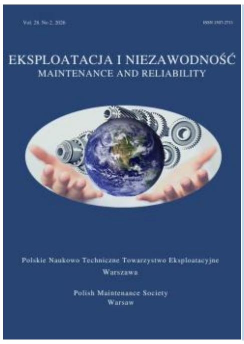

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Risk and Reliability Analysis of Critical Boiler Components

Indexed by: Web of Science Group

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Highlights

- Critical components are identified using the FMEA.
- The high RPN components reflect the action priority.
- Monte Carlo simulation is used to estimate MTTF.
- The MCS predicts the probability of failure.
- MCS optimizes the time of maintenance.

Abstract

Industrial boilers are crucial for steam generation in various production processes. This study aims to improve the reliability of boiler components by combining Failure Modes and Effects Analysis (FMEA) with Monte Carlo Simulations (MCS). A novel approach integrates predictive maintenance using real-time operational data, alongside Multi-Criteria Decision-Making (MCDM) techniques such as AHP for prioritizing maintenance tasks. The results show that critical components, such as boiler tubes and superheaters, exhibit high Risk Priority Numbers (RPN), indicating urgent need for targeted preventive maintenance. The proposed framework optimizes maintenance scheduling, reduces unplanned downtimes, and enhances overall system reliability and safety.

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Keywords
boilers, FMEA, Monte Carlo Simulation, risk priority number, predictive maintenance, Multi-Criteria Decision Making.

1. Introduction

The GNL1K complex, located east of Skikda, Algeria, plays a strategic role in the natural gas liquefaction process. Among its key facilities, Unit 50 is responsible for supplying other industrial facilities with the steam needed to start up. This unit comprises three identical boilers, essential for ensuring a continuous supply of steam and other components. These boilers, which are essential to the steam production system, burn fuel to heat water and generate high-pressure steam.

Boilers are a key component in ensuring the optimal operation of plants, requiring consistent and high performance [1]. While this study relies on well-established methodologies such as FMEA and Monte Carlo Simulation (MCS), it introduces a novel integration of Multi-Criteria Decision-Making (MCDM) techniques, particularly AHP. This integration enhances the predictive accuracy of maintenance strategies by considering additional factors such as cost, safety, and environmental impact, beyond the traditional RPN, thus offering a more comprehensive decision-making framework. Given their pivotal role, boiler reliability and efficiency are of paramount importance. However, these units often experience outages due to malfunctions in their core components, resulting in prolonged downtime and significant productivity losses [2]. Hatala et al. [3] confirm that industrial boilers are susceptible to major failures, which directly impact their performance and

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availability. Furthermore, Stamenkovic et al. point out that: [4] Prolonged outages often result from burst pipes under high pressure.

The continuous operating cycles of boilers, designed to meet production requirements, accelerate the wear of their components. Under extreme thermal and pressure conditions, components such as superheaters and pipes endure significant mechanical and thermal stress [5]. Stamenkovic et al. [4] highlight the negative effects of thermal and pressure stress on these vital components, which often result in frequent outages, performance degradation, maintenance shutdowns, unexpected breakdowns, or structural damage.

To minimize downtime and improve system reliability, it is essential to identify the root causes of failures and assess their impacts [2, 6]. Cristea and Constantinescu [5] emphasize the critical role of thorough root cause analysis in designing sustainable solutions. While understanding root causes is foundational, it is not sufficient on its own. A comprehensive reliability analysis is necessary to enhance equipment availability, mitigate operational risks, and extend the life of critical components. Strengthening maintenance strategies for critical components directly enhances overall system reliability [7].

In recent years, several studies have sought to identify critical components, their risks, and their reliability.

Rahmania et al. (2020) applied FMEA to the boiler feed pump turbine of a thermal power plant. Their work proposed targeted maintenance types (predictive or preventive) based on the specific risk profiles of each component, thus demonstrating the practical value of RPN-based prioritization. [8], furthermore, Hatala et al. (2023) conducted a comprehensive FMEA (Failure Modes, Effects, and Criticality Analysis) on a boiler system in an Indonesian power plant. Their study demonstrated that combining risk assessment with reliability indicators such as Mean Time to Failure (MTTF) provided a more practical framework for preventive maintenance [3].

Failure Mode and Effects Analysis (FMEA) is a widely adopted method for identifying, evaluating, and prioritizing potential failure modes based on the severity, occurrence, and detectability of each. Unlike previous studies, which primarily employed FMEA and MCS separately, this study integrates these methodologies with Multi-Criteria Decision-Making (MCDM) techniques, specifically AHP. This hybrid approach allows for a more nuanced prioritization of maintenance tasks by incorporating additional operational factors like cost, downtime, and safety risks, which were previously overlooked in traditional analyses. Yet, traditional FMEA has limitations in managing uncertainties and dynamic operational conditions. To address this, recent research has increasingly favored hybrid approaches that couple FMEA with probabilistic simulations or intelligent methods. For example, Al Kautsar et al. (2022) integrated gray FMEA with root cause analysis (RCA) to study startup failures in coal-fired boilers. Their hybrid method allowed them to quantify and rank failure risks even in the presence of incomplete or uncertain data, thus providing a robust alternative to traditional scoring methods [9].

Furthermore, T. Sun et al. (2025) [10] applied a fuzzy logic-based FMEA to assess the reliability of solar-assisted air source heat pumps, demonstrating the value of intelligent inference systems in managing complex thermal system uncertainties and refining component prioritization.

However, as observed by Hatala et al., most research tends to address these aspects independently, limiting the effectiveness of proposed solutions [3]. In addition to the widely used FMEA and Monte Carlo simulation methods, alternative methodologies such as TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) and COPRAS-G (Complex Proportional Assessment of Alternatives with Grey Relations) have been introduced to improve maintenance planning [11, 12]. These methods provide a more comprehensive framework for selecting the most effective maintenance strategies, considering multiple criteria such as cost, reliability, and performance [13].

Failure Modes and Effects Analysis (FMEA) is a widely recognized systematic method for improving the reliability of industrial systems [14]. By incorporating Criticality Analysis, this study goes beyond traditional FMEA to identify the most critical components whose failure could lead to severe operational consequences, enabling more targeted maintenance strategies [15, 16]. This approach allows the identification of critical failure modes, assessment of their impacts, and proposition of solutions to mitigate their effects [17]. By evaluating each component in terms of the probability of occurrence, failure effects, and criticality, FMEA provides comprehensive documentation of the mechanisms involved [7]. As Muhammad Hudzaly Hatala notes, prioritizing risks, identifying critical failures, and planning preventive interventions are instrumental in reducing unplanned shutdowns [3].

Monte Carlo simulations offer a powerful tool for analyzing the reliability of critical components and predicting potential failures. Pamungkas and Dirhamsyah demonstrated that this method effectively models various failure scenarios by transforming random numbers into non-uniform distributions [18]. The ability of this method to simulate realistic conditions is further validated through real-world data, as confirmed by Hartini et al. [19]. These simulations not only optimize maintenance cycles and mitigate risks but also facilitate strategic decision-making in equipment management [20].

In light of this study, which combines FMEA analysis and Monte Carlo simulations, several recommendations can be made to improve the reliability of boilers and their critical components:

1). Strengthening preventive maintenance :

- ✓ Conduct regular inspections and targeted tests on critical components, such as superheaters, tubes, and water supply systems.
- ✓ Adjust maintenance cycles based on insights gained from Monte Carlo simulation results.

2). Adoption of Advanced Diagnostic Technologies:

- ✓ Integrate smart sensors and real-time analysis tools to detect early signs of failure, such as vibrations and pressure variations, improving diagnostic accuracy and minimizing unplanned shutdowns.
- ✓ Employ smart diagnostic tools, including inspection robots, as described in studies like H. Wang et al. (2019) [21], to:
  - Identify critical areas within boilers.
  - Reduce risks to human personnel.
  - Enhance the speed and accuracy of inspections.

3). Continuous Training of Technicians:

- ✓ Train maintenance teams to recognize early failure signals, such as abnormal vibrations, temperature, or pressure fluctuations.
- ✓ Provide training on using diagnostic technologies effectively.

4). Proactive Management of Critical Components:

- ✓ Prioritize the replacement of components with the highest RPN and lowest MTTF, such as boiler tubes and superheaters.
- ✓ Establish a strategic inventory of spare parts to reduce intervention delays.

By implementing these recommendations, it is possible to enhance boiler reliability, minimize operational costs associated with unplanned shutdowns, and improve the safety and overall performance of industrial facilities.

2. METHODOLOGY

This study aims to revolutionize the conventional reliability assessment and predictive maintenance strategies applied to critical systems, specifically focusing on the boilers at the Unit 50 natural gas liquefaction complex in Skikda, Algeria. The plant, integral to the country's natural gas liquefaction process, employs three boilers that are essential for providing steam to power other production units. These boilers operate under extreme thermal and mechanical stresses, often leading to premature component failure. Addressing this, our study introduces an advanced methodological framework that integrates real-time sensor data, machine learning algorithms, fuzzy logic techniques, and multi-criteria decision-making (MCDM), marking a significant departure from traditional FMEA and Monte Carlo Simulation (MCS) applications. This innovative approach aims to provide a more dynamic, adaptive, and accurate system for failure prediction and maintenance optimization.

2.1. Overview of the Facility and Data Collection Process

The Unit 50 boilers are exposed to high operational loads, making their reliability critical to ensuring uninterrupted production. Given this importance, data collection was done using real-time operational data, gathered from smart sensors strategically deployed across the boilers. These sensors monitor the following key parameters, which are directly related to component degradation and failure risks:

- **Temperatures**: Thermal stress is one of the leading causes of failure in high-temperature systems. Temperature sensors were deployed in critical components such as the economizer, combustion chamber, and superheaters to monitor temperature fluctuations that may lead to material failure or warping.

- **Pressures**: The pressure in key sections such as the steam drums, superheaters, and feedwater lines was measured continuously. Over-pressurization or sudden pressure drops often result in mechanical failures. Monitoring these fluctuations ensures that pressure is maintained within safe operational limits, preventing potential breakdowns.
- **Vibrations**: Vibration sensors placed on the burners, fans, and superheaters detect anomalies such as misalignments, wear, or loose parts. Abnormal vibrations are early indicators of potential mechanical failures and can be used to predict maintenance needs before a complete failure occurs.

These real-time data were integrated into the central monitoring system of the facility, where they were analyzed continuously using machine learning models. The integration of predictive maintenance models that use real-time operational data marks a significant innovation in maintenance practices, making the process more adaptive and efficient.

2.2. Reliability Assessment Using FMEA, MCS, and Advanced Methodologies

The core of this research lies in combining traditional FMEA and MCS with fuzzy logic and machine learning to enhance the reliability prediction accuracy. This novel integration not only addresses the limitations of traditional methodologies but also introduces new dimensions in reliability assessment that account for uncertainty and real-time operational variability.

