A Hybrid Method for Identifying Critical Failure Modes in a Ball Mill

A. P. Akintola[1*], O. M. Muvengei[2], J. K. Kimotho[3], A. K. Muchiri[4]

[1]Department of Mechanical Engineering, Pan African University, Institute for Basic Sciences, Technology and Innovation, Nairobi, Kenya.

[2,3,4]Department of Mechanical Engineering, Jomo Kenyatta University of Agriculture and Technology, Kenya.

ABSTRACT: The reliability of a ball mill is crucial for the seamless operation of ore processing and other industrial plants, where unexpected equipment failure or downtime can result in significant financial losses and reduced production efficiency. Thus, this paper examined a hybrid method for identifying critical failure modes in a ball mill using the Failure Modes, Effects, and Criticality Analysis combined with the Complex Proportional Assessment with Grey Numbers (COPRAS-G). The COPRAS-G method was employed to assess the criticality of various failure modes by determining the weights of significant failure modes in the bearing, gearbox, motor, and shaft components of a ball mill. It was observed that gear seal failure is the most critical failure with percentage contribution (N_i) of 100%, while bearing wear is the least critical failure with percentage contribution (N_i) of 62%. The result suggests that failure modes of gear seal failure, gear pitting, motor bearing fatigue, and shaft fracture are regarded as the main contributors to failure with percentage contribution (N_i) of 100%, 97%, 87% and 83% respectively. Current ball mill maintenance includes corrective, preventive and predictive maintenance. For failure modes with high criticality, predictive maintenance was advised, while for moderate and low criticality, corrective and preventive maintenance were advised.

KEYWORDS: Failure Mode and Effects Analysis, Ball Mill, Reliability Engineering, Mineral Processing.

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I. INTRODUCTION

Reliability and performance are pivotal in industrial processes and machinery, as they directly impact operational efficiency, production continuity and financial outcomes. They are crucial to reliability engineers and maintenance professionals for maintaining system readiness, by facilitating the identification of condition-based problems, comparing potential failure patterns and optimizing maintenance plans (Pancholi and Bhatt, 2016). In the context of ore processing plants, the reliability of a ball mill is essential, as unexpected equipment failures or downtime can lead to significant financial losses and reduced overall production efficiency.

A ball mill is a versatile machine used in various industries to grind solid materials, which are placed in a drum along with media balls. Particle breakage within the ball mill occurs through impact, friction and abrasion between the steel balls and the material being processed (Kimura et al., 2007; Byiringiro et al., 2020). The crucial need to ensure the reliability of ball mills necessitates a comprehensive understanding of potential failure modes and their consequences. This understanding can be systematically achieved through the use of Failure Mode, Effects, and Criticality Analysis (FMECA).

It extends the traditional Failure Mode and Effects Analysis (FMEA) by incorporating a quantitative assessment of criticality, thus prioritizing failures based on their likelihood and severity (Cristea and Constantinescu, 2017). FMEA was originally developed by Grumman in 1950 and adopted by the Ford Motor Company (Kiran, 2022). It is a systematic approach for identifying potential failure modes and their consequences (Kiran, 2022). It has been widely applied in industries such as aerospace and automotive due to its simplicity (Bowles and Peldez, 1995). However, FMEA has limitations, including subjective assessments of severity, occurrence, and detection indexes, and it does not consider the costs associated with different failure modes.

FMECA prioritizes failures based on the likelihood of their occurrence and the severity of their effects (Nardo et al., 2022). Certain studies have attempted to assign equal weights to occurrence (O), severity (S), and detection (D) factors, such as the work by (Liu et al., 2011). Furthermore, Dinmohammadi et al. (2016) developed a reliability-centered maintenance program for wind turbines using FMECA, highlighting the need for comprehensive models in assessing failure criticality.

Recent advancements in the field have led to the integration of hybrid approaches with FMECA to improve its effectiveness. Jun and Huobi (2012) explored the application of FMECA to enhance the reliability of aircraft equipment. In another study, Dabbagh and Yousefi (2019) combined FMECA with multi-objective optimization and failure chain model (FCM) methodologies to assess occupational health and safety risks. The hybrid approach demonstrated superior performance over traditional methods such as the Risk Priority Number (RPN).

