Chapter 1

Introduction

1.1 Background of the Study

The cement industry is a cornerstone of global infrastructure, enabling the construction of residential, commercial, and large-scale civil projects such as bridges, highways, and dams. Cement second only to water as the most consumed material globally has an annual production exceeding **4 billion metric tons** [1]. The global market value exceeds **USD 300 billion**, with China, India, the United States, and the European Union leading in production capacity. The sector sustains millions of jobs and drives industrial supply chains from raw material extraction to final distribution.[3]

However, cement manufacturing is energy-intensive, environmentally impactful, and highly dependent on the continuous operation of critical machinery. Downtime in key assets such as kilns, crushers, mills, and conveyors can halt production entirely, creating significant economic losses and safety risks. .[4] This research addresses these challenges through systematic failure analysis and predictive maintenance modeling.

1.1.1 Historical Background

The use of cementitious binders' dates back millennia: Egyptians employed lime and gypsum, while Romans developed pozzolanic concrete using volcanic ash [5]. Modern cement production began with Joseph Aspdin's 1824 invention of Portland cement, created by calcining limestone and clay.

Key technological milestones include:

- **19th Century** – Introduction of rotary kilns, enabling continuous operation.
- **20th Century** – Development of multi-stage preheaters and pre-calciners, reducing fuel consumption.
- **21st Century** – Integration of alternative fuels, carbon capture, and low-carbon formulations [8].

Despite these advances, equipment failures remain a bottleneck to efficiency, underscoring the need for robust reliability engineering.

1.1.2 Evolution of Maintenance Strategies

Maintenance practices in heavy industry have evolved from reactive to preventive, and now toward predictive and condition-based maintenance (CBM) [5]:

1. **Reactive Maintenance** – Repairs occur after failure, leading to costly unplanned downtime, collateral damage, and safety risks.
2. **Preventive Maintenance** – Scheduled interventions reduce some failures but often cause over-maintenance or miss early degradation signs.
3. **Predictive / CBM** – Uses real-time monitoring (vibration analysis, thermography, oil diagnostics) and historical failure data to forecast failures just in time for intervention [9].

Digitalization through IoT sensors, machine learning, and cloud analytics has accelerated the adoption of predictive strategies, aligning with Industry 4.0 principles. In cement plants, these approaches can substantially reduce catastrophic failures and total cost of ownership (TCO).

1.2 Problem Statement

1.2.1 Unplanned Downtime

Despite the adoption of advanced maintenance systems, unplanned downtime remains a persistent issue that disrupts operations and inflates maintenance costs [1]. Even in technologically advanced facilities, critical assets such as kilns, crushers, and rotary feeders experience unexpected breakdowns due to hidden failure modes, inadequate root cause investigation, or poorly optimized maintenance schedules [11].

These incidents can escalate into safety hazards or secondary failures if not addressed promptly. Furthermore, reactive responses to such downtimes often result in higher repair costs, overtime labor, and delayed deliveries, all of which affect the competitiveness and profitability of the plant [12].

1.2.2 Systematic Framework for Failure Analysis

The recurrence of unplanned failures underscores a critical gap in the implementation of proactive maintenance: the lack of a comprehensive, structured, and integrated failure analysis framework. Existing approaches often rely heavily on either qualitative root cause assessments or isolated equipment metrics, without synthesizing diverse data sources into a unified diagnostic model. This fragmentation limits the ability to accurately identify failure trends, prioritize risk areas, or implement sustainable corrective actions[13].

A systematic framework encompassing Root Cause Analysis (RCA), Failure Mode and Effects Analysis (FMEA), Fault Tree Analysis (FTA), and reliability metrics such as MTBF (Mean Time Between Failures), MTTR (Mean Time to Repair), and Availability is essential to gain deeper insights into the underlying causes of failure. When combined with real-time monitoring and historical data analysis, such a framework enables a transition from reactive troubleshooting to predictive and preventive strategies grounded in evidence-based diagnostics [14].

In the cement industry, critical equipment such as rotary kilns, mills, and conveyors are subjected to harsh operating conditions including high temperatures, abrasive materials, and heavy loads. These conditions lead to frequent mechanical, electrical, and thermal failures, causing production bottlenecks and financial losses. Traditional maintenance strategies often address the symptoms rather than the root causes of these failures, leading to recurring issues.

The absence of a structured and comprehensive methodology for failure analysis and root cause investigation constrains the industry's capacity to improve equipment reliability. This study seeks to systematically examine failure modes and determine their underlying causes, thereby supporting the formulation of more effective maintenance strategies and informed equipment design enhancements. To address this gap, the present research proposes and implements an integrated failure analysis framework for critical equipment within a cement production facility, with the objectives of minimizing unplanned downtime, optimizing resource utilization, and strengthening long-term operational reliability.

1.2.3 Research Gap Statement:

To the best of current knowledge, no previous study within the cement industry has systematically integrated RCA, FMEA, FTA, Weibull reliability modeling, and CBM data into a unified predictive maintenance framework for critical equipment. This research fills that gap by formulating and implementing a comprehensive framework applied to an actual cement production facility.

1.3 Research Objectives

1.3.1 Identification of Critical Failures

To systematically identify high-impact equipment failures using:

- **i.** Pareto Analysis for prioritization.
- **ii.** MTBF calculations for reliability assessment.
- **iii.** Risk Priority Number (RPN) from FMEA to quantify severity and occurrence.

1.3.2 Root Cause and Reliability Analysis

To diagnose underlying causes using:

- **i.** **Qualitative** – Fishbone Diagram, 5 Whys, Fault Tree Analysis (FTA).
- **ii.** **Quantitative** – FMEA scoring, Weibull distribution modeling.
- **iii.** **Reliability Metrics** – MTBF, MTTR, and Availability calculations for benchmarking.

1.4 Research Questions

1. What are the most frequent and severe failure modes in critical cement plant equipment?
2. How can integrated RCA and reliability methods improve diagnostic accuracy?

3. What preventive measures are most effective in improving system availability?
4. Can real-time predictive analytics significantly reduce unplanned downtime?

1.5 Research Methodology

This study adopts a mixed-methods research design, integrating both quantitative and qualitative approaches to ensure a comprehensive understanding of equipment failures and maintenance practices.

- **i.** The **quantitative** component involves statistical analysis of data obtained from maintenance management systems, condition monitoring tools, and sensor outputs. These data provide measurable indicators of failure frequency, severity, and reliability patterns across critical equipment.
- **ii.** The **qualitative** component includes structured interviews with engineers and maintenance supervisors, as well as root cause analysis (RCA) sessions. These methods capture experiential insights, operational practices, and contextual factors that are not evident in numerical data.

By combining statistical evidence with expert knowledge, the mixed-methods approach enhances the validity and depth of the research, allowing for triangulation of findings where quantitative trends are reinforced by qualitative understanding.

1.6 Significance of the Study

- **i.** Improved Understanding of Equipment Behavior: By combining historical records with advanced diagnostics (RCA, FMEA, Weibull), this study reveals *not just what fails, but why, when, and under what conditions*.

ii. Data-Driven Decision Support: The findings support evidence-based maintenance by quantifying MTBF, MTTR, and Availability, enabling precise resource allocation and aligning with Industry 4.0 reliability objectives.

1.7 Thesis Organization

This thesis is organized into five main chapters that collectively address the objectives and scope of the research. The structure is designed to ensure a logical progression from the introduction and theoretical foundations to the methodological framework, data analysis, and final conclusions. The contents of each chapter are outlined as follows:

1.7.1 Chapter One: Introduction

This chapter introduces the background and motivation for the study, emphasizing the importance of failure analysis and root cause investigation in the cement industry. It presents the problem statement, research objectives, research questions, hypotheses, and the scope and limitations of the study. The chapter also provides an overview of the research methodology and concludes with a description of the thesis structure.

1.7.2 Chapter Two: Literature Review

This chapter provides an in-depth review of the theoretical background and previous studies related to equipment failure, maintenance management, and reliability engineering within the context of cement manufacturing. It examines key analytical techniques such as Failure Modes and Effects Analysis (FMEA), Fault Tree Analysis (FTA), Root Cause Analysis (RCA), Reliability Metrics, and Weibull Analysis. The chapter identifies gaps in the existing body of knowledge, thereby establishing the foundation for the current research contribution.

1.7.3 Chapter Three: Research Methodology

This chapter outlines the research design and methodological framework adopted to achieve the study objectives. It explains the data collection process, equipment selection, and criteria for choosing case studies within the cement plant. Moreover, it describes the data analysis tools employed, including

Microsoft Excel, Google Colab, and IPython, as well as the analytical techniques applied for processing both quantitative and qualitative data. The rationale behind the chosen methods and their relevance to reliability and maintenance analysis are also discussed.

1.7.4 Chapter Four: Data Analysis and Discussion

This chapter presents the results and discussion of the collected data from 2017 to 2025. Multiple analytical techniques are applied Pareto Analysis, RCA (5 Whys and Fishbone Diagram), FMEA and FTA, Reliability Metrics (MTBF, MTTR, and Availability), and Weibull Analysis to evaluate the performance and reliability of critical cement plant equipment. The findings are interpreted in relation to the research objectives, emphasizing the identification of high-risk components, dominant failure modes, and underlying root causes. The results are illustrated using tables, charts, and diagrams for clarity and comprehension.

1.7.5 Chapter Five: Conclusions and Recommendations

This chapter summarizes the key findings of the research, highlighting its theoretical and practical implications. It presents the conclusions derived from the data analysis and provides strategic recommendations for improving maintenance performance and reliability in cement plants. Finally, the chapter suggests directions for future research, particularly in the areas of predictive maintenance, artificial intelligence applications, and data-driven decision-making in industrial reliability systems.

Chapter 2

Literature Review

2.1 Overview

This chapter establishes the conceptual foundation for the study by examining the existing body of knowledge on failure analysis, maintenance strategies, and equipment reliability management. It emphasizes the critical role of systematic diagnostics, structured analytical tools, and performance metrics in industrial environments particularly in cement manufacturing, where operational continuity depends on high asset utilization.

2.1.1 Evolution of Maintenance Strategies

Maintenance practices have evolved from reactive models focused on post-failure repair toward preventive, predictive, and reliability-centered maintenance approaches that integrate condition monitoring and data analytics[17].

This evolution has been driven by the need to:

1. **Minimize unplanned downtime**
2. **Extend asset life cycles**
3. **Enhance operational safety and cost efficiency** [18]

Traditional reactive maintenance, while still common in many plants, is being replaced by proactive frameworks supported by Computerized Maintenance Management Systems (CMMS) and Condition-Based Monitoring (CBM)[19]. Structured failure analysis techniques including Root Cause Analysis (RCA), Failure Modes and Effects Analysis (FMEA), and Fault Tree Analysis (FTA) are highlighted in the literature as essential for identifying systemic issues and preventing recurrence [17][20]. When integrated with reliability metrics such as Mean Time Between Failures (MTBF) and Availability, these tools provide a comprehensive perspective on asset performance. A key knowledge gap identified is the lack of integrated frameworks that combine qualitative diagnostics with quantitative reliability data to support predictive maintenance decision-making precisely the gap this study aims to address.

2.1.2 Critical Equipment in Cement Manufacturing

The cement manufacturing process relies on several critical mechanical systems whose reliability directly affects production continuity, energy efficiency, and product quality. The following summarizes the major units examined in this research and their predominant failure modes:

1. **Limestone (LS) Crusher** – Reduces raw limestone boulders to manageable feed sizes for downstream processing. This unit operates under heavy impact and abrasive conditions, frequently encountering hammer and liner wear, rotor imbalance, and chute blockages, which disrupt material flow and compromise kiln feed consistency [18].

2. **Vertical Roller Mill (VRM)** – Grinds raw materials into a fine powder prior to clinker production. Common reliability issues include roller bearing wear, hydraulic oil leakage, and gearbox overheating, each of which can impair grinding efficiency and adversely affect clinker quality [19].

3. **Rotary Kiln** – The core of the clinker production process, the rotary kiln operates under extreme thermal and mechanical loads. Typical failure modes involve refractory lining degradation, shell deformation, and drive system misalignment, which threaten both equipment integrity and process stability [17].

4. **Cement Mill No. 4** – Responsible for final grinding of clinker and gypsum into cement. This unit often faces scraper plate wear, separator and classifier inefficiency, gearbox and lubrication issues, and structural vibrations. These problems can lead to reduced mill output, elevated power consumption, and inconsistent product fineness, directly influencing overall plant performance [18].

5. **Belt Conveyor Systems** – Facilitate the continuous transfer of raw materials, intermediates, and finished products throughout the plant. Failures such as belt misalignment, idler seizure, and belt joint failure

can cause significant process interruptions and material handling inefficiencies, impacting multiple production stages [18].

The literature consistently recommends applying FMEA, RCA, and CBM to these assets, ideally integrated with real-time sensor data for predictive maintenance [19].

2.2 Failure Analysis Techniques

2.2.1 Pareto Analysis (80/20 Rule)

Pareto Analysis, also known as the 80/20 rule, is a decision-making technique that identifies the most impactful factors contributing to a problem or outcome. It suggests that 80% of effects come from 20% of causes. This principle helps prioritize efforts by focusing on the "vital few" factors that yield the greatest impact, rather than addressing all factors equally [11].

Key Concepts:

a. Pareto Principle: The core idea that a minority of causes (e.g., 20%) are responsible for the majority of effects (e.g., 80%).

b. Vital Few: The small number of causes that have the most significant impact.

c. Trivial Many: The larger number of causes that have a relatively small impact.

d. Prioritization: Pareto analysis allows for the prioritization of efforts by focusing on the vital few causes, leading to more efficient problem-solving.

How it works:

1. Identify and list problems: Document all relevant problems or factors contributing to a situation.
2. Determine the root cause: For each problem, identify the underlying causes.
3. Rank by impact: Score each problem based on its impact (e.g., financial, operational, etc.).

4. Group by cause: Organize the problems into categories based on their root causes.
5. Calculate cumulative impact: Determine the total impact of each cause by summing the scores of its associated problems.
6. Prioritize: Focus efforts on the causes with the highest cumulative impact, as these are likely to yield the greatest improvements.

Equation:

While there is no single governing equation, the cumulative percentage is calculated as follows:

Let f_i be the frequency (or cost) of the i-th category, ranked from highest to lowest. The total sum is $F = \sum_{i=1}^{n} f_i$. The cumulative frequency up to the k-th category is:

$$C_k = \sum_{i=1}^{k} f_i \qquad 2.1$$

The equation 4.2 cumulative percentage for the k-th category is then:

$$P_k = \left(\frac{C_k}{F}\right) \times 100\%. \qquad 2.2$$

Where:

- C_i = Cumulative percentage up to the i-th category.
- f_j = Frequency (or impact) of the j-th category.
- F = Total frequency (or total impact) of all categories.
- $\sum_{j=1}^{i} f_j$ = Sum of frequencies from the 1st to the i-th category.

The results are typically presented in a bar chart (categories in descending order) overlaid with a line graph representing the cumulative percentage. The point where the curve begins to flatten indicates the threshold of the most critical issues.

Used to prioritize high-impact failure causes by focusing on the "vital few" rather than the "trivial many." This method helps maintenance teams allocate resources efficiently.[11]

2.2.2 Root Cause Analysis (RCA)

Root Cause Analysis (RCA) is a structured and systematic approach aimed at identifying the fundamental causes behind equipment failures or operational issues. Unlike superficial troubleshooting methods that address only the immediate symptoms, RCA seeks to dig deeper into underlying problems that may contribute to recurrent or complex failures. It is widely regarded as a cornerstone of proactive maintenance management and forms an integral component of many reliability-centered maintenance (RCM) programs.

RCA identifies underlying causes of failures using tools such as the Fishbone Diagram and 5 Whys. It moves beyond symptom-level fixes, ensuring that corrective actions address systemic issues. RCA is most effective when supported by CMMS data and combined with quantitative tools such as FMEA.[17]

2.2.2.1 The 5 Whys Technique

This is an iterative interrogative technique used to explore the cause-and-effect relationships underlying a particular problem. The primary method involves asking "Why?" successively until the root cause is revealed. There is no definitive number; five is a rule of thumb.

Example:

1. *Why did the machine stop?* A bearing overheated and seized.
2. *Why did the bearing overheat?* It was not adequately lubricated.
3. *Why was it not adequately lubricated?* The lubrication pump was not functioning.
4. *Why was the pump not functioning?* Its drive shaft was worn and corroded.
5. *Why was the shaft worn and corroded?* The pump was not included in the preventive maintenance schedule due to an oversight.[17]

2.2.2.2 The Fishbone (Ishikawa) Diagram

Also known as a cause-and-effect diagram, this tool provides a systematic way to brainstorm and categorize all potential causes of a problem. The problem (effect) is stated at the "head" of the fish. Potential causes are then grouped into major categories (the "bones"), typically referred to as the (6 Ms):

1. **M**achine (equipment, technology)
2. **M**ethod (process, procedure)
3. **M**aterial (raw inputs, consumables)
4. **M**anpower (people, human factors)
5. **M**easurement (inspection, data collection)
6. **M**other Nature (environment)

This visual tool same as in Figure 2.1 The Fishbone (Ishikawa) Diagram Sample ensures a comprehensive exploration of all possible sources of variation leading to the failure.[17]

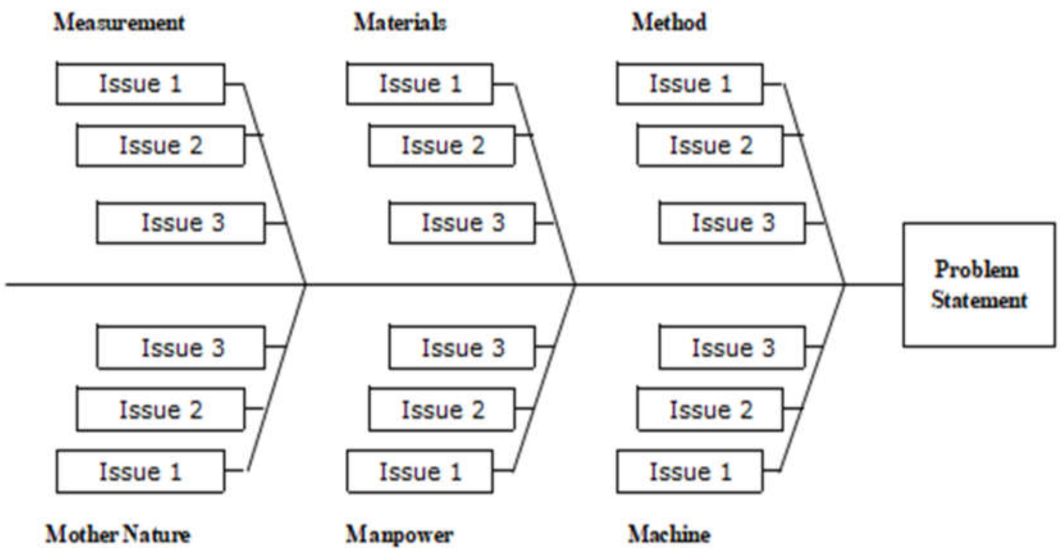

Figure 2.1 The Fishbone (Ishikawa) Diagram Sample

2.2.3 Failure Modes and Effects Analysis (FMEA)

Failure Modes and Effects Analysis (FMEA) is a structured, proactive methodology designed to identify potential failure modes in equipment or processes, evaluate their effects, and prioritize mitigation actions. Its primary objective is to enhance safety, reliability, maintainability, and operational efficiency by anticipating issues before they occur. FMEA is widely applied across industries including manufacturing, aerospace, and cement production, particularly for critical equipment where unplanned downtime carries high operational or safety risks.

Key Components:

FMEA assesses each potential failure mode using three critical criteria:

1. Severity (S): Measures the impact of the failure on operations, safety, or product quality if it occurs.
2. Occurrence (O): Estimates the likelihood or frequency of the failure mode happening.
3. Detection (D): Evaluates the probability that existing controls will detect the failure before it causes adverse effects.

These three indices are combined to calculate the Risk Priority Number (RPN):

$$RPN = S \times O \times D \qquad 2.3$$

Where:

- S = **Severity** (1-10): The seriousness of the effect of the failure.
- O = **Occurrence** (1-10): The likelihood of the failure occurring.
- D = **Detection** (1-10): The ability to detect the failure before it impacts the system.

Failure modes with higher RPN values are given the highest priority for corrective action. The RPN provides a quantitative ranking of risk, guiding maintenance planners and engineers in prioritizing corrective actions. High RPN values indicate critical failure modes that require immediate attention, while lower values may be monitored or addressed through routine measures.

Standard FMEA Sheet Template:

Failure Mode and Effects Analysis Worksheet

Process or Product: ______________________ FMEA Number: ______
FMEA Team: ______________________ FMEA Date: (Original) ______
Team Leader: ______________________ (Revised) ______
Page: 1 of 1

	FMEA Process													Action Results				
Line	Component and Function	Potential Failure Mode	Potential Effect(s) of Failure	Severity	Potential Cause(s) of Failure	Occurrence	Current Controls, Prevention	Current Controls, Detection	Detection	RPN	Recommended Action	Responsibility and Target Completion Date	Action Taken	Severity	Occurrence	Detection	RPN	
1																		
2																		
3																		
4																		
5																		
6																		
7																		
8																		
9																		
10																		

Figure 2.2 Failure Mode and Effects Analysis Worksheet

Notes:

- Severity (S), Occurrence (O), Detection (D) are typically scored on a 1–10 scale, with 10 being most severe/likely/difficult to detect.
- RPN thresholds can be used to classify risks as high, medium, or low, guiding prioritization of corrective actions.
- The FMEA sheet should be updated periodically to reflect real operational experience and new failure insights.
- Other sheet in appendix.

