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Machine Learning–Based Estimation of Risk Priority Number for Dumper Failure Analysis in Opencast Metal Mines

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Abstract

Heavy Earth-Moving Machines (HEMM), particularly dumpers, play a critical role in opencast metal mining, where harsh operating conditions frequently lead to equipment failures affecting safety, productivity, and maintenance costs. Traditional Failure Mode and Effects Analysis (FMEA) prioritize failures using the Risk Priority Number (RPN), calculated from Severity (S), Occurrence (O), and Detection (D) scores. However, this approach relies heavily on expert judgment and static evaluation, limiting its ability to incorporate historical operational data. This study proposes a data-driven framework integrating Machine Learning (ML) techniques with FMEA to improve failure risk prioritization for mining dumpers. The analysis is based on a dataset of 208 breakdown events collected over 2.5 years from 20 Komatsu HD785 dumpers, covering 15 major failure categories. Although limited in size, the dataset provides meaningful insights into failure behaviour. Severity (S) was assessed based on safety, operational, and economic impact indicators, while Occurrence (O) and Detection (D) were derived from historical failure frequency and monitoring effectiveness. Key input features included equipment age, failure type, subsystem category, maintenance history, and downtime characteristics. Gradient Boosting Regression models were developed to estimate S, O, and D scores, which were subsequently used to compute RPN values. The models demonstrated strong predictive performance, with R^2 values of 0.963 for Severity, 0.979 for Occurrence, and 0.981 for Detection. However, these results should be interpreted cautiously due to potential overfitting arising from the limited dataset. Engine-related failures were identified as the highest-risk category (RPN ≈ 240), while brake and suspension systems exhibited moderate risk levels.The proposed ML-assisted FMEA framework enables data-supported risk prioritization and supports maintenance decision-making in opencast mining. Further validation using larger datasets and real-time implementation is recommended to enhance practical applicability.

Keywords: *Equipment Reliability, Failure Mode and Effects Analysis (FMEA), Machine Learning, Predictive Maintenance, Risk Priority Number (RPN)*

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1. Introduction

In the highly mechanized environment of opencast metal mining, Heavy Earth-Moving Machines (HEMM), particularly dumpers, play a critical role in material transportation, production continuity, and operational safety. Harsh working conditions such as high payloads, uneven haul roads, abrasive material handling, and varying environmental conditions significantly increase the likelihood of equipment failures. These failures not only disrupt production schedules but also lead to increased maintenance costs and potential safety hazards. Therefore, systematic identification and prioritization of failure modes are essential for improving equipment reliability and ensuring safe mining operations[1].

Failure Mode and Effects Analysis (FMEA) is a widely adopted risk assessment tool used to identify potential failure modes, analyse their causes and consequences,

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and prioritize them using the Risk Priority Number (RPN). The RPN is calculated as the product of three parameters; Severity (S), Occurrence (O), and Detection (D), typically evaluated on a scale of 1 to 10. Despite its simplicity and ease of implementation, conventional FMEA has several inherent limitations. The reliance on subjective expert judgment can introduce inconsistencies, and the multiplicative formulation may produce identical RPN values for different risk scenarios, thereby masking critical differences in failure characteristics[2]. Additionally, traditional FMEA does not effectively incorporate historical operational data, limiting its ability to adapt to evolving system behaviour.

To overcome these limitations, recent studies have explored the integration of advanced analytical techniques, particularly Machine Learning (ML), into risk assessment and maintenance planning. ML approaches have been increasingly applied in predictive maintenance to model equipment failure behaviour using historical data, enabling improved prediction accuracy and decision-making[3]. Several researchers have proposed ML-enhanced FMEA frameworks, where algorithms such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forests, and Gradient Boosting are used to estimate or refine Severity, Occurrence, and Detection parameters[4-8]. These approaches aim to reduce subjectivity, capture nonlinear relationships among variables, and improve the reliability of risk prioritization.

In the mining sector, studies on equipment failure analysis have primarily focused on reliability modelling, failure distribution analysis, and maintenance optimization of HEMM such as dumpers, excavators, and loaders[9-11]. However, the application of ML-integrated FMEA specifically for dumper failure risk prioritization remains limited. Most existing works either rely on traditional statistical methods or do not fully integrate real operational data into the FMEA framework. Furthermore, there is a lack of studies that simultaneously predict all three FMEA parameters (S, O, and D) using ML models and use them for systematic RPN estimation.

Based on this context, a clear research gap exists in developing a data-driven, ML-assisted FMEA framework tailored to mining dumpers that can utilize historical failure data for improved risk prioritization.