*Corresponding author: adebisi_tunji@yahoo.com

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Additionally, Yousefi et al. (2018) utilized grey relational analysis and data envelopment analysis (DEA) for failure categorization and prioritization, addressing issues with RPN-based approaches. Chang et al. (2014) used the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and Decision-Making Trial and Evaluation Laboratory (DEMATEL) processes to prioritize risks in the spare parts industry.

Sahoo et al. (2008) emphasized FMECA's role in reducing maintenance costs across various industries, while Liu et al. (2015) proposed an innovative FMEA approach incorporating combination weighting and the fuzzy-VIKOR method. This method addresses uncertainties stemming from human subjectivity in risk evaluation. Lo et al. (2018) applied FMEA and multi-criteria decision-making methodologies in the electronics industry, incorporating anticipated costs into the RPN calculation.

Adhikary et al. (2014) applied FMECA in conjunction with the Complex Proportional Assessment with Grey numbers (COPRAS-G) method to evaluate failure modes in coal-fired thermal power plants. Pancholi and Bhatt (2018) utilized COPRAS-G to prioritize maintenance tasks in the aluminum wire rolling mill industry, showcasing its potential application across different process sectors.

The review of relevant literature depicted the gap in the application of the COPRAS-G-based multi-criteria decision-making approach specifically to ball mills within the mining sector. Thus, this paper examines a hybrid method for identifying critical failure modes in a ball mill using the FMECA combined with the COPRAS-G. By integrating grey numbers into traditional FMECA, the COPRAS-G method offers a sophisticated and nuanced assessment of uncertainties present in real-world systems. The primary objective is to systematically identify and prioritize critical failure modes in ball mill components, evaluate their impacts, and develop tailored maintenance strategies to enhance the reliability and efficiency of ball mills. The findings are expected to inform and optimize maintenance practices, thereby reducing downtime and improving overall operational efficiency in industries dependent on ball mills.

II. THEORETICAL ANALYSIS

Complex Proportional Assessment with Grey Numbers (COPRAS-G) utilized the grey number theory with unknown upper and lower bounds of the grey number's value, but the range in which it falls is known. COPRAS-G method for failure modes criticality evaluation is expressed using the subsequent steps of:

A. Choosing a set of different criteria and failure modes, then place them in the decision matrix along the rows and columns accordingly.

B. Creating a decision matrix (X), which displays the criteria's ranking in intervals of grey numbers.

$$X = [a_{ij}; b_{ij}] = \begin{bmatrix} [a_{11}; b_{11}] & \cdots & [a_{1n};\ b_{1n}] \\ \vdots & \ddots & \vdots \\ [a_{m1}; b_{m1}] & \cdots & [a_{mn}; b_{mn}] \end{bmatrix} \quad (1)$$

Each cell in the matrix contains a pair of values representing a grey number interval $[a_{ij}, b_{ij}]$, where a_{ij} is the lower value and b_{ij} is the upper value of the interval. $i = 1, 2 ...,$ m which represents the failure modes along the row and $j = 1, 2 \ldots, n,$ which represents the criteria along the column in decision matrix.

C. Normalizing the decision matrix (X) to ensure that all criteria are on a common scale.

$$a1_{ij} = \frac{a_{ij}}{\left(\frac{1}{2}\right)\left(\sum_{j=1}^{n} a_{ij} + \sum_{j=1}^{n} b_{ij}\right)} = \frac{2a_{ij}}{\left(\sum_{j=1}^{n} a_{ij} + \sum_{j=1}^{n} b_{ij}\right)} \quad (2)$$

$$b1_{ij} = \frac{b_{ij}}{\left(\frac{1}{2}\right)\left(\sum_{j=1}^{n} a_{ij} + \sum_{j=1}^{n} b_{ij}\right)} = \frac{2b_{ij}}{\left(\sum_{j=1}^{n} a_{ij} + \sum_{j=1}^{n} b_{ij}\right)} \quad (3)$$

Normalized decision-making matrix $X1$ is as follows:

$$X1 = \begin{bmatrix} [a1_{11}; b1_{11}] & \cdots & [a1_{1n};\ b1_{1n}] \\ \vdots & \ddots & \vdots \\ [a1_{m1}; b1_{m1}] & \cdots & [a1_{mn}; b1_{mn}] \end{bmatrix} \quad (4)$$