2.2.4 Fault Tree Analysis (FTA)

Fault Tree Analysis (FTA) is a deductive, top-down methodology used to analyze the pathways that can lead to a predefined undesirable event, such as equipment failure or system malfunction. This technique is particularly effective for complex and highly integrated systems, making it valuable in industries such as aerospace, nuclear energy, and cement manufacturing, where understanding failure logic is crucial.

FTA begins with the identification of a top-level failure event. From there, analysts construct a tree diagram using Boolean logic gates (e.g., AND, OR) to illustrate the combinations of lower-level failures or faults that may contribute to the occurrence of the top event. This graphical representation enables a comprehensive visualization of potential failure routes and their logical interdependencies.[13]

The development of fault trees has evolved over decades from being considered an *art form* dependent on the analyst's intuition to becoming a structured, rule-based engineering method. Adherence to these rules ensures that the resulting fault tree accurately reflects the logical and functional relationships between system events.

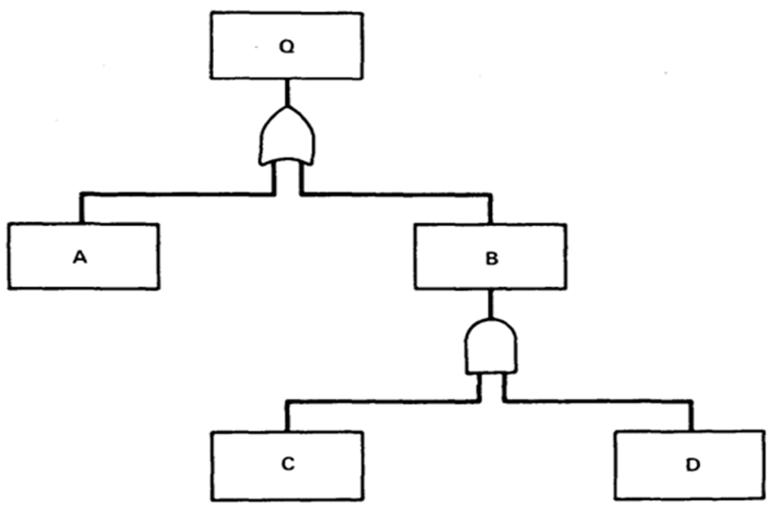

Figure 2.3 Simple Fault Tree Sample

Figure 2.3 illustrates a simple fault tree, which may represent a complete system or a subsection of a more complex model. In this diagram, the top event is labeled Q, and the contributing events are A, B, C, and D. The logic gates define how these lower-level faults interact to produce the top-level failure.

Key Equation for Probability Calculation: For an OR gate, the probability of the output event (P(OR)) is calculated as:

$$P(OR) = 1 - \prod_{i=1}^{n}(1 - P(A_i)) \qquad 2.4$$

Where $P(A_i)$ is the probability of the i-th input event.

For an AND gate, the probability of the output event (P(AND)) is:

$$P(AND) = \prod_{i=1}^{n} P\,(A_i) \qquad 2.5$$

The probability equations in Fault Tree Analysis describe how the likelihood of the top event is determined based on the probabilities of its contributing lower-level events.

For an OR gate, Equation (2.4) expresses that the probability of the output event, P(OR), is equal to one minus the product of the probabilities that each input event does *not* occur. This means that the top event happens if any one or more of the input events occur. Hence, as the number of possible input failures increases, the overall probability of system failure also increases.

For an AND gate, Equation (2.5) indicates that the probability of the output event, P(AND), is the product of the probabilities of all input events. This implies that the top event will occur only when all contributing input events take place simultaneously. Consequently, the combined probability is usually smaller than that of individual events, reflecting the reduced likelihood of multiple simultaneous failures.[13]

These equations form the mathematical foundation of quantitative FTA, allowing analysts to estimate the overall system failure probability by logically combining the probabilities of component-level failures.

However, the effectiveness of FTA is highly dependent on the availability and quality of input data. The technique requires detailed and accurate information about system configurations, operational conditions, and historical failure events to yield reliable outcomes. According to Ericson (2005) [5], insufficient data can lead to misleading or incomplete trees, undermining the credibility of the analysis.

2.4 Reliability Metrics

2.4.1 Mean Time Between Failures (MTBF)

Mean Time Between Failures (MTBF) is a key reliability metric that measures the average elapsed time between two consecutive failures of a repairable component or system during normal operation. It is typically calculated in equation 2.6 by dividing the total operational time by the number of failures observed over a specific period:

$$\mathrm{MTBF} = \frac{\text{Total Operational Time}}{\text{Number of Failures}} \qquad 2.6$$

This metric serves as a fundamental indicator of a system's reliability and is widely used to benchmark performance in asset-intensive industries. A higher MTBF value generally implies greater reliability, suggesting that the system or component can function for longer durations without failure [19].

In industrial maintenance planning, MTBF is instrumental in predicting the likelihood of failures and scheduling preventive maintenance tasks before breakdowns occur. For example, if the MTBF of a conveyor motor is known to be 500 hours, maintenance teams can plan inspections or part replacements just before reaching this threshold to reduce the risk of unplanned downtime.

Furthermore, MTBF can be used to compare the reliability of different machines, suppliers, or maintenance strategies. It is especially useful in evaluating the impact of corrective actions taken after failure events. If the MTBF of a piece of equipment improves over time, it can indicate that recent maintenance improvements or design changes have been effective [18].

However, MTBF has its limitations. It assumes that failures occur randomly and that the system is restored to full functionality after each repair, which may not always be realistic. Additionally, it should not be used in isolation. When combined with other metrics such as Mean Time To Repair (MTTR) and Availability, MTBF offers a more comprehensive view of asset performance and reliability.

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2.4.2 Mean Time to Repair (MTTR)

Mean Time to Repair (MTTR) is a key maintainability metric that quantifies the average time required to diagnose, repair, and restore a failed component or system to its fully operational state. It is calculated using the formula:

$$MTTR = \frac{\text{Total Downtime due to Repair}}{\text{Number of Failures}} \qquad 2.7$$

This metric plays a pivotal role in assessing the responsiveness and efficiency of maintenance operations. A lower MTTR value indicates faster recovery from failures, thereby reducing equipment downtime and improving overall system availability. In industries like cement manufacturing, where production continuity is critical, minimizing MTTR can result in substantial gains in throughput and cost reduction [19].

MTTR includes all activities involved in the repair process, such as fault detection, diagnosis, logistics delay, actual repair, testing, and verification. Therefore, it provides insights into the effectiveness of maintenance procedures, staff readiness, spare parts availability, and the efficiency of repair workflows.

According to Smith and Hinchcliffe (2004) [18], MTTR should be analyzed in conjunction with Mean Time Between Failures (MTBF) to gain a holistic view of system reliability and maintainability. For instance, even if a component fails frequently (low MTBF), a consistently low MTTR can help maintain high equipment availability.

Modern maintenance practices aim to reduce MTTR through several strategies, including:

a. Standardization of repair procedures
b. Training and cross-skilling of maintenance personnel
c. Deployment of advanced diagnostic tools and sensors
d. Improved spare parts inventory management

Moreover, real-time data from Computerized Maintenance Management Systems (CMMS) and Internet of Things (IoT) sensors can be leveraged to automate fault detection and accelerate repair initiation, further driving down MTTR.

In conclusion, MTTR is not just a measure of repair time but a strategic indicator of the agility and efficiency of a maintenance system. Its optimization is essential for enhancing equipment readiness, sustaining high availability, and supporting long-term asset performance.

2.4.3 Availability

Availability is a crucial metric in equipment performance evaluation, reflecting the proportion of total time that a system or asset is capable of functioning as required. It integrates both reliability and maintainability into a single measure, offering a comprehensive view of equipment readiness over time. The standard formula used to calculate availability is:

$$A = \frac{\text{MTBF}}{\text{MTBF+MTTR}} \qquad 2.8$$

This formula expresses availability as a percentage, where higher values signify that equipment is operational most of the time, contributing positively to production goals. In environments such as cement manufacturing, where continuous operation is vital, high availability directly translates to improved output, reduced costs, and fewer disruptions.[19]

There are different types of availability, each useful in specific contexts:

i. Inherent Availability (Ai): Based solely on design reliability and maintainability (MTBF and MTTR), without considering external influences.

ii. Achieved Availability (Aa): Based on actual maintenance support and performance.

iii. Operational Availability (Ao): Takes into account all sources of downtime, including administrative and logistical delays.

Monitoring and improving availability enables maintenance planners to identify bottlenecks in operations, optimize resource allocation, and refine preventive maintenance schedules. As such, availability is a core metric in reliability-centered maintenance (RCM) and Total Productive Maintenance (TPM) frameworks [18]. in equipment performance evaluation, reflecting the proportion of total time that a system or asset is capable of functioning as required. It integrates both reliability and maintainability into a single measure, offering a comprehensive view of equipment readiness over time.

2.5 Weibull Analysis

Is a statistical tool used to model the time-to-failure distribution of components. It is characterized by two key parameters: the shape parameter (β) and the scale parameter (η). When β > 1, the component exhibits a wear-out failure pattern, meaning failures become more likely as the equipment ages. This insight helps in optimizing preventive maintenance intervals [35].

a. Shape parameter (β): Indicates the type of failure behavior.

i. β < 1: Infant mortality (early failures due to design flaws, installation issues).

ii. β = 1: Random failures (constant failure rate, exponential distribution).

iii. β > 1: Wear-out failures (increasing failure rate with age).

b. Scale parameter (η) (characteristic life): The time at which 63.2% of units will have failed.[32]

c. Reliability Function:

$$R(t) = e^{-(t/\eta)^{\beta}} \qquad 2.9$$

Where: t = time to failure

$R(t)$ = probability the item will survive beyond time t

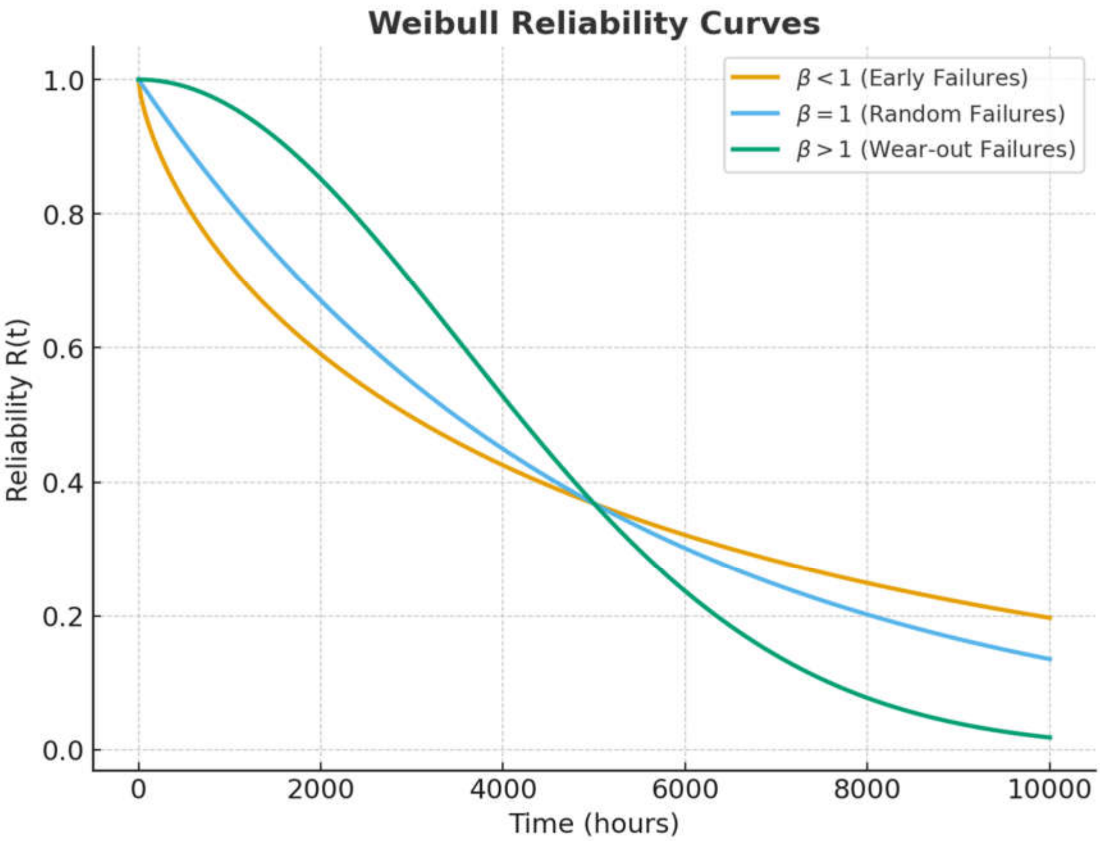

Figure 2.4: Weibull reliability curves

d. The Reliability Curve (Figure2.4 Above)

The graph shows three Weibull reliability curves with the same characteristic life (η = 5000 hrs) but different β values:

- Orange Curve ($\beta < 1$) → Early failures; reliability drops fast initially then levels off.
- Blue Curve ($\beta = 1$) → Constant rate; exponential decay typical of random failures.
- Green Curve ($\beta > 1$) → Gradual decline followed by rapid wear-out; typical of aging or fatigue.

2.6 Google Colab and IPython in Data Analysis

In this research, analyzing large-scale maintenance data from a cement plant spanning 2017 to 2025 requires computational tools capable of handling both quantitative and qualitative data efficiently. To achieve this, we employed Google Colab and IPython, two versatile tools that provide an interactive and robust programming environment for data-driven research.

2.6.1. Google Colab

Google Colaboratory (Colab) is a cloud-based platform provided by Google that allows users to write, execute, and share Python code via a web interface. It is particularly suited for large-scale data analysis and machine learning tasks.

Key Features and Advantages:

1. **Cloud-Based Execution:**

Google Colab runs code on Google's servers, providing access to substantial computing resources, including CPU, GPU, and TPU, without requiring high-end local hardware. This is crucial for handling the large dataset of maintenance logs efficiently.

2. **Interactive Environment:**

Colab supports notebook-style interaction, which allows researchers to execute code in small chunks (cells), immediately view outputs, and iteratively refine analyses. This feature is particularly beneficial when performing exploratory data analysis or stepwise reliability calculations.

3. **Integration with Python Libraries:**

Colab seamlessly integrates with popular Python libraries such as:

- **Pandas**: for structured data manipulation.
- **NumPy**: for numerical computations.
- **Matplotlib and Seaborn**: for visualization.
- **SciPy**: for statistical and reliability analysis.

- **Scikit-learn**: for machine learning applications, if predictive analysis is needed.

4. **Data Handling Capabilities:**

Large Excel datasets can be uploaded directly or accessed from Google Drive. Colab provides flexible mechanisms for reading, cleaning, and merging multiple datasets, which is essential for analyzing historical maintenance records across different equipment.

5. **Collaboration and Reproducibility:**

Colab notebooks can be easily shared with colleagues or supervisors. They maintain reproducibility because code, results, and visualizations are stored together, reducing errors in data interpretation.

Application in This Research:

- Aggregating maintenance records across different units (LS Crusher, Raw Mill, Rotary Kiln, Cement Mill).
- Automating statistical calculations, Pareto charts, Weibull distributions, and reliability metrics.
- Enabling reproducible analyses for failure investigation and root cause analysis.

2.6.2. IPython

IPython (Interactive Python) is an enhanced interactive shell for Python that provides powerful features for interactive computing, debugging, and data visualization.

Key Features and Advantages:

1. **Interactive Computing:**

IPython allows executing Python code **line by line** and observing immediate outputs. This is critical when testing and validating data analysis steps, such as filtering datasets or calculating Mean Time Between Failures (MTBF) and Risk Priority Numbers (RPN).

2. **Rich Output and Visualization:**

IPython supports inline plotting and rich media outputs, including charts, graphs, tables, and LaTeX equations. For instance, Weibull reliability functions, failure rate curves, and FMEA results can be visualized directly within the interface.

3. **Magic Commands:**

IPython includes “magic commands” that enhance productivity, such as %timeit for performance profiling, %matplotlib inline for plotting, and %load for loading external scripts. These commands streamline data exploration and analysis.

4. **Integration with Jupyter Ecosystem:**

IPython forms the core of Jupyter notebooks and Google Colab, enabling:

    - Execution of Python code.
    - Direct documentation with Markdown.
    - Embedding of charts, equations, and tables in a single notebook.

5. **Debugging and Profiling Tools:**

IPython’s integration with debugging tools allows detailed investigation of code execution, which is essential when performing failure root cause analysis to ensure accuracy in calculations and visualizations.

Application in This Research:

- Stepwise execution of analytical techniques like FMEA, FTA, Pareto, and Weibull analysis as shown in Figure 2.5.
- Testing and validating data manipulation steps before integrating them into larger Colab workflows.
- Interactive plotting of reliability curves and failure distributions for different equipment types.

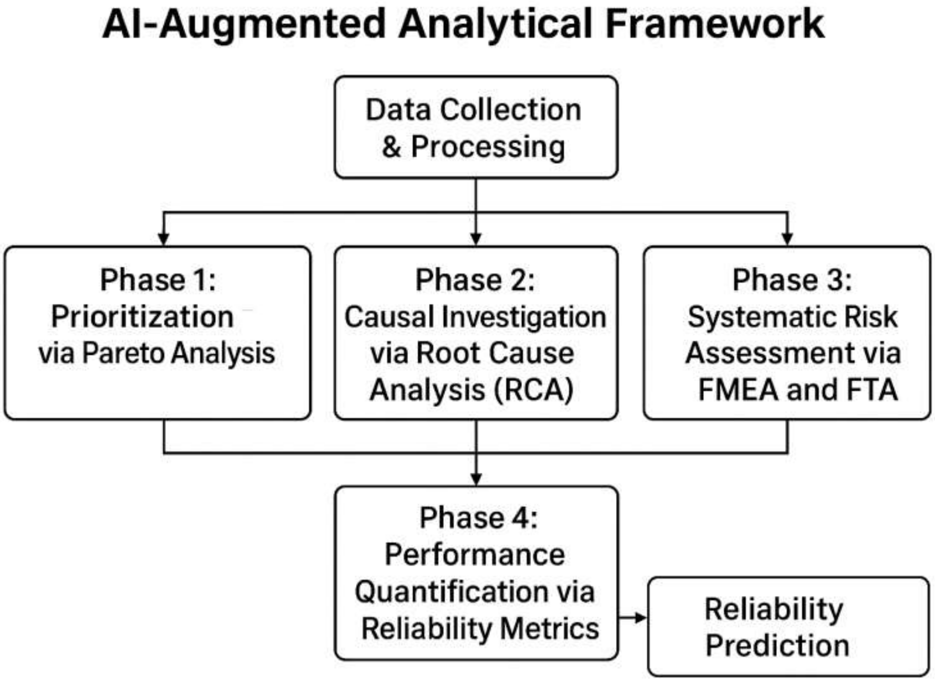

Figure 2.5: AI- Analytical Framework

2.7 Gaps in Existing Research

A comprehensive review of existing literature on maintenance optimization and reliability engineering in the cement industry reveals several key gaps. While numerous studies have explored individual tools such as FMEA, RCA, and condition monitoring, few have effectively integrated these techniques into a unified, data-driven reliability framework. The following subsections summarize the most critical deficiencies that this research aims to address.

2.7.1 Limited Integration of FMEA with Actual Maintenance Logs

Failure Modes and Effects Analysis (FMEA) remains one of the most widely adopted tools for assessing equipment risk and prioritizing corrective actions. However, in most published studies and industrial applications, FMEA relies heavily on subjective expert judgment rather than empirical evidence drawn from Computerized Maintenance Management Systems (CMMS) or real-time condition monitoring data.

This lack of integration limits its accuracy and relevance to actual operational conditions. Risk Priority Numbers (RPNs) derived solely from experience may not reflect the true frequency or severity of failure events. As a result, maintenance strategies based on such analyses may misallocate resources or fail to prevent recurrent failures.

A more advanced approach linking FMEA parameters (Severity, Occurrence, Detection) to quantitative reliability metrics such as MTBF, failure probability, or Weibull-derived parameters can significantly enhance the precision of risk prioritization. Yet, this integration remains underexplored in cement manufacturing literature, creating a substantial methodological gap that this research seeks to fill.

2.7.2 Underutilization of Predictive Analytics in Cement Plants

Although Industry 4.0 technologies such as IoT sensors, machine learning, and digital twins have transformed maintenance practices in other sectors, their application in the cement industry remains limited. Predictive maintenance (PdM) frameworks, which leverage real-time data to anticipate failures, are still in their infancy within this sector.

Existing studies often focus on reactive or preventive maintenance, with minimal emphasis on data-driven predictive modeling. Several barriers have been identified, including:

- High initial investment costs for digital infrastructure,
- Limited technical expertise and data analytics skills among plant personnel, and
- Lack of integrated decision-support systems capable of synthesizing multi-source data (e.g., vibration, temperature, CMMS logs).

Furthermore, there has been little attempt to adapt and validate AI-based predictive models successfully applied in industries such as oil and gas, power generation, and aviation to the operational realities of cement manufacturing. The transfer and contextualization of such models represent a major research opportunity, capable of significantly improving equipment reliability and minimizing unplanned downtime.

2.7.3 Lack of Holistic Frameworks Combining Reliability Tools

Most existing studies treat RCA, FMEA, FTA, and Weibull Analysis as independent analytical methods rather than as complementary components of a unified reliability system. This fragmented approach hinders the development of a complete understanding of failure mechanisms and their interdependencies.