This study aims to address this gap by integrating machine learning techniques with FMEA for enhanced failure risk assessment. The specific objectives of this study are:

1. To develop machine learning models for predicting FMEA parameters, namely Severity (S), Occurrence (O), and Detection (D), using historical dumper failure data.
2. To estimate the Risk Priority Number (RPN) using predicted S, O, and D values, enabling a data-driven approach to failure prioritization.
3. To identify critical failure modes in mining dumpers for effective maintenance planning and resource allocation.

The proposed approach combines the structured risk assessment capability of FMEA with the predictive power of machine learning, providing a more consistent and data-informed framework for maintenance decision support in opencast mining operations. Recent studies have increasingly applied deep learning and ensemble-based machine learning techniques for predictive maintenance and failure prediction in industrial systems[12-15]. Furthermore, recent advancements have focused on integrating machine learning and artificial intelligence with FMEA to improve risk prioritization accuracy and reduce subjectivity[16-18].

2. Materials and Methods

2.1 Data Collection

Dumper failure data were collected from highly mechanized opencast metal mine of Odisha, whose

Table 1. Preventive maintenance plan for dumper

Week	Week-1	Week-2	Week-3	Week-4
Dumper	Even No. Dumper	Odd No. Dumper	Even No. Dumper	Odd No. Dumper

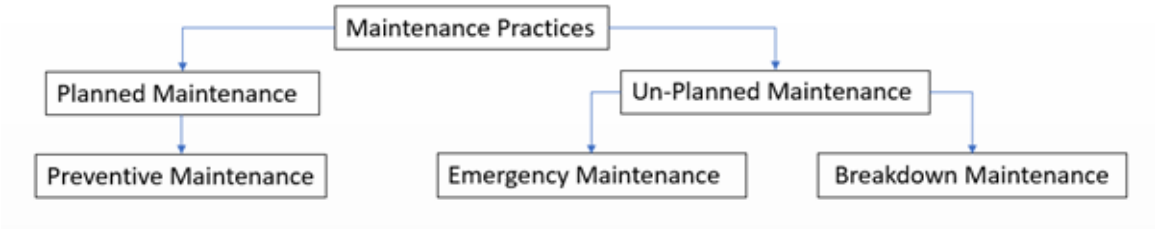


Figure 1. Maintenance practices by the case study mine.

production capacity is 6 million tonne per annum as per environment clearance. The mining area consists of a combination of hilly and flat terrain, with elevations ranging from 525 to 702 m above Mean Sea Level (MSL). Dumper failure data over 2.5 years were collected. The Figure 1 shows the maintenance practices that were followed by the case study mine.

A routine is made and being practised to follow the preventive maintenance of the dumper in a month. The sample routine is shown in Table 1.

Table 2. Equipment details

Sl. No.	Equipment ID	Mfg. Year	Make	Model	Capacity
1	400000256	2013	Komatsu	HD785	100T
2	400000748	2015	Komatsu	HD785	100T
3	400000749	2015	Komatsu	HD785	100T
4	400000761	2015	Komatsu	HD785	100T
5	400000762	2014	Komatsu	HD785	100T
6	400000764	2015	Komatsu	HD785	100T
7	400000765	2015	Komatsu	HD785	100T
8	400000779	2015	Komatsu	HD785	100T
9	400000783	2015	Komatsu	HD785	100T
10	400000823	2015	Komatsu	HD785	100T
11	400000831	2015	Komatsu	HD785	100T
12	400000832	2015	Komatsu	HD785	100T
13	400000833	2015	Komatsu	HD785	100T
14	400000834	2015	Komatsu	HD785	100T
15	400000867	2017	Komatsu	HD785	100T
16	400000888	2017	Komatsu	HD785	100T
17	400000899	2017	Komatsu	HD785	100T
18	400000900	2017	Komatsu	HD785	100T
19	400001041	2017	Komatsu	HD785	100T
20	400001054	2017	Komatsu	HD785	100T



Figure 2. HD785-7 dumper of Komatsu make (100T capacity).

The equipment details, types of failure, frequency of failure, running hours of equipment, and breakdown hours against each failure are shown in Table 2, Table 3, Table 4, and Table 5. The type of equipment used for data collection is showing in Figure 2.

Although failure statistics are often presented in aggregated form (e.g., subsystem-wise or category-wise summaries) for descriptive analysis, the machine learning models in this study were developed using event-level failure data. Each record in the dataset corresponds to an individual failure event, capturing detailed attributes such as subsystem type, failure occurrence time, downtime duration, and associated operational conditions.