D. Calculating weight of each criterion based on Shannon's entropy concept where initially we have to calculate entropy ej and from it weight wj for jth criteria by:

computing entropy (ej) for each criterion as follows:

$$eaj = -\frac{1}{Inm} \sum_{i=1}^{n} a_{ij} Ina_{ij} \quad (5)$$

$$ebj = -\frac{1}{Inm} \sum_{i=1}^{n} b_{ij} Inb_{ij} \quad (6)$$

and calculating the weight (wj) for each criterion based on the entropy values:

$$w_{aj} = \frac{1 - e_{aj}}{\sum_{j=1}^{n}(1 - e_{aj})} \quad (7)$$

$$w_{bj} = \frac{1 - e_{bj}}{\sum_{j=1}^{n}(1 - e_{bj})} \quad (8)$$

E. Determining weighted normalized decision matrix by: multiplying each normalized value in the decision matrix by its corresponding weight to obtain the weighted normalized matrix (X2) using Eqn. 9 and 10:

$$a2_{ij} = a1_{ij} . w_{ij} \quad (9)$$

$$b2_{ij} = b1_{ij} . w_{ij} \quad (10)$$

The weighted normalized decision matrix $X2$ is obtained as follows:

$$X2 = \begin{bmatrix} [a2_{11}; b2_{11}] & \cdots & [a2_{1n};\ b2_{1n}] \\ \vdots & \ddots & \vdots \\ [a2_{m1}; b2_{m1}] & \cdots & [a2_{mn}; b2_{mn}] \end{bmatrix} \quad (11)$$

F. Calculating the weighted mean normalized sums (P_i) for beneficial criteria and (Q_i) for non-beneficial criteria using the formulas:

$$P_i = \frac{1}{2} \sum_{j=1}^{k} (a2_{ij} + b2_{ij}) \quad (12)$$

$$R_i = \frac{1}{2} \sum_{j=k+1}^{k} (a2_{ij} + b2_{ij}) \quad (13)$$

where k is the number of beneficial criteria, and (m-k) is the number of non-beneficial criteria. The beneficial criteria are initially positioned in the decision-making matrix, followed by the non-beneficial criteria.

G. Calculating the relative significance/weight (Q_i) of each alternative using the formula:

$$Q_i = P_i + \frac{\text{Rmin} \sum_{i=1}^{m} \text{Ri}}{\text{Ri} \sum_{i=1}^{m} (\text{Rmin}/\text{Ri})} = P_i + \frac{\sum_{i=1}^{m} \text{Ri}}{\text{Ri} \sum_{i=1}^{m} (1/\text{Ri})} \tag{14}$$

where, R_{min} is the minimum value of all weighted mean normalized sums R_i of non-beneficial criteria. Each alternative's priority is established based on the MCI. That is, options with a greater MCI value are prioritized above others. MCI_{max} is the maximum value of relative significance among all alternatives.

H. Calculating the degree of unity in percentage contribution (N_i) for each failure cause using the formula:

$$N_i = \frac{MCI_i}{MCI_{max}} * 100 \tag{15}$$

where MCI_{max} is the highest value of relative significance value of all available alternatives.

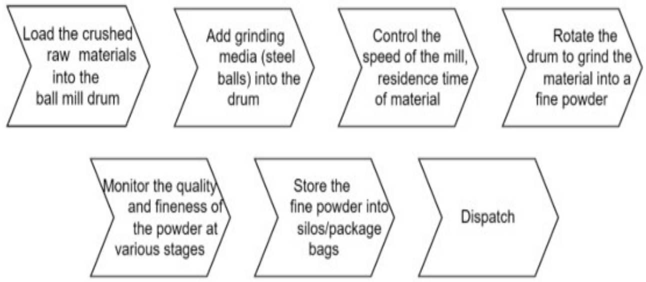

Figure 1. Industrial ball mill process flow

III. EXPERIMENTAL PROCEDURE

A. *Description of the ball mill*

The ball mill is a mechanical device widely used for grinding and mixing materials in industries such as mining, cement, and manufacturing. It comprises several essential components that work together to ensure efficient grinding. At the heart of the ball mill is the drum, a cylindrical structure where the actual grinding occurs. Inside the drum, grinding media (usually steel balls) and the material to be ground are placed. The rotation of the drum, driven by the motor and transmitted through the gearbox, causes the balls to tumble and crush the material. The gearbox reduces the rotational speed of the motor to the optimal level required for grinding, ensuring smooth and efficient operation of the drum.

