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Reliability and Safety Assessment of Dumper Operations in Opencast Metal Mines Using Risk Analysis and Machine Learning

Sangram Kishore Mallick* and **Bijay Mihir Kunar**

National Institute of Technology Karnataka, Surathkal - 575025, Karnataka, India; sangrammallick1106@gmail.com

Abstract

Dumpers are critical components of Heavy Earth Moving Machinery (HEMM) used in opencast mining operations for transporting overburden and ore. These devices are subject to frequent breakdowns, operational inefficiencies, and safety risks owing to their continuous operation in challenging environmental and operating circumstances. In addition to decreasing production efficiency, unplanned breakdowns increase maintenance costs and jeopardize the safety of adjacent workers and operators.' Thus, enhancing the dependability and safety of dumper operations is crucial for environmentally friendly mining methods. This study investigated the reliability and safety performance of dumpers operating in two opencast metal mines in Odisha, India. A comprehensive framework integrating Hazard Identification and Risk Analysis (HIRA), Failure Mode and Effects Analysis (FMEA), and machine learning techniques was adopted. Operational data from 20 dumpers, spanning approximately 2.5 years, were analyzed, including failure frequency, breakdown duration, equipment utilization, and maintenance records. Exploratory data analysis revealed that tyre issues (15.9%), suspension failures (11.1%), and oil leakage (10.6%) were the most frequent failure categories, which aligns with similar failure trends reported in mining equipment studies. This study also evaluated existing functional safety systems, such as proximity sensors, fatigue monitoring systems, tyre pressure monitoring systems, and automatic fire detection systems, installed in modern dumpers. This study also proposes a machine-learning-based approach to enhance risk prioritization and predictive maintenance, which has been widely recognized as effective in modern industrial systems. Additionally, failure statistics such as frequency, downtime, and criticality are utilized for data-driven manpower planning, ensuring optimal allocation of skilled personnel and improved maintenance response. The results highlight the importance of integrating reliability engineering, risk assessment techniques, and data-driven maintenance planning to enhance dumper safety and operational efficiency in opencast mining.

Major Findings: *Critical failures in dumpers are dominated by tyre, suspension, and transmission systems, significantly impacting safety and downtime. The integrated HIRA–FMEA approach effectively prioritizes high-risk hazards such as collision and overturning. Machine learning models enable accurate prediction of risk indices, supporting proactive maintenance and improved operational reliability.*

Keywords: *Dumper Reliability, Failure Modes and Effects Analysis, Machine Learning, Opencast Mining, Predictive Maintenance, Risk Priority Number*

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*Author for correspondence

1.0 Introduction

Opencast mining operations depend heavily on the performance, availability, and reliability of Heavy Earth-Moving Machinery (HEMM), particularly dumpers, which are primarily responsible for transporting large volumes of ore and overburden across different sections of the mine[1-3]. The operational efficiency of dumpers directly influences overall mine productivity, cycle time optimization, fuel consumption, and cost-effectiveness of the mining operation[4]. Moreover, dumper performance has a significant impact on safety outcomes, as these machines operate in dynamic and high-risk environments involving steep gradients, haul roads, and continuous interaction with other equipment and personnel[4].

However, dumpers are subjected to extremely demanding working conditions characterized by high payloads, repetitive loading-unloading cycles, uneven haul roads, dust, vibration, and extreme weather conditions[5,6]. These factors accelerate wear and tear of critical components, leading to frequent mechanical failures and increased risk of operational hazards[7,8]. Equipment failures during dumper operations can result in unplanned downtime, disruption of production schedules, escalation of maintenance costs, and, in severe cases, catastrophic safety incidents[9,10]. Common failure modes observed in dumpers include brake system malfunctions, hydraulic leakage or failure, engine overheating, transmission defects, tire bursts due to excessive load or poor road conditions, and structural or suspension damage[11].

In addition to mechanical failures, human factors play a crucial role in dumper-related incidents. Operator fatigue due to long working hours, inadequate training, poor ergonomics, limited visibility (especially during night operations or adverse weather), and non-compliance with safety protocols significantly increase the probability of accidents[12]. Previous studies on mining safety have indicated that a substantial proportion of fatal and serious accidents in opencast mines are directly or indirectly associated with equipment operation, particularly haulage systems involving dumpers[13]. Therefore, improving both equipment reliability and human-machine interaction is essential for enhancing overall mine safety.

Reliability engineering plays an essential role in minimizing equipment downtime and improving operational safety in the mining industry. Furthermore, modern reliability assessment techniques for dumpers and mining equipment integrate statistical and AI-based approaches to better capture complex failure behaviors[14,15]. Reliability metrics, such as the Mean Time Between Failures (MTBF), Mean Time to Repair (MTTR), and availability, are widely used to evaluate equipment performance. Traditional reliability assessment techniques, including Failure Mode and Effects Analysis (FMEA), Fault Tree Analysis (FTA), and reliability block diagrams, help identify critical components and prioritize maintenance activities[16].

In recent years, the integration of advanced data-driven techniques has significantly transformed reliability analysis in industrial systems. Machine learning techniques have emerged as powerful tools for predictive maintenance and failure analysis. These approaches help identify hidden patterns in operational data and predict failures before their occurrence, thereby reducing downtime and improving system reliability[17-19]. Studies have also emphasized that machine learning-based predictive maintenance significantly reduces downtime and enhances operational efficiency[20,21]. By analyzing historical operational and maintenance data, machine learning models can detect hidden patterns and predict potential failures before they occur. The integration of reliability analysis with artificial intelligence can significantly improve equipment performance, safety, and maintenance planning.

Furthermore, ML-based predictive maintenance approaches offer significant advantages over conventional methods by enabling real-time monitoring, condition-based maintenance, and proactive decision-making[22]. Studies have demonstrated that the implementation of predictive maintenance strategies using machine learning can substantially reduce equipment downtime, lower maintenance costs, and improve operational efficiency and safety performance in mining operations[22]. By combining reliability analysis with artificial intelligence, it is possible to develop more adaptive, accurate, and dynamic models that better capture the complex failure behavior of dumpers operating in uncertain and harsh environments[22].

In this context, the present study aims to assess the reliability and safety performance of dumper operations in opencast metal mines by integrating conventional risk assessment techniques with machine learning-based predictive models. The proposed approach

seeks to enhance failure prediction accuracy, optimize maintenance planning, and contribute to safer and more efficient mining operations.

2.0 Materials and Methods

2.1 Case Study Mines

Two highly mechanized opencast metal mines located in Odisha, India, were selected for this study. These mines employ 100-ton capacity dumpers in combination with hydraulic excavators for material-handling operations. Such large-scale mining operations require robust reliability and maintenance strategies to ensure continuous production.

A total of 20 dumpers were used, and operational and maintenance data were collected over a period of approximately 2.5 years, corresponding to approximately 14,850 effective working hours.