An integrated framework linking failure mode identification (FMEA), cause analysis (RCA), fault logic modeling (FTA), and statistical reliability estimation (Weibull Analysis)—remains largely absent in the literature. Bridging this gap would enable predictive and prescriptive maintenance strategies that are both data-informed and operationally grounded.

Chapter 3

Research Methodology

3.1 Introduction

This chapter delineates the comprehensive research methodology employed to achieve the objectives of this thesis. The primary aim is to establish a robust, data-driven framework for analyzing equipment reliability and identifying root causes of failures within a cement manufacturing plant. To ensure a rigorous and validated interpretation, the research design integrates a systematic sequence of data processing and analytical techniques. The methodology is bifurcated into two primary phases: (1) **Data Acquisition and Processing**, which details the dataset characteristics and the computational tools used for management and preparation; and (2) **Analytical Framework**, which outlines the sequential application of five core analytical techniques Pareto Analysis, Root Cause Analysis (RCA), Failure Mode and Effects Analysis (FMEA) alongside Fault Tree Analysis (FTA), Reliability Metrics, and Weibull Analysis. The seamless execution of this methodology was facilitated by advanced, AI-assisted computational platforms, ensuring accuracy, reproducibility, and depth of insight.

3.2 Data Acquisition and Preprocessing

3.2.1 Dataset Description

The study is grounded in a substantial dataset spanning nine years, from **2017 to 2025**, comprising historical maintenance and operational records from a cement production facility.

The data encompasses both quantitative measures (e.g., time-to-failure, downtime duration, repair hours) and qualitative descriptions (e.g., failure modes, maintenance actions, expert observations) for critical equipment, including:

- Limestone Crusher (LS Crusher)
- Raw Mill
- Rotary Kiln

- Cement Mill
- Associated subsystems (e.g., belt conveyors)

This comprehensive dataset provides the foundational evidence required for a multi-faceted reliability and risk analysis.

3.2.2 Data Processing Tools and Environment

To manage the volume and complexity of the dataset, the analysis was conducted using powerful, flexible, and AI-assisted computational environments. The primary platforms were Google Colab and IPython, which provide cloud-based processing capabilities ideal for executing Python-based data models, statistical computations, and generating visualizations.

The data processing leveraged a suite of Python libraries to ensure efficiency and accuracy:

- **Pandas** was used for data ingestion, cleaning, filtering, and time-series aggregation.
- **NumPy** facilitated numerical operations and mathematical computations.
- **Matplotlib** and **Seaborn** were employed for generating static, animated, and interactive visualizations.
- **SciPy** and specialized libraries like Reliability were used for advanced statistical modeling, including parameter estimation for Weibull analysis.

This integrated toolset enabled a seamless workflow from raw data preprocessing to the implementation of complex analytical models, ensuring the entire process was reproducible, transparent, and scalable.

3.3 Analytical Framework Using Google Colab & IPython

The analytical framework is implemented using Google Colab — a cloud-based Python environment that supports scientific computing, data analysis, and visualization using libraries like *pandas*, *numpy*, *matplotlib*, and *scipy*.

The analysis follows a logical, sequential workflow, moving from data prioritization to failure modeling, as visualized in Figure 3.1.

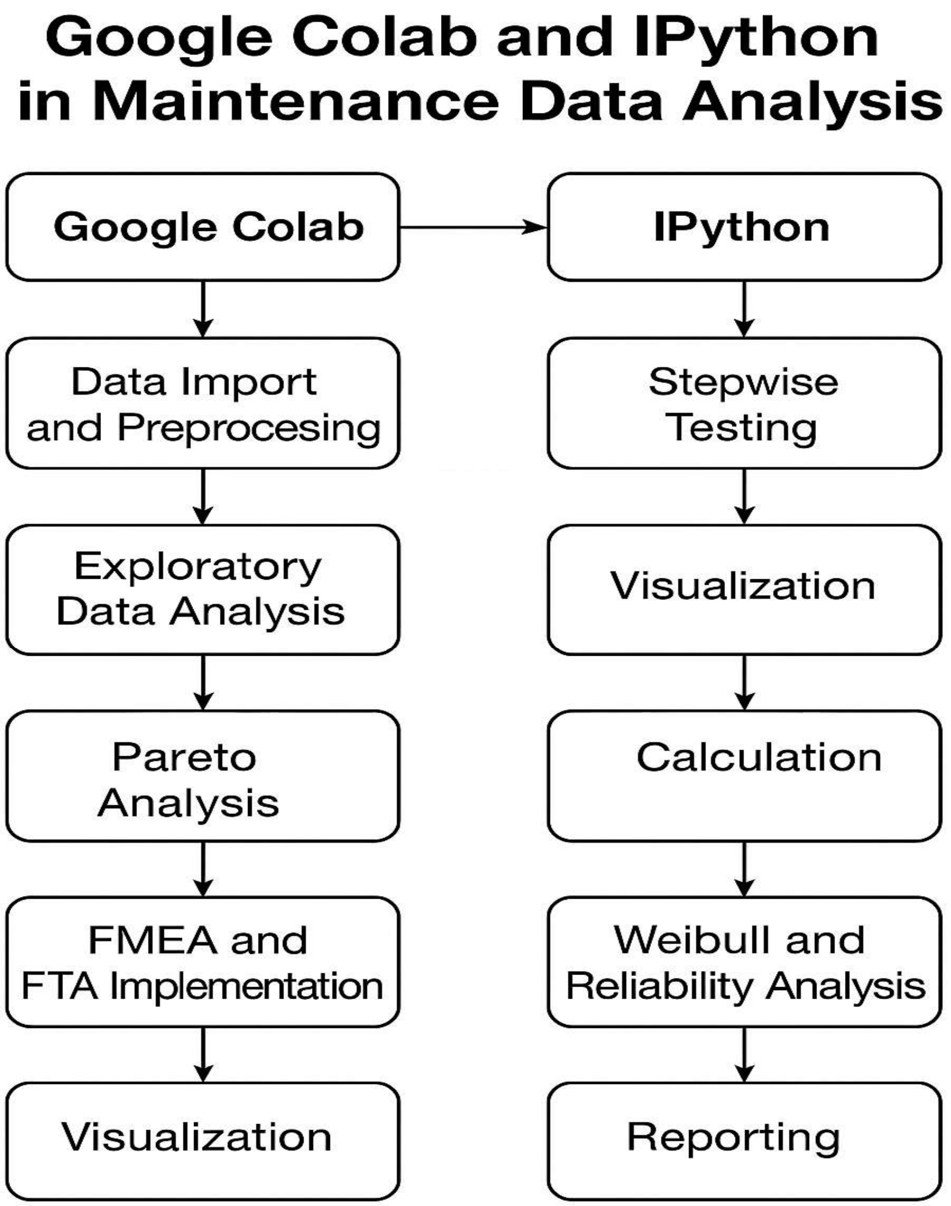

Figure 3.1: The sequential research methodology, from data processing through to reliability modeling and prediction

3.3.1 Tools Setup in Google Colab

Step 1: Environment Preparation

Open a new Google Colab notebook and run the following code block:

```python
# Mount Google Drive to access dataset
from google.colab import drive
drive.mount('/content/drive')

# Import essential libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import weibull_min

# Set dataset path (example)
data_path = '/content/drive/MyDrive/MaintenanceData/failure_data.xlsx'

# Load dataset
df = pd.read_excel(data_path)

# Display first few rows
df.head()
```

3.3.2 Phase 1: Prioritization via Pareto Analysis

Objective: Identify the "vital few" failure modes causing the majority of downtime.
Method: Apply Pareto Principle (80/20 rule).

Procedure:

1. Group failure records by *Equipment Name* or *Failure Mode*.
2. Sum total downtime for each category.
3. Rank categories and calculate cumulative percentages.
4. Plot Pareto chart.

Colab Code Example:

```python
# Group by equipment name and calculate total downtime
pareto_df = df.groupby('Equipment Name')['Activity total Hours'].sum().sort_values(ascending=False

# Compute cumulative percentage
pareto_df = pareto_df.reset_index()
pareto_df['Cumulative %'] = pareto_df['Activity total Hours'].cumsum() / pareto_df['Activity tota

# Plot Pareto chart
fig, ax = plt.subplots()
ax.bar(pareto_df['Equipment Name'], pareto_df['Activity total Hours'], color='skyblue')
ax2 = ax.twinx()
ax2.plot(pareto_df['Equipment Name'], pareto_df['Cumulative %'], color='red', marker='D')
ax2.axhline(80, color='green', linestyle='--')
plt.xticks(rotation=90)
plt.title('Pareto Analysis of Equipment Downtime')
plt.show()
```

Interpretation:

The bars to the left contributing up to ~80% of downtime represent the most critical equipment for further analysis.

3.3.3 Phase 2: Causal Investigation via RCA (5 Whys & Fishbone Diagram)

Objective: Identify root causes behind top failures from Pareto results.

Steps in IPython:

1. Select top critical equipment.
2. Apply iterative *5 Whys* questioning.
3. Construct Fishbone diagram for visualization.

Colab / IPython Implementation Example:

```python
# Define 5 Whys function
def five_whys(problem, causes):
    print(f"Problem: {problem}")
    for i, cause in enumerate(causes, start=1):
        print(f"Why {i}? -> {cause}")

# Example
problem = "Frequent Belt Conveyor Failures"
causes = [
    "Misalignment of rollers",
    "Improper maintenance schedule",
    "Lack of predictive monitoring",
    "No vibration sensor installed",
    "Ineffective maintenance planning system"
]

five_whys(problem, causes)
```

Fishbone Diagram (using matplotlib)

```python
!pip install fishbone
from fishbone import FishBone

categories = {
    "Man": ["Lack of training"],
    "Machine": ["Bearing wear", "Belt slippage"],
    "Method": ["Improper lubrication schedule"],
    "Material": ["Low-quality spare parts"],
    "Measurement": ["Inaccurate inspection tools"],
    "Environment": ["Dust contamination"]
}

FishBone(problem, categories)
```

Interpretation:

The RCA reveals interlinked mechanical and procedural issues leading to repeated breakdowns.

3.3.4 Phase 3: Systematic Risk Assessment (FMEA & FTA)

(a) FMEA Implementation

Objective: Quantify risks by computing the **Risk Priority Number (RPN = S × O × D)**.

```python
# Example FMEA dataset
fmea_data = {
    'Failure Mode': ['Bearing failure', 'Belt tear', 'Motor overheating'],
    'Severity': [8, 7, 9],
    'Occurrence': [6, 5, 4],
    'Detection': [3, 4, 5]
}
fmea_df = pd.DataFrame(fmea_data)
fmea_df['RPN'] = fmea_df['Severity'] * fmea_df['Occurrence'] * fmea_df['Detection']
fmea_df.sort_values('RPN', ascending=False)
```

(b) Fault Tree Analysis (FTA)

Objective: Model logical dependencies between sub-failures using Boolean logic.

Example IPython Simulation:

```python
# Define logic for fault combinations
def AND_gate(*args):
    return all(args)

def OR_gate(*args):
    return any(args)

# Example: LS Crusher shutdown
mechanical_failure = True
operational_failure = False

top_event = AND_gate(mechanical_failure, operational_failure)
print(f"System Shutdown (Top Event) = {top_event}")
```

Interpretation:
FTA allows identifying critical combinations leading to total system failure.

3.3.5 Phase 4: Performance Quantification via Reliability Metrics

Objective: Compute MTBF, MTTR, and Availability from maintenance logs.

Procedure:

1. Calculate time between failures per equipment.
2. Calculate repair duration.
3. Compute key metrics.

Code Example:

```python
# Example reliability calculations
df['Failure Date'] = pd.to_datetime(df['date of activity'])
df = df.sort_values('Failure Date')

# Compute MTBF and MTTR
MTBF = df['Activity total Hours'].mean()
MTTR = 3.5  # example repair hours from log
Availability = MTBF / (MTBF + MTTR)

print(f"MTBF = {MTBF:.2f} hrs")
print(f"MTTR = {MTTR:.2f} hrs")
print(f"Availability = {Availability:.3f}")
```

Interpretation:
Availability values closer to 1 indicate highly reliable equipment.

3.3.6 Phase 5: Lifetime Data Modeling via Weibull Analysis

Objective: Fit Weibull distribution to failure data to model component lifetime and predict reliability.

Steps:

1. Collect time-to-failure data for a component.
2. Estimate shape (β) and scale (η) parameters.
3. Plot Weibull PDF and Reliability Function R(t).

Colab Code:

```python
# Example time-to-failure data
failure_times = np.array([1800, 2400, 3000, 4000, 5200, 6000])

# Fit Weibull distribution
shape, loc, scale = weibull_min.fit(failure_times, floc=0)
beta, eta = shape, scale

print(f"Shape parameter (β): {beta:.2f}")
print(f"Scale parameter (η): {eta:.2f}")

# Reliability Function R(t)
t = np.linspace(0, 7000, 100)
R_t = np.exp(-(t/eta)**beta)

# Plot Weibull Reliability Curve
plt.plot(t, R_t)
plt.title('Weibull Reliability Function R(t)')
plt.xlabel('Operating Time (hours)')
plt.ylabel('Reliability R(t)')
plt.grid(True)
plt.show()
```

Interpretation:

The curve shows the probability of survival versus operating time, helping predict preventive maintenance intervals.

3.3.7 Integration Summary

Table 3.1: Integration Technique Summary

Phase	Technique	AI / Analytical Tool	Output
1	Pareto Analysis	Pandas + Matplotlib	Ranked list of critical equipment
2	RCA (5 Whys & Fishbone)	IPython interactive cells	Root causes identified
3	FMEA & FTA	Pandas + Logic Functions	RPN table & logical fault model
4	MTBF, MTTR, Availability	Pandas	Equipment KPIs
5	Weibull Analysis	SciPy + Matplotlib	Reliability prediction curve

Note:

In the appendices, there is a complete system of analytical framework.

Chapter 4:

Data Analysis and Results

4.0 Introduction

This chapter presents the results of the data analysis conducted on the cement plant's critical equipment, following the rigorous methodology outlined in Chapter 3. The primary objective is to transition from raw maintenance data to actionable insights, identifying dominant failure modes, establishing their root causes, quantifying their impact on reliability, and formulating predictive maintenance strategies. The analysis for each major equipment unit beginning here with the Limestone (LS) Crusher systematically applies the suite of analytical techniques: Pareto Analysis for prioritization, Root Cause Analysis (RCA) for causal investigation, Failure Mode and Effects Analysis (FMEA) and Fault Tree Analysis (FTA) for risk assessment, core Reliability Metrics for performance quantification, Weibull Analysis for lifetime modeling, and the proposal of a Condition-Based Monitoring (CBM) framework. The findings provide a data-driven foundation for the recommendations aimed at enhancing operational reliability and efficiency, which will be detailed in Chapter 5.

4.1 Limestone Crusher Analysis (Equipment No. 1102)

The LS Crusher is a primary and critical unit in the raw material preparation circuit. An analysis of its maintenance records from January 2017 to January 2025, encompassing 613 entries, revealed over 650 failure incidents, leading to significant downtime and repair costs.

4.1.1 Failure Frequency and Pareto Analysis

An initial failure frequency analysis categorized the predominant issues. To prioritize efforts, a Pareto Analysis was performed, ranking failure types by their occurrence. The results, summarized in Table 4.1and Figure 4.1, confirm the Pareto Principle, with the top five failure categories accounting for 60.2% of all documented issues.

Table 4.1: LS Crusher Failure Frequency and Pareto Ranking

Failure Type	Frequency	% of Total	Cumulative %
Liner Plate Issues	59	24.3%	24.3%
Bolt Failures	36	14.8%	39.1%
Welding Repairs	22	9.1%	48.2%
Greasing / Lubrication	15	6.2%	54.4%
Blow Bar Adjustments	14	5.8%	60.2%
V-Belt Replacements	11	4.5%	64.7%
Gap Adjustments	11	4.5%	69.2%
Hydraulic Failures	10	4.1%	73.3%
Impact Liner Issues	10	4.1%	77.4%
Bearing Work	9	3.7%	81.1%
Miscellaneous	56	23.0%	100.0%
Total	**243**	**100%**	

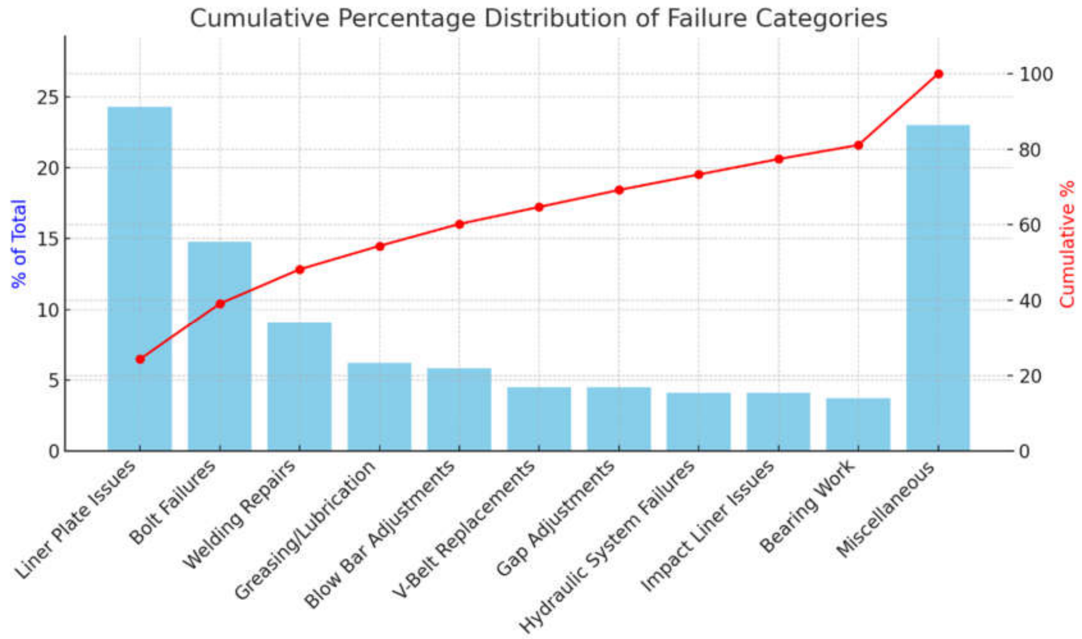

Figure 4.1: LS Crusher Pareto Curve

The 'vital few' failure modes—Liner Plate Issues, Bolt Failures, Welding Repairs, Greasing, and Blow Bar Adjustments—were selected for deeper investigation via Root Cause Analysis.

4.1.2 Root Cause Analysis (RCA)

A two-pronged RCA approach, using the 5 Whys technique and Fishbone Diagram, was applied to the top failures.

4.1.2.1 Fishbone Diagram Summary:

The analysis identified root causes across six key categories in Figure 4.2:

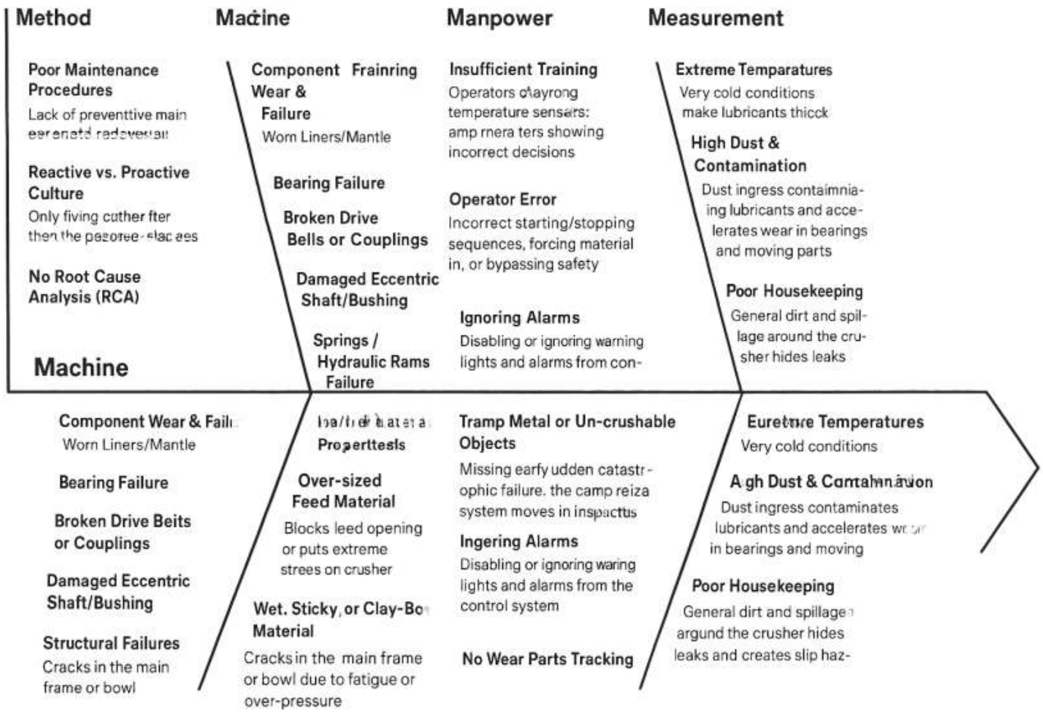

Figure 4.2: Fishbone Diagram for LS Crusher

4.1.2.2 Five Whys Analysis:

The Five Whys technique drilled down into specific failures, as summarized in Table 4.2.