2.2.1. Enhanced Failure Modes and Effects Analysis (FMEA)

Traditional FMEA relies on expert judgment to assign values for severity (S), occurrence (O), and detection (D). However, this study introduces fuzzy FMEA, which accounts for the inherent uncertainty in these ratings, offering a more flexible and realistic representation of failure risks. In fuzzy FMEA, each of the parameters is represented by fuzzy numbers, which allows for a range of values to better capture the uncertainty in real-world data.

a. Defuzzification Process to Obtain Crisp RPN:

In this study, the values for Severity, Occurrence, and Detection were represented as fuzzy triangular numbers, where each value was represented by a range, including the lower, middle, and upper bounds. These fuzzy values were processed using fuzzy arithmetic operations to obtain a crisp value for each of the parameters (Severity, Occurrence, and Detection).

b. Defuzzification Process:

1. **Fuzzy Values Representation**: The fuzzy values for Severity, Occurrence, and Detection were represented as triangular fuzzy numbers, as shown in the figure below.
2. **Fuzzy Arithmetic**: These fuzzy values were then aggregated using fuzzy arithmetic to produce a single fuzzy value for RPN.
3. **Centroid Method for Defuzzification**: The fuzzy RPN values were defuzzified into crisp values using the centroid method, where the centroid of the fuzzy set was calculated to obtain a crisp RPN value.

This process adds robustness and reliability to the risk assessment by incorporating the uncertainty inherent in operational data.

The Risk Priority Number (RPN) is then calculated using the following fuzzy-weighted formula:

$$\text{RPN} = \sum_{i=1}^{n}(S_i \times O_i \times D_i) \text{ (Fuzzy-Weighted RPN)} \quad (1)$$

By using fuzzy logic, this methodology ensures that the RPN values reflect not only the severity, occurrence, and detection but also the uncertainty associated with each of these factors, which is often ignored in conventional FMEA.

Table 1. Example of Fuzzy FMEA Calculation.

Component	Severity (S)	Occurrence (O)	Detection (D)	RPN (Fuzzy)
Boiler Tube	(9, 10)	(6, 8)	(7, 9)	504
Superheater	(8, 9)	(5, 7)	(6, 8)	336
Fan	(6, 7)	(4, 6)	(5, 7)	210

Table 1 provides an overview of the FMEA analysis for the critical components, highlighting their Risk Priority Numbers (RPN) and the associated failure modes.

This fuzzy approach adds robustness and reliability to the risk assessment process by modeling the inherent uncertainty in component behavior under different operational conditions.

In this study, **fuzzy FMEA** was applied to handle the inherent uncertainty in expert judgment when assigning values to severity, occurrence, and detection. Instead of using discrete values, each of these parameters was represented as a fuzzy number to capture the range of possible values, reflecting the expert's uncertainty.

For each parameter:

1. **Severity (S)**: Defined as a fuzzy number with a triangular membership function. The fuzzy number for severity could range from a minimum value S_{min} to a maximum value S_{max}, with a peak at the most likely severity value. For example, severity might be represented as a fuzzy number $(S\text{peak}_{max_{min}}$.
2. **Occurrence (O)**: Similarly, occurrence was modeled using a triangular fuzzy number $(O\text{peak}_{max_{min}}$, representing the range of likelihoods of failure for each component.
3. **Detection (D)**: Detection was also represented as a fuzzy number with the same triangular shape, defined as $(D\text{peak}_{max_{min}}$.

These fuzzy numbers allowed us to represent the uncertainty in the expert's judgment, with each parameter expressed in terms of a range rather than a single crisp value.

The fuzzy numbers for **Severity**, **Occurrence**, and **Detection** were represented using **triangular membership functions**, which are commonly used in fuzzy logic for their simplicity and efficiency. These triangular membership functions were defined for each parameter as follows:

- **Severity**: The membership function for severity $\mu_S(x)$ was defined as:

$$\mu_s(x) = \begin{cases} \frac{x-S_{min}}{S_{peak}-S_{min}} & for \quad S_{min} \leq x \leq S_{peak} \\ \frac{S_{max}-x}{S_{max}-S_{peak}} & for \quad S_{peak} \leq x \leq S_{max} \\ 0 & otherwise \end{cases} \quad (2)$$

- **Occurrence**: The membership function for occurrence $\mu_O(x)$ was similarly defined, capturing the uncertainty in the frequency of failure:
- **Detection**: The membership function for detection $\mu_D(x)$ was defined similarly to the others.

These triangular membership functions provided a flexible way to handle the uncertainty in assigning crisp values for each parameter, ensuring a more realistic representation of the failure risks.

As shown in Figure 1, the fuzzy values for Severity, Occurrence, and Detection are represented using triangular fuzzy numbers. These fuzzy values are then aggregated using fuzzy arithmetic, and the centroid method is applied to obtain a crisp RPN value.

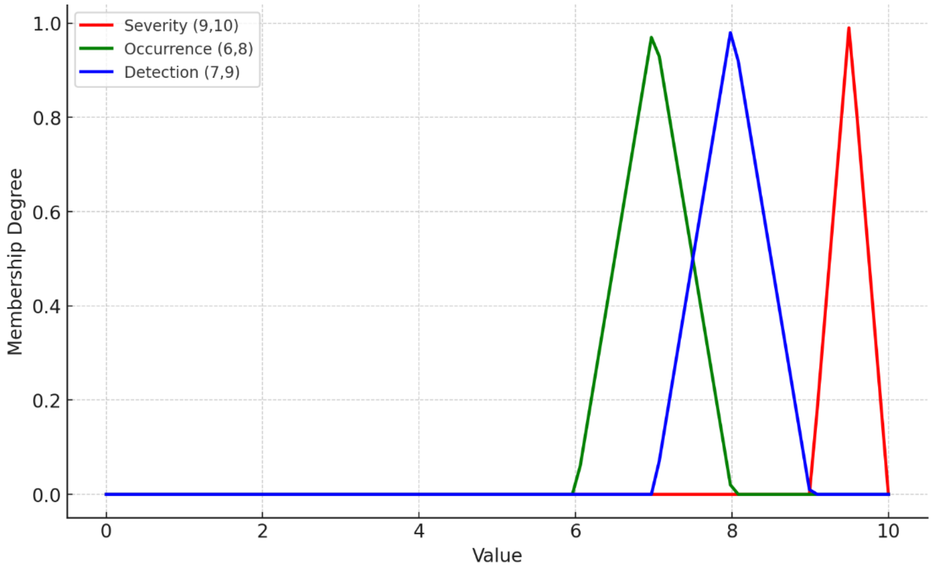

Figure. 1. Fuzzy Membership Functions for Severity, Occurrence, and Detection.

2.2.2. Monte Carlo Simulation (MCS) and Reliability Analysis

While FMEA provides valuable insights into failure modes, it cannot often predict failure times accurately. To address this, Monte Carlo Simulations (MCS) were applied to simulate the probabilistic nature of component failure under varying operational conditions. MCS allows us to account for the uncertainty in operational parameters, such as pressure fluctuations and temperature extremes, and predict failure times over a large number of iterations.

In this study, we employed the Weibull distribution, a widely used model for reliability analysis, to simulate failure times for each component. The Weibull distribution is expressed as:

Where:

- t: Time to failure
- γ : Threshold (minimum time before failure)
- θ: Scale parameter
- β: Shape parameter

By running simulations over 1000 iterations, we were able to generate failure time distributions for each component. The Mean Time to Failure (MTTF) was calculated as the average of these failure times, and the Reliability Function (R(t)) was derived for each component at various time intervals.

Table 2. Reliability Example for Superheater.

Component	MTTF (days)	Reliability (1 year)	Reliability (3 years)	Reliability (5 years)
Superheater	1608	50.98%	28.56%	20.01%
Boiler Tube	306	31.81%	1.35%	0.03%
Fan	2130	45.04%	27.15%	20.21%

Table 2 illustrates the reliability assessment results for the superheater and boiler tubes, including Mean Time to Failure (MTTF) and reliability at different time intervals.

This Monte Carlo Simulation approach, coupled with confidence intervals and uncertainty bounds, allows for a more accurate, robust, and realistic prediction of component lifespans, improving overall system reliability.

2.3. Multi-Criteria Decision-Making (MCDM) Using AHP

To ensure that maintenance tasks are prioritized not only based on RPN and MTTF but also on critical factors such as cost, safety, and environmental impact, Multi-Criteria Decision-Making (MCDM) methods were employed. In particular, Analytic Hierarchy Process (AHP) was used to assign weights to each factor and generate a priority ranking for maintenance tasks. This approach ensures that multiple dimensions of risk and impact are considered when making maintenance decisions.

Pairwise Comparison Matrix:

A pairwise comparison matrix was created, where the relative importance of factors such as cost, safety, and environmental impact was evaluated. The matrix employs a scale of comparison, where 1 indicates equal importance, 3 moderate importance, and 9 extreme importance.

Table 3. Example of Pairwise Comparison for Criteria.

Criteria	Cost	Safety	Environmental Impact
Cost	1	3	5
Safety	1/3	1	3
Environmental Impact	1/5	1/3	1

Table 3 presents the pairwise comparison matrix used for AHP, where the relative importance of criteria like cost, safety, and environmental impact was evaluated.

In the AHP method, once the pairwise comparison matrix is constructed, it is crucial to test the consistency of the weight assignments. This ensures that the judgments made by the decision-makers are reliable and coherent. The consistency of the matrix is assessed by calculating the Consistency Ratio (CR), which helps determine the degree of consistency in the comparisons.

To test consistency, the largest eigenvalue (λ_{max}) of the pairwise comparison matrix is calculated. The consistency index (CI) is then computed using the following formula:

$$CI = \frac{\lambda_{max}}{n-1} \tag{4}$$

where λ_max is the largest eigenvalue and n is the number of criteria. The Random Consistency Index (RI) is a pre-defined value that depends on the number of criteria (n). The Consistency Ratio (CR) is calculated as:

$$CR = \frac{CI}{RI} \tag{5}$$

A CR value less than 0.1 indicates that the pairwise comparisons are sufficiently consistent and that the judgments made are reliable. If the CR value exceeds 0.1, this suggests inconsistency in the comparisons, and the matrix should be revised.

In this study, the consistency of the pairwise comparison matrix was verified, yielding a CR value of 0.08, confirming that the judgments were consistent and reliable for the prioritization of criteria.

Weighted Prioritization:

After calculating the normalized weights for each criterion, the maintenance tasks were prioritized based on these weights. This approach guarantees that decisions are made with full consideration of factors beyond just risk.

Table 4. Example of Weighted Priorities for Maintenance.

Component	Cost (0.5)	Safety (0.3)	Environmental Impact (0.2)	Total Score
Boiler Tube	0.4	0.3	0.2	0.7
Superheater	0.5	0.4	0.3	0.8

Table 4 shows the weighted prioritization of maintenance tasks based on AHP, incorporating criteria such as cost, safety, and environmental impact.

This AHP-based prioritization ensures that maintenance resources are allocated where they are most needed, focusing on the components that pose the highest risk to both operational efficiency and safety.

2.4. Uncertainty Modeling and Sensitivity Analysis

To address the inherent uncertainty in failure predictions, sensitivity analysis was employed to assess how variations in the occurrence, severity, and detection ratings affect the RPN and the overall prioritization of maintenance tasks. This ensures that the model is robust, adaptable, and reflective of changes in operational conditions.