2.2 Data Collection

A total of 20 dumpers were considered in the case study. The equipment details are presented in Table 1, and the failure categories, number of failures, and corresponding breakdown hours are summarized in Table 2. Based on approximately 2.5 years of recorded data, failures were classified into 21 categories, including engine, hydraulic, tire, suspension, and transmission systems, to support effective root cause analysis.

Table 1. Equipment details

Sl. No.	SAP ID	Equipment ID	Mfg. Year	Make	Model	Capacity
1	400000256	DNU2201	2013	Komatsu	HD785	100T
2	400000748	DNU2202	2015	Komatsu	HD785	100T
3	400000749	DNU2203	2015	Komatsu	HD785	100T
4	400000761	DNU2204	2015	Komatsu	HD785	100T
5	400000762	DNU2205	2014	Komatsu	HD785	100T
6	400000764	DNU2206	2015	Komatsu	HD785	100T
7	400000765	DNU2207	2015	Komatsu	HD785	100T
8	400000779	DNU2208	2015	Komatsu	HD785	100T
9	400000783	DNU2209	2015	Komatsu	HD785	100T
10	400000823	DNU2210	2015	Komatsu	HD785	100T
11	400000831	DNU2211	2015	Komatsu	HD785	100T
12	400000832	DNU2212	2015	Komatsu	HD785	100T
13	400000833	DNU2213	2015	Komatsu	HD785	100T
14	400000834	DNU2214	2015	Komatsu	HD785	100T
15	400000867	DNU2215	2017	Komatsu	HD785	100T
16	400000888	DNU2216	2017	Komatsu	HD785	100T
17	400000899	DNU2217	2017	Komatsu	HD785	100T
18	400000900	DNU2218	2017	Komatsu	HD785	100T
19	400001041	DNU2219	2017	Komatsu	HD785	100T
20	400001054	DNU2220	2017	Komatsu	HD785	100T

Table 2. Types of failure and frequency of each failure

Type of failure	Failure Code	Frequency of Failure	Breakdown Hours
AC problem	DF1	3	13:50:00
Auto Electrical Issue	DF2	1	6:00:00
Brake issue	DF3	11	123:20:00
Differential Issue	DF4	1	46:00:00
Dump body issue	DF5	13	423:25:00
Engine Accessory Issue	DF6	2	60:15:00
Engine Air System Issue	DF7	15	366:55:00
Engine Auto Electrical Issue	DF8	8	241:50:00
Engine Cooling System Issue	DF9	13	398:40:00
Engine Fuel System Issue	DF10	3	156:20:00
Engine Lubrication System Issue	DF11	6	425:35:00
Engine Power Transmission Issue	DF12	8	175:25:00
Hydraulic System Issue	DF13	15	165:55:00
Oil leakage	DF14	22	442:40:00
Oil mixing issue	DF15	5	144:05:00
Power Line Issue	DF16	7	148:05:00
Steering issue	DF17	3	41:50:00
Suspension Issue	DF18	23	585:00:00
Torque Converter	DF19	1	60:00:00
Transmission issue	DF20	15	520:05:00
Tyre issue	DF21	33	244:55:00
Total		**208**	**4790:10:00**

This study utilized multiple data sources, including breakdown records, maintenance logs, equipment utilization data, and operational parameters such as running hours and equipment age. The integration of these datasets enabled a comprehensive assessment of dumper reliability, safety performance, and maintenance effectiveness.

2.2.1 Exploratory Data Analysis

Figure 1 shows a pie chart displaying the proportional distribution of 21 failure categories across 208 breakdown events. The analysis indicates that tyre issues (15.9%), suspension failures (11.1%), and oil leakage (10.6%) represent the largest contributors to total failures.

2.3 Hazard Identification and Risk Analysis

Hazard Identification and Risk Analysis (HIRA) are conducted according to safety management plan guidelines[23]. Risk assessment approaches similar to HIRA are widely used in mining safety studies to evaluate operational hazards and prioritize control measures[24].

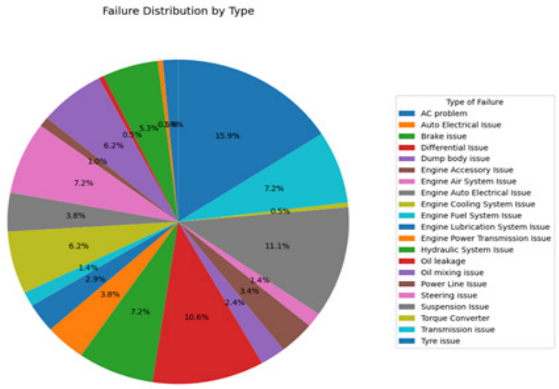


Figure 1. Failure category distribution - Pie Chart.

Risk is calculated using the following relationship as shown in the Equation (1):

Risk Score = Probability × Exposure × Consequence (Equation (1))

Hazards are categorized into three levels:

- Risk > 200: Immediate action required
- 20 < Risk < 200: Management action required
- Risk < 20: Monitoring required.

The Hazard Identification Risk Analysis of dumper operation and dumper maintenance as per the framed Safety Management Plan (SMP) is shown in Tables 3 and 4, respectively.

Table 3. Hazard identification risk analysis of dumper operation as per framed SMP

Hazardous issues/activities	Associated hazards	% Of Workers Exposed	Conse-quence	Exp-osure	Proba-bility	Risk Score	Significance
Transportation of Ore and OB using dumper	Collision with other equipment/ vehicles/structure	High >20-40%	5	10	7	350	*Requiring immediate attention*
	Run over (Persons)		5	10	7	350	
	Turn over		5	10	7	350	
	Fall/topple from bench		5	10	7	350	
	Roll over from gradient		1	10	7	70	*Requiring Management Action*
	Fire		1	10	3	30	
	Hit by spillage		1	10	7	70	
	Hit by Projectile (Rock fragments in haulage, tyre burst)		1	10	7	70	
	Uncontrolled movement due to Tyre burst		1	10	3	30	
	Dust		0.1	10	7	7	*To be watched and reviewed*
	Noise		0.1	10	7	7	
	Body vibration caused by Machine vibration		0.1	10	7	7	
	Jerk		0.1	10	10	10	
	Unauthorized riding on vehicle		1	10	3	30	Requiring Management Action
	Taking shelter under the dump box (parked vehicles)		5	10	2	100	Requiring Management Action