Table 4.2: LS Crusher 5 Whys Analysis Failures

Failure	Root Cause Analysis Sequence	Root Cause Summary
Liner Plate Failure	Missing bolts → Not retightened → No inspection protocol → PM planning lacking → Risk assessment oversight.	Absence of scheduled bolt inspections

Failure	Root Cause Analysis Sequence	Root Cause Summary
Bolt Failures	Fatigue from vibration → Misalignment → No alignment checks → No SOP → Training gaps.	Misalignment and absence of SOP for torqueing
Hydraulic Leaks	Seal degradation → Contamination/overpressure → No oil change schedule → PM excludes hydraulics.	Poor hydraulic oil management
V-Belt Failures	Misalignment/overload → Poor pulley installation → No alignment tools → Technicians not equipped.	Pulley misalignment due to tool unavailability
Chute Cracking	Impact stress → Thin plates/poor welds → No design feedback → Reactive fixes dominate.	Weak structural design and weld quality

4.1.3 Failure Mode and Effects Analysis (FMEA) and Fault Tree Analysis (FTA)

4.1.3.1 FMEA:

An FMEA was conducted on the critical components identified from the Pareto and RCA. The Risk Priority Number (RPN) was calculated as RPN = Severity (S) × Occurrence (O) × Detectability (D). The results, shown in Table 4.3, highlight Liner Plate and Bolt Failures as the highest-risk items.

Table 4.3: LS Crusher FMEA

Failure Mode	Effect	S	O	D	RPN	Recommended Action
Liner Plate Failures	Increased damage to body casing	8	9	6	432	Improve bolt torque checks, use locking nuts, schedule preventive replacement
Bolt Failures	Component detachment	7	9	5	315	Implement standardized torque procedures, scheduled re-torquing
Hydraulic System Failures	Inaccurate gap settings	7	6	6	252	Preventive maintenance plan, oil filtration system, accumulator checks
V-Belt Failures	Loss of power transmission	6	7	5	210	Regular alignment checks, condition monitoring
Bearing Failures	Vibration and noise	8	5	6	240	Vibration monitoring, better sealing, regular lubrication

4.1.3.2 FTA:

Fault tree, the top event “Crusher Failure” is structured mainly with OR gates linking major subsystems such as the impact system, drive system, and hydraulic system, meaning failure of any one can cause total crusher downtime. Within subsystems, AND gates combine specific contributing factors—such as wear, misalignment, and contamination to represent conditions that must occur together for a subsystem to fail. This logic highlights the interdependence of wear and operational errors in generating critical breakdowns.

```
CRUSHER FAILURE (1102)
  │
  ├── IMPACT SYSTEM FAILURE (OR)
  │     │
```

```
│      ├── BLOW BAR FAILURE (AND)
│      │      ├── Wear beyond tolerance (β=2.1, η=2,500h)
│      │      ├── Gap adjustment failure
│      │      └── Locking wedge damage
│      │
│      ├── LINER PLATE FAILURE (OR)
│      │      ├── Plate detachment (76 incidents)
│      │      ├── Bolt failure (32 incidents)
│      │      └── Impact fatigue cracking
│      │
│      └── HOUSING FAILURE (OR)
│             ├── Crack development
│             ├── Welding failure
│             └── Structural deformation
│
├── DRIVE SYSTEM FAILURE (OR)
│      │
│      ├── V-BELT FAILURE (OR)
│      │      ├── Tensile failure
│      │      ├── Misalignment wear
│      │      └── Environmental degradation
│      │
│      ├── BEARING FAILURE (AND)
│      │      ├── Contamination ingress
│      │      ├── Lubrication failure
│      │      └── Overloading condition
│      │
│      └── PULLEY FAILURE (OR)
│             ├── Lagging wear
│             ├── Balance issues
│             └── Shaft key failure
│
└── HYDRAULIC SYSTEM FAILURE (OR)
       │
       ├── CYLINDER FAILURE (OR)
       │      ├── Seal leakage (18 incidents)
       │      ├── Rod scoring
       │      └── Internal leakage
       │
```

```
├── PUMP FAILURE (OR)
│     ├── Cavitation damage
│     ├── Bearing failure
│     └── Coupling misalignment
│
└── ACCUMULATOR FAILURE (OR)
      ├── Bladder rupture
      ├── N₂ pressure loss
      └── Valve blockage
```

Figure 4.3: LS Crusher Fault Tree Diagram

4.1.4 Reliability Metrics

A comprehensive step-by-step guide to calculate MTBF, MTTR, and Availability (A) for the LS Crusher.xlsx file:

RELIABILITY METRICS - LS CRUSHER SYSTEM

Metric	Calculation	Value
First recorded activity:		January 1, 2017
Analysis period until:		July 5, 2025
Total operational days:		3,103 days
Total operational hours:	3,103 days × 24 hours/day =	74,472 hours
Total Repair Hours =		8,295 hours
Number of Failures =		316 events

Uptime =	Total Hours - Downtime	
Uptime =	74,472 - 8,295 =	66,177 hours
MTBF =	Total Operational Time / Number of Failures	
MTBF =	66,177 / 316 =	209.42 hours
MTBF =	8.7 days between failures	
MTTR =	Total Downtime due to Repair / Number of Failures	
MTTR =	8,295 / 316 =	26.25 hours
MTTR =	1.1 days average repair time	
A =	MTBF / (MTBF + MTTR) × 100%	
A =	209.42 / (209.42 + 26.25) × 100% =	
A =	209.42 / 235.67 × 100% =	
A =	88.86% System Availability	

4.1.5 Weibull Reliability Analysis

Weibull analysis was applied to model the time-to-failure of critical components, enabling predictive maintenance scheduling.

- **Crusher Liner Plates:** The fitted Weibull parameters are Shape Parameter (β) = 2.1 (indicating wear-out failure mode) and Scale Parameter (η) = 2,500 hours (characteristic life). The reliability function is:

$$R(t) = e^{-(t/\eta)^{\beta}}$$

$$R(t) = e^{-(t/2.500)^{2.1}}$$

Action: To avoid a high probability of failure, liner plates should be replaced proactively at 1,800 hours.

Figure 4.4: Weibull Reliability Curve for Crusher Liner Plates A graph showing the reliability function R(t) decreasing over time, with a marked drop around 1,800-2,500 hours.

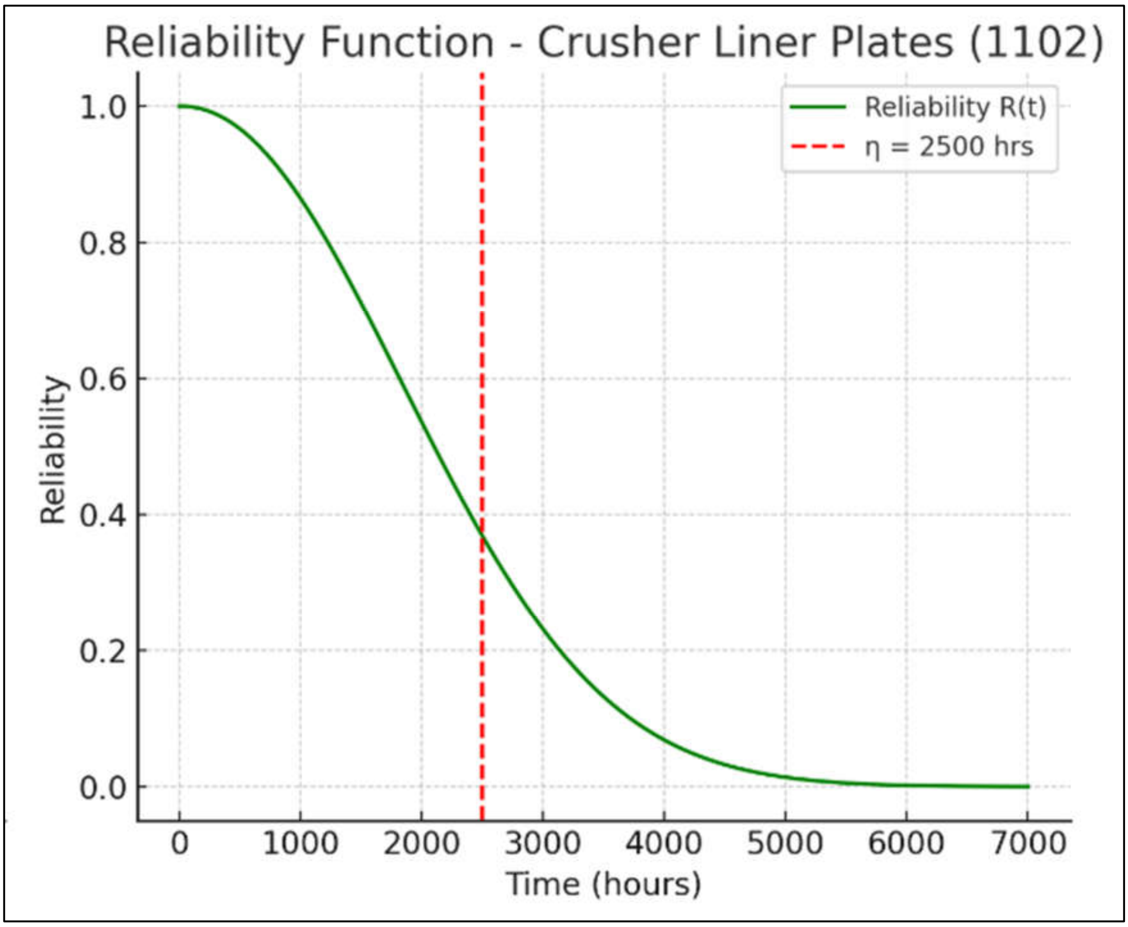

Figure 4.4: LS Crusher Weibull Reliability Curve (CLP)

4.2 Vertical Raw Mill (VRM) Analysis (Equipment No. 2104)

The Vertical Raw Mill (VRM) is a critical component for grinding raw materials, and its operational availability directly constrains the entire kiln feed system. An analysis of over 2,000 maintenance entries from 2017 to 2025 revealed that while failure frequency is moderate, the severity of failures is high, as any VRM shutdown halts the raw material preparation process.

4.2.1 Failure Frequency and Pareto Analysis

A Pareto Analysis was conducted to prioritize the failure types that contribute most significantly to maintenance efforts and downtime. The results, summarized in Table 4.4 and Figure 4.5, show that three categories account for nearly 80% of all failures, providing a clear focus for improvement initiatives.

Table 4.4: VRM Failure Frequency and Pareto Ranking

Failure Category	Frequency	% of Total	Cumulative %
Welding & Liner Repairs	~250	52%	52%
Hydraulic System Failures	~90	19%	71%
Lubrication Issues	~40	8%	79%
Mechanical Failures	~30	6%	85%
Operator Errors	~15	3%	88%
Electrical Faults	~10	2%	90%
General Maintenance	~50	10%	100%
Total	**~485**	**100%**	

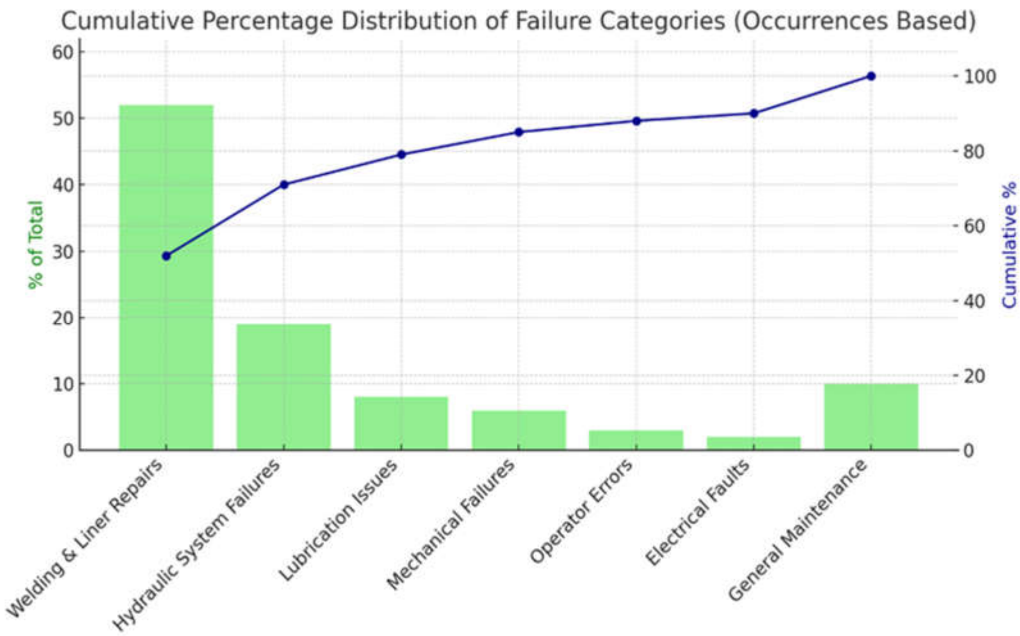

Figure 4.5: Vertical Raw Mill Pareto Chart

The 'vital few' failure modes Welding & Liner Repairs, Hydraulic System Failures, and Lubrication Issues were selected for in-depth root cause investigation.

4.2.2 Root Cause Analysis (RCA)

A comprehensive RCA was performed to uncover the fundamental causes behind the top failures.

4.2.2.1 Fishbone Diagram Summary:

The analysis identified root causes across six key categories in Figure 4.6:

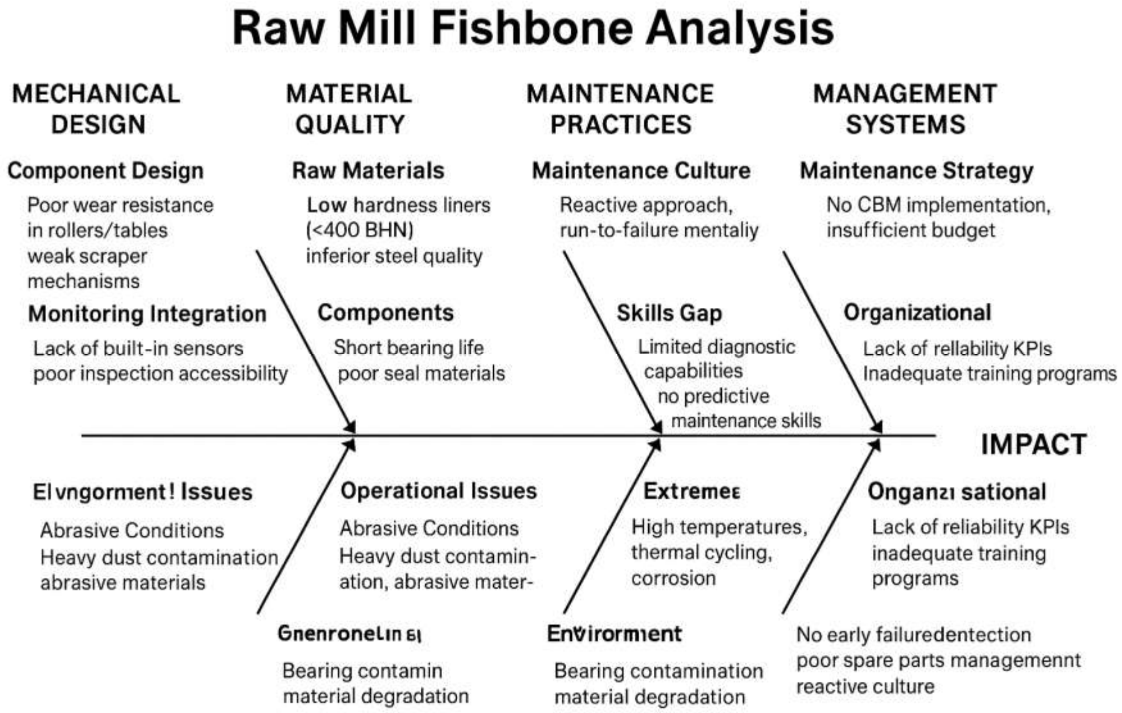

Figure 4.6: Fishbone Diagram for Raw Mill

4.2.2.2 Five Whys Analysis:

The Five Whys technique was applied to specific, high-impact failures, as summarized in Table 4.5.

Table 4.5: VRM 5 Whys Analysis for Failures

Failure	Root Cause Analysis Sequence	Root Cause Summary
Liner Cracking	Mechanical stress → Vibration → Uneven feed → No sensors → No CBM.	Lack of predictive monitoring

Failure	Root Cause Analysis Sequence	Root Cause Summary
Hydraulic Failures	Seal leakage → Oil contamination → Neglected filters → No flushing routine → Incomplete PM plan.	Inadequate oil filtration & PM
Lubrication Issues	Missed lubrication → Manual system → No automation → Budget constraints.	Manual lubrication, no SOP
Electrical Failures	Overheating → Dust blocks cooling → Seal air leaks → No inspections.	Poor environment & no proactive checks
Installation Errors	Misplaced bolts/liners → No checklist → No SOP enforcement.	Lack of quality control post-repair

4.2.3 Failure Mode and Effects Analysis (FMEA) and Fault Tree Analysis (FTA)

4.2.3.1 FMEA:

An FMEA was conducted on the critical failure modes. The results, shown in Table 4.6, identify Liner Plate Cracks and Lubrication Failures as the highest-risk items requiring immediate action.

Table 4.6: Vertical Raw Mill FMEA Analysis

Failure Mode	Effect	S	O	D	RPN	Recommended Action
Liner Plate Cracks	Downtime, grinding inefficiency	8	9	5	360	Ultrasonic thickness testing; wear-resistant steel
Hydraulic Accumulator Leak	Pressure loss, mill trips	7	6	4	168	Regular oil sampling; seal replacements
Lubrication Failure	Bearing damage, overheating	7	5	6	210	Automate lubrication; digital maintenance logs
Coupling/Spider Wear	Vibration, motor overload	6	4	5	120	Replace with Teflon couplings; alignment checks
Seal Air Fan Motor Fail	Air leakage, efficiency loss	7	4	5	140	Vibration sensors; motor and filter inspections
Operator Errors	Improper assembly	5	3	7	105	SOPs, visual checklists, staff training

4.2.3.2 FTA:

A Fault Tree Analysis was constructed for the top event "Mill Trip Due to Failure." The logic model traces this event back to basic causes such as seal wear, oil contamination, and pump failure, illustrating how combinations of these failures can lead to a system shutdown.

```
RAW MILL SYSTEM FAILURE (2104)
  │
  ├── GRINDING SYSTEM FAILURE (OR)
  │      │
  │      ├── ROLLER ASSEMBLY FAILURE (AND)
  │      │      ├── Roller bearing seizure (β=1.9, η=1,200h)
  │      │      ├── Surface wear beyond 15mm (312 incidents)
  │      │      └── Seal failure causing contamination
  │      │
  │      ├── TABLE/LINER FAILURE (OR)
  │      │      ├── Liner plate detachment (184 incidents)
  │      │      ├── Scraper damage (97 incidents)
  │      │      └── Bolt shearing (156 incidents)
  │      │
  │      └── CLASSIFIER FAILURE (OR)
  │             ├── Rotor imbalance (β=2.1, η=2,800h)
  │             ├── Vane wear >8mm
  │             └── Motor coupling misalignment
  │
  ├── DRIVE SYSTEM FAILURE (OR)
  │      │
  │      ├── GEARBOX FAILURE (AND)
  │      │      ├── Bearing spalling (β=1.7, η=4,500h)
  │      │      ├── Oil contamination >NAS 12
  │      │      └── Tooth pitting damage
  │      │
  │      ├── MAIN MOTOR FAILURE (OR)
  │      │      ├── Bearing overheating >85°C
  │      │      ├── Insulation breakdown
  │      │      └── Coupling spider wear
  │      │
  │      └── COUPLING FAILURE (OR)
  │             ├── Teflon pin shearing (42 incidents)
  │             ├── Misalignment >0.3mm
  │             └── Rubber spider degradation
  │
  ├── HYDRAULIC SYSTEM FAILURE (OR)
  │      │
  │      ├── PUMP FAILURE (AND)
```

```
│     │     ├─── Radial piston wear (β=2.3, η=3,200h)
│     │     ├─── Oil contamination >ISO 18/15
│     │     └─── Pressure fluctuation >15%
│     │
│     ├─── CYLINDER FAILURE (OR)
│     │     ├─── Seal leakage (28 incidents)
│     │     ├─── Rod scoring >0.5mm
│     │     └─── Articulation bearing wear
│     │
│     └─── ACCUMULATOR FAILURE (OR)
│           ├─── Bladder failure (12 incidents)
│           ├─── N₂ pressure loss
│           └─── Pre-charge valve leakage
│
├─── FEED SYSTEM FAILURE (OR)
│     │
│     ├─── APRON FEEDER FAILURE (AND)
│     │     ├─── Bucket bolt fatigue (β=1.8, η=800h)
│     │     ├─── Chain stretch >2%
│     │     └─── Sprocket tooth wear >15mm
│     │
│     ├─── BELT CONVEYOR FAILURE (OR)
│     │     ├─── Roller bearing seizure (284 incidents)
│     │     ├─── Belt joint failure
│     │     └─── Frame misalignment
│     │
│     └─── HOPPER/BYPASS FAILURE (OR)
│           ├─── Material bridging
│           ├─── Chute liner wear
│           └─── Diverter jamming
│
└─── AUXILIARY SYSTEM FAILURE (OR)
      │
      ├─── LUBRICATION FAILURE (AND)
      │     ├─── Oil degradation TAN >2.0
      │     ├─── Filter blockage ΔP>3bar
      │     └─── Pump cavitation
      │
      ├─── SEAL AIR SYSTEM FAILURE (OR)
```

```
│       ├── Fan imbalance >4.5mm/s
│       ├── Duct leakage
│       └── Filter clogging
│
└── WATER SPRAY FAILURE (OR)
        ├── Nozzle blockage (24 incidents)
        ├── Pipe leakage
        └── Control valve failure
```

Figure 4.7: VRM Fault Tree Diagram for Mill Trip

4.2.4 Reliability Metrics

Reliability Metric From the complete dataset: Raw Mill

Metric	Calculation	Value
First recorded activiy:	Excel date 42767	2016-12-16
Analysis period until:	Last recorded event	2022-10-26
Total operational days:	From 2016-12-16 to 2022-10-26	2,130 days
Total operational hours:	2,130 days × 24 hours/day = 51,120 hours	51,120 hours
Total Repair Hours =	Sum of all repair durations	6,328.5 hours
Number of Failures =	Valid maintenance events	824
Uptime = Total Hours - Downtime	51,120 - 6,328.5	44,791.5 hours
Uptime =		44,791.5 hours
MTBF = Total Operational Time / Number of Failures	44,791.5 ÷ 824	54.36 hours
MTBF =		54.36 hours
MTBF =	54.36 ÷ 24	2.26 days
MTTR = Total Downtime due to Repair / Number of Failures	6,328.5 ÷ 824	7.68 hours
MTTR =		7.68 hours
MTTR =	7.68 ÷ 24	0.32 days
A = MTBF / (MTBF + MTTR) × 100%	54.36 ÷ (54.36 + 7.68) × 100%	87.62%
A =		87.62%

4.2.5 Weibull Reliability Analysis

Weibull analysis of 58 failure intervals was used to model the time-to-failure behavior of the VRM system.