The Monte Carlo simulations provided confidence intervals and uncertainty bounds for each failure prediction, offering a more robust and reliable assessment of the system's vulnerability.

Table 5. Example Sensitivity Analysis for Boiler Tube.

Parameter Change	New RPN	Impact on Maintenance
Increase in Occurrence by 10%	550	Higher priority for maintenance
Decrease in Detection by 15%	600	Immediate action required

2.5. Extension to Other Industrial Systems

Although the study focuses on three boilers at a single facility, the methodology is designed to be easily transferable to other industrial systems with critical equipment such as turbines, compressors, or pumps. The flexibility of this methodology, which integrates real-time data, fuzzy FMEA, machine learning, and Monte Carlo simulations, makes it suitable for a wide variety of industrial applications, including oil and gas, chemical manufacturing, and power plants [1, 22, 23].

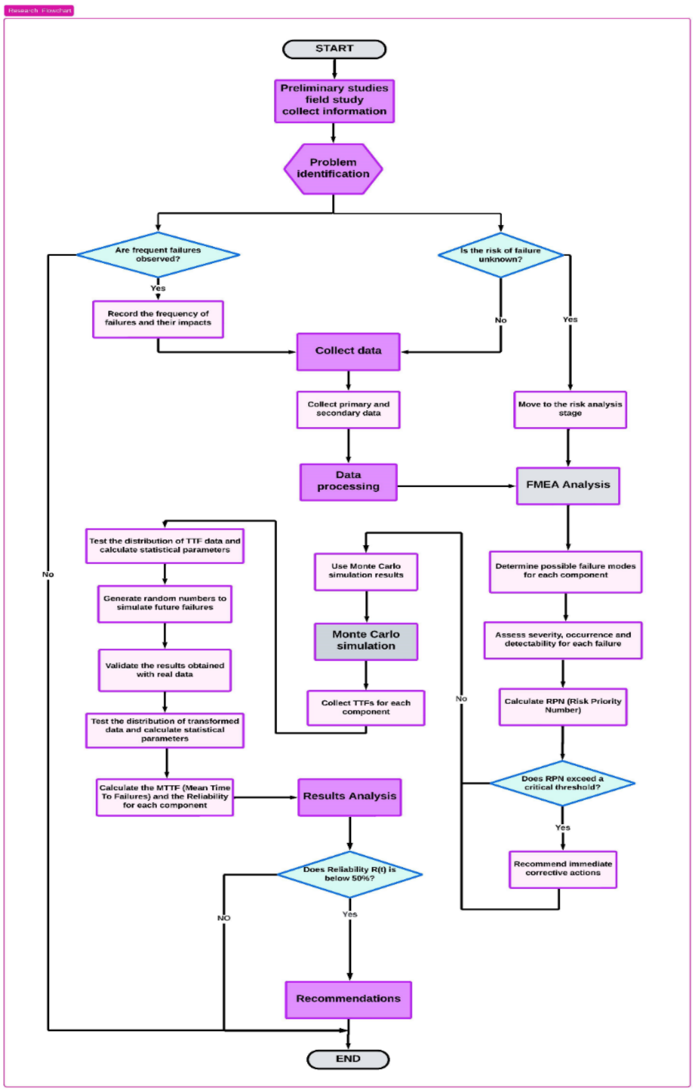

Figure. 2. Research flowchart.

Figure 2 below provides a visual representation of the methodology employed in this study. It outlines the sequence of steps from data collection, through FMEA, Monte Carlo

Simulation, AHP-based decision-making, and uncertainty modeling.

3. CASE STUDY

3.1. Description of the System Studied

The GNLK complex houses three high-pressure boilers in Unit 50, operating in parallel to generate steam at 67 bars and 480 °C. This steam is distributed to various units, including liquefaction units P5 and P6, to support critical operational processes.

An expansion station (VS/VM) reduces the steam pressure to 8 bars and 280 °C, enabling its use in two key processes:

- **Secondary Expansion:** feeding a secondary expansion station (VM/VU) to supply steam at 4 bars and 180 °C for utility operations.
- **Desalination:** Supplying a desalter to distill seawater, producing distilled water for equipment cooling.

The distilled water undergoes further treatment in a demineralizer to ensure high purity before being reinjected into the boiler system, maintaining a consistent and high-quality water supply for steam generation. (See Figure. 2).

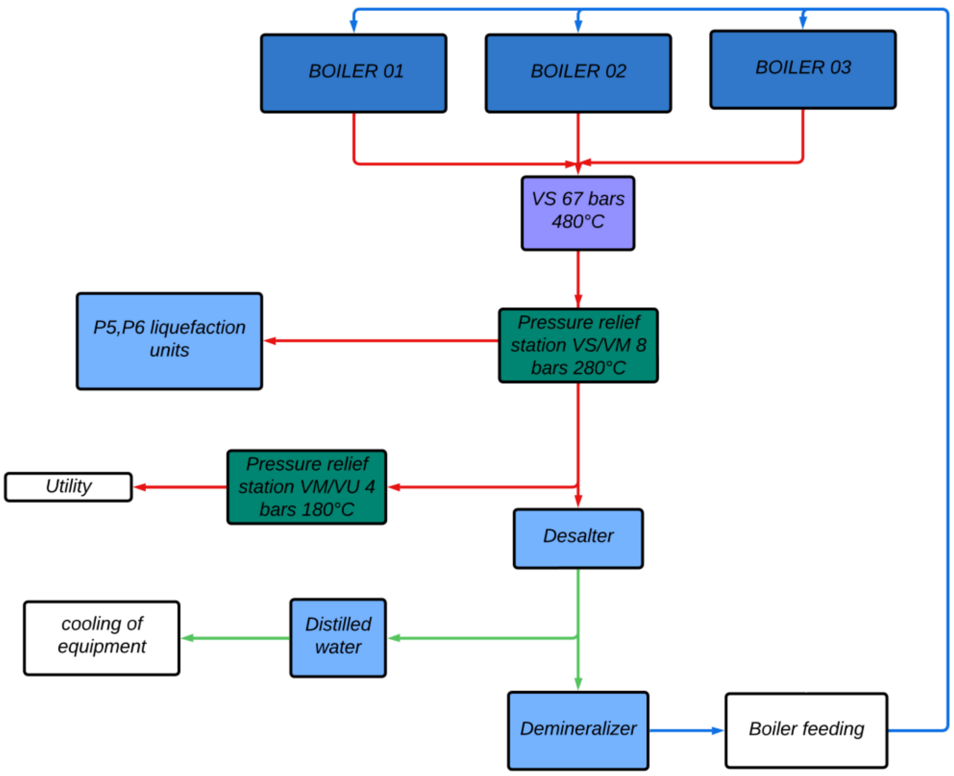

Figure 3. Steam production process.

The flow chart illustrates the operation of the boiler used in Unit 50 (Figure 3). This boiler was selected for the study due to its high frequency of failures compared to other components.

The process begins with water entering the economizer, where it is preheated using the residual heat from the boiler exhaust gases. The preheated water then flows into the lower drum located within the combustion chamber. At this stage, the burner generates the necessary heat to transform the water into steam, with air supplied by the fan to optimize combustion.

The generated steam rises to the upper drum, where water and steam are partially separated in the separation drum. The steam then flows to the superheater, where it is heated further to reach the required temperature for superheated steam. Depending on industrial requirements, the superheated steam may pass through the desuperheater to adjust its temperature. The final output is high-pressure, high-temperature steam (VS) that is ready for use in various industrial processes.

The exhaust flue gases are evacuated through the chimney after their residual heat has been utilized across the boiler's various sections. This cycle optimizes heat recovery and ensures high-efficiency steam production.

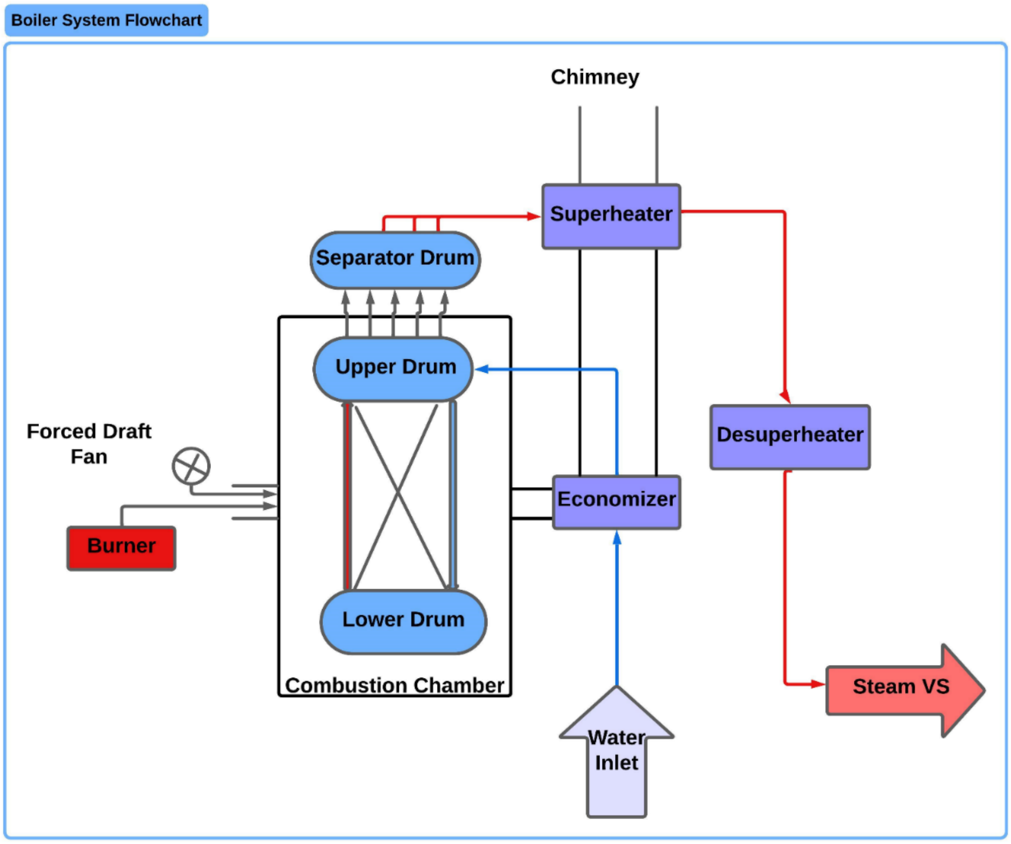

Figure 4. Flow chart of the boiler system in Unit 50, highlighting its main components and operational flow.

3.2. Identification of critical components

The FMEA (failure mode and effects analysis) method is designed to identify, mitigate, and reduce failures in various industrial sectors, including steam boilers. This method evaluates risks using three key criteria:

- **Severity (S):** The potential impact of a failure, rated on a scale from 1 to 10.
- **Occurrence (O):** The probability of the failure occurring, also rated on a scale from 1 to 10.
- **Detection (D):** The ability to detect the failure before it occurs, rated on a scale from 1 to 10.