Table 4. Hazard identification risk analysis of dumper maintenance

Hazardous issues/ activities	Associated hazards	% Of Workers Exposed	Conse-quence	Expo-sure	Proba-bility	Risk Score	Significance
Maintenance of HEMM	Undesirable movement or starting of vehicle without clearance/ signalling	10-20% (Medium)	1	10	10	100	*Requiring Management Action*
	Fall from height (Dumper)		1	10	7	70	*To be watched and reviewed*
	Fall of material during heavy material handling		1	10	10	100	Requiring Management Action
	Tyre burst		1	10	7	70	
	Tyre handling		0.3	10	7	21	
	Fire on vehicle		1	10	3	30	
	Hydraulic pipe burst		0.1	10	7	7	*To be watched and reviewed*
	Trapping of body parts		1	10	7	70	*Requiring Management Action*
	Fall on same level		0.1	10	7	7	*To be watched and reviewed*
	pressurized system: compressor vessels		5	10	3	150	*Requiring Management Action*
	Fire and explosion during welding, gas cutting		5	10	3	150	Requiring Management Action
	Noise		0.1	10	10	10	*To be watched and reviewed*
	Hot material or surface		0.01	10	10	1	
	Auto electrical system: Electrocution		1	10	3	30	*Requiring Management Action*
	Handling of battery		0.3	10	7	21	
	Run over due failure of park brake		1	10	3	30	
	Improper parking		1	10	3	30	
	Tools and machine parts with sharp edges		0.1	10	7	7	To be watched and reviewed

2.4 Failure Mode and Effects Analysis (FMEA)

Failure modes are evaluated using FMEA to determine their effects on safety and equipment reliability. FMEA is a widely accepted tool in maintenance engineering for identifying critical failure modes and improving system reliability. Risk Priority Numbers (RPN) are calculated based on severity, occurrence, and detection parameters to identify critical failure modes requiring priority maintenance actions which is stated in Equation (2).

RPN = Severity x Occurrence x Detection
(Equation (2))

2.4.1 Evaluation of Risk Priority Number - Gradient Boosting Regression ML process

The primary objective of this study is to develop an automated, data-driven Risk Priority Number (RPN) calculation system using machine learning techniques to enhance the objectivity and reliability of failure risk assessment. The proposed system aims to achieve a prediction accuracy exceeding 95% for all RPN components, that is, severity, occurrence, and detection, thereby ensuring high confidence in risk ranking outcomes.

2.4.1.1 ML Model Performance

All three models achieved exceptional prediction accuracy, as shown in Table 5 and visualized in Figure 2.

Figure 2 demonstrates that all three component models exceed the 80% accuracy threshold, with the severity model achieving the highest R2 score of 100%. This exceptional performance validates the machine-learning approach for RPN prediction. The high accuracy across all models enables confident automated RPN calculation, eliminating the need for time-consuming manual brainstorming sessions while maintaining the prediction quality.

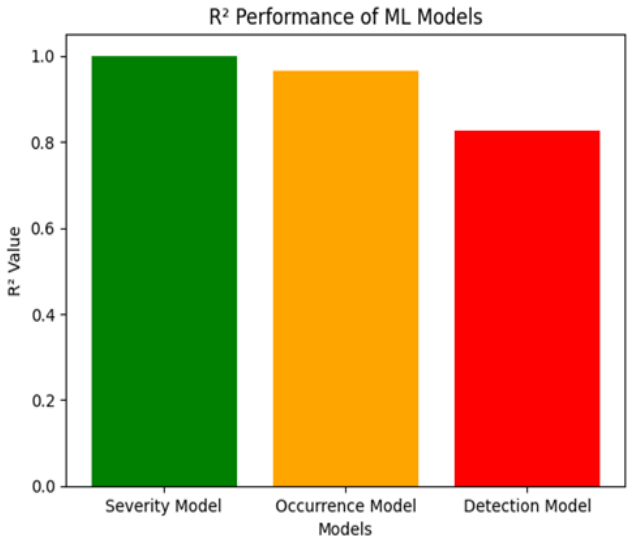


Figure 2. Machine learning model performance comparison.

2.4.1.2 RPN Analysis Results

Table 6 presents the complete RPN analysis for the top 15 failure categories:

Table 5. Machine learning model performance metrics

Model	Purpose	R2	RMSE
Severity Model	Severity prediction (S)	1.0	0.0001
Occurrence Model	Occurrence prediction (O)	0.9662	0.4524
Detection Model	Detection prediction (D)	0.8245	0.5991
Overall RPN Model	RPN prediction	0.6938	21.1018

Table 6. RPN analysis results by failure category

Rank	Category	Severity	Occurrence	Detection	Frequency	RPN	Risk Level
1	Transmission Issue	5	5	6	15	150	MEDIUM
2	Suspension Issue	3	7	5	23	105	MEDIUM
3	Dump Body Issue	5	4	5	13	100	MEDIUM
4	Engine Lubrication System Issue	10	2	4	6	80	LOW

5	Engine Air System Issue	4	5	4	16	80	LOW
6	Tyre Issue	1	10	8	33	80	LOW
7	Engine Cooling System Issue	4	4	4	13	64	LOW
8	Oil Leakage	3	7	2	22	42	LOW
9	Brake Issue	2	3	7	11	42	LOW
10	Hydraulic System Issue	2	5	4	15	40	LOW
11	Engine Power Transmission Issue	3	2	6	8	36	LOW
12	Engine Auto Electrical Issue	4	2	4	8	32	LOW
13	Torque converter issue	8	1	4	1	32	LOW
14	Power Line Issue	3	2	5	7	30	LOW
15	Differential Issue	6	1	5	1	30	LOW

2.4.1.3 Visual Analysis of Results (RPN Ranking by Category)

Figure 3 shows the FMEA Risk Priority Number (RPN) distribution for 21 failure categories arranged in descending order. Transmission (150) had the highest RPN, followed by suspension (105) and Dump Body (100), indicating the most critical failure components. Moderate risks were observed in systems such as engine lubrication, engine air system, and tyres, whereas components such as steering, auto electrical,

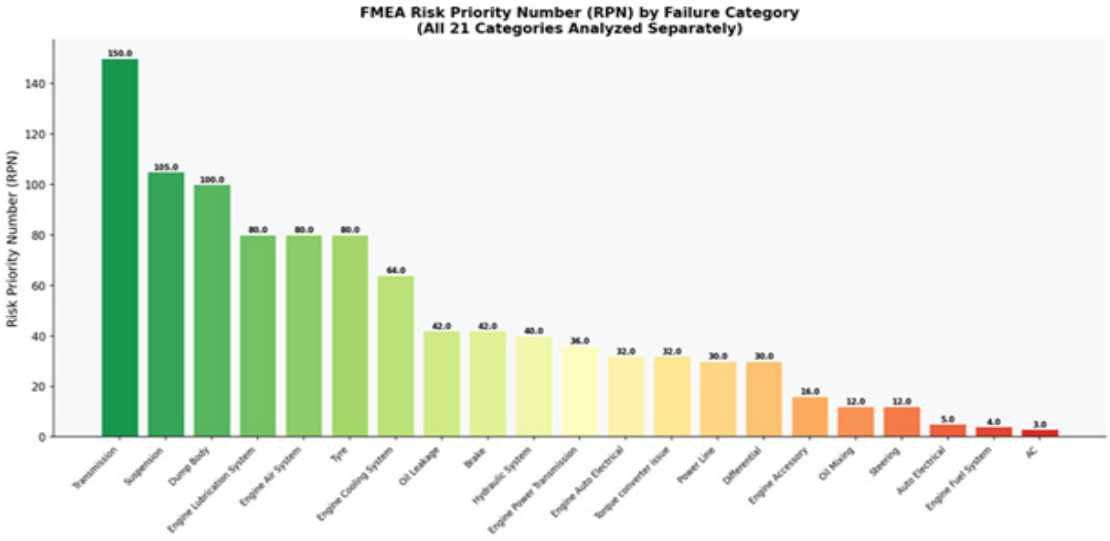


Figure 3. Failure categories ranked by risk priority number.

engine fuel system, and AC showed relatively low RPN values.