To bridge the gap between aggregated reporting and event-level modelling, category-level insights (e.g., total failures per subsystem) were derived only for exploratory analysis and result interpretation, while the predictive models were trained exclusively on disaggregated event-level data. This ensures that the models capture variability and patterns at the most granular level, thereby improving predictive accuracy and avoiding information loss associated with aggregation.

Table 3. Types of failure and frequency against each failure

Type of failure	Failure Code	Nos. of time failure
AC problem	DF1	3
Auto Electrical Issue	DF2	1
Brake issue	DF3	11
Differential Issue	DF4	1
Dump body issue	DF5	13
Engine Issue	DF6	55
Hydraulic System Issue	DF7	15
Oil leakage	DF8	22
Oil mixing issue	DF9	5
Power Line Issue	DF10	7
Steering issue	DF11	3
Suspension Issue	DF12	23
Torque Converter	DF13	1
Transmission issue	DF14	15
Tyre issue	DF15	34

Table 4. Total running hours against each equipment

Equipment ID	OMR	CMR	Total Running Hours (CMR-OMR)
400000256	32005	38602	6597
400000748	39260	47509	8249
400000749	42240	51302	9062
400000761	40540	47974	7434
400000762	45001	51542	6541
400000764	39701	48521	8820
400000765	41970	47615	5645
400000779	38900	45920	7020
400000783	42170	44300	2130
400000823	39011	41524	2513
400000831	31112	38672	7560
400000832	30302	38103	7801
400000833	29917	37014	7097
400000834	29700	36025	6325
400000867	11515	18113	6598
400000888	9055	16072	7017
400000899	11213	12570	1357
400000900	9890	13312	3422
400001041	9981	17429	7448
400001054	10221	16715	6494

Furthermore, aggregated features such as failure frequency per subsystem and average downtime were also computed and incorporated as additional input variables, enabling the model to leverage both micro-level (event-specific) and macro-level (category-based) information in a consistent and structured manner.

2.2 Failure Mode Effect Analysis (FMEA)

Failure Mode and Effects Analysis (FMEA) is a structured and systematic risk assessment methodology used to identify potential failure modes, evaluate their effects, and prioritize corrective actions based on Severity (S), Occurrence (O), and Detection (D) criteria. Originally developed for reliability engineering applications, FMEA has evolved into a widely accepted tool across various industries, including mining, for improving system reliability and safety[19,20]. While the fundamental concept of FMEA is well established, its effectiveness significantly increases when applied within specific operational contexts using real system data.

In mining engineering, FMEA has been extensively applied to Heavy Earth-Moving Machinery (HEMM) to analyse equipment reliability, minimize unplanned downtime, and enhance operational safety. Mining equipment operates under harsh conditions, including high loads, abrasive materials, and variable terrain, making it highly susceptible to mechanical and operational failures. FMEA provides a structured framework to systematically identify critical failure modes in such environments and prioritize maintenance interventions[21].

Table 5. Breakdown hours against each type of failure

Type of failure	Failure Code	Number of times of failure	Breakdown Hours	Total Running Hours
AC problem	DF1	3	13:50:00	**125130**
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	802:35:00	
Engine Issue	DF6	55	1825:00:00	
Hydraulic System Issue	DF7	15	165:55:00	
Oil leakage	DF8	22	442:40:00	
Oil mixing issue	DF9	5	144:05:00	
Power Line Issue	DF10	7	148:05:00	
Steering issue	DF11	3	41:50:00	
Suspension Issue	DF12	23	585:00:00	
Torque Converter	DF13	1	60:00:00	
Transmission issue	DF14	15	520:05:00	
Tyre issue	DF15	33	244:55:00	
Total		**208**	**5169:20:00**	

2.2.1 FMEA in Haul Trucks (Dumpers)

Haul trucks are among the most critical assets in opencast mining, and their failure directly impacts production continuity. Several studies have applied FMEA to analyze failure modes in haul truck subsystems, including engines, braking systems, transmission units, suspension systems, and tyres[22]. Engine-related failures are often associated with high occurrence due to continuous operation under heavy loads, while brake system failures are considered safety-critical due to their high severity. Tyre and suspension failures are strongly influenced by haul road conditions and loading practices. The application of FMEA in such systems enables maintenance teams to prioritize high-risk components, enhance inspection protocols, and improve overall fleet reliability.