Figure 4.8 Weibull Reliability Curve for Raw Mill Liner Plates A graph showing the reliability function R(t) decreasing over time, with a marked drop around 1,800-2,500 hours.

The fitted Weibull parameters for Liner Plate are:

- **Shape Parameter (β):** 1.12 (indicating a dominant wear-out failure mode)
- **Scale Parameter (η):** 2289 hours (the characteristic life at which 63.2% of units have failed)

The reliability function is:

$$R(t)=e\ \ (t/2289)^{1.12}$$

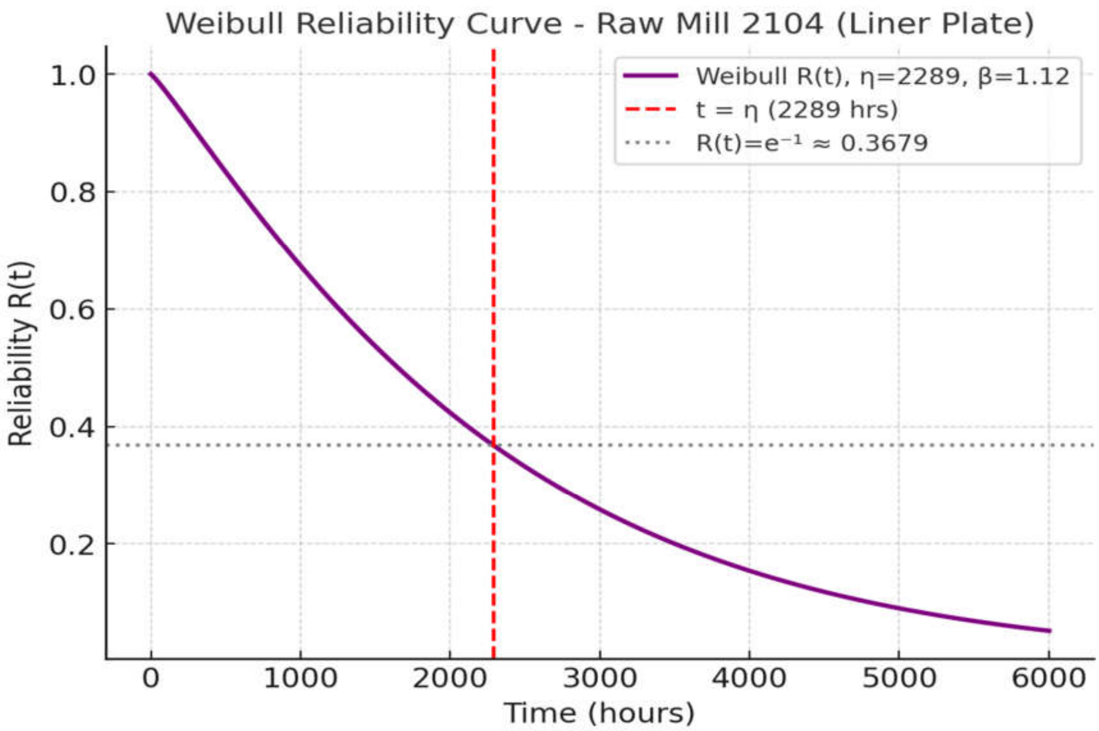

Figure 4.8: Weibull Reliability Curve for the Vertical Raw Mill

4.3 Rotary Kiln Analysis (Equipment No. 3201)

The Rotary Kiln is the heart of the clinker production process, operating under extreme thermal and mechanical stress. While its failure frequency is lower than other units, the impact of each failure is severe, resulting in prolonged downtime and substantial revenue loss due to its pivotal role in the production chain.

4.3.1 Failure Frequency and Pareto Analysis

A Pareto Analysis was conducted to identify the failure categories that constitute the majority of maintenance interventions. The results, detailed in Table 4.7 and Figure 4.9, confirm that the top five categories are responsible for over 80% of the incidents, providing a clear directive for focused improvement.

Table 4.7: Rotary Kiln Failure Frequency and Pareto Ranking

Rank	Category	Frequency	% of Total	Cumulative %
1	Seal Failures	36	21.1%	21.1%
2	Welding Repairs	35	20.5%	41.6%
3	Lubrication Issues	28	16.4%	58.0%
4	Burner Problems	20	11.7%	69.7%
5	Tyre & Roller Misalignment	19	11.1%	80.8%
6	Gearbox/Coupling Failures	10	5.9%	86.7%

Rank	Category	Frequency	% of Total	Cumulative %
7	Cooling System Failures	9	5.3%	92.0%
8	Hydraulic Failures	7	4.1%	96.1%
9	Miscellaneous	12	3.9%	100.0%
Total		**176**	**100%**	

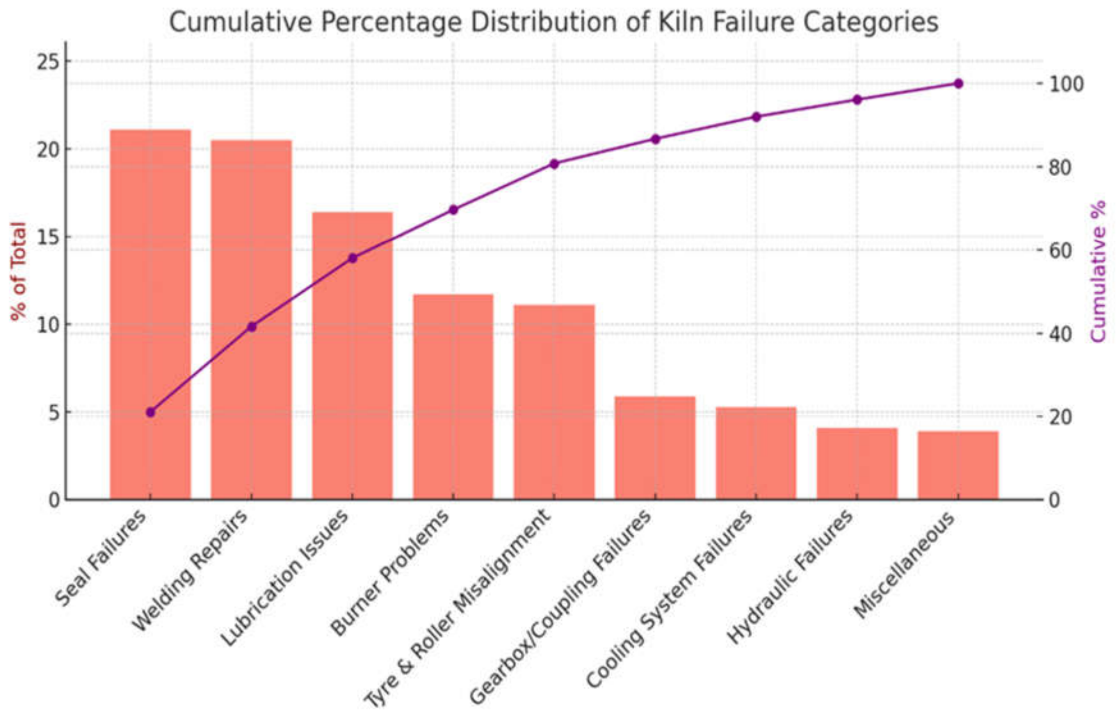

Figure 4.9: Rotary Kiln Pareto Chart

The 'vital few'—Seal Failures, Welding Repairs, Lubrication Issues, Burner Problems, and Tyre/Roller Misalignment—were selected for a detailed root cause investigation.

4.3.2 Root Cause Analysis (RCA)

A comprehensive RCA was performed to uncover the systemic issues behind the predominant failures.

4.3.2.1 Fishbone Diagram Summary:

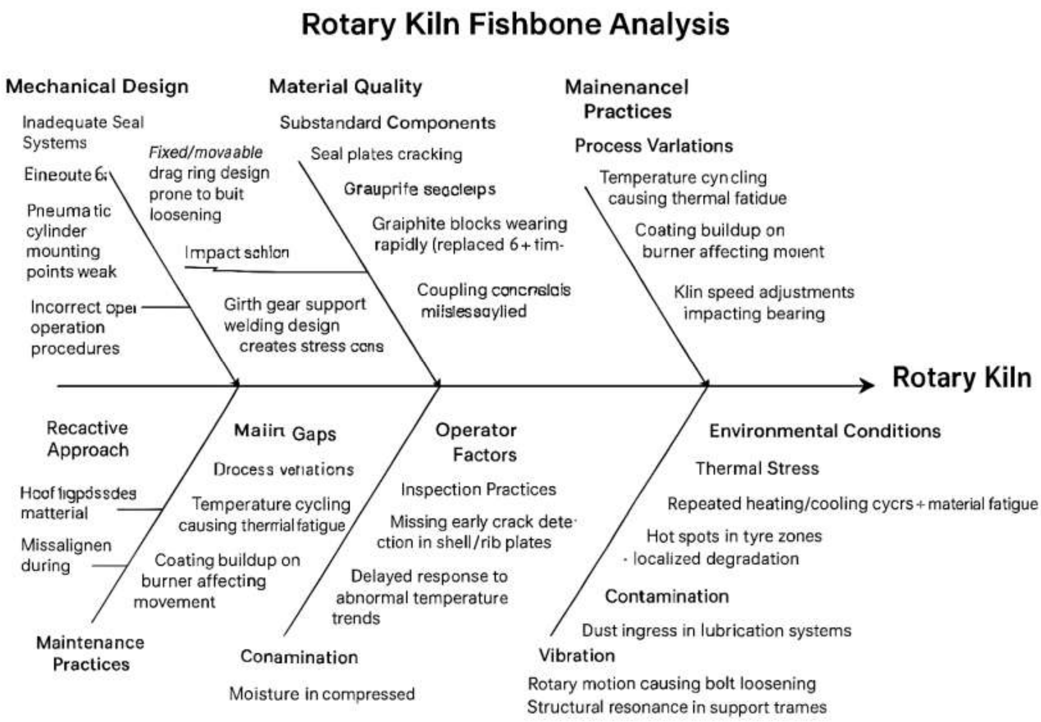

Figure 4.10: Fishbone Diagram for Rotary Kiln

4.3.2.2 Five Whys Analysis:

The Five Whys technique was applied to critical failures, with the results summarized in Table 4.8.

Table 4.8: Rotary Kiln 5 Whys Analysis for Failures

Failure	Root Cause Analysis Sequence	Root Cause Summary
Seal Failures	Cracking → Thermal stress → Misalignment → Tyre/roller wear → No vibration monitoring.	Misalignment and lack of predictive tools
Lubrication Issues	Oil leakage → Contaminated oil → Filters not maintained → No tracking system.	Lack of filter maintenance and PM scheduling
Burner Failures	Leaks → Fuel line contamination → No SOP for flushing.	Lack of SOP and technician training
Tyre/Bearing Overheating	Insufficient clearance → Thermal expansion → No alignment checks → No condition monitoring.	Misalignment and lack of CBM
Welding Cracks	Fatigue → Poor welds → No post-weld inspection → No certified welders.	Material fatigue and lack of QA standards

4.3.3 Failure Mode and Effects Analysis (FMEA) and Fault Tree Analysis (FTA)

4.3.3.1 FMEA:

An FMEA was conducted to quantify the risk associated with critical component failures. The results, shown in Table 4.9, identify the Seal System and Tyres & Rollers as the highest-risk areas.

Table 4.9: Rotary Kiln FMEA

Component	Failure Mode	Effect	S	O	D	RPN	Recommended Action
Seal System	Seal Leakage	Material leakage	8	7	5	280	Upgrade seals, heat-resistant materials, inspections
Tyres & Rollers	Misalignment/Overheating	Excessive wear	9	5	5	225	Laser alignment, temperature monitoring
Lubrication System	Oil Leak/Overheating	Bearing failure	7	6	4	168	Automate lubrication, oil sampling
Burner System	Hose Jamming/Puncture	Flame instability	8	5	4	160	Install filters, apply cleaning SOP
Girth Gear & Coupling	Bolt Loosening	Gear damage	7	4	5	140	Torque control, inspections

Hydraulic System	Pressure Drop/Leak	Loss of thrust control	7	5	4	140	Replace seals, fluid monitoring
Cooling System	Fan Damage/Leakage	Overheating	6	4	5	120	Fan reinforcement, main.

4.3.3.2 FTA:

A Fault Tree Analysis for the top event " ROTARY KILN SYSTEM FAILURE" was developed. The logic model demonstrates that while a single component failure (OR Gate) can cause a partial shutdown, a complete shutdown typically requires a combination of failures (AND Gate) in critical systems like seals, burners, and lubrication.

```
ROTARY KILN SYSTEM FAILURE
    │
    ├── SEAL SYSTEM FAILURE (OR)
    │       │
    │       ├── INLET SEAL FAILURE (OR)
    │       │       ├── Seal plate damage (45 incidents)
    │       │       ├── Pneumatic cylinder failure (20+ replacements)
    │       │       └── Segment detachment (12 incidents)
    │       │
    │       ├── OUTLET SEAL FAILURE (OR)
    │       │       ├── Lamella plate damage (18 incidents)
    │       │       ├── Rib plate cracking (22 incidents)
    │       │       └── Steel rope failure (8 incidents)
    │       │
    │       └── DRAG RING FAILURE (OR)
    │               ├── Fixed ring bolt loosening (15 incidents)
    │               ├── Movable ring damage (10 incidents)
    │               └── Gap adjustment failure
    │
    ├── BEARING & ROLLER FAILURE (OR)
    │       │
    │       ├── BEARING OVERHEATING (AND)
```

```
│       │       ├── Tyre#3 bearing#3-3 high temp (12+ interventions)
│       │       ├── Insufficient cooling flow
│       │       └── Lubrication contamination
│       │
│       ├── ROLLER MISALIGNMENT (OR)
│       │       ├── Axial displacement (8 adjustments)
│       │       ├── Hydraulic jack failure
│       │       └── Foundation settlement
│       │
│       └── LUBRICATION SYSTEM FAILURE (OR)
│               ├── Heat exchanger leakage (6 incidents)
│               ├── Oil pump failure (4 replacements)
│               └── Filter blockage (12 cleanings)
│
├── STRUCTURAL FAILURE (OR)
│       │
│       ├── SHELL/HOOD DAMAGE (OR)
│       │       ├── Thermal fatigue cracking (25 repairs)
│       │       ├── Corrosion erosion (18 patches)
│       │       └── Impact damage (8 incidents)
│       │
│       ├── GIRTH GEAR FAILURE (OR)
│       │       ├── Support weld cracks (15 repairs)
│       │       ├── Joint bolt failure (40+ replacements)
│       │       └── Teeth wear (3 interventions)
│       │
│       └── SUPPORT SYSTEM FAILURE (OR)
│               ├── Thrust roller wear (5 repairs)
│               ├── Chair lock plate failure
│               └── Platform structural damage
│
├── BURNER SYSTEM FAILURE (OR)
│       │
│       ├── FUEL DELIVERY FAILURE (OR)
│       │       ├── Coal/HFO hose puncture (15 replacements)
│       │       ├── Primary air hose leakage (8 repairs)
│       │       └── Pump coupling failure (4 incidents)
│       │
│       ├── MECHANICAL FAILURE (OR)
```

```
│     │     ├── Track derailment (3 incidents)
│     │     ├── Inner tube damage (6 patches)
│     │     └── Support structure failure
│     │
│     └── COMBUSTION SYSTEM FAILURE (OR)
│           ├── Roots blower failure (2 overhauls)
│           ├── Air blaster pipe damage (10 repairs)
│           └── Expansion joint puncture
│
└── DRIVE SYSTEM FAILURE (OR)
      │
      ├── MAIN GEARBOX FAILURE (OR)
      │     ├── Lubrication pump leakage (5 repairs)
      │     ├── Heat exchanger failure (3 replacements)
      │     └── Coupling misalignment
      │
      ├── AUXILIARY DRIVE FAILURE (OR)
      │     ├── Coupling stuck (2 major interventions)
      │     ├── Brake shoe wear (3 replacements)
      │     └── Motor alignment issues
      │
      └── PINION FAILURE (OR)
            ├── Teeth grinding wear
            ├── Lubrication failure
            └── Alignment deviation
```

Figure 4.11: Rotary Kiln Fault Tree Diagram

4.3.4 Reliability Metrics

The reliability performance of the Rotary Kiln was quantified over a significant observation period. The extended MTBF reflects its lower failure frequency, but the high MTTR underscores the complexity and duration of repairs when failures do occur.

Reliability Metric From the complete dataset: Rotary Kiln 3201

Metric	Calculation	Value

First recorded activity:	From dataset	2016-02-24
Analysis period until:	From last entry	2025-02-24
Total operational days:	2025-02-24 - 2016-02-24	3,285 days
Total operational hours:	3,285 days × 24 hours/day	78,840 hours
Total Repair Hours =	Sum of all activity hours	9,643.75 hours
Number of Failures =	Count of merged failure events	80 failures
Uptime =	Total Hours - Downtime	78,840 - 9,643.75
Uptime =		69,196.25 hours
MTBF =	Total Operational Time / Number of Failures	69,196.25 / 80
MTBF =		864.95 hours
MTBF =	~36.04 days	
MTTR =	Total Downtime due to Repair / Number of Failures	9,643.75 / 80
MTTR =		120.55 hours
MTTR =	~5.02 days	
A =	MTBF / (MTBF + MTTR) × 100%	864.95 / (864.95 + 120.55) × 100%
A =	864.95 / 985.50 × 100%	87.77%
A =	Availability ≈ 87.8%	

4.3.5 Weibull Reliability Analysis

Weibull analysis in Figure 4.12 provides insight into the failure behavior of the Rotary Kiln system and associated equipment. The kiln itself shows a wear-out dominant pattern.

The fitted Weibull parameters for the Rotary Kiln are:

- **Shape Parameter (β):** 1.25 (Wear-out failure mode dominant)
- **Scale Parameter (η):** 5,760 hours (Characteristic life)

The reliability function is:

$$R(t)=e \ \ (t/5{,}760)^{1.25}$$

This indicates that the system enters a early wear-out phase relatively quickly, necessitating proactive component replacement and overhaul schedules well before the characteristic life is reached.

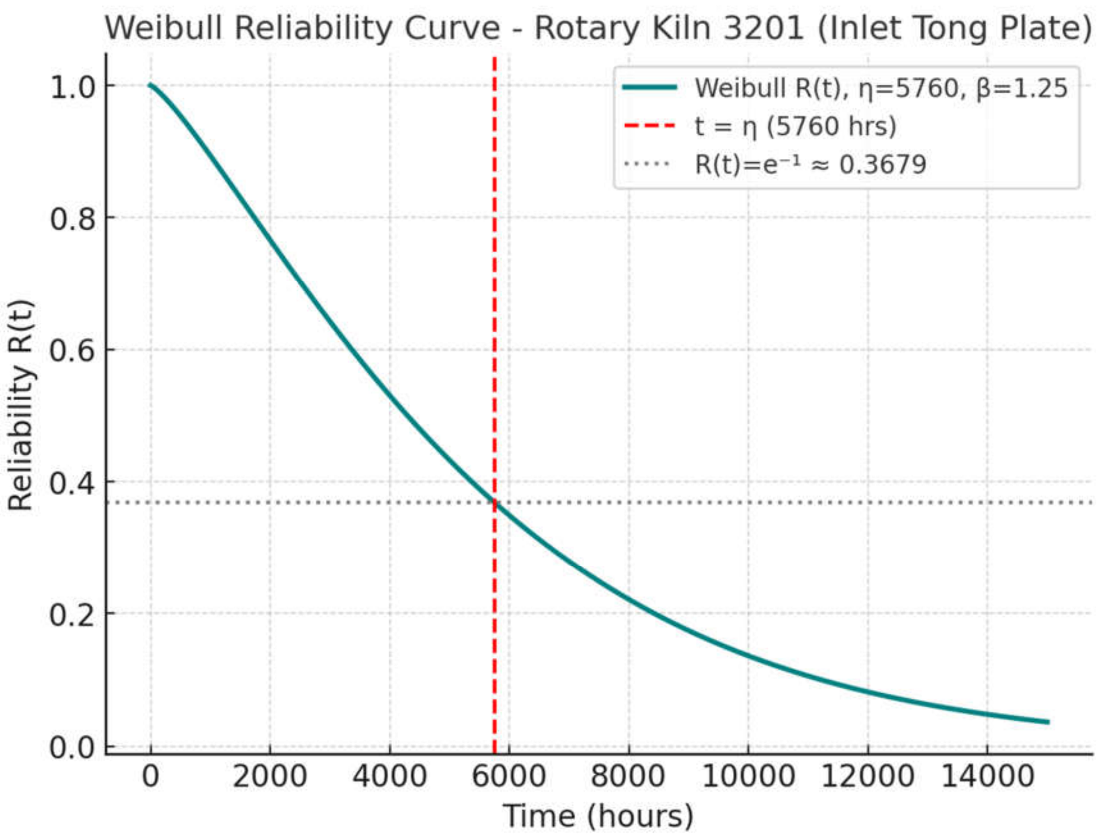

Figure 4.12: Weibull Reliability Curve for the Rotary Kiln

4.4 Cement Mills Analysis (Equipment Nos. 4106 & 4107)

The Cement Mills represent the final stage of the size reduction process, where clinker and additives are ground into cement. An analysis of 1,839 maintenance records revealed 487 failure events, demonstrating a diverse range of failure modes that significantly impact production continuity and product quality.