2.5 Machine Learning Analysis

Machine learning models are increasingly used in mining operations for predictive maintenance, fault detection, and operational optimization. These models significantly enhance failure prediction capability and reduce unexpected downtime.

2.5.1 K-Means Clustering (Elbow and Silhouette Analysis)

Figure 4 presents the K-Means clustering evaluation using the Elbow method and Silhouette score to determine

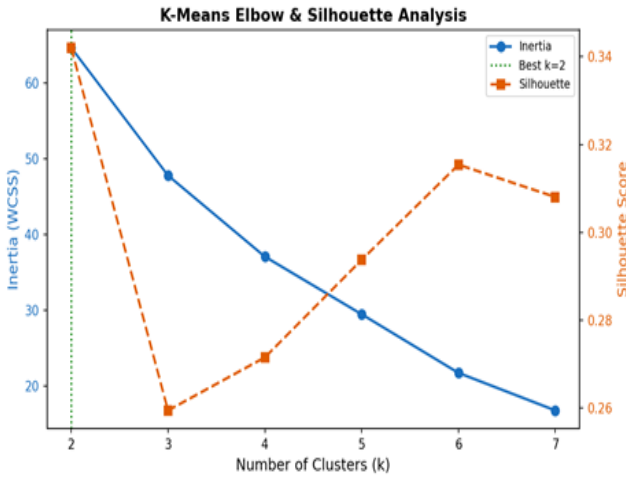


Figure 4. Elbow curve (WCSS) and Silhouette scores vs. k. Optimal k=3 at peak silhouette.

the optimal number of clusters (k). The inertia (WCSS) curve shows a sharp decrease from k = 2 to k = 4, after which the reduction becomes more gradual, indicating a diminishing improvement in cluster compactness. The silhouette score, which measures cluster separation and cohesion, reaches its highest value at k = 2 (≈0.34) and then decreases at k = 3, with only moderate improvement for higher values of k.

The vertical dashed line highlights k = 2 as the optimal number of clusters, as it provides the best balance between cluster compactness and separation. Therefore, the dataset is best grouped into two distinct clusters, indicating that the equipment units can be effectively categorized into two reliability or performance groups based on the selected features.

2.5.2 Cluster Scatter

Figure 5 presents the K-means clustering result (k = 2), showing the relationship between the running hours (HMR) and total breakdown hours for each equipment unit. The clustering algorithm divides the equipment into two distinct groups based on operational usage and breakdown behavior.

Cluster 0 mainly consists of equipment with lower running hours (approximately 11,000–15,000 HMR) but relatively high breakdown hours, indicating a comparatively lower reliability or higher failure intensity at a lower operational life. In contrast, Cluster 1 includes equipment with higher running hours (approximately 30,000–47,000 HMR) and a wide variation in breakdown hours, suggesting differences in maintenance conditions, utilization patterns, or component wear across high-usage machines.

Some equipment units, such as 0900, 0748, and 0834, showed significantly higher breakdown hours, indicating critical maintenance attention points. Overall, the clustering highlights two operational behavior groups,

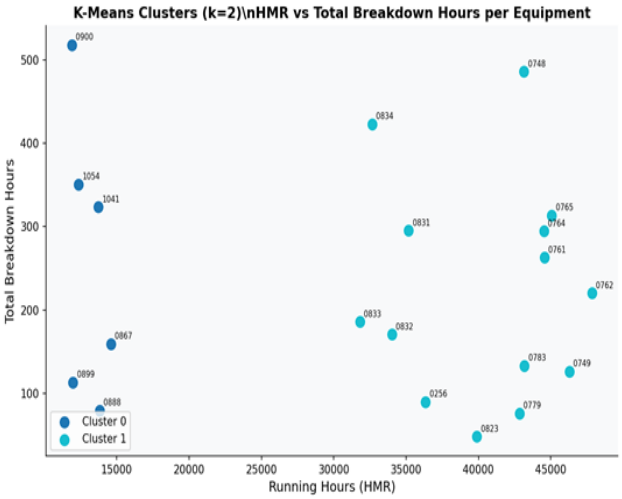


Figure 5. Cluster assignment per equipment - HMR vs. total breakdown hours.

which can assist in identifying high-risk equipment and improving maintenance planning and reliability management.

2.5.3 K-Nearest Neighbour (KNN) Classification (k vs. Accuracy)

Figure 6 illustrates the K-Nearest Neighbors (KNN) model performance evaluated using cross-validation accuracy for different values of k (number of neighbors) in the failure category classification task. The results show that the accuracy initially increases from 0.108 at k = 3 to a maximum of 0.129 at k = 5, indicating improved classification performance as the model considers a slightly larger neighborhood size.

Beyond k = 5, the cross-validation accuracy gradually decreased to 0.107 at k = 7, 0.086 at k = 9, and 0.079 at k = 11, suggesting that larger values of k reduce the model's ability to distinguish between failure categories owing to the excessive smoothing of decision boundaries. Therefore, k = 5 was identified as the optimal value, as highlighted by the vertical dashed line, providing the best classification performance among the tested configurations. This result indicates that considering the five nearest neighbors offers the most balanced prediction capability for the dataset.

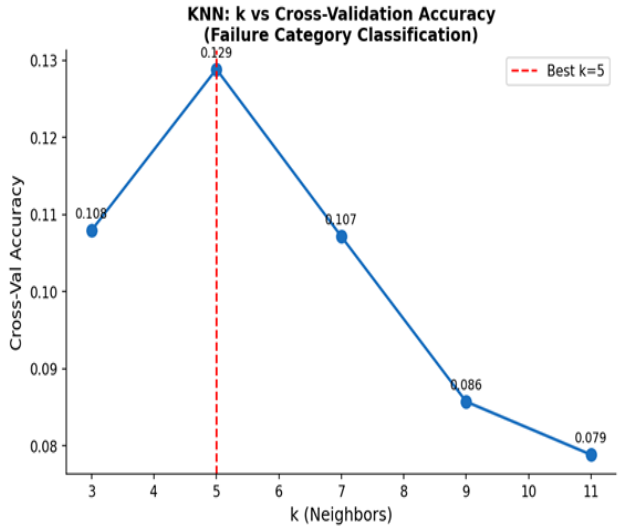


Figure 6. Cross-validation accuracy vs. k for KNN classification.