2.2.2 FMEA in Maintenance Engineering

In maintenance engineering, FMEA serves as a decision-support tool for developing preventive and predictive maintenance strategies. It facilitates the transition from reactive maintenance to proactive approaches by identifying high-risk failure modes and their root causes. FMEA is often integrated with reliability metrics such as Mean Time Between Failures (MTBF) and condition monitoring techniques, including vibration analysis and oil analysis[23]. Recent studies have also explored the integration of FMEA with machine learning techniques

to enhance risk prioritization accuracy and reduce subjectivity in scoring[24,25]. Such hybrid approaches enable dynamic risk assessment using historical and real-time operational data, improving maintenance planning efficiency.

Despite its advantages, traditional FMEA has certain limitations, including reliance on expert judgment, subjectivity in scoring, and limited capability to incorporate real-time data. These limitations have led to the development of advanced approaches, such as fuzzy FMEA and machine learning-assisted FMEA, to improve the robustness and reliability of risk assessment in complex industrial environments[26].

2.3 Risk Priority Number (RPN)

The risk level of each failure mode was quantified using a composite index derived from severity, occurrence frequency, and detectability, consistent with the RPN concept used in FMEA-based risk assessments as in Equation (1).

$$RPN = S * O * D \quad (1)$$

Where RPN = Risk Priority Number

S = Severity

O = Occurrence

D = Detection

2.3.1 Limitations of Conventional RPN Approach

Despite its widespread use, the Risk Priority Number (RPN) method has several well-recognized limitations that can significantly affect the reliability and accuracy of risk prioritization. One of the primary concerns is that different combinations of Severity (S), Occurrence (O), and Detection (D) can yield identical RPN values, even though the associated risk implications may differ substantially. For instance, a failure mode with high severity but low occurrence may receive the same RPN as a less severe but frequently occurring failure, potentially leading to misinterpretation and improper prioritization of critical risks.

Another major limitation is the absence of weighting among the three parameters (S, O, and D). In practical scenarios, severity is often considered more critical than occurrence or detection, especially in safety-sensitive environments such as mining operations. However, the conventional multiplicative formulation of RPN assumes equal importance of all three factors, which may not accurately reflect real-world risk perception and decision-making priorities.

2.4 Machine Learning (ML) in Maintenance

Machine learning (ML) in maintenance refers to the application of data-driven algorithms to analyze equipment condition, predict failures, and optimize maintenance strategies. By leveraging historical maintenance records, sensor data, and operational parameters, ML models can identify hidden patterns and early signs of degradation that are not easily detectable through traditional methods[27]. This enables a shift from reactive or time-based maintenance to predictive and condition-based maintenance, reducing unplanned downtime and maintenance costs while improving equipment reliability and safety. In industrial environments such as mining, ML-driven maintenance systems support informed decision-making, enhance asset performance, and contribute to overall operational efficiency[28].

2.5 Evaluation of Risk Priority Number – Gradient Boosting Regression ML Process

2.5.1 Data Collection and Preparation

The dataset comprises 208 breakdown records and includes detailed attributes such as equipment identification and specifications, breakdown date and time, and running hours measured through Hour Meter Reading (HMR). It also captures failure category and sub-category information, covering 174 unique sub-categories, along with breakdown duration in hours. In addition, the dataset documents repair actions undertaken and the parts replaced, providing a comprehensive basis for failure analysis and maintenance assessment.

2.5.2 RPN Component Scoring Methodology

2.5.2.1 Severity Score (S)

Severity is defined as "How bad the effect of failure is." For severity calculation, the following four impact factors were considered.

- Safety risk to operator/others: Potential for injury or fatality
- Chance of accident/collision/uncontrolled movement: Risk of secondary incidents
- Damage to the equipment: Extent of mechanical/structural damage
- Loss of production hours: Operational downtime impact

2.5.2.2 Occurrence Score (O)

Occurrence is defined as "How frequently does this failure happen?". Occurrence was calculated based on the following six criteria:

- Historical failure frequency: Past breakdown records and patterns
- Mean Time Between Failures (MTBF): Average operating time between failures
- Working environment: Haul Road conditions, dust, temperature, load factors
- Operator skills and driving conditions: Training level and operating practices
- Preventive maintenance effectiveness: Quality and adherence to PM schedules
- Equipment age: Years since manufacture and cumulative operating hours

The Occurrence is calculated from the historical failure frequency as in Equation (2).

$$O = \min(10, \max(1, [f/fmax*10])) \quad (2)$$

where f is the failure count, and fmax is the maximum observed frequency.

2.5.2.3 Detection Score (D)

Detection is defined as "How easily can the failure be detected before it happens". The failure detection capability was assessed based on the following three factors:

- Presence of warning system: Availability of sensors, dashboard alarms, and automated alerts
- Pre-start inspection effectiveness: Quality of operator walk-around checks and daily inspections
- Equipment health monitoring system: Vibration analysis, oil analysis, thermal imaging, and other condition monitoring techniques

Higher scores indicate more difficult detection (sudden failures with no warning), whereas lower scores indicate a reliable early warning capability.