The motor powers the entire system, converting electrical energy into mechanical energy to drive the ball mill. This energy is transmitted to the drum via the shaft, which is supported by bearings to reduce friction and allow for smooth rotation. The bearings are crucial to the ball mill's operation, ensuring minimal wear and tear during the grinding process. Additionally, the control box provides operators with a user-friendly interface to regulate and monitor the motor's speed and overall operation. The ball mill is housed on a frame that provides structural support, holding the components securely in place and ensuring stability during operation.

Figure 1 provides a thorough schematic of the process, giving an overall view of the ball mill's design and operation. Figure 2 illustrates a collection of grinding media typically used in the ball mill. The primary components of the ball mill, including the motor, drum, bearing, gearbox, control box, shaft, and frame support, are shown in Figure 3. Figure 4 presents the front view of the ball mill, highlighting key components such as the cylindrical drum, which holds the grinding media and materials, as well as the supporting structure, gearbox, and motor. Figure 5 shows the side view of the ball mill, providing additional details of its structure and operational components, including a clear depiction of the control box. Based on previous failure data, it has been determined that the bearing, gearbox, motor, and shaft are the most crucial components of the ball mill, requiring particular attention for maintenance and monitoring.

Figure 2. Grinding balls of a ball mill

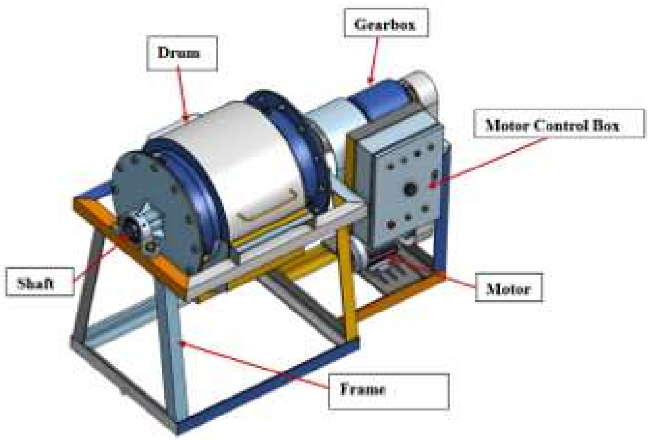

Figure 3. Small scale ball mill fabricated in JKUAT

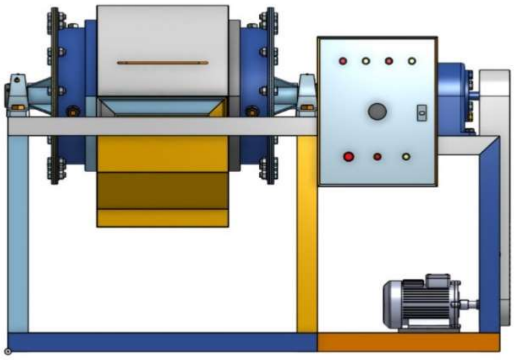

Figure 4. Front view of the ball mill

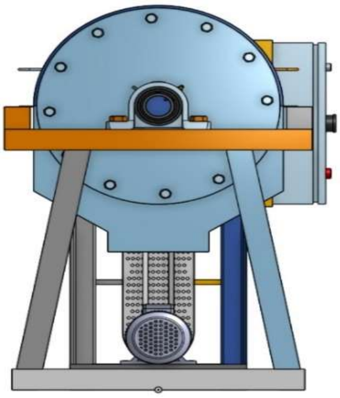

Figure 5. Side view of the ball mill

To systematically assess these failure modes, two main sources of data were utilized:

I. Historical Failure Data: Historical failure data was analyzed to identify patterns in past component failures, providing insights into the frequency and nature of these failures.

II. Expert Questionnaires: Insight was gathered from experts on the likelihood, detectability, and impact of failure modes from operators, managers, and maintenance staff.

Tables 2, 3, 4, 5, and 6 present the obtainable scores of severity (S), occurrence (O), detection (D), spare parts (SP) and economic cost (EC), respectively. A scale of 1 to 5 is used to rank these scores for each failure modes for each of the several criteria. When evaluating the influence of factors, a scale of 1 to 5 indicates least to most consideration. These ratings are determined using surveys given to maintenance personnel, floor operators, managers.