2.5.4 ML Model Performance Summary

Performance summary of applied machine learning models for failure risk prediction, equipment risk grouping, anomaly detection, and failure category classification in mining equipment reliability analysis is shown in Table 7.

3.0 Results and Discussions

3.1 Failure Frequency Analysis

An analysis of the failure records revealed 208 breakdown events across the dumper fleet. Analysis of failure records revealed that tire, suspension, and oil leakage issues were the most frequent. Similar findings have been reported in mining equipment reliability studies, where wear-related components dominate the failure patterns. The most frequent failures are listed in Table 8.

Tyre failures accounted for approximately 15.9% of total breakdowns, indicating significant operational stress on dumper tyres due to harsh haul road conditions.

3.2 Breakdown Duration Analysis

The breakdown duration varied significantly across the failure types, ranging from approximately 6 hours to over 585 hours. Suspension and transmission failures

Table 7. ML model performance summary

Model	Task	Primary Metric	Score	Notes
Gradient Boosting Regresson	RPN Prediction (FMEA)	R^2	1.0	208→21 category-level
K-Means Clustering	Equipment Risk Grouping	Silhouette Score	0.342	k=2, 20 equipment
KNN Classifier	Failure Category Classification	CV Accuracy	0.1288	k=5

Table 8. Failure frequency

Failure Type	Frequency
Tyre issue	33
Suspension issue	23
Oil leakage	22
Transmission issue	15
Hydraulic system issue	15

contributed to the highest downtime, consistent with findings from reliability studies on heavy mining equipment, highlighting their critical impact on equipment availability.

Most failures occurred within the low-to-medium downtime range (<200 hours), suggesting that routine maintenance practices are effective for resolving minor faults. However, several high-duration failures indicate the need for improved predictive maintenance.

3.3 Pareto Analysis of Downtime

A Pareto analysis revealed that a small number of failure modes contributed to the majority of equipment downtime. This principle aligns with the reliability engineering theories applied to mining systems.

Figure 7 shows the Pareto chart, which presents the breakdown hours associated with different failure types and the cumulative percentage of total downtime. The bars represent the downtime contribution (in hours) of each failure type, whereas the line indicates the cumulative percentage of the total downtime. Suspension issues contributed to the highest downtime (~585 hours). Transmission issues were the second major contributor (~520 hours). Oil Leakage, engine lubrication system issues, and dump body issues also cause significant downtime. The downtime Pareto analysis indicates that a small number of failure modes contribute to most of the equipment downtime.

These failures collectively account for a major portion of the downtime and should be prioritized in maintenance planning.

3.4 Safety Risk Evaluation

Hazard analysis identified several high-risk scenarios, such as dumper collisions, run-over incidents, and

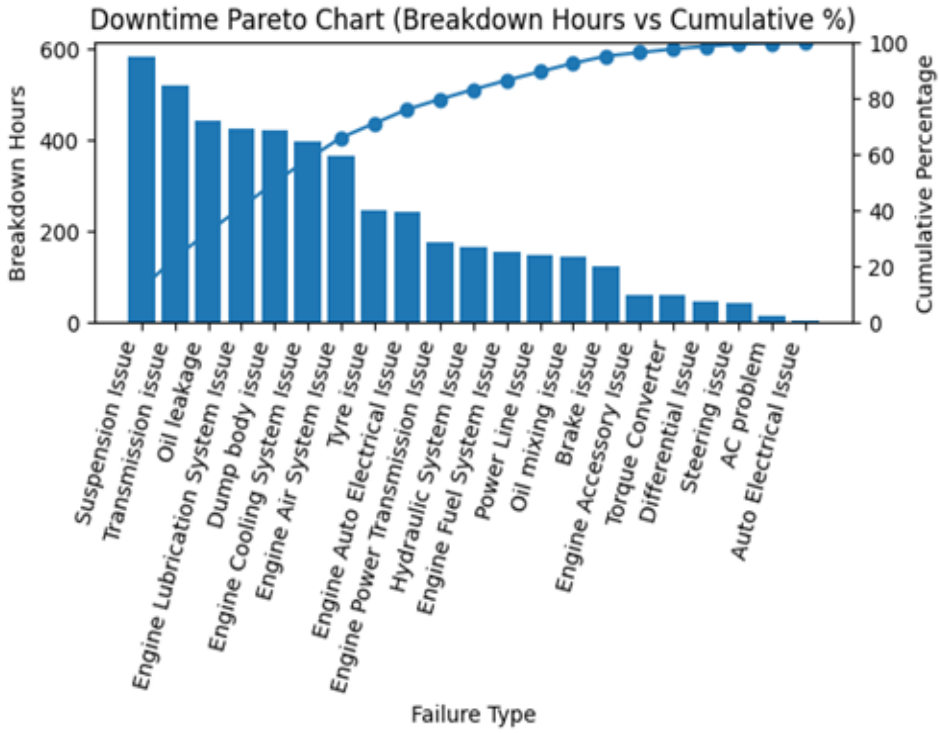


Figure 7. Average breakdown duration by category.

overturning events. Similar high-risk categories have been identified in mining accident analysis studies.

These hazards received risk scores exceeding 200, indicating the need for immediate corrective action.

3.5 Functional Safety Systems

Modern dumpers are equipped with advanced safety technologies, such as fatigue monitoring, dynamic proximity detection, and auto fire detection and suppression systems. The adoption of such technologies significantly improves operational safety and reduces the risk. of accidents

These technologies play crucial roles in preventing accidents and enhancing operator safety.

3.6 Evolution of Risk Indices Over Time

Risk indices such as Severity (S), Occurrence (O), Detection (D), and Risk Priority Number (RPN) are not static; they evolve over time due to changes in operating conditions, maintenance practices, equipment ageing, and safety interventions. Monitoring their temporal variation provides a powerful tool for predictive maintenance planning and risk mitigation in opencast mining operations.

3.6.1 Methodology for Time-Based Risk Evaluation

The Risk Priority Number is evaluated periodically (monthly/quarterly) as per Equation (3):

$$RPN_t = S_t \times O_t \times D_t \qquad \text{(Equation (3))}$$

Where S_t = Severity over time,
O_t = Occurrence over time
D_t = Detection over time

Time-series data is generated using failure frequency logs, maintenance records and inspection and detection efficiency.

3.6.2 Temporal Dataset of Risk Indices

A sample structure regarding monthly evolution of risk indices shown in the Table 8 as per the actual mines data.