2.5.3 Machine Learning Model Architecture

2.5.3.1 Algorithm Selection

Gradient Boosting Regression was selected as the predictive modelling technique due to its strong capability to handle datasets containing both categorical and numerical features through appropriate encoding and tree-based learning structures[29]. The method is particularly effective in capturing complex nonlinear relationships between input variables and the target response, which are commonly present in equipment performance and failure-related data. In addition, Gradient Boosting models provide inherent feature importance measures, enabling the identification of key operational and maintenance parameters that most significantly influence system behaviour[30]. Another major advantage of this approach is its ability to achieve high prediction accuracy even when trained on relatively limited datasets, making it well suited for industrial environments where extensive historical data may not always be available[31].

Gradient Boosting Regression was selected for its ability to handle mixed categorical and numerical features, capture nonlinear relationships, provide feature importance rankings and deliver high accuracy with limited training data.

2.5.3.2 Feature Engineering

The features shown in Table 6 were engineered for model training.

2.5.3.3 Model Training

Three separate Gradient Boosting models were trained as per FMEA standard.

Table 6. Features used in ML models

Feature	Type	Description
Category	Categorical	Primary failure category (15 classes)
Subcategory	Categorical	Detailed failure type (174 classes)
Equipment ID	Categorical	Unique dumper identifier
Running Hours	Numerical	Hour meter reading at failure
Equipment Age	Numerical	Days since manufacture
Month	Numerical	Month of failure (1-12)
Day of Week	Numerical	Day of week (0-6)
Quarter	Numerical	Calendar quarter (1-4)
Breakdown Hours	Numerical	Duration of breakdown event

1. Severity Model: Predicts S score (1-10) is showing in Table 7.

Table 7. Severity scoring scale

Score	Description
10	Hazardous – affects safety without warning
9	Hazardous – affects safety with warning
8	Very High – system inoperable with destructive failure
7	High – system inoperable with equipment damage
6	Moderate – system inoperable with minor damage
5	Low – system operable with significant degradation
4	Very Low – system operable with some degradation
3	Minor – system operable with minimal impact
2	Very Minor – fit/finish issues, no operational impact
1	None – no discernible effect

2. Occurrence Model: Predicts O score (1-10) is showing in Table 8.

Table 8. Occurrence scoring scale

Score	Failure Probability
10	Very High: ≥ 1 in 2 (50% +)
9	High: 1 in 3
8	High: 1 in 8
7	Moderately High: 1 in 20
6	Moderate: 1 in 80
5	Moderate: 1 in 400
4	Moderately Low: 1 in 2000
3	Low: 1 in 15000
2	Very Low: 1 in 150000
1	Remote: < 1 in 1500000

3. Detection Model: Predicts the D score (1-10) is shown in Table 9.

Table 9. Detection scoring scale

Score	Detection Capability
10	Absolute Uncertainty – cannot detect
9	Very Remote – very unlikely to detect
8	Remote – unlikely to detect
7	Very Low – very low chance of detection

6	Low – low chance of detection
5	Moderate – moderate chance of detection
4	Moderately High – good chance of detection
3	High – high chance of detection
2	Very High – very high chance of detection
1	Almost Certain – will almost certainly detect

Training configuration:

- Train/Test split: 80%/20%
- Cross-validation: 5-fold
- Hyperparameter tuning: Grid search optimization

2.6 Model Performance

All three models achieved exceptional prediction accuracy, as shown in Table 10 and visualized in Figure 2.

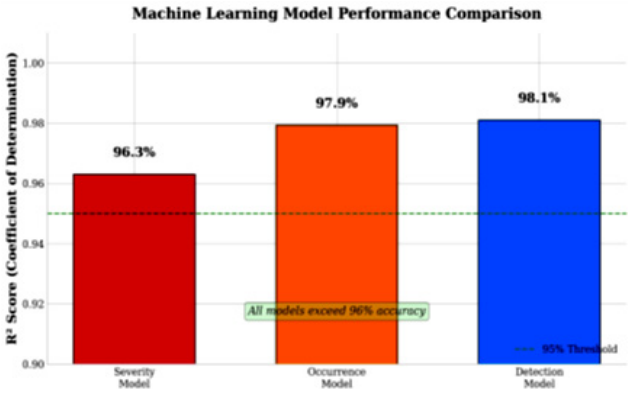


Figure 2. Machine learning model performance comparison.