These factors are combined to calculate a risk priority number (RPN), which helps prioritize components for intervention [3, 5, 17, 24-26].

The Severity (S), Occurrence (O), and Detection (D) scores used in the FMEA analysis were assigned based on actual operational data, notably drawn from maintenance records, incident reports, and field observations. This estimation relies on the in-depth knowledge of the equipment and processes by engineers, technicians, and operators familiar with the analyzed system.

While this approach enables a realistic qualitative assessment, it introduces a degree of subjectivity. Therefore, a sensitivity analysis was conducted to evaluate the influence of uncertainties related to the S, O, and D scores on the RPN results. This analysis was performed using extreme scenarios (pessimistic, realistic, optimistic), thus providing a better assessment of the robustness of the prioritizations proposed by the FMEA.

In this study, ten boiler components frequently subject to failure were analyzed in terms of their failure modes, root causes, and potential effects. The analysis was applied to three boilers, and the results, including the RPN values, are presented in Table 6. These table provide a detailed breakdown of the failure mode and effect analysis (FMEA) for the critical components, enabling targeted maintenance and mitigation strategies.

Table 2. FMEA analysis of critical components in Boilers, highlighting risk priority numbers (RPN).

Components	Failure mode	Causes of Failure	Effects of failures	Boiler 01				Boiler 02				Boiler 03			
				O	D	G	RPN	O	D	G	RPN	O	D	G	RPN
Boiler tubes	Tube leaks or bursts. Significant leaks in purge lines and valves. Steam leaks on drums	Corrosion Thermal fatigue Overpressure	Loss of thermal efficiency Unplanned system shutdowns Prolonged downtime for repair	7	5	8	280	7	5	9	315	7	5	8	280
Superheater	Bursting of components or steam leakage	Wear caused by repeated cycles of high temperature and pressure	Prolonged boiler shutdown Safety risks for personnel	6	5	9	270	5	5	8	200	6	5	9	270
Water supply	Valve leaks Pumping issues	Wear on feed pumps and check valves, poor valve sealing. Wear on seals or valves.	Temporary system shutdown to prevent overheating. Decrease in water supply pressure. Excessive fuel consumption.	5	5	7	175	5	5	7	175	5	5	6	180
Fan	Damper blockage. Excessive vibration or abnormal noise. Coupling deterioration.	Mechanical wear of bearings and dampers. Misalignment of mechanical components. Bearing wear.	Reduced combustion efficiency. Unexpected system shutdown.	5	5	6	150	5	4	7	140	5	5	7	175
Burner	Ignition issues, gas pressure irregularities, and flame detection problems.	Flame sensor malfunction or improper calibration of gas valves.	Risk of inefficient combustion and unexpected boiler shutdown.	5	4	7	140	3	5	6	90	6	4	7	168
Control and security	Failure of safety or control systems.	Defective detectors or sensors, communication errors, and component wear.	Risks of undetected overpressure or underpressure Unexpected system shutdown	4	4	6	96	2	6	7	84	3	7	6	126
Combustion chamber	Cracks or deterioration of the walls	Thermal fatigue and degradation of refractory materials thermal expansion mismatch between refractory materials.	Thermal losses and reduced combustion efficiency Increased fuel consumption	3	6	7	86	3	4	6	72	2	6	7	84
Desuperheater	Leaks on flanges and desuperheater valve	Seal wear or mechanical failure.	Steam overheating, premature wear of components	3	7	6	86	2	5	7	70	2	4	6	48
Economizer	Leakage in tubes and valves	Corrosion caused by poor water quality	Reduced combustion efficiency. Excessive fuel consumption Shutdowns for repairs	2	5	7	70	1	7	6	42	1	6	7	42
Chimney	Torn flue casing	Corrosion Mechanical fatigue Overpressure in the chamber	Poor gas evacuation Decreased efficiency	1	6	7	42	1	6	7	42	1	5	7	35

4. Results and discussion

4.1. Results and Analysis (FMEA)

In this analysis, the boiler system consists of ten components frequently subject to interference or damage. Among these, at least five components record the most critical RPN values and are classified as critical components. The superheater in boiler 02 recorded the highest RPN value of 315. Other critical components based on high RPN values include boiler tubes, water supply systems, burners, and fans. A comparative analysis of the FMEA results for the three boilers is presented in Table 7, focusing on critical components, failure modes, and RPN values. This comparison highlights significant trends, enabling informed conclusions and targeted maintenance strategies.

Table 7. Comparison of RPNs by Component.

Components	RPN Boiler 1	RPN Boiler 2	RPN Boiler 3	RPN Average
Boiler tubes	270	315	270	285
Superheater	280	200	280	253
Water supply	175	175	175	175
Fan	168	140	140	149
Burner	180	90	150	140

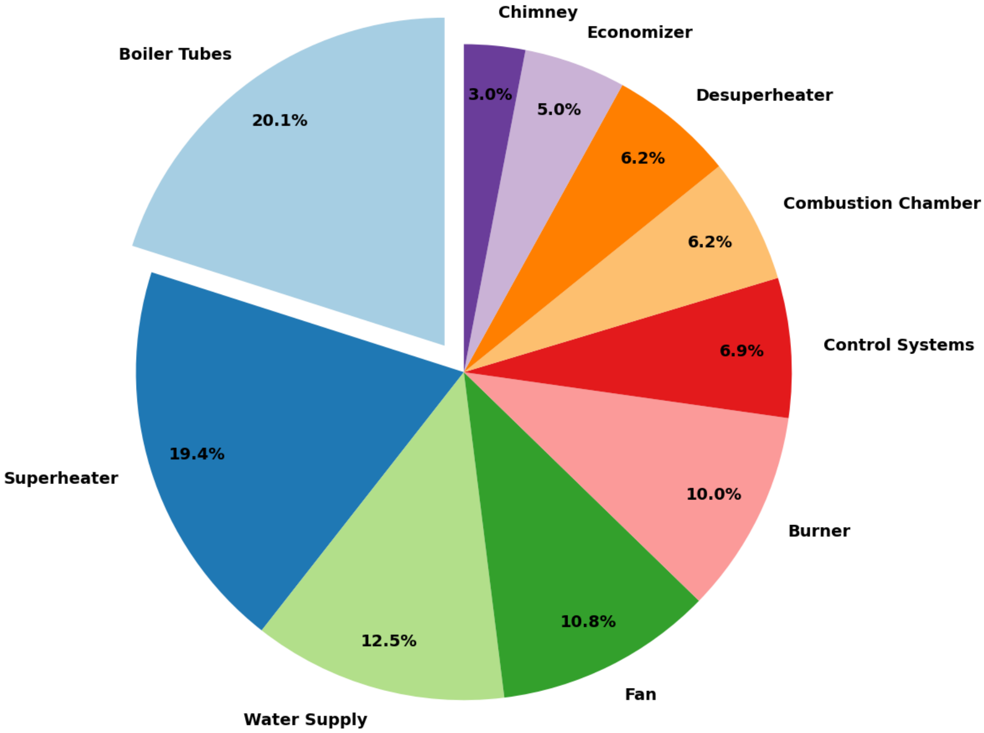

Figure 5. Proportion of Critical Components Based on RPN.

❖ **Observations**

Boiler tubes: Critical components in all boilers, with frequent failures due to high thermal and pressure conditions.

Superheater: A component also at high risk, particularly in boilers 1 and 3. Requires an enhanced maintenance program.

Water supply: Moderate risk, but regular monitoring is necessary to prevent unexpected failures.

Fan: Slightly higher risk in boiler 1, requiring improved management of ignition systems.

Burner: Variable risk, with particular attention required for boilers 1 and 3, where the risk is higher.

❖ **Comparative analysis**

The analysis of the RPNs of the three boilers highlights the superheater and boiler tubes as the most critical components, with high average RPNs of 285 and 253, respectively. These values indicate significant risks associated with high thermal and pressure conditions, particularly in boilers 1 and 3.

Feedwater systems show stable, moderate risk (average RPN of 175) across all boilers, necessitating regular maintenance to prevent failures. The burner shows slightly higher risk levels in Boiler 1 (RPN of 168), likely due to ignition or flame detection issues, whereas Boilers 2 and 3 demonstrate greater stability in this regard.

The fan displays significant variability in its risk indicators, with Boiler 1 presenting a higher RPN of 180, indicative of frequent vibration or friction issues, compared to Boiler 2, which has a significantly lower RPN of 90.

In summary, priority actions should focus on superheaters and boiler tubes, while burners and fans, particularly in boilers 1 and 3, would benefit from enhanced calibration and more frequent inspections.

Based on the conducted analysis, the superheater and boiler tubes are identified as the most critical components across all boilers. Enhanced preventive measures should be implemented to reduce their RPN and mitigate associated risks. For components such as the burner and fan, although the risk is moderate, significant differences between boilers highlight the need for tailored condition-based maintenance strategies that address the specific risk profiles of each boiler. These findings underline the importance of adaptive maintenance plans to improve overall reliability and operational efficiency.

Figure 5 represents the proportion of critical components based on their Risk Priority Numbers (RPN). It highlights the components with the highest failure risks that require targeted maintenance.

4.2. Critical component reliability assessment

The critical components of the boiler were identified through the previously conducted FMEA analysis. Of the ten components evaluated, five were identified as critical, primarily due to their significantly elevated Risk Priority Numbers (RPNs). These components will undergo a detailed reliability assessment using Monte Carlo simulation techniques.

The selected probability distributions for analysis include normal, lognormal, Weibull, and exponential distributions [4, 18, 27]. Prior to selecting a distribution, Dixon or Grubb tests are applied to identify and exclude potential outliers, particularly extreme values that may skew the analysis. Removing these values reduces dataset variability, justifying the use of Monte Carlo simulation for reliability modeling [20].

Several statistical tests are referenced in the literature to assess the suitability of the distribution, such as the Anderson-Darling (AD) test, Kolmogorov-Smirnov (K-S) test, Chi-square test, Pearson correlation coefficient, and Shapiro-Wilk test. The distribution will be applied to real-time-to-failure (TTF) data, with the most appropriate method determined by the sample characteristics [4, 18, 20]. Parameters for the reliability model are then calculated based on the selected distribution [18].