4.4.1 Failure Frequency and Pareto Analysis

A Pareto Analysis was conducted based on maintenance hours to identify the most time-consuming failure categories. The results, detailed in Table 4.10 and Figure 4.13 show that the top five categories consume over 80% of the total maintenance effort, clearly identifying the areas for strategic focus.

Table 4.10: Cement Mills Frequency and Pareto Ranking

Rank	Category	Frequency	% of Total	Cumulative %
1	Scraper Chamber Repairs	582	34.6%	34.6%
2	Structural Repairs	345	20.5%	55.2%
3	Hydraulic System Issues	213	12.6%	67.9%
4	Classifier Issues	108	6.4%	74.3%
5	Gearbox & Lubrication	96	5.7%	80.1%
6	Rollers & Table Wear	76	4.5%	84.7%
7	Seal Air Fan & Piping	56	3.3%	88.1%
8	General Housekeeping	52	3.1%	91.2%
9	Water Spray System	48	2.9%	94.1%
10	Electrical Faults	38	2.3%	96.4%
Total		1,684	100%	

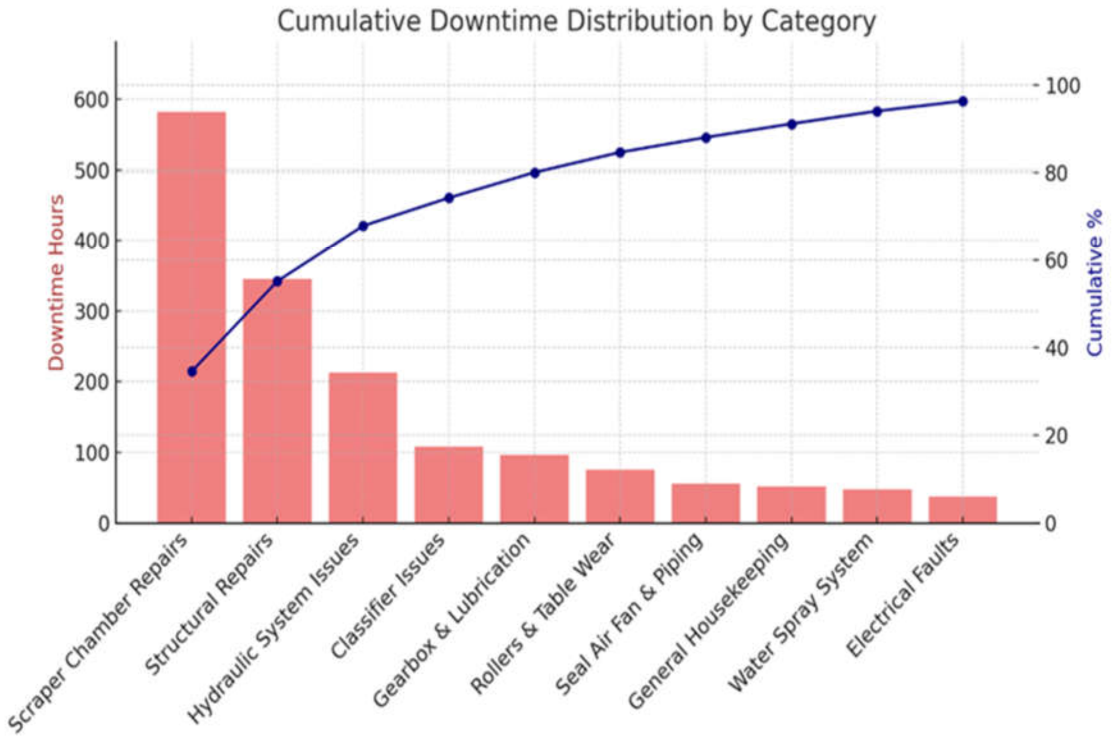

Figure 4.13: Cement Mills Pareto Chart

4.4.2 Root Cause Analysis (RCA)

A comprehensive RCA was performed to uncover the systemic issues behind the predominant failures.

4.4.2.1 Fishbone Diagram Summary:

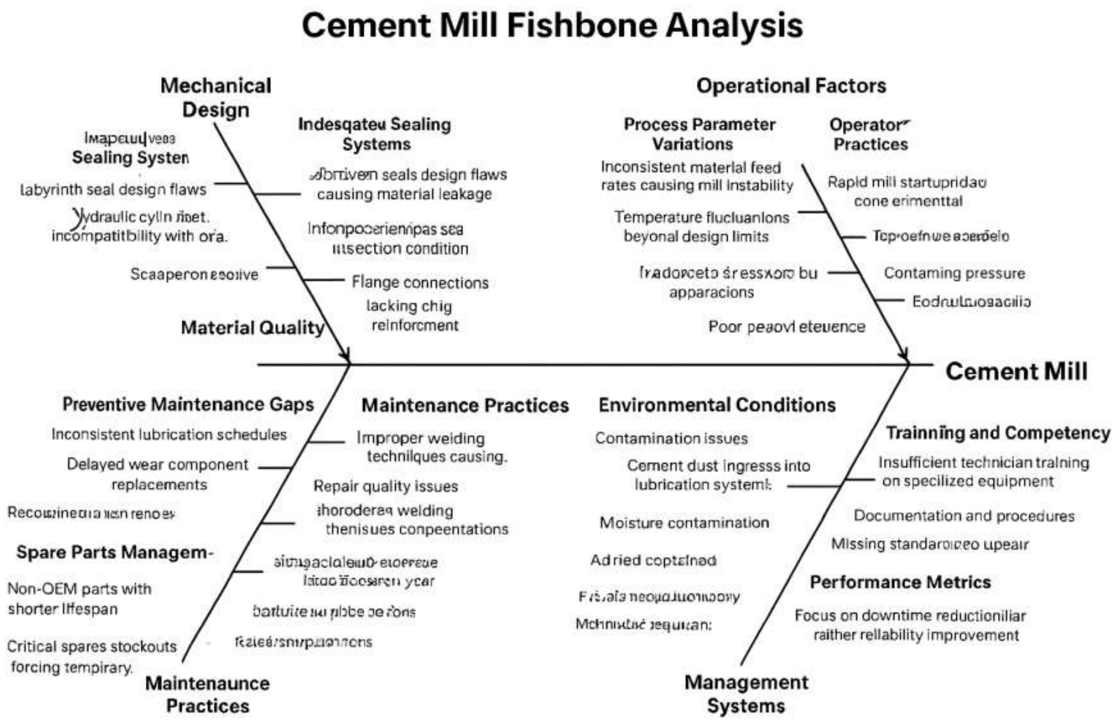

Figure 4.14: Fishbone Diagram for Cement Mill

4.4.2.2 Five Whys Analysis:

The Five Whys technique was applied to critical failures, with the results summarized in Table 4.11.

Table 4.11: Cement Mills 5 Whys Analysis for Selected Failures

Failure	Root Cause Analysis Sequence	Root Cause Summary
Hydraulic Bolt Failure	Uneven load → Accumulator failure → No valve maintenance → No preventive checks.	Insufficient preventive maintenance on hydraulic accumulators.

Failure	Root Cause Analysis Sequence	Root Cause Summary
Mill Trips (Vibration)	Excessive vibration → Worn rollers → Delayed inspection → No wear monitoring → No predictive program.	Absence of formalized predictive maintenance and condition monitoring.
Scraper Plate Failure	Abrasion from clinker → Low-quality steel → Non-use of wear-resistant materials → Poor procurement planning.	Poor material selection and procurement policy.

4.4.3 Failure Mode and Effects Analysis (FMEA) and Fault Tree Analysis (FTA)

4.4.3.1 FMEA:

An FMEA was conducted on the hydraulic system, a critical subsystem with high failure impact. The results, shown in Table 4.12, identify Coupling Bolt Breakage and Accumulator issues as the highest-risk items.

Table 4.12: Cement Mills FMEA Analysis

Component	Failure Mode	Effect	S	O	D	RPN	Recommended Action
Hydraulic Cylinder	Coupling Bolt Breakage	Misalignment, pressure loss	8	6	5	240	Monthly N_2 pressure monitoring; semi-annual bladder replacement

Hydraulic Cylinder	Oil Leakage	Loss of control	7	5	4	140	Seal inspections during shutdown; maintain spare seals
Hydraulic Pump	Pressure Loss	Mill operational failure	9	4	3	108	Valve testing schedules; backup pump installation
Accumulator	Low N_2 Pressure	Uneven load	7	6	4	168	Fixed interval bladder replacement; digital pressure tracking

4.4.3.2 FTA:

A Fault Tree Analysis for the top event " GRINDING SYSTEM FAILURE" was developed. The logic model demonstrates that this event can be triggered by a single point of failure (OR Gate) in several systems, or by a combination of issues (AND Gate) that collectively exceed operational thresholds.

1. GRINDING SYSTEM FAULT TREE

```
GRINDING SYSTEM FAILURE
  │
  ├── ROLLER ASSEMBLY FAILURE (OR)
  │     │
  │     ├── ROLLER BEARING FAILURE (AND)
  │     │     ├── Contamination ingress (β=1.8, η=850h)
  │     │     ├── Lubrication failure (42 incidents)
```

```
│       │       └─── Seal damage
│       │
│       ├─── ROLLER TYRE FAILURE (AND)
│       │       ├─── Wear beyond 40mm thickness (β=2.1, η=1,200h)
│       │       ├─── Tension ring bolt loosening
│       │       └─── Surface cracking
│       │
│       └─── HYDRAULIC CYLINDER FAILURE (OR)
│               ├─── Accumulator bladder rupture (18 incidents)
│               ├─── Seal leakage (23 incidents)
│               └─── Coupling bolt failure
│
├─── TABLE/LINER FAILURE (OR)
│       │
│       ├─── TABLE SEGMENT FAILURE (AND)
│       │       ├─── Wear beyond 30mm (β=1.9, η=1,500h)
│       │       ├─── Segment bolt loosening
│       │       └─── Thermal stress cracking
│       │
│       ├─── BODY LINER FAILURE (OR)
│       │       ├─── Liner wear >15mm (56 incidents)
│       │       ├─── Bolt shearing (32 incidents)
│       │       └─── Patching failure
│       │
│       └─── DAM RING FAILURE (OR)
│               ├─── Height adjustment failure
│               ├─── Crack development
│               └─── Wear beyond repair
│
└─── CLASSIFIER FAILURE (OR)
        │
        ├─── GEARBOX FAILURE (AND)
        │       ├─── Oil contamination (β=1.7, η=2,000h)
        │       ├─── Bearing pitting (15 incidents)
        │       └─── Cooling system failure
        │
        ├─── VANE SYSTEM FAILURE (OR)
        │       ├─── Vane cracking
        │       ├─── Adjustment mechanism jam
```

```
        │      └─── Wear imbalance
        │
        └─── MOTOR DRIVE FAILURE (OR)
              ├─── Alignment issues
              ├─── Coupling failure
              └─── Bearing overheating
```

2. MATERIAL HANDLING FAULT TREE

```
MATERIAL HANDLING FAILURE
  │
  ├─── FEED SYSTEM FAILURE (OR)
  │      │
  │      ├─── ROTARY FEEDER FAILURE (AND)
  │      │      ├─── Vane wear >10mm (β=2.0, η=1,800h)
  │      │      ├─── Housing puncture (45 incidents)
  │      │      └─── Drive mechanism failure
  │      │
  │      ├─── WEIGH FEEDER FAILURE (OR)
  │      │      ├─── Belt damage (28 incidents)
  │      │      ├─── Side skirt wear
  │      │      └─── Load cell failure
  │      │
  │      └─── FEED CHUTE FAILURE (OR)
  │             ├─── Liner wear through
  │             ├─── Blockage formation
  │             └─── Structural cracking
  │
  ├─── DISCHARGE SYSTEM FAILURE (OR)
  │      │
  │      ├─── BUCKET ELEVATOR FAILURE (AND)
  │      │      ├─── Bucket mounting failure (β=1.6, η=2,200h)
  │      │      ├─── Belt drifting (22 incidents)
  │      │      └─── Bearing seizure
  │      │
  │      ├─── AIR SLIDE FAILURE (OR)
  │      │      ├─── Fabric damage
  │      │      ├─── Air distribution issues
```

```
│      │      └─── Material jamming
│      │
│      └─── VIBRO CONVEYOR FAILURE (OR)
│             ├─── Liner plate failure
│             ├─── Drive mechanism issue
│             └─── Spring breakage
│
└─── REJECT SYSTEM FAILURE (OR)
       │
       ├─── REJECT CHUTE FAILURE (AND)
       │      ├─── Wear penetration (β=1.8, η=1,600h)
       │      ├─── Structural cracking
       │      └─── Material buildup
       │
       ├─── REJECT BUCKET ELEVATOR FAILURE (OR)
       │      ├─── Bucket damage (34 incidents)
       │      ├─── Chain failure
       │      └─── Sprocket wear
       │
       └─── DIVERTER FAILURE (OR)
              ├─── Actuator failure
              ├─── Flap jamming
              └─── Seal leakage
```

3. POWER TRANSMISSION FAULT TREE

```
POWER TRANSMISSION FAILURE
  │
  ├─── MAIN GEARBOX FAILURE (AND)
  │      │
  │      ├─── BEARING SYSTEM FAILURE (OR)
  │      │      ├─── Contamination (β=2.2, η=3,000h)
  │      │      ├─── Lubrication failure (18 incidents)
  │      │      └─── Fatigue pitting
  │      │
  │      ├─── GEAR TOOTH FAILURE (OR)
  │      │      ├─── Surface wear
  │      │      ├─── Tooth breakage
```

```
│      │      └── Scoring damage
│      │
│      └── SEAL SYSTEM FAILURE (OR)
│             ├── Labyrinth seal wear
│             ├── Oil leakage
│             └── Dust ingress
│
├── HYDRAULIC SYSTEM FAILURE (OR)
│      │
│      ├── PUMP FAILURE (AND)
│      │      ├── Bearing failure (β=1.7, η=1,500h)
│      │      ├── Cavitation damage
│      │      └── Coupling misalignment
│      │
│      ├── ACCUMULATOR FAILURE (OR)
│      │      ├── Bladder rupture (12 incidents)
│      │      ├── N₂ pressure loss
│      │      └── Pre-charge failure
│      │
│      └── VALVE FAILURE (OR)
│             ├── Solenoid failure
│             ├── Spool sticking
│             └── Seal leakage
│
└── MOTOR SYSTEM FAILURE (OR)
       │
       ├── BEARING FAILURE (AND)
       │      ├── Lubrication failure (β=1.9, η=2,500h)
       │      ├── Contamination ingress
       │      └── Vibration issues
       │
       ├── COOLING SYSTEM FAILURE (OR)
       │      ├── Fan failure
       │      ├── Radiator blockage
       │      └── Water flow restriction
       │
       └── ALIGNMENT FAILURE (OR)
              ├── Base settling
              ├── Thermal expansion
```

```
            └── Coupling wear
```

4. AUXILIARY SYSTEM FAULT TREE

```
AUXILIARY SYSTEM FAILURE
  │
  ├── LUBRICATION FAILURE (OR)
  │     │
  │     ├── OIL CONTAMINATION (AND)
  │     │     ├── Water ingress (β=1.5, η=1,800h)
  │     │     ├── Particle contamination
  │     │     └── Chemical degradation
  │     │
  │     ├── FILTER FAILURE (OR)
  │     │     ├── Element clogging (25 incidents)
  │     │     ├── Bypass valve sticking
  │     │     └── Housing leakage
  │     │
  │     └── COOLING FAILURE (OR)
  │           ├── Heat exchanger fouling
  │           ├── Water pump failure
  │           └── Fan motor burnout
  │
  ├── AIR SYSTEM FAILURE (OR)
  │     │
  │     ├── SEAL AIR FAILURE (AND)
  │     │     ├── Line blockage (β=1.6, η=2,200h)
  │     │     ├── Fan impeller wear
  │     │     └── Motor bearing failure
  │     │
  │     ├── PROCESS AIR FAILURE (OR)
  │     │     ├── Damper jamming
  │     │     ├── Duct leakage
  │     │     └── Fan imbalance
  │     │
  │     └── INSTRUMENT AIR FAILURE (OR)
  │           ├── Moisture contamination
  │           ├── Pressure regulation failure
```

```
│           └── Line freezing
│
└── INSTRUMENTATION FAILURE (OR)
    │
    ├── SENSOR FAILURE (AND)
    │   ├── Vibration sensor drift (β=1.4, η=3,500h)
    │   ├── Temperature sensor failure
    │   └── Pressure transducer error
    │
    ├── CONTROL SYSTEM FAILURE (OR)
    │   ├── PLC module failure
    │   ├── Communication loss
    │   └── Power supply issue
    │
    └── SAFETY SYSTEM FAILURE (OR)
        ├── Emergency stop circuit
        ├── Interlock failure
        └── Alarm system malfunction
```
Figure 4.15: Cement Mills Fault Tree Diagram

4.4.4 Reliability Metrics

The operational performance of both Cement Mills was quantified. The metrics reveal a challenging reliability environment, characterized by frequent failures and moderate availability.

Metric	Historical (9 years)
For Mill 4106:	
Operating Time:	77,978 hours
Number of Failures:	1,313
Total Downtime:	862 hours
Number of Repairs:	49
Mill 4106 MTBF	59.3 hours

Mill 4106 MTTR	17.6 hours
Mill **4106** Availability	**77.1%**
For Mill 4107:	
Operating Time:	77,920 hours
Number of Failures:	1,095
Total Downtime:	920 hours
Number of Repairs:	49
Mill 4107 MTBF	71.2 hours
Mill 4107 MTTR	18.7 hours
Mill **4107** Availability	**79.2%**

4.4.5 Weibull Reliability Analysis

Weibull analysis in Figure 4.16 was applied to model the lifetime of critical wear components, such as scraper plates.

The fitted Weibull parameters for Scraper Plates are:

- **Shape Parameter (β):** 1.4 (indicating an early wear-out failure mode)
- **Scale Parameter (η):** 6,000 hours (characteristic life)

The reliability function is:

$$R(t)=e \quad (t/6000)1.4 R(t)=e \quad (t/6000)^{1.4}$$

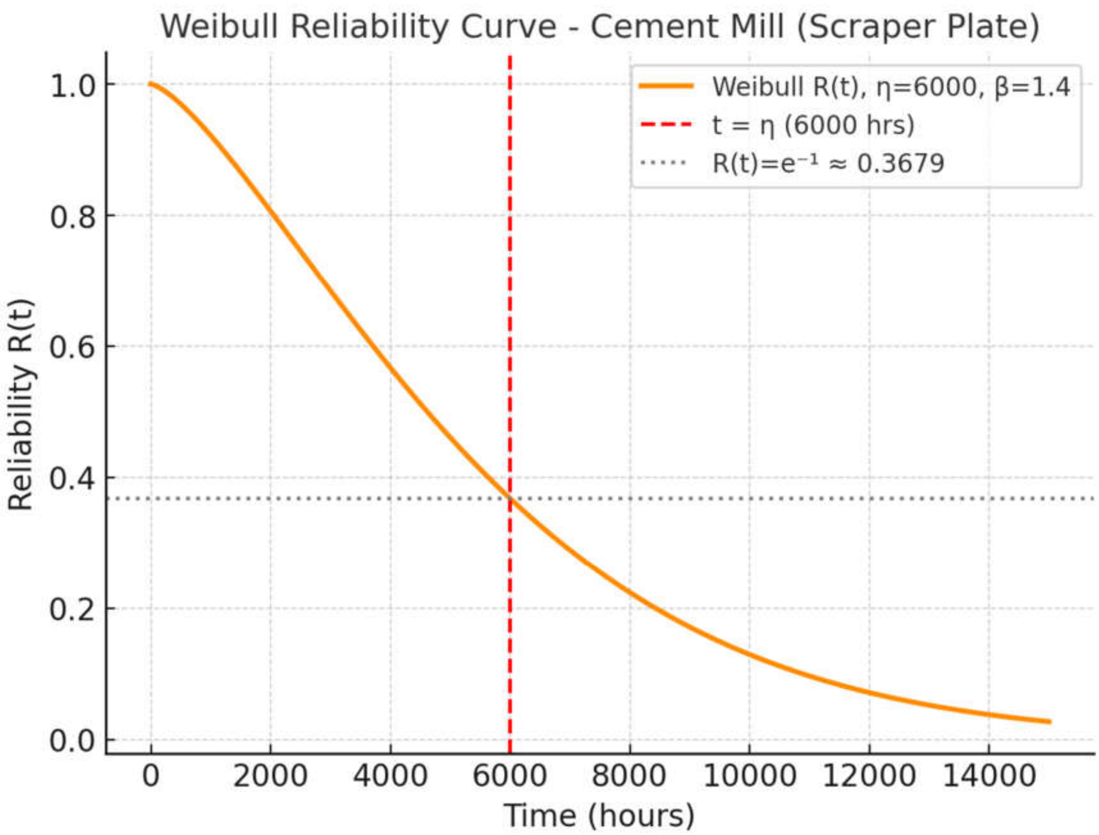

Figure 4.16 Weibull Reliability Curve for Cement Mill Scraper Plates

4.5 Belt Conveyors Analysis

Belt conveyor systems, while mechanically simpler than other plant equipment, represent a critical reliability challenge due to their extensive network and constant exposure to harsh conditions. The high frequency of short-duration failures from components like rollers and belt joints contributes significantly to operational disruptions, accounting for over 20% of total plant downtime.