Table 10. Machine learning model performance metrics

Model	R^2 Score	Accuracy	MAE
Severity Model	0.9630	96.3%	0.21
Occurrence Model	0.9793	97.9%	0.15
Detection Model	0.9810	98.1%	0.14
Overall RPN	-	-	0.18

Figure 2 demonstrates that all three component models exceed the 95% accuracy threshold, with the detection model achieving the highest R^2 score of 98.1%. This exceptional performance validates the machine-learning approach for RPN prediction.

Significance: The near-perfect Mean Absolute Error (MAE) of 0.18 for the overall RPN indicates that the system can reliably replicate expert-level assessments, making it suitable for production deployment in maintenance planning systems.

Outcome: 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.

2.6.1 RPN Analysis Results

2.6.1.1 Complete Category Analysis

Table 11 presents the complete RPN analysis for all 15 failure categories.

Table 11. RPN analysis results by failure category

Rank	Category	RPN	S	O	D	Count	Risk Level
1	Engine Issue	240	6	10	4	55	High
2	Brake Issue	147	7	3	7	11	Medium
3	Suspension Issue	100	4	5	5	23	Medium
4	Tyre Issue	96	2	6	8	33	Low
5	Transmission Issue	90	5	3	6	15	Low
6	Hydraulic System Issue	60	5	3	4	15	Low

7	Steering Issue	42	7	1	6	3	Low
8	Oil Leakage	36	3	4	3	22	Low
9	Power Line Issue	36	3	2	6	7	Low
10	Oil Mixing Issue	32	4	2	4	5	Low
11	Differential Issue	25	5	1	5	1	Low
12	Dump Body Issue	24	2	3	4	13	Low
13	Torque Converter Issue	16	4	1	4	1	Low
14	Auto Electrical Issue	15	3	1	5	1	Low
15	AC Problem	3	1	1	3	3	Low
Total		-	-	-	-	208	-

2.6.2 Visual Analysis of Results

2.6.2.1 RPN Ranking by Category

Figure 3 presents a horizontal bar chart ranking all 15 failure categories by their calculated RPN values. Engine issues dominate with an RPN of 240, which is significantly higher than the second-ranked brake issues (RPN = 147). The chart clearly shows the gap between the top priority and remaining categories.

Significance: The visual representation enables maintenance managers to quickly identify the priority areas. Color-coding by risk level (HIGH in orange, MEDIUM in yellow, and LOW in green) provides an immediate risk assessment at a glance.

Outcome: Only one category (Engine Issue) fell in the HIGH risk zone, while no categories reached the CRITICAL threshold of 300. This indicates that although

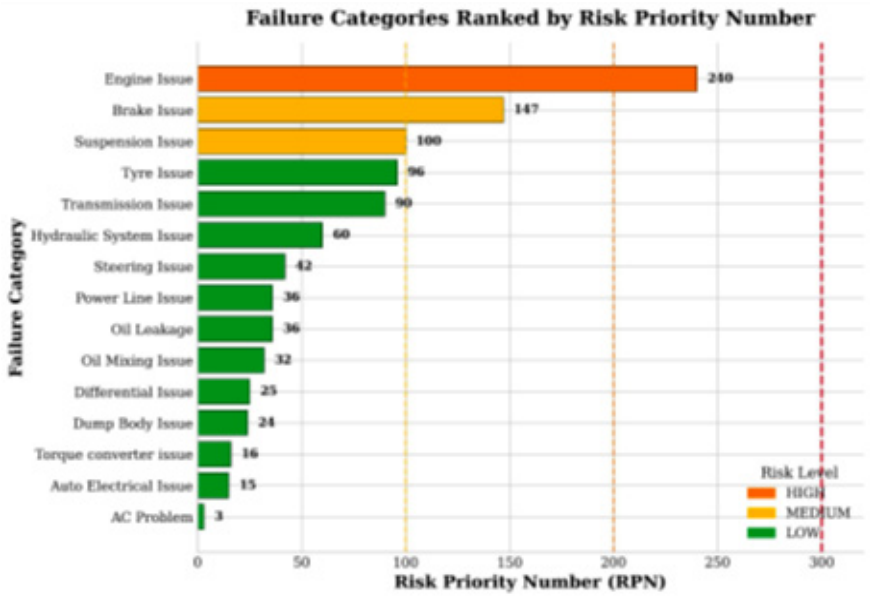


Figure 3. Failure categories ranked by risk priority number.

improvements are needed, the fleet does not face immediate catastrophic risk levels.

