC Press, 2002. doi: 10.1201/9781420031843.

[4] Z. Ma, Y. Ren, X. Xiang, and Z. Turk, “Data-driven decision-making for equipment maintenance,” *Autom. Constr.*, vol. 112, no. January, p. 103103, 2020, doi: 10.1016/j.autcon.2020.103103.

[5] A. Al-Refaie and B. A. Hamdieh, “A Data Mining Framework for Maintenance Prediction of Faulty Products Under Warranty,” *J. Adv. Manuf. Syst.*, vol. 23, no. 1, pp. 35–59, 2024, doi: 10.1142/S0219686724500021.

[6] R. M. . Ratnayake and T. Markeset, “Technical integrity management measuring HSE awareness using AHP in selecting a maintenance strategy,” 2010.

[7] S. Narayanagounder and K. Gurusami, “A new approach for prioritization of failure modes in design FMEA using ANOVA,” *World Acad. Sci.*

Eng. Technol., vol. 37, pp. 524–531, 2009.

[8] A. Al-Refaie and A. Al-Hawadi, "Optimal fuzzy repairs' scheduling and sequencing of failure types over multiple periods," *J. Ambient Intell. Humaniz. Comput.*, vol. 13, no. 1, pp. 201–217, 2022, doi: 10.1007/s12652-021-02896-5.

[9] N. Xiao, H. Z. Huang, Y. Li, L. He, and T. Jin, "Multiple failure modes analysis and weighted risk priority number evaluation in FMEA," *Eng. Fail. Anal.*, vol. 18, no. 4, pp. 1162–1170, 2011, doi: 10.1016/j.engfailanal.2011.02.004.

[10] S. Kamaruddin and I. A. Azid, "Maintenance policy selection: a review towards building proper selection model 'Maintenance policy selection: a review towards building proper selection model,'" 2012.

[11] H. C. Liu, L. Liu, and N. Liu, "Risk evaluation approaches in failure mode and effects analysis: A literature review," Feb. 01, 2013. doi: 10.1016/j.eswa.2012.08.010.

[12] N. Farajiparvar, "Maintenance policy selection using fuzzy FMEA and key performance indicators," pp. 1–161, 2016.

[13] M. Niraj and P. Kumar, "FMECA Analysis (A Heuristic Approach) For Frequency of Maintenance and Type of Maintenance," *Int. J. Sci. Eng. Res.*, vol. 3, no. 1, pp. 1–5, 2012.

[14] Olufemi Oluseun Sanyaolu, Ayodele Samuel Onawumi, Abiola Olufemi Ajayeoba, and Nathaniel Abidemi Akinrinade, "Failure Mode and Effect Analysis (FMEA) of a Taurus 60 Gas Turbine Power Plant System (GTPPS), in Mowe, Nigeria," *World J. Adv. Eng. Technol. Sci.*, vol. 8, no. 2, pp. 175–182, 2023, doi: 10.30574/wjaets.2023.8.2.0082.

[15] T. J. . Ross, *Fuzzy logic with engineering applications*. John Wiley, 2010.

[16] E. A.- CASTRO, *Principles of Statistical Analysis*. Cambridge University Press, 2021.

[17] H. Ghasemian, Q. Zeeshan, and D. A. Firouzi, "Failure Mode and Effect Analysis of Gas Turbine Power Plant Systems (GTPPSs)," no. January, 2017.