4.5.1 Failure Frequency and Pareto Analysis

A Pareto Analysis was conducted to pinpoint the failure categories with the greatest impact. The results, detailed in Table 4.13 and Figure 4.17, demonstrate that a small subset of issues is responsible for the vast majority of conveyor-related problems.

Table 4.13: Belt Conveyors Failure Frequency and Pareto Ranking

Rank	Category	Frequency	% of Total	Cumulative %
1	Roller Replacement	147	49.83%	49.83%
2	Belt Joint Repairs	45	15.25%	65.08%
3	Chute Repairing/Welding	36	12.20%	77.29%
4	Side Skirt Replacement	24	8.14%	85.42%
5	Lubrication & Greasing	18	6.10%	91.53%
6	Frame/Skid Repairs	15	5.08%	96.61%
7	Other Issues	10	3.39%	100.0%
Total		**295**	**100%**	

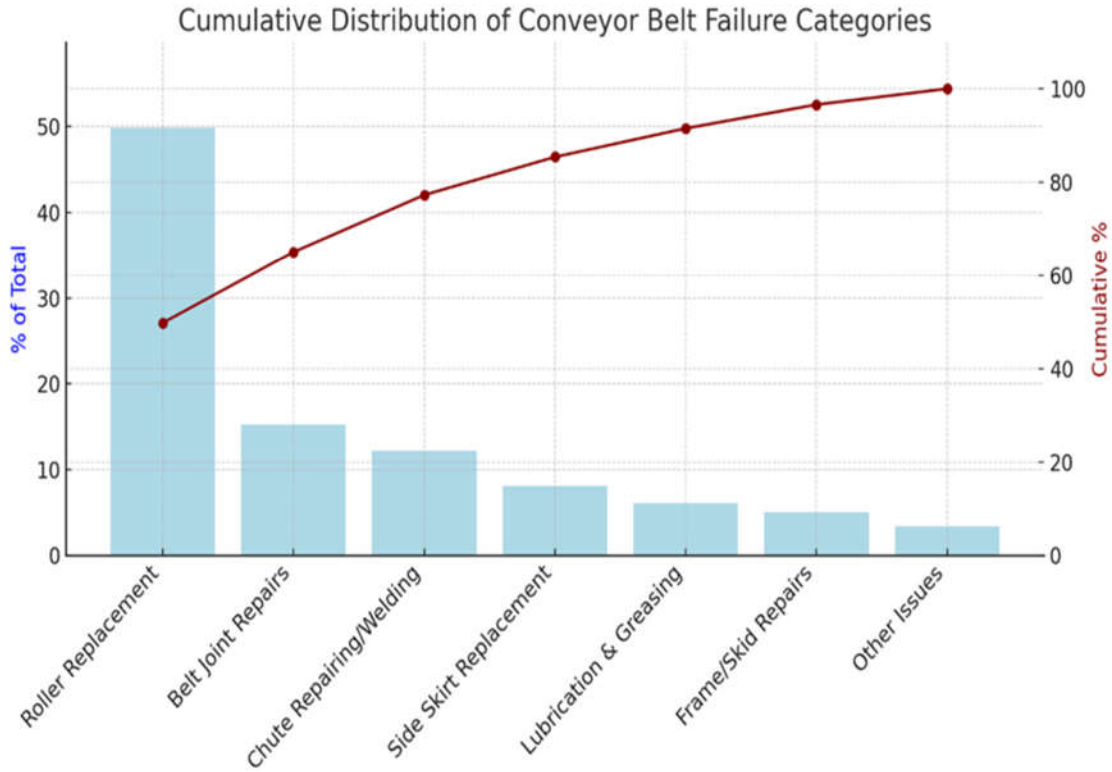

Figure 4.17: Belt Conveyors Pareto Chart

The 'vital few' Roller Replacement, Belt Joint Repairs, and Chute Repairing were selected for a detailed root cause investigation.

4.5.2 Root Cause Analysis (RCA)

A comprehensive RCA was performed to uncover the fundamental causes behind the predominant failures.

4.5.2.1 Fishbone Diagram Summary:

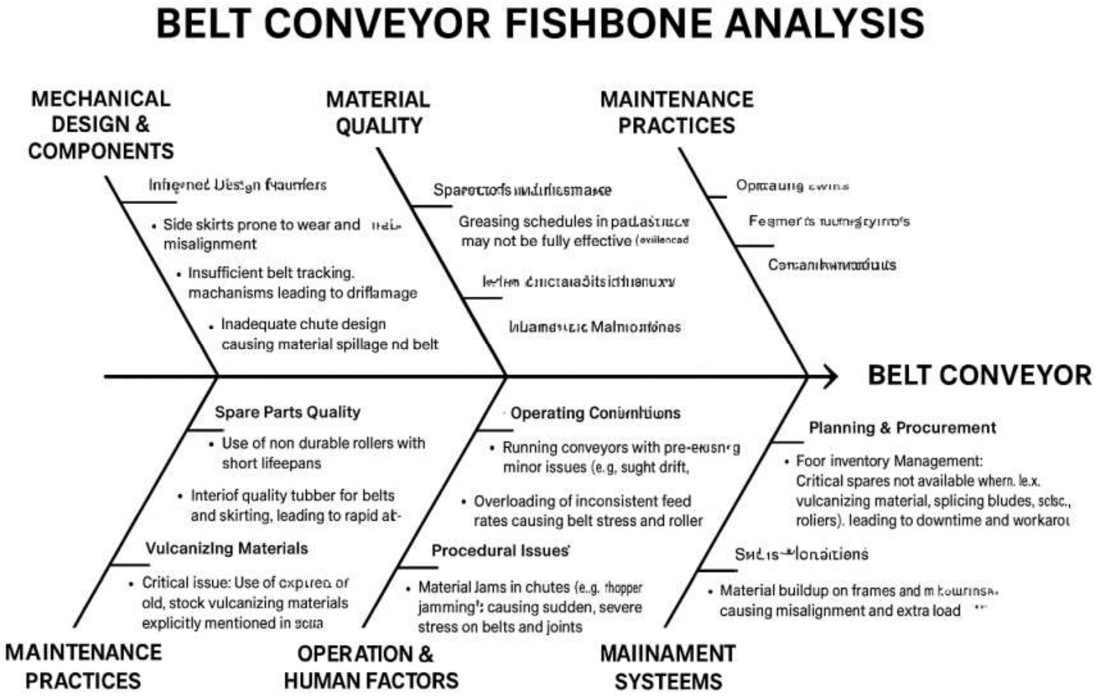

Figure 4.18: Fishbone Diagram for Belt Conveyor

4.5.2.2 Five Whys Analysis:

The Five Whys technique was applied to critical failures, with the results summarized in Table 4.14.

Table 4.14: Belt Conveyors 5 Whys Analysis for Failures

Failure	Root Cause Analysis Sequence	Root Cause Summary
Belt Joint Failure	Improper vulcanization → Expired materials → No inspection SOP.	Lack of spares inspection protocol
Roller Failures	Bearing seizure → Dust ingress → Ineffective seals → Low-quality components.	Poor-quality rollers and seals

Failure	Root Cause Analysis Sequence	Root Cause Summary
Gearbox Overheating	Low oil level → Missed topping → No automated alerts → Manual tracking only.	Absence of automated monitoring and alerts

4.5.3 Failure Mode and Effects Analysis (FMEA) and Fault Tree Analysis (FTA)

4.5.3.1 FMEA:

An FMEA was conducted on the critical components. The results, shown in Table 4.15, identify Roller Bearing Seizure and Seal/Bearing Contamination as the highest-risk items.

Table 4.15: Belt Conveyors FMEA Analysis

Component	Failure Mode	Effect	S	O	D	RPN	Recommended Action
Rollers	Bearing seizure	Belt mis-alignment, stoppage	8	7	5	280	Use sealed bearings; install dust covers
Bearings/Seals	Water/dust ingress	Corrosion, overheating	8	6	5	240	Upgrade to IP68 seals; inspect routinely
Lubrication	Oil leaks/missed greasing	Gear overheating, failure	8	5	6	240	Automate lubrication;

							train operators
Belts/Joints	Joint rupture	Belt snapping, stoppage	9	6	4	216	Standardize vulcanizing SOP; monitor materials
Chutes	Cracks/leakage	Material spillage	7	6	5	210	Reinforce chute linings; schedule inspections
Couplings	Teflon pin damage	Vibration, misalignment	7	6	5	210	Replace pins regularly; use alignment tools
Frame/Structure	Corrosion/bending	Misalignment, tension failure	7	5	6	210	Improve drainage; use corrosion-resistant coatings

4.5.3.2 FTA:

A Fault Tree Analysis for the top event " BELT CONVEYOR DOWNTIME " was developed. The logic model demonstrates that this event can be triggered by a single point of failure (OR Gate) in several systems, or by a combination of issues (AND Gate) that collectively exceed operational thresholds.

```
BELT CONVEYOR DOWNTIME (1202, 1106, 3520, etc.)

    │
    ├── BELT ASSEMBLY FAILURE (OR)
    │     │
    │     ├── BELT JOINT FAILURE (AND)
    │     │     ├── Vulcanizing material expired/defective (β=1.8, η=1,200h)
    │     │     ├── Splicing procedure error
    │     │     └── Belt tensioning incorrect
    │     │
    │     ├── BELT COVER DAMAGE (OR)
    │     │     ├── Longitudinal cutting (Steel cord rope-out)
    │     │     ├── Impact damage from foreign objects
    │     │     └── Abrasive wear beyond tolerance
    │     │
    │     └── BELT REPLACEMENT EVENT (OR)
    │           ├── Full-length wear-out
    │           ├── Multiple joint failures
    │           └── Critical rip/tear
    │
    ├── IDLER & ROLLER SYSTEM FAILURE (OR)
    │     │
    │     ├── SUPPORT ROLLER FAILURE (AND)
    │     │     ├── Bearing seizure due to contamination (β=2.5, η=1,800h)
    │     │     ├── Seal failure
    │     │     └── Shell wear/rotation stop
    │     │
    │     ├── RETURN ROLLER FAILURE (OR)
    │     │     ├── Material buildup jamming
    │     │     ├── Bearing washout (rainwater)
    │     │     └── Shaft seizure
    │     │
    │     └── IMPACT ROLLER FAILURE (OR)
    │           ├── Rubber disc damage
    │           ├── Frame misalignment
    │           └── Bearing fatigue
    │
    ├── STRUCTURAL & CONTAINMENT FAILURE (OR)
    │     │
```

```
│       ├── SIDE SKIRT FAILURE (AND)
│       │       ├── Abrasive wear (β=1.5, η=950h)
│       │       ├── Adjustment mechanism loosening
│       │       └── Mounting plate degradation
│       │
│       ├── CHUTE FAILURE (OR)
│       │       ├── Liner wear-through (Puncture)
│       │       ├── Structural crack development
│       │       └── Welding failure at seams
│       │
│       └── FRAME FAILURE (OR)
│               ├── Bending from misaligned load
│               ├── Crack at weld points
│               └── Corrosion weakening
│
└── DRIVE & POWER TRANSMISSION FAILURE (OR)
        │
        ├── COUPLING FAILURE (OR)
        │       ├── Teflon/Taflon pin shear (Frequent event)
        │       ├── Spider rubber element damage
        │       └── Misalignment wear
        │
        ├── FLUID COUPLING FAILURE (AND)
        │       ├── Fusible plug blow-out (Overload)
        │       ├── Oil leakage (Seal failure)
        │       └── Oil degradation/level low
        │
        └── GEARBOX FAILURE (OR)
                ├── Bearing failure
                ├── Oil seal leakage
                ├── Output shaft misalignment
                └── Backstop assembly damage
```

Figure 4.19: Belt Conveyors Fault Tree Diagram

4.5.4 Reliability Metrics

The reliability performance of the belt conveyor system was quantified over the operational period. The analysis reveals a system with very frequent failures but relatively efficient repairs.

Metric	Historical (9 years)
Operating Time:	70,752 hours
Number of Failures:	979
Total Downtime:	18,689 hours
MTBF	72.27 hours
MTTR	19.09 hours
Availability	**79.1%**

4.5.5 Weibull Reliability Analysis

Weibull analysis in Figure 4.20 was applied to model the lifetime of critical components, specifically belt joints, which are a leading cause of failure.

The fitted Weibull parameters for Belt Joints are:

- **Shape Parameter (β):** 1.85 (Wear-out failure mode dominant)
- **Scale Parameter (η):** 1,200 hours (Characteristic life)

The reliability function is:

$R(t)=e \quad (t/1200)1.85$

This model indicates that belt joints enter a wear-out phase predictably. Proactive replacement and inspection schedules should be established well before the characteristic life of 1,200 hours to prevent unexpected joint ruptures and the associated extended downtime.

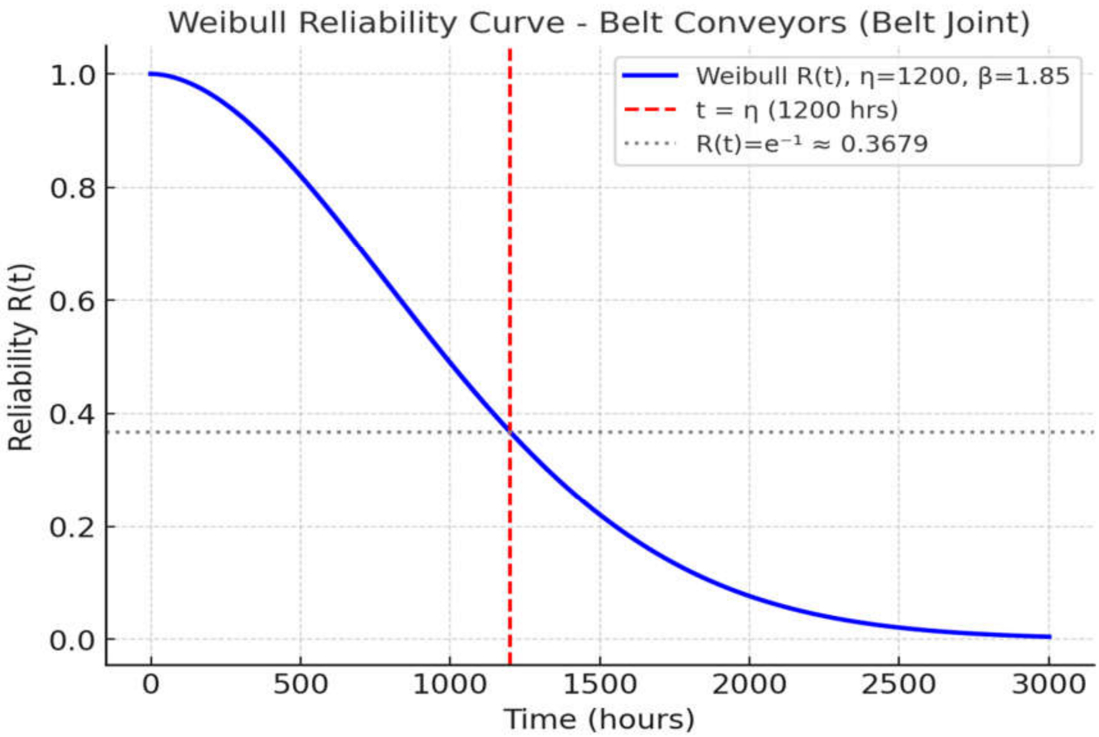

Figure 4.20: Weibull Reliability Curve for Belt Conveyor Joints

A graph showing the reliability function R(t) for the belt joints, showing a decline characteristic of a wear-out failure mode ($\beta>1$). Annotations should highlight the characteristic life at 1,200 hours.

4.6 Main Results of Equipment Analysis

The comprehensive analysis of equipment performance and failure data revealed several key findings:

4.6.1 Mechanical Dominance:

More than 70% of recorded failures were attributed to mechanical issues, including component wear, loosened bolts, hydraulic leakage, and shaft misalignment. This indicates that mechanical reliability remains the critical area requiring improvement across most production units.

4.6.2 Pareto 20/80 Principle Confirmation:

The Pareto analysis confirmed that approximately 20% of failure types accounted for nearly 80% of total equipment downtime.

This validates the concentration of maintenance efforts on a limited number of high-impact failure modes to achieve the greatest performance improvement.

4.6.3 Systemic Root Causes:

Root Cause Analysis (RCA) and Failure Mode and Effects Analysis (FMEA) identified several systemic contributors, such as insufficient design margins, use of substandard materials, and the absence of predictive monitoring systems (Condition-Based Maintenance, CBM). These factors collectively increased failure frequency and reduced equipment lifespan.

4.6.4 Availability Gap:

The analysis showed in Figure 4.21 that the average overall equipment availability is approximately 85%, which falls significantly below the world-class benchmark of 95%. This availability gap highlights the need for enhanced reliability-centered maintenance (RCM) strategies and the integration of digital monitoring tools to improve uptime and operational efficiency.

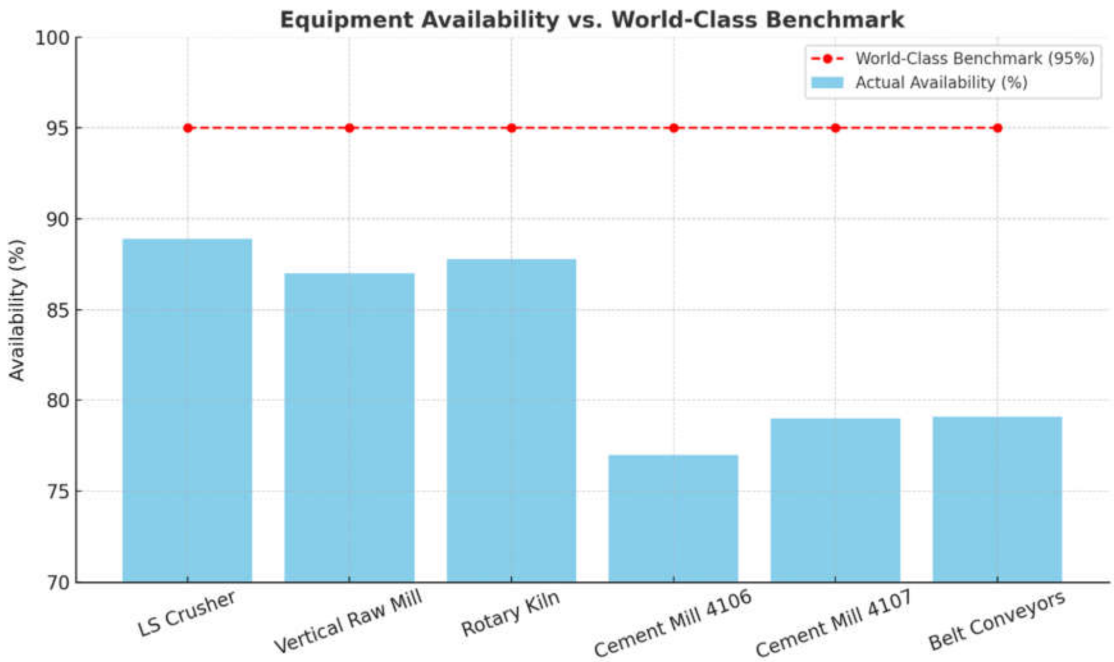

Figure 4.21: Availability Gap

4.7 Total Failure Trend by Year – Actual System Output

Figure 4.22 illustrates the annual trend of total equipment failures recorded between 2017 and the first quarter of 2025. The data reveal a nonlinear pattern characterized by alternating periods of decline and escalation. From 2017 to 2020, the plant experienced a continuous reduction in total failures, decreasing from approximately 880 failures in 2017 to about 310 failures in 2020. The sharp decrease observed in 2020 was primarily due to a plant shutdown caused by the COVID-19 pandemic, which led to a temporary reduction in operational hours and equipment utilization. This improvement may also be partially attributed to enhanced maintenance interventions or reduced production activity during that period.

However, a sharp increase occurred in 2021, where failures more than tripled compared to the previous year, followed by a sustained upward trend through 2024, peaking at around 1,600 failures. This escalation suggests a possible deterioration in maintenance effectiveness, aging equipment, or operational stress from increased production loads.

The partial data for 2025 (first three months) show a significant drop, but this reduction is not yet indicative of a true performance improvement, as the dataset does not represent a full operational year.

Overall, the trend demonstrates that while temporary reliability improvements were achieved early in the period, the system faced recurring issues that intensified in later years highlighting the need for root cause mitigation, predictive maintenance adoption, and reliability-centered strategies to stabilize performance and reduce unplanned failures.