- **Example for Boiler 03 (Boiler Tubes):**

The following results were obtained using R code for the boiler tubes component of boiler 01 (Figures 6 and 7):

```
[1] " Fitting the lognormal distribution :
"
Lognormal distribution parameters:
 meanlog    sdlog
4.775856 1.088089

[1] " Fitting the 2-pWeibull distribution:
"
2P-Weibull distribution parameters :
     shape       scale
  0.9448552 205.4193369

[1] " Fitting the 3-pWeibull distribution
 ."
[3P-Weibull distribution parameters (data
TTF):
[1]   0.7443159 211.5290595  11.9990000

  Distribution       AIC      BIC
1    Lognormal 330.5193 333.0355
2   2P-Weibull 334.2707 336.7869
3   3P-Weibull 329.2105 332.9848
Best distribution according to AIC: 3P-
Weibull
```

Figure 6. Flow chart of the boiler system in Unit 50, highlighting its main components and operational flow.

```
[1] " Dixon test results:"

        Dixon test for outliers

data:  data
Q = 0.64989, p-value < 2.2e-16
alternative hypothesis: highest value 1862 is an out
lier

[1] " Grubbs test results  :"

        Grubbs test for one outlier

data:  data
G = 3.91151, U = 0.38891, p-value = 1.992e-05
alternative hypothesis: highest value 1862 is an out
lier

Outliers detected: 1862
[1] "Test d'Anderson-Darling :"
Anderson-Darling normality test

data:  ttf_data_clean
A = 2.5137, p-value = 1.525e-06

[1] "Test de normalitė de Shapiro-Wilk :"
Shapiro-Wilk normality test

data:  ttf_data_clean
W = 0.71412, p-value = 8.325e-06
[1] "Test de Kolmogorov-Smirnov pour la distribution
 lognormale :"

        Exact one-sample Kolmogorov-Smirnov test

data:  ttf_data_clean
D = 0.097489, p-value = 0.9455
alternative hypothesis: two-sided

[1] "Test de Kolmogorov-Smirnov pour la distribution
 de Weibull :"

        Exact one-sample Kolmogorov-Smirnov test

data:  ttf_data_clean
D = 0.15918, p-value = 0.4771
alternative hypothesis: two-sided
```

Figure 7. Tests results.

❖ **Interpretation of the results obtained**

- ✓ **Dixon's Test for Outlier Values:** Dixon's test identifies 1862 as a significant outlier in the data sample, with an extremely low critical p-value ($< 2.2 \times 10^{-16}$).
- ✓ **Grubbs's Test for Outlier Value:** Grubbs's test corroborates the results of Dixon's test, also identifying 1862 as a statistically significant outlier, with a very low p-value (1.992×10^{-5}).
- ✓ **Anderson-Darling Normality Test:** The Anderson-Darling test indicates a rejection of the normality hypothesis with a critical p-value of 1.525×10^{-6}. This confirms that the data do not follow a normal distribution.
- ✓ **Shapiro-Wilk Normality Test:** The Shapiro-Wilk test also rejects the normality hypothesis, with a very low p-value (8.325×10^{-6}). This reinforces the conclusion that the TTF data are not normally distributed.

❖ **Summary of Test Results**

The TTF data reveal a statistically significant outlier (1862) and do not conform to a normal distribution. Lognormal and Weibull distributions are suitable candidates for modeling these data. Based on the AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) criteria, the 3P-Weibull distribution provides the best fit. This distribution incorporates an initial threshold of 12 days before failure, accurately reflecting the observed data trends.

The AIC and BIC are two measures of the quality of a statistical fit that allow for the comparison of multiple distribution models and the selection of the one that best fits the data, while penalizing overly complex models. A model can be justified as the most efficient if it achieves the lowest AIC and BIC scores.

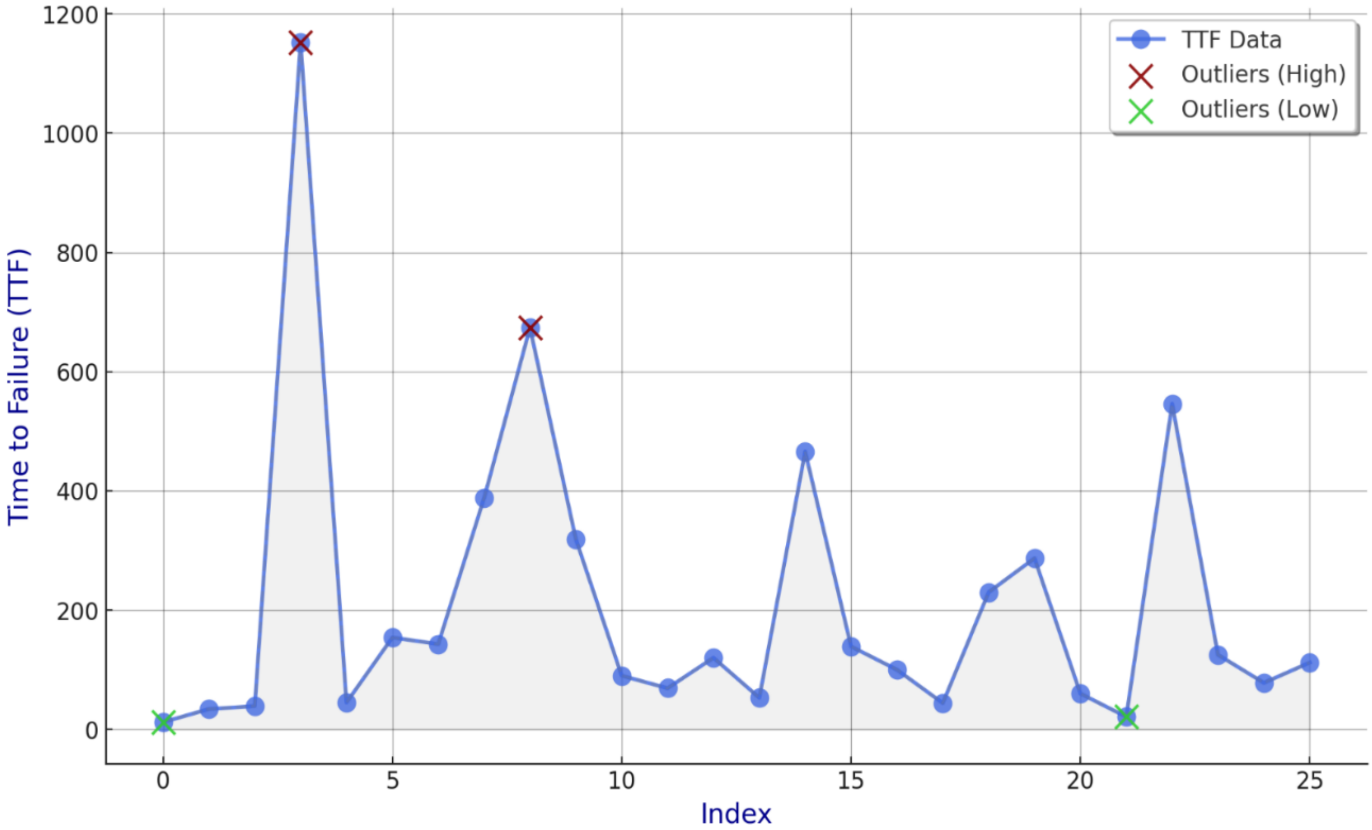

Figure 8. Dixon and Grubbs Test Results.

Figure 8 above represent the results of Dixon and Grubbs tests for identifying outliers. The Dixon test curve identifies potential outliers based on a statistical decay, and the Grubbs test curve focuses on extreme values in the dataset.

Table 8 provides a detailed summary of the selected distributions and parameters for each component.

Table 8. Summary of the best distribution and parameters for real-time failure.

Boiler	Components	Distribution	Parameters		
			Shape (β)	scale (θ)	Threshold (γ)
Boiler 01	*Superheater*	3P-Weibull	0.47	899.87	124
	Boiler tubes	2P-Weibull	1.27	311.36	/
	Water supply	3P-Weibull	0.60	263.14	18
	Burner	3P-Weibull	0.70	337.05	9
	Fan	3P-Weibull	0.38	509.98	102
Boiler 02	*Superheater*	3P-Weibull	0.51	572.39	53
	Boiler tubes	3P-Weibull	0.49	431.43	129
	Water supply	3P-Weibull	0.42	372.24	38
	Burner	2P-Weibull	1.50	712.40	/
	Fan	3P-Weibull	0.32	934.16	117
Boiler 03	*Superheater*	3P-Weibull	0.46	771.22	31
	Boiler tubes	3P-Weibull	0.74	211.53	12
	Water supply	3P-Weibull	0.44	432.42	3
	Burner	3P-Weibull	0.66	209.60	14
	Fan	3P-Weibull	0.53	551.78	151

4.2.1. Generating random numbers and transforming random number data

This study employs an integrated methodology for assessing the reliability of critical boiler components. The framework includes three main methods: Failure Modes and Effects Analysis (FMEA), Monte Carlo Simulation (MCS), and Analytic Hierarchy Process (AHP). Each method contributes uniquely to the analysis, from identifying failure risks to simulating system behavior and prioritizing components for improvement. The following sections provide a detailed description of each method's role in the overall framework.

Monte Carlo simulations require transforming uniformly distributed random numbers in the range (0,1) into non-uniform distributions such as Weibull and lognormal. The inversion transformation method is commonly used for this purpose due to its efficiency and simplicity [19]. This method relies on inverting the cumulative distribution function (CDF) of the desired distribution. If F(t) represents the CDF of a given distribution, the random variable t can be obtained as follows:

$$t = F^{-1}(X) \tag{3}$$

where X is a uniformly distributed random number in the range (0,1).

For Weibull and lognormal distributions, the random variable t is calculated using the following equations [19]:

- Weibull distribution :

$$t = \gamma + \theta(-\ln(X))^{1/\beta} \tag{4}$$

where γ is the threshold parameter, θ is the scale parameter, and β is the shape parameter.

- Lognormal distribution :

$$t = e^{\mu+\sigma.X} \tag{5}$$

where μ is the mean of the logarithmic values, and σ is the standard deviation.

In this study, 1000 random numbers are generated and transformed into the target distributions. Table 4 presents an example of the transformed random numbers for the boiler tubes of boiler 03.

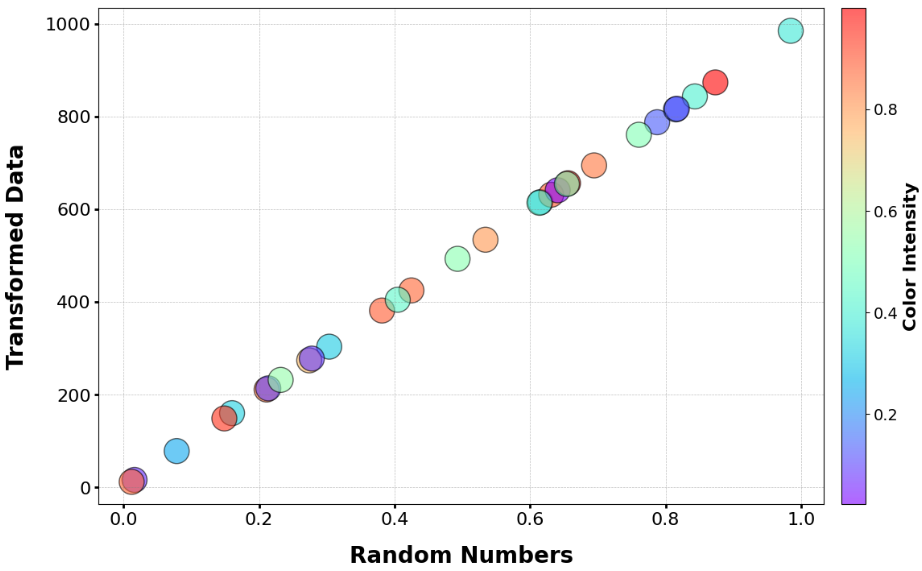

Figure 9. Scatter Plot: Random Numbers vs Transformed Data.