3.6.3 Trend Analysis of Risk Indices

Figure 7 illustrates a monthly variation of Risk Priority Number (RPN) which exhibits a fluctuating trend, with peaks observed during high operational stress periods such as monsoon and production surges. An increasing RPN indicates deterioration in system reliability, while

Table 8. Monthly evolution of risk indices (sample structure based on actual mine data)

Month	Severity (S)	Occurrence (O)	Detection (D)	RPN (S X O X D)	Risk Level
Jan	8	6	5	240	High
Feb	8	5	5	200	High
Mar	7	5	4	140	Medium
Apr	7	4	4	112	Medium
May	6	4	3	72	Low
Jun	6	3	3	54	Low
Jul	7	4	4	112	Medium
Aug	8	5	5	200	High
Sep	8	6	6	288	Very High
Oct	7	5	4	140	Medium
Nov	6	4	3	72	Low
Dec	6	3	3	54	Low

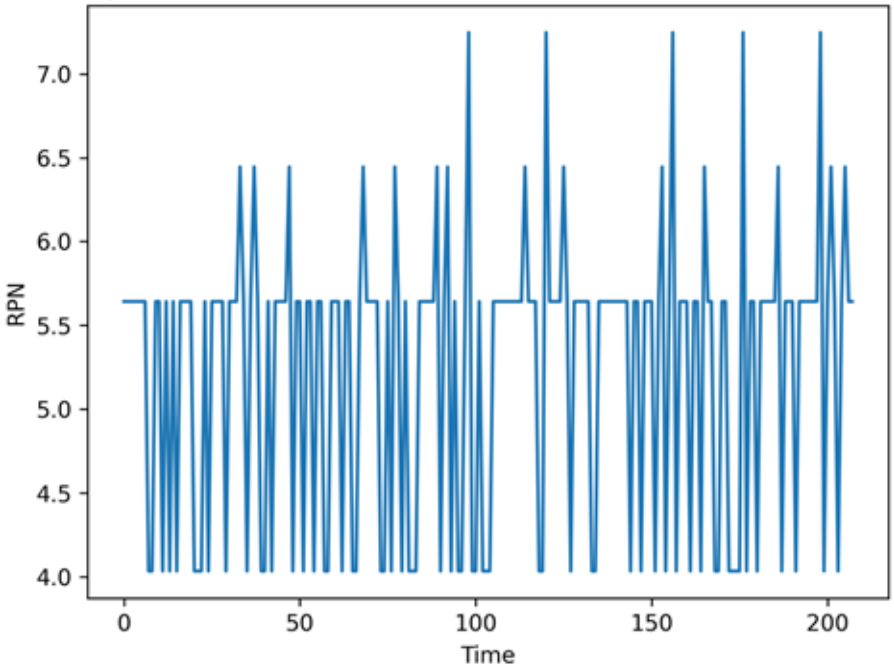


Figure 7. Time series variation of RPN.

sudden spikes highlight critical failure events requiring immediate attention. Conversely, a declining trend reflects the effectiveness of maintenance interventions and improved operational control. Overall, the RPN trend provides a useful basis for identifying high-risk periods and optimizing maintenance strategies.

3.7 Integration of Risk Indices into Preventive Maintenance Optimization

3.7.1 Conceptual Framework

Risk indices derived from Hazard Identification and Risk Analysis (HIRA) and Failure Mode and Effects Analysis (FMEA) can be effectively integrated into preventive maintenance scheduling to optimize both preventive and corrective maintenance programs in opencast mining systems. Conventional time-based maintenance often results in either excessive maintenance or unexpected equipment failures, whereas risk-based maintenance enables prioritization based on failure criticality, probability, and detectability.

The integration of severity, occurrence, and detection parameters allows maintenance planners to align maintenance actions with actual operational risk. This approach is consistent with modern risk-based maintenance (RBM) and Reliability-Centered Maintenance (RCM) methodologies, which enhance system reliability and reduce lifecycle costs[25,26].

3.7.2 Risk-Based Maintenance Decision Matrix

Risk indices can be mapped to maintenance strategies as presented in Table 9.

Table 9. Risk-based maintenance strategy matrix

RPN Range	Risk Level	Maintenance Strategy	Action Frequency	Type of Maintenance
>150	High	Immediate intervention	Daily/Weekly	Predictive + Corrective
100–150	Medium	Planned preventive maintenance	Weekly/Monthly	Preventive
50–100	Low	Condition monitoring	Monthly/Quarterly	Condition-Based
<50	Very Low	Routine inspection	Quarterly	Preventive

Table 9 illustrates that high-risk components require immediate predictive intervention, while medium- and low-risk components are managed through scheduled and condition-based maintenance. This structured prioritization minimizes unnecessary maintenance activities and improves resource allocation efficiency[27,28].

3.7.3 Optimization of Preventive and Corrective Maintenance

Risk-based maintenance shifts the strategy from reactive to proactive by identifying critical failures before occurrence, thereby reducing breakdown frequency and downtime[29,30]. Table 10 shows the optimization using risk-based maintenance.

Table 10. Optimization using risk-based maintenance

Parameter	Conventional Approach	Risk-Based Approach
Maintenance Trigger	Fixed time interval	Risk-based (RPN)
Preventive Maintenance	Static schedule	Dynamic schedule
Corrective Maintenance	Post-failure	Reduced through prediction
Equipment Downtime	High	Reduced
Maintenance Cost	Higher	Optimized
Safety Performance	Reactive	Proactive

3.7.4 Role of Data-Driven and Predictive Techniques

Advanced data-driven approaches, including machine learning and condition monitoring systems, enhance the effectiveness of risk-based maintenance by enabling real-time risk prediction and dynamic decision-making. These techniques improve fault detection accuracy, reduce maintenance delays, and support predictive maintenance strategies[31-33].

3.8 Integration of Failure Statistics for Optimized Manpower Planning in Mine Maintenance

One of the recurring challenges in opencast mine maintenance is the optimal selection and deployment of skilled manpower. Improper allocation of personnel often leads to increased downtime, inefficient repairs, and safety risks. Traditionally, manpower planning is based on experience and fixed staffing patterns; however, the availability of detailed failure statistics enables a data-driven approach to workforce planning[34,35]. Failure statistics, including failure frequency, breakdown duration, and criticality (RPN), can be systematically used to develop specialized, experienced, and risk-focused maintenance teams[36,37].

Failure data collection, risk assessment, and skill mapping form the foundation of workforce allocation strategies, enabling alignment between maintenance demand and workforce capability[38].

3.8.1 Manpower Optimization Using Failure Statistics

Failure-based manpower allocation ensures optimal resource utilization by aligning workforce size and

Table 11. Failure-based manpower allocation strategy

Failure Characteristic	Manpower Strategy
High Frequency	Increase workforce size
High RPN	Assign expert personnel
High Downtime	Deploy specialized repair team
Low Frequency	Shared manpower
Predictable Failures	Scheduled maintenance teams

expertise with maintenance requirements[39,40]. Table 11 shows the failure-based manpower allocation strategy.