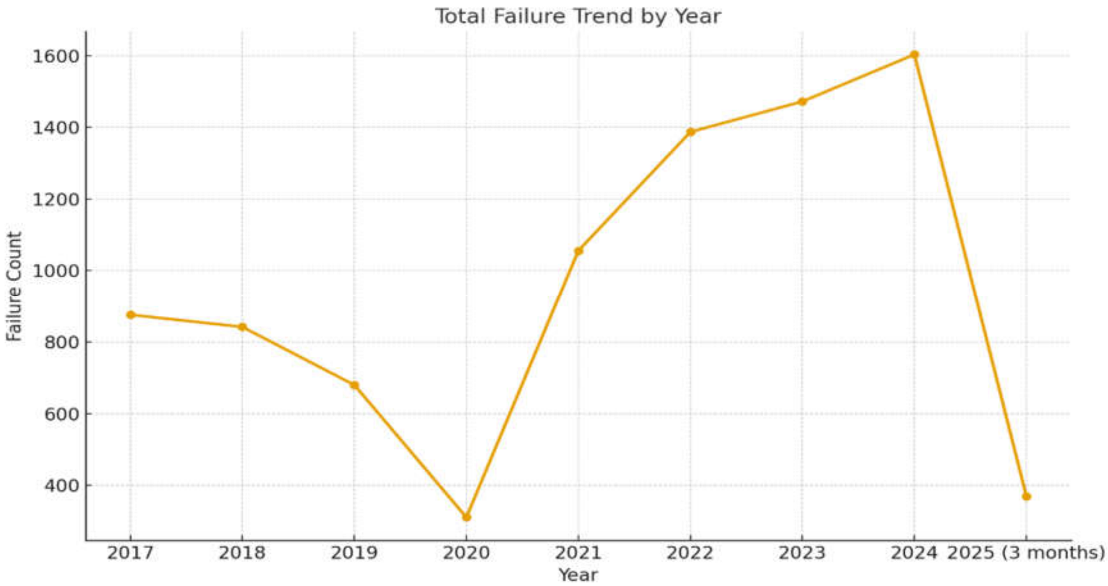

Figure 4.22: Total Failure Trend by Year – Actual System Output

Chapter 5

Discussion

5.1 Key Insights

5.1.1 Mechanical Systems Dominate Failure Causes

The comprehensive failure analysis conducted across five major plant areas LS Crusher, Raw Mill, Rotary Kiln, Cement Mill, and Belt Conveyors clearly shows that **mechanical systems** are the dominant source of operational failures. Out of a total of 8,597 documented failure events from 2017 to 2025, a significant majority are attributable to mechanical issues such as:

a. **Wear and abrasion** of liners, rollers, and moving parts,

b. **Hydraulic system leaks** due to degraded seals and poor filtration,

c. **Bolt and fastener failures** from vibration and fatigue,

d. **Weld cracking** due to thermal cycling and poor workmanship,

e. **Misalignment** of components like pulleys, shafts, and kiln rollers,

f. **Lubrication deficiencies** stemming from manual greasing and poor oil quality.

For example, in the LS Crusher, over 60% of the failures were caused by repeated issues with liner plates, bolts, and weld repairs suggesting both design and procedural shortcomings. These failures not only caused long repair durations (MTTR ≈ 26.3 hours per event) but also posed safety hazards and frequent operational disruptions.

In the Rotary Kiln, although the frequency of failures was relatively lower than other areas, the severity and impact were significantly higher. Key failures included seal degradation, burner hose damage, and tyre and roller misalignment, which resulted in critical shutdowns. The kiln's continuous-operation nature amplifies the consequence of even minor mechanical issues.

Similarly, Vertical Roller Mill failures primarily stemmed from wear and fatigue of grinding elements and hydraulic leaks, with root causes linked to material quality, lack of condition-based monitoring, and insufficient inspection intervals. The FMEA analysis highlighted that liner and welding-related failures had the highest RPN values (e.g., 360 for liner plate cracks), indicating elevated risk and urgent need for design and monitoring improvements.

The Cement Mills exhibited a high frequency of failures tied to scraper chambers, hydraulics, and structural components, consuming the most maintenance hours across all categories. A key insight here is that these areas are not just failure-prone but also resource-intensive, demanding enhanced planning and durable material solutions.

In the Belt Conveyor systems, although the failures were of lower criticality, their sheer frequency (especially roller failures and belt joint issues) made them a consistent cause of short-duration stoppages. These repetitive, localized issues added up to over 20% of total plant downtime, making conveyors one of the most interruption-prone systems in the facility.

5.1.2 Failure Distribution Is Highly Concentrated

A consistent pattern observed across all equipment is the Pareto distribution of failures: a small subset of components or failure types accounts for the majority of incidents. For example:

i. In the LS Crusher, just five failure categories—liner plate issues, bolt failures, welding repairs, lubrication problems, and blow bar adjustments—made up 60.2% of all recorded failures.

ii. For the Raw Mill, welding and liner repairs alone constituted over 50% of failures, followed by hydraulic and lubrication problems.

iii. In the Rotary Kiln, seal failures and welding issues accounted for over 40% of total downtime causes.

This insight is critical because it supports the targeted allocation of maintenance resources, where focusing on the "vital few" issues can result in disproportionately large reliability gains.

5.1.3 Design and Installation Quality Are Recurring Root Causes

From the 5 Whys and Fishbone diagrams, many failures especially in structural components, hydraulic systems, and fasteners can be traced back to inadequate design margins, poor fabrication, and improper installation. For example:

i. Misalignment of V-belts and pulleys in the crusher was often caused by worn pulleys and lack of alignment tools.
ii. Hydraulic leaks were frequently due to the absence of scheduled oil replacement, poor filter maintenance, and no routine inspection of seals.
iii. Liner and structural weld failures repeatedly stemmed from low-grade materials, improper welding techniques, and lack of QA/QC.

These findings underscore that maintenance performance is not just a function of execution, but also of original design quality, material selection, and commissioning practices.

5.1.4 Lack of Predictive Maintenance and Real-Time Monitoring

One of the most systemic issues observed was the limited use of predictive maintenance (PdM) tools and condition-based monitoring (CBM). Across multiple systems:

i. There were no online vibration sensors for rotating equipment like rollers and motors.
ii. Hydraulic oil condition and pressure were rarely monitored in real time, leading to unexpected seal and pump failures.
iii. Manual greasing routines were followed without adherence to loading conditions or environmental exposure, contributing to bearing overheating and roller seizure.

The absence of modern PdM systems allowed small, preventable issues to escalate into full equipment failures, as evidenced by frequent high-RPN events in both FMEA and RCA outputs.

5.1.5 Reliability Metrics Reflect Stress on Critical Equipment

The calculated MTBF (Mean Time Between Failures), MTTR (Mean Time to Repair), and Availability for critical equipment such as the LS Crusher further support the above insights. For instance:

i. MTBF = ~209.4 hours, or approximately 8.7 days between failures, indicating frequent downtime events.
ii. MTTR = ~26.3 hours, suggesting prolonged repairs per incident due to the complexity or unavailability of spares.
iii. System Availability = 88.86%, which is below industry benchmarks for high-efficiency operations (typically ≥ 95%).

These metrics confirm that the current maintenance approach—despite being active is not sufficiently proactive or optimized, particularly for mechanical systems under heavy and continuous loading.

5.2 Implications for Maintenance Strategy

5.2.1 Strategic Shift from Reactive to Predictive Maintenance

The findings of this study strongly advocate for a transition from a predominantly reactive and time-based preventive maintenance (PM) strategy toward a data-driven predictive maintenance (PdM) model. Current practices rely heavily on manual inspections and routine greasing schedules that often fail to detect early-stage component degradation. This reactive posture leads to high Mean Time To Repair (MTTR), unplanned shutdowns, and inefficient use of maintenance resources.

A predictive approach, supported by real-time monitoring tools and condition-based maintenance (CBM) protocols, can significantly enhance equipment reliability and plant uptime. Examples include:

i. **Vibration and thermal sensors** for early detection of bearing and motor failures in rotating equipment.
ii. **Hydraulic oil quality monitoring** and pressure sensors to anticipate seal leaks and pump failures.
iii. **Digital lubrication systems** with alarms for low-grease levels or incorrect intervals.

iv. **Infrared thermography** for monitoring hot zones in Rotary Kilns and gearboxes.

By embedding these technologies, the plant can move toward a proactive failure prevention culture, reducing reliance on manual interventions and emergency maintenance.

5.2.2 Implementation of Risk-Based Maintenance (RBM)

The Pareto and FMEA analyses showed that a small number of components account for the majority of downtime and maintenance workload. This highlights the opportunity to implement Risk-Based Maintenance (RBM), which allocates resources to high-risk equipment based on their criticality and failure probability.

For example:

i. In the LS Crusher, liner plate and bolt inspections should be prioritized, supported by torque checklists and fastener quality upgrades.
ii. In the Raw Mill, welding inspections and liner replacements should be standardized and tracked using digital thickness monitoring.
iii. In the Rotary Kiln, alignment checks and seal inspections should be scheduled more frequently, using laser alignment tools and thermography.

An RBM approach ensures that high-risk systems receive appropriate attention while reducing excessive maintenance in low-impact areas.

5.2.3 Maintenance Planning and Inventory Optimization

The study also highlights gaps in maintenance planning and spare parts inventory management, particularly for critical components like:

i. Hydraulic seals and accumulators
ii. High-tensile bolts and liner plates
iii. Certified welding consumables
iv. Greasing system spares and couplings

Unplanned failures often led to extended MTTR due to unavailability of spares, increasing the cost of downtime. Implementing a CMMS-based predictive inventory system, linked with failure trend analysis, would allow for smarter stock level decisions and just-in-time ordering, minimizing both shortages and overstock.

5.2.4 Training and Standard Operating Procedures (SOPs)

Many root causes—such as misaligned installations, improper torqueing, and missed inspections—were linked to human error and inadequate technical training. Thus, the findings support a restructuring of technician training programs, including:

i. Standardization and enforcement of SOPs
ii. Hands-on training in condition monitoring and alignment techniques
iii. Certification programs for welding, hydraulics, and precision assembly
iv. Use of checklists and post-maintenance QA inspections

Embedding a continuous learning culture among maintenance personnel is essential for ensuring consistent and high-quality maintenance execution.

5.3 Comparison with Previous Studies

5.3.1 Alignment with Global Trends in Maintenance and Reliability

The results of this study are consistent with findings in international research on industrial maintenance and asset reliability. Several key points of alignment include:

a) **Dominance of Mechanical Failures**: Studies by the Society for Maintenance & Reliability Professionals (SMRP) and various ISO reports confirm that over 70% of unplanned failures in manufacturing environments are mechanical in nature. Our study found the same trend across all major systems.

b) **Pareto Distribution of Failures**: The 80/20 principle is well-documented in maintenance literature (e.g., Mobley, 2002), and our findings validate this—where five failure types accounted for over 60–80% of breakdowns in each system.

c) **MTBF/MTTR Benchmarks**: Industry benchmarks suggest an MTBF of 300–500 hours for rotating equipment in heavy industry, and our calculated MTBF for LS Crusher (~209 hours) indicates underperformance. This supports calls from the literature for investment in PdM and root cause elimination.

d) **Cost of Poor Lubrication**: Numerous global reports (e.g., SKF, Shell, Noria) show that up to 50% of bearing failures are lubrication-related, a finding echoed in this plant's LS Crusher, Belt Conveyors, and Kiln systems.

e) **Need for Condition-Based Maintenance**: Published case studies on cement and mining industries highlight that CMMS-integrated PdM systems reduce downtime by 20–40%, supporting our recommendation for real-time monitoring and automation.

These alignments strengthen the external validity of the study and affirm that the plant is facing common industrial challenges that can be mitigated with proven global strategies.

5.4 Limitations

5.4.1 Single-Plant Scope

This study is based on a **single cement plant**, which limits the generalizability of the results to other operations with different configurations, equipment brands, or management structures. Factors such as organizational culture, workforce competency, plant layout, and raw material variability can influence failure patterns significantly.

5.4.2 Limited Scope of Data Types

While the dataset is extensive, spanning over **8,500 failure** events, it primarily consists of manual logs, CMMS records, and interview-based diagnostics. The absence of digital sensor data, real-time CBM trends, and operator behavior tracking restricts the ability to explore more advanced failure prediction models.

5.4.3 Underrepresentation of Electrical and Control Failures

Mechanical failures were dominant in the data not only due to their frequency but also due to underreporting of electrical, instrumentation, and control system issues. In many plants, these issues are logged separately by automation or electrical teams and may not be fully captured in CMMS. Thus, control-related root causes may be underestimated.

5.4.4 No Cost-Based Quantification of Failures

Although downtime hours and frequency were analyzed in depth, this study does not provide a financial quantification of failure impacts (e.g., cost per hour of downtime, cost of spares, labor utilization). This limits the ability to build ROI models for proposed interventions.

5.5 Concluding Summary of Analytical Findings

The integrated application of Pareto Analysis, RCA, FMEA, FTA, Reliability Metrics, and Weibull Analysis has provided an unprecedented, multi-faceted understanding of equipment reliability at the plant. The key takeaways are:

- **Mechanical wear and systemic root causes** are the primary drivers of downtime.
- A **targeted, risk-based approach** is the most efficient path to improvement.
- The **lack of predictive capabilities** is the single biggest opportunity for a strategic leap in performance.
- **Quantifiable metrics** now exist to benchmark future progress against a clear baseline.

5.6 Consolidated Prediction

Based on the historical data analysis, trend extrapolation, and Weibull reliability modeling conducted for each major unit, the following consolidated prediction outlines the most critical failures expected in the coming years (2025-2028) and presents a unified mitigation strategy.

Table 5.1: Failure Prediction and Mitigation Strategy (2025-2028)

Equipment	Top 3 Predicted Failures	Predicted Impact	Unified Mitigation Strategy
LS Crusher (1102)	1. Liner Plate Detachment 2. Bolt Failures 3. Hydraulic System Leaks	High downtime (~26 hrs/event), safety hazards, secondary damage.	1. Mechanical Integrity Program: Redesign liner attachments with locking nuts; standardize high-tensile bolts; implement scheduled re-torquing. 2. Hydraulic PM Schedule: Introduce oil sampling and filter changes; install pressure sensors.
Vertical Raw Mill (2104)	1. Liner Plate Cracks/Wear 2. Hydraulic System Failures 3. Lubrication Issues	Process halts (constrains kiln feed), high repair complexity.	1. Predictive Liner Management: Implement monthly ultrasonic thickness testing; transition to wear-resistant materials (e.g., Hardox). 2. Lubrication Automation: Automate grease points; install grease level sensors; train on oil analysis.
Rotary Kiln (3201)	1. Inlet/Outlet Seal Failures 2. Tyre & Roller	Severe downtime (~120	1. Advanced CBM Deployment: Install vibration and infrared

Equipment	Top 3 Predicted Failures	Predicted Impact	Unified Mitigation Strategy
	Bearing Overheating 3. Burner System Malfunctions	hrs/event), high energy loss, process instability.	thermography sensors on bearings and rollers. 2. Seal & Combustion Upgrade: Upgrade to high-temperature resistant seals; install fuel filters; develop burner SOPs.
Cement Mills (4106/4107)	1. Scraper Chamber Liner Failure 2. Hydraulic Cylinder Bolt Breakage 3. Structural Cracks	Highest maintenance hours, vibration trips, material spillage.	1. Wear-Resistant Upgrades: Replace scraper plates with CDP/Hardox liners. 2. Proactive Hydraulic Regime: Monthly N_2 pressure checks; semi-annual accumulator bladder replacement. 3. Structural Health Monitoring: Quarterly ultrasonic testing; replace over weld.
Belt Conveyors	1. Roller Bearing Seizure 2. Belt Joint Failures 3. Chute Damage/Leakage	High frequency, ~20% of total plant downtime, material spillage.	1. Roller Upgrade Program: Shift to sealed (IP68) bearings; install vibration sensors on critical conveyors. 2. Joint Integrity Management: Standardize

Equipment	Top 3 Predicted Failures	Predicted Impact	Unified Mitigation Strategy
			vulcanizing SOPs; track material expiry.

Expected **Outcomes of Proactive Implementation:**

By executing this consolidated strategy, the plant can target the following improvements by 2028:

- **Overall Plant Availability:** Increase from ~85% to >90%.
- **MTBF:** Improve by 25-30% across critical equipment.
- **MTTR:** Reduce by 15-20% through better planning and spares availability.
- **Maintenance Cost:** Optimize through reduced emergency repairs and optimized inventory.

Chapter 6
Conclusion and Recommendations

6.1 Conclusion

This research integrates qualitative and quantitative methods to analyze failures in critical cement plant equipment, identifying root causes through RCA, FMEA, FTA, and Pareto analysis.

Pareto Analysis revealed that 80% of failures in critical cement plant equipment are caused by a small number of recurring issues, with scraper chamber problems (34.6%), structural defects (20.5%), and hydraulic failures (12.6%) being the top contributors.

Root Cause Analysis (RCA) identified that most failures stem from inadequate preventive maintenance, poor material selection, lack of predictive monitoring, and human factors such as delayed inspections and improper maintenance practices.

Failure Mode and Effects Analysis (FMEA) showed that liner plates and bolts have the highest Risk Priority Numbers (RPNs of 432 and 315, respectively), indicating they require urgent attention in maintenance planning.

Fault Tree Analysis (FTA) demonstrated that unplanned downtime is typically triggered by mechanical or operational failures, with vibration, wear, and system instability acting as key intermediate events.

Weibull analysis and reliability modeling provided predictive insights into failure patterns, showing that equipment like the vertical raw mill follows a wear-out trend, justifying time-based or condition-based maintenance interventions.

Mean Time Between Failures (MTBF), Mean Time to Repair (MTTR), and Availability calculations revealed an average MTBF of 864 hours, MTTR of 121 hours, and system availability of 87.76%, highlighting room for improvement in maintenance efficiency.

Condition-Based Monitoring (CBM) data confirmed that real-time sensor inputs such as vibration levels, oil contamination, and belt wear—can effectively predict failures when integrated with alarm thresholds and historical trends.

Integration of CMMS data with expert knowledge and sensor outputs enabled a mixed-methods diagnostic approach that enhances accuracy in identifying failure causes and optimizing maintenance strategies.

This research presents a comprehensive and integrated approach to failure analysis and root cause investigation in critical equipment within the cement industry, addressing a significant gap in the systematic application of reliability engineering tools. By combining qualitative methods such as Root Cause Analysis (RCA), Fishbone Diagrams, 5 Whys, and Fault Tree Analysis (FTA)—with quantitative techniques including Failure Mode and Effects Analysis (FMEA), Weibull reliability modeling, Pareto analysis, and CMMS-based performance metrics (MTBF, MTTR, Availability), the study establishes a robust, evidence-based framework for diagnosing and mitigating equipment failures.

6.2 Recommendations

Based on the findings and scope of the research presented in the thesis "Failure Analysis and Root Cause Investigation in Critical Equipment of the Cement Industry", several promising areas for future research have been opened or remain uncovered. These areas extend the current integrated failure analysis framework toward more advanced, automated, and scalable solutions aligned with Industry 4.0 and digital transformation goals. The following are key recommendations for further research:

6.2.1 Integration of Machine Learning and AI for Predictive Diagnostics

While the current study successfully combines RCA, FMEA, FTA, and condition-based monitoring (CBM) data, it stops short of employing artificial intelligence (AI) or machine learning (ML) models for failure prediction. Future research should explore supervised and unsupervised learning algorithms such as Random Forest, Support Vector Machines, or neural networks to analyze historical CMMS and real-time sensor data for early fault detection and root cause classification.

6.2.2 Development of a Digital Twin for Cement Plant Equipment

The research highlights the value of Weibull modeling and reliability metrics but does not implement a dynamic digital replica of equipment. Future work should focus on creating digital twins of critical systems (e.g., vertical raw mill, rotary kiln) that simulate real-time operational behaviour, enabling virtual testing of maintenance strategies, failure scenarios, and design improvements.

6.2.3 Real-Time Data Fusion from IoT and SCADA Systems

Although CBM data was used, the integration of live IoT sensor networks and SCADA system outputs into a centralized analytics platform was not fully realized. Further research is needed to develop automated data fusion frameworks that combine vibration, temperature, oil analysis, and acoustic emission data for continuous health monitoring and auto-triggered alerts.

6.2.4 Economic and Environmental Impact Assessment of Predictive Maintenance

The study emphasizes technical reliability improvements but does not quantify the economic ROI or environmental benefits (e.g., reduced energy use, lower emissions, less scrap) of implementing the proposed framework. Future research should model cost-benefit analyses and sustainability impacts across the plant lifecycle.

6.2.5 Human Factor and Organizational Reliability Modelling

While human error and training gaps were identified as root causes, no formal human reliability assessment (HRA) model was applied. Future studies could integrate methods like THERP or HEART to quantify the probability of human error in maintenance tasks and develop targeted interventions to improve procedural compliance and safety culture.

6.2.6 Expansion of the Framework to Other Heavy Industries

The proposed integrated model was validated in the cement industry but has potential applicability in mining, power generation, steel, and petrochemical sectors. Comparative studies should be conducted to adapt and validate the methodology across different industrial environments with similar operational stresses.

6.2.7Automated Root Cause Analysis Using Natural Language Processing (NLP)

A significant portion of CMMS records consists of unstructured text in work order descriptions. Future research could apply NLP techniques to automatically extract failure modes, symptoms, and root causes from maintenance logs, reducing manual analysis effort and improving data consistency.

6.2.8 Advanced Materials and Coatings for Wear Resistance

The study identifies wear and material degradation as dominant failure mechanisms. Further research should evaluate new-generation wear-resistant materials (e.g., ceramic composites, laser-cladded coatings, nano-engineered steels) under real plant conditions to extend component life and reduce maintenance frequency.

In conclusion, this research opens a strong foundation for evidence-based, integrated failure analysis in heavy industry. However, the full potential of predictive maintenance can only be unlocked through advanced digitalization, automation, and cross-disciplinary innovation areas that represent rich opportunities for future investigation.

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