Table 1: Survey Participation Summary: Distribution, Respondents, and Response Rates

Category	**Total Questionnaire Distributed**	**Number of Respondents**	**Response rate (%)**
Maintenance Personnel	25	18	72
Floor Operators	20	12	60
Managers	5	3	60
Total	50	33	66

Each failure mode was scored based on five criteria: severity (S), occurrence (O), detection (D), spare parts (SP), and economic cost (EC). The scoring process involved:

Severity (S): Assesses the potential impact on system performance and safety. Higher scores indicate more severe consequences.

Occurrence (O): Evaluates the likelihood of failure. Higher scores indicate higher frequency.

Detection (D): Measures detectability before significant issues arise. Lower scores indicate better detection.

Spare Parts (SP): Considers the importance of spare part availability. Higher scores indicate higher criticality.

Economic Cost (EC): Reflects the financial impact. Lower scores suggest lower costs.

Table 2: Scores for Severity (S)

Scores for Occurrence (O)	
Criteria for Occurrence	**Score**
Very Unlikely	1
Unlikely	2
Moderate occurrence	3
Likely	4
Very Likely	5

Table 3: Scores for Occurrence (O)

Scores for Detection (D)	
Criteria for Detection	**Score**
Very High Detectability	1
High Detectability	2
Moderate Detectability	3
Low Detectability	4
Very Low Detectability	5

Table 4: Scores for Detection (D)

Scores for Severity (S)	
Criteria for Severity	**Score**
Low Severity	1
Moderate Severity	2
Significant Severity	3
High Severity	4
Critical Severity	5

Table 5: Scores for Spare Parts (SP)

Scores for Spare Parts (SP)	
Criteria for Spare Parts	**Score**
Not Necessary	1
Low Priority	2
Moderate Priority	3
High Priority	4
Critical	5

Table 6: Scores for Economic Cost (EC)

Scores for Economic Cost (EC)	
Criteria for Economic cost	**Score**
Very Low Cost	1
Low Cost	2
Moderate Cost	3
High Cost	4
Very High Cost	5

B. Failure mode, effects, and criticality analysis with assignment of scores using grey numbers

FMECA was conducted to identify and assess potential failure modes in components such as bearings, gearboxes, motors, and shafts. Failure modes were identified through root cause analysis. The scores for severity (S), occurrence (O), detection (D), spare parts (SP) and economic cost (EC) for various failure modes are ordered on a scale of 1-5 according to the grey number range idea in [a_{ij}, b_{ij}] according to Tables 2-6, where a_{ij} is the lower value and b_{ij} is the upper value of the interval as shown in Table 8.

C. Significance of COPRAS-G

COPRAS-G is a robust multi-criterion decision-making (MCDM) technique that integrates the strengths of COPRAS with the grey system theory. This hybrid approach is particularly valuable in scenarios where assigning ratings and classifying them into varying criticality by maintenance personnel is practically challenging. In order to get around this challenge, the scores are provided as an interval, or grey number, rather than a specific value. In the context of failure mode analysis, COPRAS-G facilitates the identification and ranking of critical failure modes by considering not only the quantitative data but also the qualitative aspects that may be difficult to measure precisely.

IV. RESULTS AND DISCUSSION

The analysis focused on identifying and ranking the critical failure modes of the ball mill's key components, including the bearings, gearbox, motor, and shaft based on severity, occurrence, detection, spare parts and economic cost. Table 7 presents the Failure Modes Effects and Criticality Analysis (FMEA) for the ball mill's critical components. It details potential failure modes, causes, effects, and mitigation strategies for components such as bearings, gearbox, motor, and shaft. For example, bearing failure modes include wear, misalignment, high temperature, deformation, and corrosion, caused by factors like continuous operation, improper installation, and environmental exposure. Mitigation strategies, such as lubrication and alignment checks, are recommended to reduce the risk of failure.

In Table 8, the decision matrix lists the scores for each failure mode based on severity, occurrence, detection, spare parts availability, and economic cost. These scores were derived from expert questionnaires providing a quantitative assessment of each failure mode's potential impact on system reliability. Table 9 shows the normalized decision matrix, where the scores from Table 8 are adjusted to a common scale. This normalization process ensures that all criteria are evaluated consistently, allowing for a fair comparison of the different failure modes.

Table 10 and 11 presents the logarithmic calculations used to determine the weights of each criterion. The entropy values calculated from these logs help in assessing the relative importance of each criterion, contributing to a more nuanced evaluation of the failure modes. The weighted normalized decision matrix in Table 12 applies the criterion weights to the normalized scores. This table is crucial for identifying the most critical failure modes, as it considers both quantitative data and expert judgment to assign relative importance to each mode.