Figure 9 above illustrates the relationship between random numbers and their corresponding transformed data. It helps visualize the correlation between the original and transformed datasets.

Table 9. Results of Random Number Generation and Transformation (Boiler tubes of Boiler 03).

Selected random number group : 1] 0.6154411698 0.8150036929 0.3430093485 0.3882764990 0.0146181230 0.1578017345 0.5783333324 [8] 0.1069918287 0.9727296822 0.0404412686 0.1766726782 0.1780670269 0.3710839346 0.1676601360 ……… ……… [981] 0.6967233189 0.5801492480 0.2947124066 0.0954643143 0.1648187668 0.8703669664 0.7532430857 [988] 0.8154430322 0.4617513919 0.7397549737 0.7263432376 0.7650615645 0.9757218659 0.3212862888 [995] 0.5557329513 0.6763559836 0.9170438380 0.0272347340 0.1226700931 0.0941418891
Transformed data : [1] 211.02346 439.21520 77.96473 93.45017 12.73042 31.83287 185.68493 23.32273 1195.28052 [10] 14.92059 35.42654 35.70139 87.33919 33.68101 467.13804 149.05809 935.14417 21.61949 ……… ……… [982] 186.85217 63.45062 21.63279 33.14179 564.37399 344.21842 440.02416 123.14986 327.35504 [991] 311.64112 359.96680 1246.85881 71.19479 171.72482 260.71606 732.34220 13.70104 25.76605 [1000] 21.44481

Goodness-of-Fit Tests for Weibull Distribution Selection:

In this study, Weibull distributions were chosen to model the failure times of critical boiler components. However, to justify the selection of Weibull distributions over other alternatives, goodness-of-fit statistics were conducted for each component's failure data. The following fit tests were applied to assess how well the Weibull distribution fits the observed data:

1. **Kolmogorov-Smirnov (K-S) Test**: This test compares the empirical distribution function (ECDF) of the data with the cumulative distribution function (CDF) of the fitted distribution. The p-value from this test indicates how well the Weibull distribution fits the data. A p-value greater than the significance level (usually 0.05) suggests that the Weibull distribution is a good fit for the data.
2. **Anderson-Darling (A-D) Test**: Similar to the K-S test, the A-D test assesses the fit by giving more weight to the tails of the distribution. A low p-value from the A-D test would indicate a poor fit, while a high p-value suggests that the Weibull distribution adequately fits the failure data.

The following table provides the results of these fit tests for each component:

Table 10. Distribution Fit Tests for Boiler Components Using Kolmogorov-Smirnov and Anderson-Darling Tests.

Component	p-value (Kolmogorov-Smirnov)	p-value (Anderson-Darling)
Superheater	0.92	0.86
Boiler Tube	0.85	0.90
Water Supply	0.76	0.80
Burner	0.89	0.87
Fan	0.91	0.88

Table 10 presents the results of the distribution fit tests for boiler components, where the Kolmogorov-Smirnov and Anderson-Darling tests were applied to the failure data. The high p-values (greater than 0.05) for both tests indicate that the data fits well with the chosen distribution, enhancing the reliability of the analysis and the selection of the appropriate distribution for each component.

These p-values demonstrate that the Weibull distribution is a reasonable fit for the failure data of all components, as the p-values are all above the typical significance level of 0.05. Therefore, the Weibull distribution was chosen for further reliability analysis.

Alternative Distributions:

Although Weibull distributions were selected based on the goodness-of-fit tests, alternative distributions such as **Log-Normal** and **Exponential** were also considered. However, the results from the Kolmogorov-Smirnov and Anderson-Darling tests indicated that these alternative distributions did not fit the failure data as well as the Weibull distribution, as evidenced by their lower p-values. For instance, the Log-Normal distribution yielded p-values below 0.05 for most components, indicating poor fit, while the Exponential distribution showed significant deviation from the observed failure times, particularly in the tail distributions. Therefore, the Weibull distribution was chosen for its superior fit.

4.2.2. Validity Test

Validation plays a crucial role in the model development process. It ensures that the model's predictions align closely with real-world data, thereby enhancing the reliability of the analysis. In this study, the Mann-Whitney U test is used to compare the results of the random number transformations with actual data to assess whether there are significant differences [4, 18, 19].

As an illustration, the validation process is applied to the boiler tubes of boiler 03 to evaluate the accuracy of the transformation results.

For illustration, the verification process is applied to the three boiler elements to evaluate the accuracy of the transformation results in Table 11.

Table 11. Results of Random Number Generation and Transformation.

Boiler	Components	W	p-value	Greater than the standard alpha threshold of 0.05?
Boiler 01	*Superheater*	3523	0.98	Yes
	Boiler tubes	10603	0.94	Yes
	Water supply	775	0.26	Yes
	Burner	8911	0.73	Yes
	Fan	2530	0.96	Yes
Boiler 02	*Superheater*	4842	0.86	Yes
	Boiler tubes	4222	0.75	Yes
	Water supply	438	0.66	Yes
	Burner	3887	0.89	Yes
	Fan	285	0.84	Yes
Boiler 03	*Superheater*	4251	0.77	Yes
	Boiler tubes	13116	0.94	Yes
	Water supply	6896	0.71	Yes
	Burner	15104	0.48	Yes
	Fan	3523	0.96	Yes

Table 11 illustrates the value p-value is greater than the conventional significance threshold of 0.05, indicating that the Mann-Whitney U test fails to reject the null hypothesis. This result suggests that the real TTF data and the transformed data are statistically similar in terms of distribution.

4.2.3. Calculation of parameters for random number transformation

To accurately model the failure behavior of critical components, it is essential to determine the most appropriate statistical distribution and its parameters. These parameters are derived from a distribution test applied to the real-time-to-failure (TTF) data. The calculated parameters are then used for random number transformations in Monte Carlo simulations.

The results obtained from the distribution test and parameter calculation serve as inputs for the simulation process. Table 12 provides a summary of the best-fitting distributions and their optimal parameters for transforming random numbers.

Table 12. Best distribution and parameters for the random number transformations.

Boiler	**Components**	**Distribution**	**Parameters**		
			Shape (β)	**scale (θ)**	**Threshold (γ)**
Boiler 01	*Superheater*	3P-Weibull	0.44	585.10	124
	Boiler tubes	3P-Weibull	1.20	324.28	1.95
	Water supply	3P-Weibull	0.59	145.82	18
	Burner	3P-Weibull	0.65	290.28	9
	Fan	3P-Weibull	0.37	484.81	102
Boiler 02	*Superheater*	3P-Weibull	0.53	536.60	53
	Boiler tubes	3P-Weibull	0.49	364.77	129
	Water supply	3P-Weibull	0.41	160.91	38
	Burner	2P-Weibull	1.48	756.42	/
	Fan	3P-Weibull	0.33	509.91	117
Boiler 03	*Superheater*	3P-Weibull	0.46	684.64	31
	Boiler tubes	3P-Weibull	0.69	183.82	12
	Water supply	3P-Weibull	0.56	221.48	18
	Burner	3P-Weibull	0.62	179.26	14
	Fan	3P-Weibull	0.50	454.51	151

4.2.4. MTTF calculation and reliability results from Monte Carlo simulation

The Mean Time to Failure (MTTF) and the reliability level were calculated using Eqs. (6), (7), and (8) [28]. The MTTF formula was chosen based on the Weibull distribution parameters.

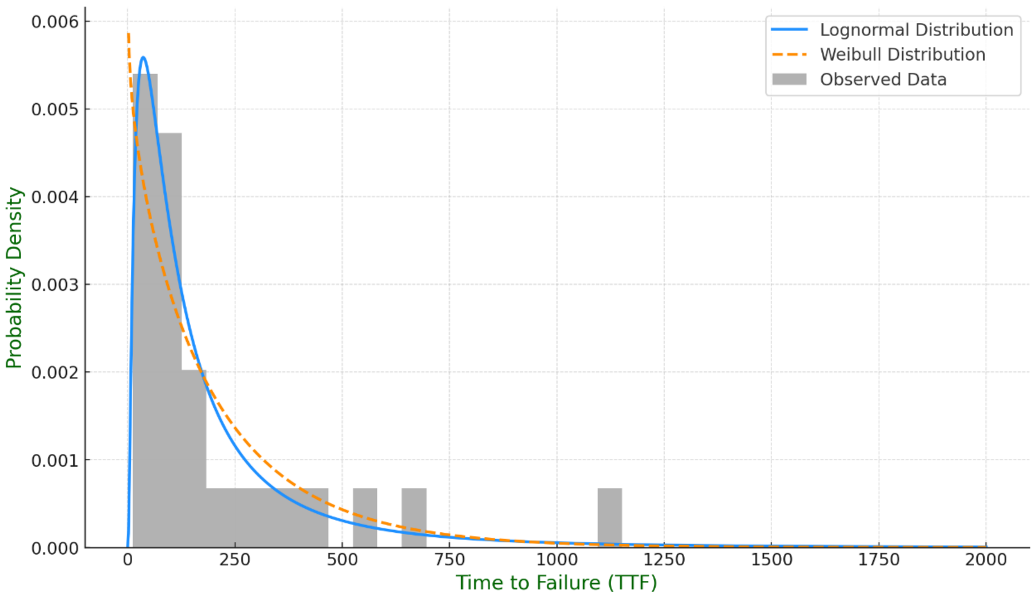

Figure 10. Failure Time Distribution for Critical Boiler Components (Weibull Distribution).

For a 2P-Weibull distribution:

$$MTTF = \theta * \Gamma(1 + \frac{1}{\beta}) \quad (6)$$

For a 3P-Weibull distribution:

$$MTTF = \gamma + \theta * \Gamma(1 + \frac{1}{\beta}) \quad (7)$$

Using the boiler tube component of boiler 03 as an example:

MTTF = 12+ 183.82× Γ (1 + 1/0.69)

MTTF = 12+ 183.82× Γ (2.44)

MTTF = 277.069≈ 277 days.

Reliability Calculation, R(t):

$$R(t) = e^{-\left(\frac{t-\gamma}{\theta}\right)^{\beta}} \quad (8)$$

With numerical values:

$R(t) = e^{-(277.07 - 12/183.82)^{0.693}}$

R(t) = 0.2755 = 27.55%

Figure 10 illustrates the Weibull distribution for the failure times of critical components. It helps to understand the failure behavior of the system and indicates the likelihood of component failures over time.

The results of these calculations are summarized in Table 13, which provides the MTTF and reliability values based on Monte Carlo simulations for the boiler tube component.

Table 13. MTTF and reliability results based on Monte Carlo simulation.