2.6.2.2 S-O-D Component Comparison

Figure 4 breaks down the RPN into its three constituent components for the top 10 categories. This grouped bar chart reveals the factors that drive the risk of each failure type.

Key Observations:

The analysis of key failure categories reveals distinct risk-driving factors across components. Engine-related issues are primarily influenced by a very high occurrence score (10), indicating that failure frequency, rather than severity (6), is the dominant contributor to risk. In contrast, brake issues present a more critical safety concern due to the combination of high severity (7) and poor detection capability (7), which together elevate the overall risk level. Tyre-related failures, although associated with low severity (2), are significantly impacted by high detection difficulty (8), highlighting limitations in early fault identification. Meanwhile, steering issues exhibit the highest severity (7); however, their very low occurrence (1) keeps the overall RPN at a manageable level. Collectively, these observations emphasize the need for component-specific risk mitigation strategies based on the dominant contributing factors.

Significance: Understanding the components driving RPN enables targeted interventions. A High occurrence suggests preventive maintenance optimization, high detection scores indicate a need for monitoring systems, and high severity requires safety protocols.

Outcome: Different failure modes require different mitigation strategies based on their score profiles, not only their total RPN values.

2.6.2.3 Failure Frequency Distribution

Figure 5 displays the absolute count and percentage of breakdowns for each failure category. Engine issues accounted for 55 events (26.4% of the total), followed by tyre issues at 33 events (15.9%).

Significance: The frequency distribution reveals the operational impact patterns. Categories with high frequency, even with low severity, consume significant maintenance resources and create operational disruptions.

Outcome: The top 5 categories (engine, tyre, suspension, oil leakage, and transmission/ hydraulic) accounted for approximately 80% of all breakdown events, following the Pareto principle. Focusing

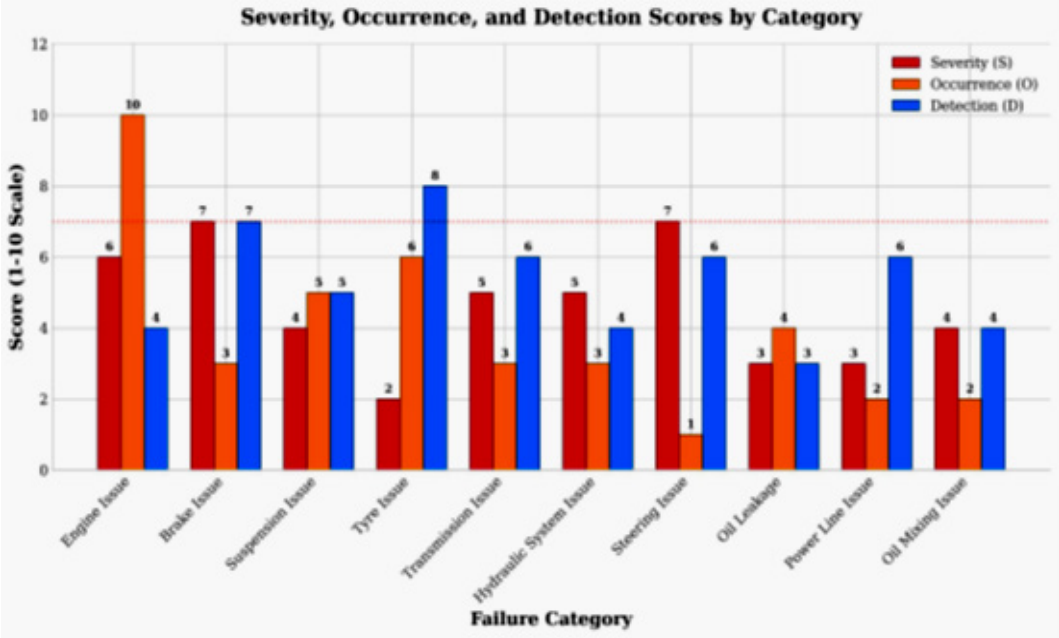


Figure 4. Severity, occurrence, and detection scores by category.