Every crucial component's dependability is computed. The degree of unity in percentage contribution (N_i) for each failure modes of the components is found out. BM1, BM2, BM3, BM4, BM5, BM6, BM7, BM8, BM9, BM10, BM11, BM12, BM13 and BM14 represent each failure modes of four critical components of the ball mill. Table 13 demonstrates the relative importance of every failure mode (Q_i), their percentage contribution (N_i) and rank. From Table 13, it can be observed that gearbox seal failure (BM8) is the most critical failure while bearing wear (BM1) is the least critical failure. It is recommended that the maintenance strategy as stated in Table 14, be observed. Failure modes (BM8, BM11, BM7 and BM12) with a high value of (Q_i) should be kept under predictive maintenance, while failure modes (BM4, BM5, BM9, BM13, BM14) with moderate value of (Q_i) should be kept under preventive maintenance, and failure modes (BM1, BM2, BM3, BM6 and BM10) with low (Q_i) should be kept under corrective maintenance.

Table 7: FMEA of Identified Critical Components

Critical Components	Potential Failure Mode	Potential Causes	Effects	Mitigation	Notation
Bearing	Bearing wear	Continuous operation & cyclic loading	Increased friction and eventual failure	Lubrication and monitoring	BM1
	Bearing misalignment	Shaft deflection	Uneven load distribution and accelerated wear	Alignment check	BM2
	Bearing high temperature	Improper lubrication	Potential damage to bearings	Temperature monitoring	BM3
	Bearing deformation	Excessive loads, mechanical shock	Structural damage	Stress reduction and replacement plan	BM4
	Bearing corrosion	Exposure to moisture, aggressive chemicals, or corrosive environments	Pitting, surface roughness	Environmental control	BM5
Gearbox	Gear tooth breakage	Excessive loads	Loss of torque transmission	Load reduction	BM6
	Gear pitting	Continuous operation and high loads	Surface damage such as pitting	Lubrication maintenance	BM7
	Gearbox seal failure	Improper installation and inadequate maintenance	Lubrication loss	Seal replacement	BM8
Motor	Motor overheating	High ambient temperatures	Insulation degradation	Proper ventilation	BM9
	Electrical damage	Loose connections and faulty wiring	Voltage drops, overheating	Electrical repairs and wiring check	BM10
	Motor bearing fatigue	Insufficient lubrication, contamination	Increased vibration, noise, and reduced motor performance	Bearing replacement	BM11
Shaft	Shaft fracture	Excessive loads, improper shaft sizing	Shaft bending	Load reduction	BM12
	Shaft misalignment	Incorrect installation or deformation of other components	Excessive vibration, uneven wear patterns	preventive maintenance	BM13
	Shaft abrasion	Continuous rotation and contact with other components	Reduced performance, increased vibration, and eventual shaft failure	Surface coating	BM14

Table 8: Decision Matrix-X for COPRAS-G

	S		**O**		**D**		**SP**		**EC**	
Potential Failure Causes	**Severity**		**Occurrence**		**Detection**		**Spare Parts**		**Economic Cost**	
	a_{ij}	b_{ij}	a_{ij}	b_{ij}	a_{ij}	b_{ij}	a_{ij}	b_{ij}	a_{ij}	b_{ij}
BM1	1	5	1	3	1	4	1	2	2	3
BM2	2	5	1	2	1	4	1	2	2	3
BM3	1	5	1	3	1	5	1	5	2	5
BM4	4	5	1	3	1	2	1	5	1	5
BM5	2	5	1	4	1	5	1	3	2	5
BM6	4	5	1	3	1	5	1	5	4	5
BM7	2	5	1	4	1	5	1	5	3	4
BM8	2	5	2	5	1	3	1	2	1	2
BM9	2	5	1	3	1	4	1	3	1	5
BM10	3	5	1	3	1	4	1	2	1	4
BM11	2	5	1	4	2	5	1	5	3	5
BM12	4	5	1	2	1	2	2	4	3	5
BM13	3	5	1	3	1	3	1	4	3	5
BM14	2	5	1	4	1	3	1	4	3	5
	34	70	15	46	15	54	15	51	31	61