Boiler	**Components**	**MTTF (days)**	**R (MTTF) %**	**R (365) %**	**R (1095) %**	**R (1825) %**
Boiler 01	*Superheater*	1608	22.01	50.98	28.56	20.01
	Boiler tubes	306	39.62	31.81	01.35	00.03
	Water supply	242	27.57	18.84	03.84	01.19
	Burner	404	29.45	31.91	09.41	03.67
	Fan	2130	18.30	45.04	27.15	20.21
Boiler 02	*Superheater*	1027	25.40	47.19	24.17	15.26
	Boiler tubes	896	23.78	44.53	20.05	12.08
	Water supply	524	20.57	26.14	11.28	06.63
	Burner	684	42.29	72.26	17.68	02.47
	Fan	3143	16.29	45.56	28.84	22.36
Boiler 03	*Superheater*	1027	25.40	48.67	29.41	21.13
	Boiler tubes	277	27.55	20.74	03.25	00.74
	Water supply	524	20.57	27.60	08.77	03.55
	Burner	624	42.26	21.91	04.71	01.48
	Fan	1064	24.26	50.31	23.69	14.71

4.3. Results and analysis (MCS)

Monte Carlo simulations applied to the five critical components of the boilers reveal the following insights:

(1) High Reliability: Among all components, fans display the longest mean time to failureamong all components. They demonstrate stable reliability over time, requiring less frequent maintenance.

(2) Low Reliability: Burners and hot tubes display shorter MTTF values and rapid declines in reliability, highlighting their higher susceptibility to failure. These components require frequent maintenance or replacement to prevent system disruptions.

Moderate Reliability: Superheaters and feedwater components show moderate MTTF values with gradual

(3) declines in reliability. While more reliable than burners and tubes, they remain less stable compared to fans.

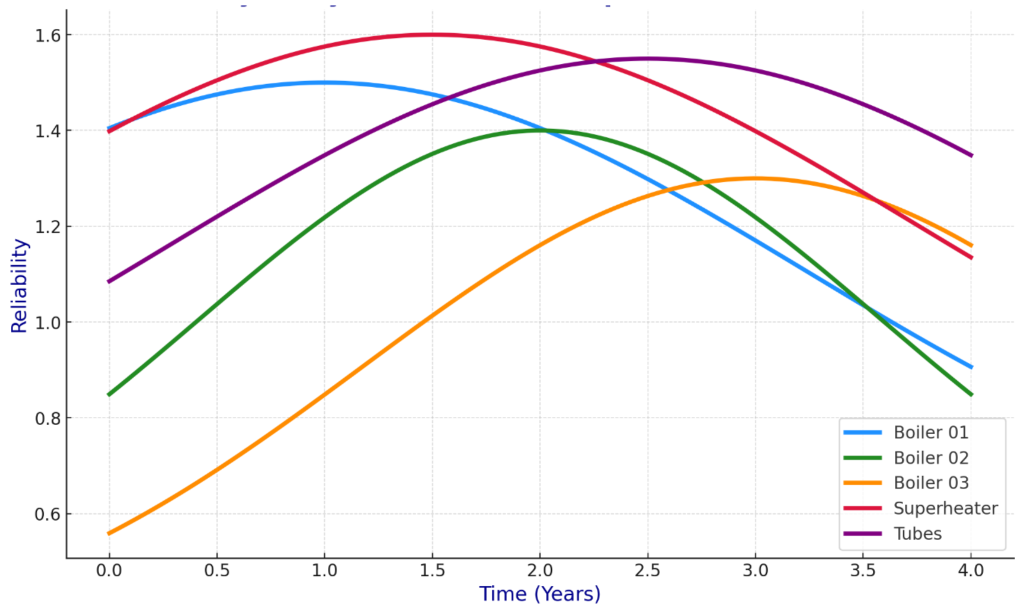

Figure 11. Reliability Analysis of Critical Components (Smooth Curves).

Figure 11 shows how the reliability of different components (Superheater, Boiler Tubes, Water Supply, Burner, and Fan) varies over time periods of 1 year, 3 years, and 5 years. As time progresses, the reliability of certain components decreases, indicating the need for timely maintenance.

Simulation results reveal an average system reliability under 50%, indicating elevated risk of shutdowns and degraded efficiency. This value was derived using Monte Carlo simulation techniques, which modeled the failure scenarios of components under varying operational conditions. The reliability estimates were based on the failure data and statistical distributions applied to each element. The result indicates a high likelihood of failure for these components within a short period, emphasizing the need for timely preventive maintenance. In industrial contexts, a reliability value below 50% suggests that these components are at risk of causing unplanned downtimes and significant disruptions in production. This finding underscores the importance of implementing frequent maintenance schedules and early detection techniques to improve overall system performance and reduce operational losses.

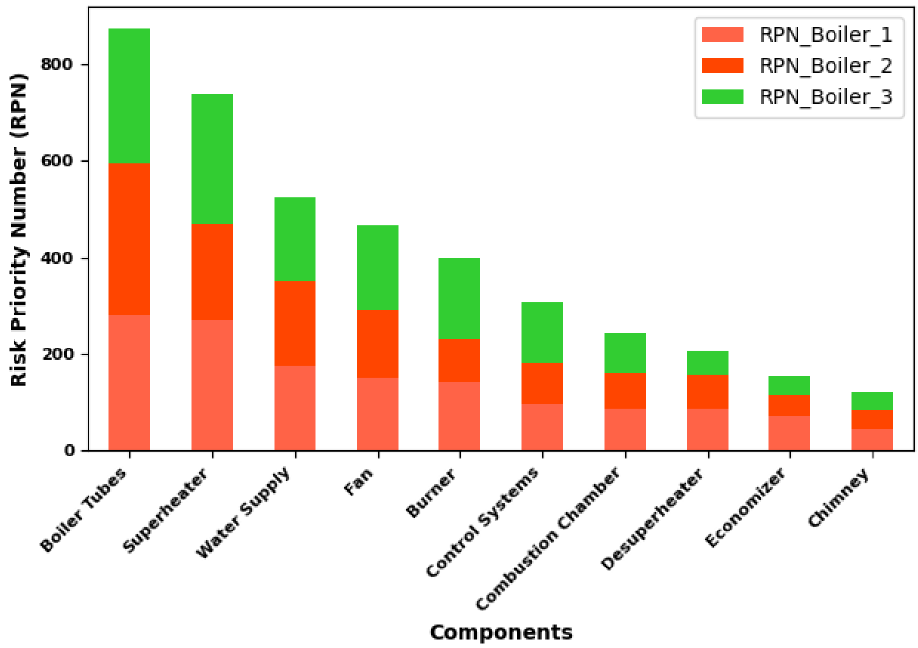

Figure 12. RPN Analysis for Critical Boiler Components Across Different Boilers.

Figure 12 above represents the Risk Priority Number (RPN) for critical boiler components. It shows the risk distribution across different boilers, highlighting components that require immediate maintenance attention.

These findings provide a basis for prioritizing maintenance activities and managing spare part inventories effectively. For instance, fans require less attention, while burners and tubes should be the focus of immediate preventive measures. Strategic recommendations based on these results can enhance boiler performance and minimize downtime.

In real-**world applications, the prioritization of maintenance tasks should not rely** solely on RPN and MTTF values, as these factors do not fully capture the operational context. Therefore, we have integrated Multi-Criteria Decision-Making (MCDM) techniques, such as Analytic Hierarchy Process (AHP) and TOPSIS, to consider additional criteria that are crucial for effective maintenance planning.

1. **Cost**: Maintenance decisions are influenced by the **cost** of replacing or repairing components. Components with high RPN and high maintenance cost should be prioritized for preventive maintenance.
2. **Downtime**: The **cost of downtime** can be substantial in terms of lost production and operational delays. Components that, if failed, would lead to significant downtime are prioritized higher.
3. **Part Availability**: The availability of replacement parts is critical. Components with long lead times for spare parts should be given higher priority to prevent long outages.
4. **Safety**: For critical components, the **safety risks** associated with failure should be evaluated. Components that pose a higher risk to personnel safety in case of failure are given priority.

By using **AHP** or **TOPSIS**, a **weighting system** is applied to each of these factors, and maintenance priorities are determined based on their overall impact. These methods provide a **holistic assessment** that goes beyond RPN and MTTF, ensuring that decisions are made not only based on risk but also on broader operational concerns.

The following recommendations are based on the results of the combined FMEA and Monte Carlo Simulation (MCS) analysis, to enhance the reliability, safety, and performance of industrial boilers:

1. **Enhanced Monitoring of Critical Components**
   - Prioritize inspections of superheaters and boiler tubes, identified as the most at-risk components.
   - Implement alert thresholds based on Monte Carlo simulation results (e.g., reliability < 30%).
2. **Tailored Predictive Maintenance**
   - Adjust maintenance intervals using estimated life distributions (e.g., 3-parameter Weibull).
   - Use decision-support software tools to schedule shutdowns based on risk profiles.
3. **Integration of Advanced Diagnostic Tools**
   - Install smart sensors (for pressure, vibration, temperature) to detect early signs of failure.
   - Deploy robotic inspection technologies for areas that are difficult to access.
4. **Ongoing Training for Maintenance Personnel**
   - Organize targeted training sessions focused on interpreting predictive tool data.
   - Train technicians to identify early warning signs of component failure.
5. **Proactive Spare Parts Management**
   - Establish an inventory of critical components characterized by high Risk Priority Numbers and low mean time to failure, to reduce intervention delays.
   - Set up automatic replenishment thresholds for components with a high likelihood of failure.

Implementing these measures would significantly reduce costs associated with unplanned downtimes, extend the lifespan of key components, and improve service continuity in thermal systems.

5. FUTURE RESEARCH DIRECTIONS

The findings of this study pave the way for several promising research directions aimed at enhancing the reliability and predictive maintenance of industrial boilers. These future avenues focus on integrating advanced technologies, refining existing models, and exploring innovative methodological approaches to address current limitations and improve system performance.

One key area for future research is the integration of advanced technologies. Digital monitoring and diagnostic systems, equipped with smart sensors and real-time analysis tools, could significantly improve the detection of failures in thermal power plants. These systems would enable faster responses to anomalies, reducing unplanned downtime and enhancing operational efficiency. Additionally, advancements in materials, such as corrosion-resistant and thermal fatigue-resistant alloys, along with the adoption of new energy production technologies like hybrid renewable energy systems, could enhance the durability and reliability of industrial boilers. These innovations would not only extend the lifespan of critical components but also reduce maintenance costs and improve energy efficiency.

Another important direction is the improvement of risk assessment models. Future studies could explore the integration of additional risk factors, such as environmental impacts, maintenance costs, and production losses, to provide a more comprehensive analysis of risks. This holistic approach would enable better prioritization of maintenance actions and more informed decision-making. Furthermore, enhancing the generalization of models by testing them across diverse industrial systems and operational environments would strengthen their robustness and applicability. The integration of machine learning, particularly deep learning, as suggested by Rao et al. (2024) [29], could also offer significant advancements in predictive maintenance. These techniques could enable more precise modeling of failure scenarios and more accurate predictions of failure times, improving overall system reliability. Additionally, combining multiple models, such as fuzzy methods, Monte Carlo simulations, and machine learning, could enhance the accuracy and robustness of predictions. For instance, the ExJ-PSI model proposed by Patil et al. (2022) could integrate expert judgments while reducing uncertainties in risk assessment [23].