Tyre and suspension failures require more manpower due to high frequency, while transmission failures require fewer but highly skilled personnel. Hydraulic and electrical failures benefit from cross-functional teams[41].

3.8.2 Skill Development and Training Based on Failure Trends

Failure statistics provide a foundation for targeted training programs. Frequent failures necessitate rapid troubleshooting skills, while critical failures require advanced technical expertise and safety-focused training. High-frequency and high-risk failure categories demand the highest training intensity, ensuring workforce readiness and improved system reliability[42].

3.8.3 Benefits of Failure-Based Manpower Planning

Failure-based manpower planning offers significant advantages in improving the overall effectiveness of maintenance operations in mining environments. By aligning manpower deployment with actual failure patterns and equipment criticality, maintenance efficiency is substantially enhanced, ensuring that the right skills are available at the right time. This approach minimizes equipment downtime by enabling quicker response to breakdowns and reducing delays in repair activities. It also promotes better utilization of skilled manpower, avoiding both overstaffing and underutilization. Furthermore, targeted allocation of experienced personnel contributes to enhanced safety performance, as critical failures are addressed more competently. Faster fault diagnosis and repair are achieved due to the availability of specialized expertise, which in turn leads to reduced maintenance costs through optimized resource use and prevention of repetitive failures. These benefits are well supported by reliability-centered and risk-based maintenance principles[43].

3.8.4 Integration with Predictive Maintenance

When integrated with predictive maintenance techniques, failure data can be used to forecast failures and pre-allocate manpower resources. This enables optimized shift planning and proactive maintenance execution.

4.0 Conclusion

This study presents a comprehensive reliability and safety assessment of dumper operations in opencast metal mines by integrating conventional risk assessment techniques with advanced machine-learning approaches. The analysis of 20 dumpers over approximately 2.5 years revealed that tire, suspension, and oil leakage failures are the most frequent, whereas suspension and transmission failures contribute the highest downtime, significantly affecting equipment availability and productivity.

The application of Hazard Identification and Risk Analysis (HIRA) identified critical safety risks, such as collision, run-over, and overturning, all of which require immediate attention as per Table 3. Failure Mode and Effects Analysis (FMEA) further highlighted the transmission, suspension, and dump body systems as the most critical components based on Risk Priority Number (RPN) rankings as per Table 6.

The incorporation of machine learning techniques, particularly Gradient Boosting Regression, demonstrated high accuracy in predicting RPN parameters, enabling automated and data-driven risk prioritization. Clustering analysis successfully categorized the equipment into distinct reliability groups, whereas KNN classification provided insights into failure pattern recognition, albeit with moderate accuracy.

Risk indices (S, O, D, and RPN) evolve over time and their monitoring enables identification of high-risk periods, supporting proactive and predictive maintenance planning. Integrating HIRA–FMEA-based risk assessment with risk-based maintenance strategies improves reliability, reduces downtime, and optimizes resource allocation. Additionally, failure-driven manpower planning enhances workforce efficiency, safety, and overall maintenance performance in opencast mining operations.

Overall, this study confirms that integrating reliability engineering, risk assessment methods, and machine learning significantly enhances the effectiveness of maintenance planning and safety management in mining operations. The findings support the adoption of predictive maintenance strategies and advanced safety systems to reduce unplanned downtime, improve operational efficiency, and ensure safer dumper operation.

This integrated approach provides a practical framework for improving the reliability and safety performance of Heavy Earth Moving Machinery (HEMM) in opencast mining environments.

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It is further acknowledged that the dataset used in this study is limited in size; however, it has been carefully analyzed to derive meaningful insights. Future studies with larger datasets are recommended to further validate and enhance the robustness of the proposed approach. The data analyzed in this research are site specific. So, the result may vary with different location.

6.0 References

1. Kumar U, Klefsjö B. Reliability analysis of hydraulic systems of LHD machines using the power law process model. Reliab Eng Syst Saf. 1992; 35(3):217-24. https://doi.org/10.1016/0951-8320(92)90080-5
2. Barabady J, Kumar U. Reliability analysis of mining equipment: a case study of a crushing plant at Jajarm bauxite mine in Iran. Reliab Eng Syst Saf. 2008; 93(4):647-53. https://doi.org/10.1016/j.ress.2007.10.006
3. Hall RA, Daneshmend LK. Reliability modelling of surface mining equipment: data gathering and analysis methodologies. Int J Surf Min Reclam Environ. 2003; 17(3):139-55. https://doi.org/10.1076/ijsm.17.3.139.14773
4. Elevli S, Elevli B. Performance measurement of mining equipments by utilizing OEE. Acta Montan Slovaca. 2010; 15(2):95.
5. Zio E. Reliability engineering: old problems and new challenges. Reliab Eng Syst Saf. 2009; 94(2):125-41. https://doi.org/10.1016/j.ress.2008.06.002
6. Jardine AK, Lin D, Banjevic D. A review on machinery diagnostics and prognostics implementing condition-based maintenance. Mech Syst Signal Process. 2006; 20(7):1483-510. https://doi.org/10.1016/j.ymssp.2005.09.012
7. Lee J, Wu F, Zhao W, Ghaffari M, Liao L, Siegel D. Prognostics and health management design for reliability-based maintenance. Mech Syst Signal Process. 2014; 45(1):314-32. https://doi.org/10.1016/j.ymssp.2013.06.004 PMCID: PMC11696779.
8. Sharma A, Yadava GS, Deshmukh SG. A literature review and future perspectives on maintenance optimization. J Qual Maint Eng. 2011; 17(1):5-25. https://doi.org/10.1108/13552511111116222
9. Susto GA, Schirru A, Pampuri S, McLoone S, Beghi A. Machine learning for predictive maintenance: a multiple classifier approach. IEEE Trans Ind Inform. 2014; 11(3):812-20. https://doi.org/10.1109/TII.2014.2349359
10. Khan S, Yairi T. A review on the application of deep learning in system health management. Mech Syst Signal Process. 2018; 107:241-65. https://doi.org/10.1016/j.ymssp.2017.11.024
11. Lei Y, Li N, Guo L, Li N, Yan T, Lin J. Machinery health prognostics: a systematic review from data acquisition to RUL prediction. Mech Syst Signal Process. 2018; 104:799-834. https://doi.org/10.1016/j.ymssp.2017.11.016
12. Zhang W, Yang D, Wang H. Data-driven methods for predictive maintenance of industrial equipment: a survey. IEEE Syst J. 2019; 13(3):2213-27. https://doi.org/10.1109/JSYST.2019.2905565
13. Liu R, Yang B, Zio E, Chen X. Artificial intelligence for fault diagnosis of rotating machinery: a review. Mech Syst Signal Process. 2018; 108:33-47. https://doi.org/10.1016/j.ymssp.2018.02.016
14. Moniri-Morad A, Sattarvand J. A comparative study between system reliability evaluation methods: case study of mining dump trucks. J Eng Appl Sci. 2023; 70(1):103. https://doi.org/10.1186/s44147-023-00272-y
15. Odeyar P, Apel DB, Hall R, Zon B, Skrzypkowski K. A review of reliability and fault analysis methods for heavy equipment used in mining. Energies. 2022; 15:6263. https://doi.org/10.3390/en15176263
16. Ghodrati B, Kumar U. Reliability and operating environment-based spare parts estimation approach: a case study in Kiruna mine, Sweden. J Qual Maint Eng. 2005; 11(2):169-84. https://doi.org/10.1108/13552510510601366
17. Polverino L, Abbate R, Manco P, Perfetto D, Caputo F, Macchiaroli R, Caterino M. Machine learning for prognostics and health management of industrial mechanical systems and equipment:

A systematic literature review. Int J Eng Bus Manag. 2023; 15:18479790231186848. https://doi.org/10.1177/18479790231186848
18. Zhao R, Yan R, Chen Z, Mao K, Wang P, Gao RX. Deep learning and its applications to machine health monitoring. Mech Syst Signal Process. 2019; 115:213-37. https://doi.org/10.1016/j.ymssp.2018.05.050
19. Carvalho TP, Soares FA, Vita R, Francisco RD, Basto JP, Alcalá SG. A systematic review of machine learning methods applied to predictive maintenance. Comput Ind Eng. 2019; 137:106024. https://doi.org/10.1016/j.cie.2019.106024
20. Kannan R, Abdul Halim HU, Ramakrishnan K, Ismail S, Wijaya DR. Machine learning approach for predicting production delays: a quarry company case study. J Big Data. 2022; 9(1):94. https://doi.org/10.1186/s40537-022-00644-w PMID: 35875725 PMCID: PMC9287717.
21. Li W, Li T. Comparison of deep learning models for predictive maintenance in industrial manufacturing systems using sensor data. Sci Rep. 2025; 15(1):23545. https://doi.org/10.1038/s41598-025-08515-z PMID: 40603551 PMCID: PMC12223142.
22. Wang T, Yu J, Siegel D, Lee J. A similarity-based prognostics approach for remaining useful life estimation of engineered systems. In: Proc Int Conf Progn Health Manag; 2008 Oct 6; IEEE. p. 1-6. https://doi.org/10.1109/PHM.2008.4711421
23. Directorate General of Mines Safety. DGMS (Tech) (S&T) Circular No. 13 of 2002. Dhanbad; 2002 Dec 31.
24. Kecojevic V, Komljenovic D, Groves W, Radomsky M. Equipment-related fatal accidents in US mining operations: 1995-2005. Saf Sci. 2007; 45(8):864-74. https://doi.org/10.1016/j.ssci.2006.08.024
25. Smith AM, Hinchcliffe GR. RCM—gateway to world class maintenance. Elsevier; 2003.
26. Eti MC, Ogaji SO, Probert SD. Reducing cost of preventive maintenance through adopting a proactive reliability-focused culture. Appl Energy. 2006; 83(11):1235-48. https://doi.org/10.1016/j.apenergy.2006.01.002
27. Carazas FG, Souza GF. Risk-based decision making method for maintenance policy selection of thermal power plant equipment. Energy. 2010; 35(2):964-75. https://doi.org/10.1016/j.energy.2009.06.054
28. Arunraj NS, Maiti J. Risk-based maintenance: techniques and applications. J Hazard Mater. 2007; 142(3):653-61. https://doi.org/10.1016/j.jhazmat.2006.06.069 PMID: 16887261.
29. Swanson L. Linking maintenance strategies to performance. Int J Prod Econ. 2001; 70(3):237-44. https://doi.org/10.1016/S0925-5273(00)00067-0
30. Tsang AH. Strategic dimensions of maintenance management. J Qual Maint Eng. 2002; 8(1):7-39. https://doi.org/10.1108/13552510210420577
31. Carvalho TP, Soares FA, Vita R, Francisco RD, Basto JP, Alcalá SG. A systematic literature review of machine learning methods applied to predictive maintenance. Comput Ind Eng. 2019; 137:106024. https://doi.org/10.1016/j.cie.2019.106024
32. Heng A, Zhang S, Tan AC, Mathew J. Rotating machinery prognostics: state of the art, challenges and opportunities. Mech Syst Signal Process. 2009; 23(3):724-39. https://doi.org/10.1016/j.ymssp.2008.06.009
33. Si XS, Wang W, Hu CH, Zhou DH. Remaining useful life estimation: a review on statistical data-driven approaches. Eur J Oper Res. 2011; 213(1):1-14. https://doi.org/10.1016/j.ejor.2010.11.018
34. Alsyouf I. The role of maintenance in improving companies' productivity and profitability. Int J Prod Econ. 2007; 105(1):70-8. https://doi.org/10.1016/j.ijpe.2004.06.057
35. Garg A, Deshmukh SG. Maintenance management: literature review and directions. J Qual Maint Eng. 2006; 12(3):205-38. https://doi.org/10.1108/13552510610685075
36. Khan FI, Haddara MM. Risk-based maintenance: a quantitative approach. J Loss Prev Process Ind. 2003;16(6):561-73. https://doi.org/10.1016/j.jlp.2003.08.011
37. Sharma RK, Kumar D, Kumar P. Systematic failure mode effect analysis using fuzzy linguistic modelling. Int J Qual Reliab Manag. 2005; 22(9):986-1004. https://doi.org/10.1108/02656710510625248
38. Ben-Daya M, Duffuaa SO, Raouf A, Knezevic J, Ait-Kadi D, editors. Handbook of maintenance management and engineering. London: Springer; 2009. https://doi.org/10.1007/978-1-84882-472-0
39. Duffuaa SO, Raouf A. Planning and control of maintenance systems: modelling and analysis. Springer; 2015. https://doi.org/10.1007/978-3-319-19803-3
40. Pintelon L, Parodi-Herz A. Maintenance: an evolutionary perspective. In: Complex system maintenance handbook. London: Springer; 2008. p. 21-48. https://doi.org/10.1007/978-1-84800-011-7_2
41. Eti MC, Ogaji SO, Probert SD. Integrating reliability, availability, maintainability and supportability with risk

analysis. Appl Energy. 2007; 84(2):202-21. https://doi.org/10.1016/j.apenergy.2006.05.001
42. Samanta B. Gear fault detection using artificial neural networks and support vector machines. Mech Syst Signal Process. 2004; 18(3):625-44. https://doi.org/10.1016/S0888-3270(03)00020-7
43. Moubray J. Reliability-centered maintenance. Industrial Press; 2001.

Author Contribution

Sangram Kishore Mallick: Conceptualization, methodology development, data collection from Case Study Mine, data curation, software application formal analysis, visualization, and original draft preparation. Bijay Mihir Kunar: Validation of results, technical review, supervision, and critical revision of the manuscript for important intellectual content.

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