Table 9: Normalized Decision Matrix-X for COPRAS-G

	S		**O**		**D**		**SP**		**EC**	
Potential Failure Causes	**Severity**		**Occurrence**		**Detection**		**Spare Parts**		**Economic Cost**	
	$a1_{ij}$	$b1_{ij}$	$a1_{ij}$	$b1_{ij}$	$a1_{ij}$	$b1_{ij}$	$a1_{ij}$	$b1_{ij}$	$a1_{ij}$	$b1_{ij}$
BM1	0.0192	0.0962	0.0328	0.0984	0.0290	0.1159	0.0303	0.0606	0.0435	0.0652
BM2	0.0385	0.0962	0.0328	0.0656	0.0290	0.1159	0.0303	0.0606	0.0435	0.0652
BM3	0.0192	0.0962	0.0328	0.0984	0.0290	0.1449	0.0303	0.1515	0.0435	0.1087
BM4	0.0769	0.0962	0.0328	0.0984	0.0290	0.0580	0.0303	0.1515	0.0217	0.1087
BM5	0.0385	0.0962	0.0328	0.1311	0.0290	0.1449	0.0303	0.0909	0.0435	0.1087
BM6	0.0769	0.0962	0.0328	0.0984	0.0290	0.1449	0.0303	0.1515	0.0870	0.1087
BM7	0.0385	0.0962	0.0328	0.1311	0.0290	0.1449	0.0303	0.1515	0.0652	0.0870
BM8	0.0385	0.0962	0.0656	0.1639	0.0290	0.0870	0.0303	0.0606	0.0217	0.0435
BM9	0.0385	0.1176	0.0328	0.0984	0.0290	0.1159	0.0303	0.0732	0.0217	0.1639
BM10	0.0577	0.1176	0.0328	0.0984	0.0290	0.1159	0.0303	0.0488	0.0217	0.1311
BM11	0.0385	0.1176	0.0328	0.1311	0.0580	0.1449	0.0303	0.1220	0.0652	0.1639
BM12	0.0769	0.0962	0.0328	0.0656	0.0290	0.0580	0.0606	0.1212	0.0652	0.1087
BM13	0.0577	0.0962	0.0328	0.0984	0.0290	0.0870	0.0303	0.1212	0.0652	0.1087
BM14	0.0385	0.0962	0.0328	0.1311	0.0290	0.0870	0.0303	0.1212	0.0652	0.1087

Table 11: Logarithmic Calculation for Each Criteria

	S		O		D		SP		EC	
Potential Failure Causes	**Severity**		**Occurrence**		**Detection**		**Spare Parts**		**Economic Cost**	
	$a_{ij}\ln a_{ij}$	$b_{ij}\ln b_{ij}$	$a_{ij}\ln a_{ij}$	$b_{ij}\ln b_{ij}$	$a_{ij}\ln a_{ij}$	$b_{ij}\ln b_{ij}$	$a_{ij}\ln a_{ij}$	$b_{ij}\ln b_{ij}$	$a_{ij}\ln a_{ij}$	$b_{ij}\ln b_{ij}$
BM1	0.0000	8.0472	0.0000	3.2958	0.0000	5.5452	0.0000	1.3863	1.3863	3.2958
BM2	1.3863	8.0472	0.0000	1.3863	0.0000	5.5452	0.0000	1.3863	1.3863	3.2958
BM3	0.0000	8.0472	0.0000	3.2958	0.0000	8.0472	0.0000	8.0472	1.3863	8.0472
BM4	5.5452	8.0472	0.0000	3.2958	0.0000	1.3863	0.0000	8.0472	0.0000	8.0472
BM5	1.3863	8.0472	0.0000	5.5452	0.0000	8.0472	0.0000	3.2958	1.3863	8.0472
BM6	5.5452	8.0472	0.0000	3.2958	0.0000	8.0472	0.0000	8.0472	5.5452	8.0472
BM7	1.3863	8.0472	0.0000	5.5452	0.0000	8.0472	0.0000	8.0472	3.2958	5.5452
BM8	1.3863	8.0472	1.3863	8.0472	0.0000	3.2958	0.0000	1.3863	0.0000	1.3863
BM9	1.3863	8.0472	0.0000	3.2958	0.0000	5.5452	0.0000	3.2958	0.0000	8.0472
BM10	3.2958	8.0472	0.0000	3.2958	0.0000	5.5452	0.0000	1.3863	0.0000	5.5452
BM11	1.3863	8.0472	0.0000	5.5452	1.3863	8.0472	0.0000	8.0472	3.2958	8.0472
BM12	5.5452	8.0472	0.0000	1.3863	0.0000	1.3863	1.3863	5.5452	3.2958	8.0472
BM13	3.2958	8.0472	0.0000	3.2958	0.0000	3.2958	0.0000	5.5452	3.2958	8.0472
BM14	1.3863	8.0472	0.0000	5.5452	0.0000	3.2958	0.0000	5.5452	3.2958	8.0472
	8.3178	40.236	0.0000	16.819	0.0000	28.571	0.0000	22.163	5.5452	30.733