The integration of fuzzy and hybrid methods also presents a valuable research opportunity. Fuzzy methods, when incorporated into Failure Modes, Effects Analysis (FMEA), can improve the accuracy of risk identification by accounting for uncertainties and subjective expert judgments. This approach, as highlighted by Wang et al. (2021) and Khodadadi-Karimvand and Shirouyehzad (2021) [30, 31], would allow for more effective prioritization of maintenance actions. Similarly, hybrid methods, such as combining Fuzzy TOPSIS with FMEA, could enhance risk prioritization in complex industrial settings. As demonstrated by Magalhães and Lima Junior (2021) [32], this combination offers a robust framework for managing uncertainties and multiple criteria, leading to more effective risk management and maintenance planning.

In conclusion, these future research directions aim to strengthen the reliability of industrial boilers by leveraging advanced technologies, refining risk assessment models, and exploring innovative methodological approaches. By combining these efforts, researchers and practitioners can develop more adaptive, efficient, and robust predictive maintenance systems. This will not only reduce operational costs but also enhance the safety, performance, and sustainability of industrial facilities, ensuring their long-term reliability in demanding operational environments.

6. CONCLUSIONS

This study demonstrates that the integration of Failure Mode and Effects Analysis (FMEA) with Monte Carlo Simulation (MCS) provides a comprehensive and robust framework for improving the reliability of critical boiler components. FMEA enables a structured identification and prioritization of failure modes based on their severity, occurrence, and detectability, while MCS adds a probabilistic dimension by simulating realistic failure scenarios and estimating the Mean Time to Failure (MTTF).

The analysis highlighted that components such as superheaters and boiler tubes show high RPN values and weak reliability, warranting top maintenance priority.

This combined approach enhances maintenance planning by refining inspection intervals, improving resource allocation, and anticipating component failures. It is also adaptable to various industrial systems beyond steam generation.

Future work could explore the integration of real-time monitoring systems and AI-driven predictive models to further enhance failure detection and reduce uncertainties. Expanding the dataset through continuous data acquisition and including additional variables such as cost, environmental impact, and energy efficiency would further refine maintenance planning.

In conclusion, the joint use of FMEA and MCS is a valuable decision-support tool for improving equipment reliability, reducing operational risks, and extending the life of critical components in complex industrial environments.

References

1. S. Purseth, J. Dansena, and M. S. Desai, "Performance analysis and efficiency improvement of boilera review," *International Journal of Engineering Applied Sciences and Technology,* vol. 5, no. 12, pp. 326-331, 2021. https://doi.org/10.33564/IJEAST.2021.v05i12.057
2. A. H. A. Melani, C. A. Murad, A. C. Netto, G. F. M. de Souza, and S. I. Nabeta, "Criticality-based maintenance of a coal-fired power plant," *Energy,* vol. 147, pp. 767-781, 2018. https://doi.org/10.1016/j.energy.2018.01.048
3. M. H. Hatala, B. P. Sukarsono, and D. Nukertamanda, "Risk and reliability improvement analysis of boiler system using the failure mode effect analysis & critical analysis (FMECA) method," *Spektrum Industri,* vol. 21, no. 1, pp. 8-20, 2023. https://doi.org/10.12928/si.v21i1.98
4. O. S. Stamenković, G. M. Stupar, D. R. Tucaković, and B. M. Bošković, "Detection of cause of pipe burst in economizer of process CO steam boiler," *Tehnika,* vol. 77, no. 1, pp. 55-69, 2022. https://doi.org/10.5937/tehnika2201055S
5. G. Cristea and D. M. Constantinescu, "A comparative critical study between FMEA and FTA risk analysis methods," in *IOP Conference Series: Materials Science and Engineering*, 2017, vol. 252, no. 1: IOP Publishing, p. 012046.
6. M. Yazdi, "Reliability-centered design and system resilience," in *Advances in Computational Mathematics for Industrial System Reliability and Maintainability*: Springer, 2024, pp. 79-103. https://doi.org/10.1007/978-3-031-53514-7_5
7. B. Puthillath and R. Sasikumar, "Selection of maintenance strategy using failure mode effect and criticality analysis," *International Journal of Engineering and Innovative Technology (IJEIT),* vol. 1, no. 6, pp. 73-79, 2012.
8. W. S. Rahmania, H. E. G. Prasetya, and F. H. Sholihah, "Maintenance analysis of boiler feed pump turbine using failure mode effect analysis (FMEA) methods," in *2020 International Electronics Symposium (IES)*, 2020: IEEE, pp. 54-59. https://doi.org/10.1109/IES50839.2020.9231886
9. T. AlKautsar and A. Saputra, "Analysis of Boiler Start-Up Failure Risk with Grey FMEA and RCA Methods in Pt. PLTU Nagan Raya," *Jurnal Inotera,* vol. 7, no. 2, pp. 109-119, 2022. https://doi.org/10.31572/inotera.Vol7.Iss2.2022.ID181
10. T. Sun *et al.*, "Risk and reliability assessment of solar-assisted air source heat pumps using fuzzy logic-based failure modes and effects analysis," *Journal of Building Engineering,* vol. 103, p. 112155, 2025.
11. H. Ramdani, Z. Aoulmi, M. Louafi, M. Attia, and M. Mebarkia, "Enhancing sustainability through drilling machine efficiency: A comparative analysis of TOPSIS and VIKOR methods for energy optimization," *International Journal of Computational Methods and Experimental Measurements,* vol. 12, no. 1, pp. 45-52, 2024. https://doi.org/10.18280/ijcmem.120105
12. M. Debbouz, Z. Aoulmi, C. Fehdi, and M. Attia, "Sustainable Transportation Planning for Djebel Onk's Open-Pit Phosphate Mine in Algeria: Using Queuing Theory and Cost-Emission Analysis," *International Journal of Sustainable Development & Planning,* vol. 19, no. 5, 2024. https://doi.org/10.18280/ijsdp.190504
13. G. Tian *et al.*, "A survey of multi-criteria decision-making techniques for green logistics and low-carbon transportation systems," *Environmental Science and Pollution Research,* vol. 30, no. 20, pp. 57279-57301, 2023. https://doi.org/10.1007/s11356-023-26577-2
14. R. Moghrani, Z. Aoulmi, and M. Attia, "Hybrid RPI-MCDM Approach for FMEA: A Case Study on Belt Conveyor in Bir El Ater Mine, Algeria," *Journal Européen des Systèmes Automatisés,* vol. 56, no. 3, p. 465, 2023. https://doi.org/10.18280/jesa.560314
15. A. Moussa and Z. Aoulmi, "Improving Electric Vehicle Maintenance by Advanced Prediction of Failure Modes Using Machine Learning Classifications," *Eksploatacja i Niezawodność – Maintenance and Reliability,* 2025-02-21 2025, doi: 10.17531/ein/201372.
16. T. Sun *et al.*, "Risk and reliability assessment of solar-assisted air source heat pumps using fuzzy logic-based failure modes and effects analysis," *Journal of Building Engineering,* p. 112155, 2025. https://doi.org/10.1016/j.jobe.2025.112155
17. G. P. Putra and H. Hardi Purba, "Failure mode and effect analysis power plant boiler," *Journal of Optimization in Industrial Engineering,* vol. 11, no. 2, pp. 1-5, 2018.
18. I. Pamungkas and M. Dirhamsyah, "Monte Carlo simulation for predicting the reliability of a boiler in the Nagan Raya steam power plant," in *IOP Conference Series: Materials Science and Engineering*, 2019, vol. 523, no. 1: IOP Publishing, p. 012071.
19. E. Hartini, H. Adrial, and S. Pujiarta, "Reliability analysis of primary and purification pumps in RSG-GAS using Monte Carlo simulation approach," *Jurnal Teknologi Reaktor Nuklir Tri Dasa Mega,* vol. 21, no. 1, pp. 15-22, 2019. https://doi.org/10.17146/tdm.2019.21.1.5311
20. A. Haouam, R. Khelif, and S. Haouam, "Analyse fiabiliste du comportement mécanique du rotor d'un turbocompresseur de réfrigération."
21. J. Yang, H. Wang, J. Zhang, and X. Zhou, "Towards intelligent maintenance of thermal power plants: a novel robot for checking water wall

tube," in *International Conference on Intelligent Robotics and Applications*, 2019: Springer, pp. 726-737. https://doi.org/10.1007/978-3-030-27541-9_60

22. Q. D. Feng, J. S. Xia, L. Wen, and M. Yazdi, "Failure analysis of floating offshore wind turbines based on a fuzzy failure mode and effect analysis model," *Quality and Reliability Engineering International,* vol. 40, no. 5, pp. 2159-2177, 2024. https://doi.org/10.1002/qre.3505
23. S. S. Patil *et al.*, "A new approach for failure modes, effects, and criticality analysis using ExJ-PSI model—a case study on boiler system," *Applied Sciences,* vol. 12, no. 22, p. https://doi.org/10.3390/app122211419.
24. J. Singh, S. Singh, and A. Singh, "Distribution transformer failure modes, effects and criticality analysis (FMECA)," *Engineering Failure Analysis,* vol. 99, pp. 180-191, 2019. https://doi.org/10.1016/j.engfailanal.2019.02.014
25. K.-H. Chang, T.-Y. Fang, and Z.-S. Li, "Using a Flexible Risk Priority Number Method to Reinforce Abilities of Imprecise Data Assessments of Risk Assessment Problems," *Electronics (2079-9292),* vol. 14, no. 3, 2025. https://doi.org/10.3390/electronics14030518
26. J. E. Naranjo, J. S. Alban, M. S. Balseca, D. F. Bustamante Villagómez, M. G. Mancheno Falconi, and M. V. Garcia, "Enhancing Institutional Sustainability Through Process Optimization: A Hybrid Approach Using FMEA and Machine Learning," *Sustainability,* vol. 17, no. 4, p. 1357, 2025. https://doi.org/10.3390/su17041357
27. S. Robinson, *Simulation: the practice of model development and use*. Bloomsbury Publishing, 2014.
28. D. J. Smith, *Reliability, maintainability and risk: practical methods for engineers*. Butterworth-Heinemann, 2021.
29. D. A. V. S. S. R. Rao, Kulkarni, D. S., Bhatia, D. S. K., Sambasivarao, L. V., & Singh, K. S. , "Advanced Machine Learning Algorithms for Predictive Maintenance in Industrial Manufacturing Systems," *South Eastern European Journal of Public Health,* vol. Volume XXV 2024, pp. 716–723, 2024, doi: 10.70135/seejph.vi.2057.
30. L. Wang, L. Sun, J. Kang, Y. Wang, and H. Wang, "Risk identification of FPSO oil and gas processing system based on an improved FMEA approach," *Applied Sciences,* vol. 11, no. 2, p. 567, 2021. https://doi.org/10.3390/app11020567
31. M. Khodadadi-Karimvand and H. Shirouyehzad, "Well drilling fuzzy risk assessment using fuzzy FMEA and fuzzy TOPSIS," *Journal of fuzzy extension and applications,* vol. 2, no. 2, pp. 144-155, 2021.
32. W. R. d. Magalhães and F. R. Lima, "A model based on FMEA and Fuzzy TOPSIS for risk prioritization in industrial processes," *Gestão & Produção,* vol. 28, no. 4, p. e5535, 2021. https://doi.org/10.1590/1806-9649-2020v28e5535