Table 13: Criticality ranking based on P_i, Q_i and N_i

Notation	Potential Failure Causes	P_i	Q_i	N_i	Rank
BM1	Bearing wear and fatigue	0.1176	0.1176	62	14
BM2	Bearing misalignment & improper mounting	0.1222	0.1222	65	12
BM3	Bearing high temperature	0.1479	0.1479	79	10
BM4	Bearing deformation or fracture	0.1490	0.1490	79	9
BM5	Bearing corrosion	0.1509	0.1509	80	7
BM6	Seal and gasket failure	0.1882	0.1882	100	1
BM7	Gear pitting	0.1630	0.1630	87	3
BM8	Gear tooth breakage	0.1191	0.1191	63	13
BM9	Motor overheating	0.1492	0.1492	79	8
BM10	Electrical damage	0.1467	0.1467	78	11
BM11	Motor bearing fatigue	0.1835	0.1835	97	2
BM12	Shaft fracture	0.1564	0.1564	83	4
BM13	Shaft corrosion	0.1556	0.1556	83	5
BM14	Shaft abrasion and wear	0.1510	0.1510	80	6

Table 14: Comparison matrix for deciding maintenance strategy

No.	Failure cause	Maintenance plan	Impact of Q_i & N_i
1	BM1	Corrective maintenance	Low Q_i & N_i
2	BM2	Corrective maintenance	Low Q_i & N_i
3	BM3	Corrective maintenance	Low Q_i & N_i
4	BM4	Preventive maintenance	Moderate Q_i & N_i
5	BM5	Preventive maintenance	Moderate Q_i & N_i
6	BM6	Corrective maintenance	Low Q_i & N_i
7	BM7	Predictive maintenance	High Q_i & N_i
8	BM8	Predictive maintenance	High Q_i & N_i
9	BM9	Preventive maintenance	Moderate Q_i & N_i
10	BM10	Corrective maintenance	Low Q_i & N_i
11	BM11	Predictive maintenance	High Q_i & N_i
12	BM12	Predictive maintenance	High Q_i & N_i
13	BM13	Preventive maintenance	Moderate Q_i & N_i
14	BM14	Preventive maintenance	Moderate Q_i & N_i

V. CONCLUSION

A successful application of a hybrid method was conducted to identify and rank the critical failure modes of a ball mill's components. The method combined FMECA with COPRAS-G. While the primary focus was on the bearing, gearbox, motor, and shaft, which are essential to the ball mill's reliability and performance. The key findings are summarized as follows:

I. The COPRAS-G method was effective in determining the weights of significant failure modes. It was observed that gearbox seal failure is the most critical, with a percentage contribution (Ni) of 100%, while bearing wear and fatigue is the least critical, with a percentage contribution (Ni) of 62%.

II. The failure modes such as seal and gasket failure (BM8), gear pitting (BM7), motor bearing fatigue (BM11), and shaft fracture (BM12) were identified as the main contributors to the overall failure of the ball mill components. These modes require special attention and predictive maintenance to ensure reliability.

III. Based on the criticality rankings (Qi and Ni), we recommended tailored maintenance strategies for each failure mode. Predictive maintenance was suggested for high-criticality modes, while preventive and corrective maintenance were recommended for moderate and low-criticality modes, respectively.

Future research can extend to other industries, such as petrochemical plants and textile mills, where machinery and conditions differ. However, the methods for identifying and prioritizing failure modes remain widely applicable

AUTHOR CONTRIBUTIONS

A. P. Akintola: Methodology, Visualization, Formal analysis, Writing – original draft. **O. M. Muvengei:** Resources, Writing – review & editing, Supervision, Validation. **J. K. Kimotho:** Conceptualization, Project Administration, Writing – review & editing, Supervision. **A. K. Muchiri:** Writing – review & editing, Supervision, Validation.

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