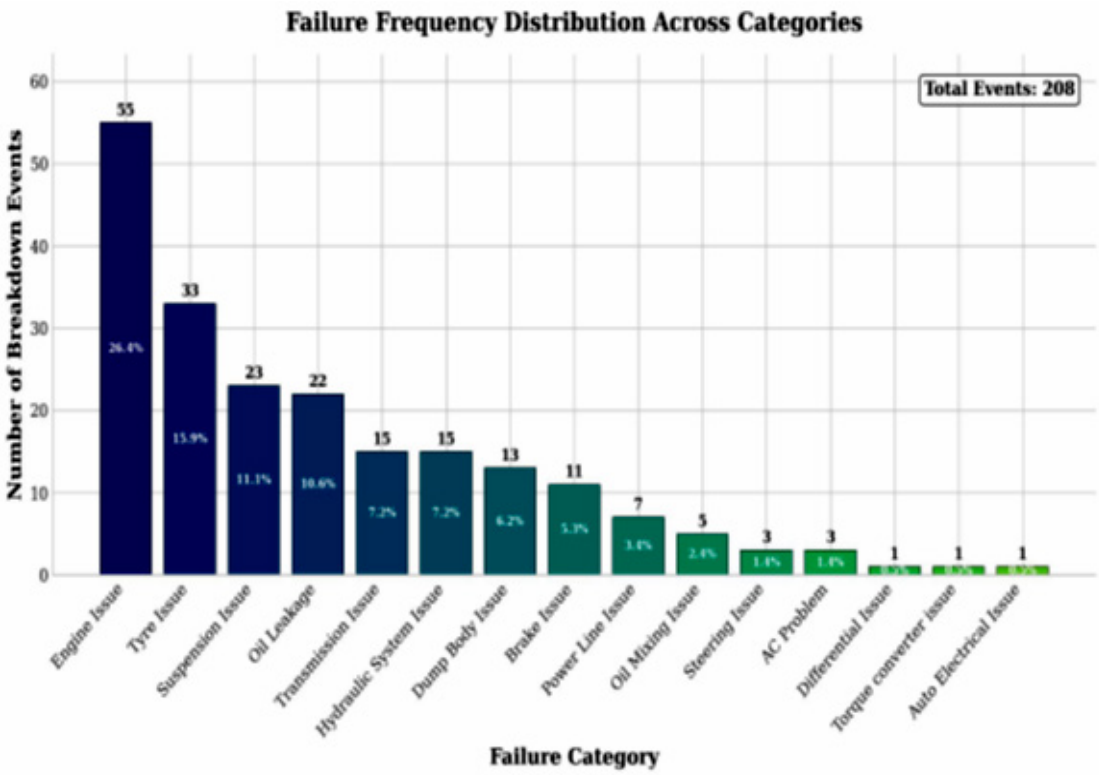


Figure 5. Failure frequency distribution across categories.

improvement efforts on these categories will yield the greatest operational benefits for the company.

2.6.2.4 RPN Value Distribution

Figure 6 shows a histogram of the RPN values for all 208 breakdown events. The distribution was right-skewed, with most events falling in the LOW risk zone (RPN < 100). The mean RPN was approximately 117, with a median of approximately 96.

Significance: The distribution pattern indicates that while most failures are manageable (LOW risk), a significant cluster of events in the 200-250 RPN range

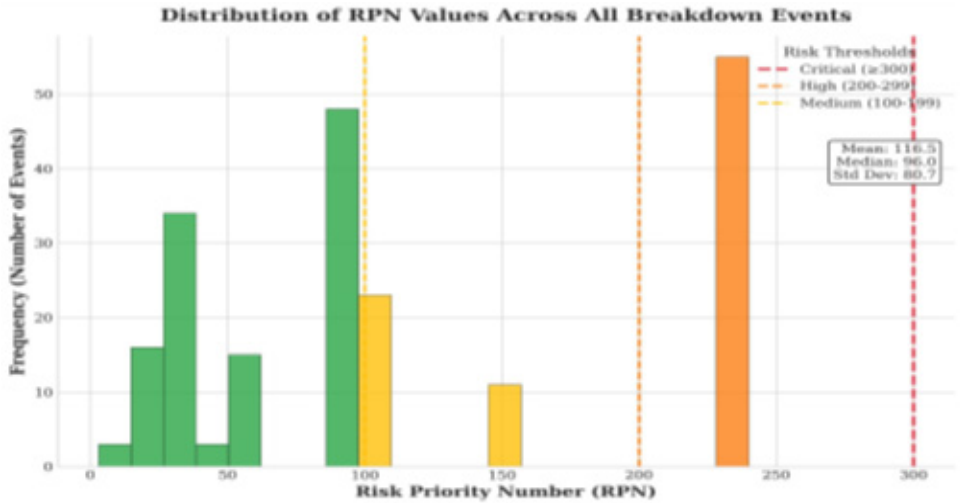


Figure 6. Distribution of RPN values across all breakdown events.

requires attention. No events exceeded the critical threshold of 300.

Outcome: The overall risk profile of the fleet was moderate. The absence of critical-level events suggests that current maintenance practices prevent catastrophic failures, but the HIGH-risk cluster indicates room for improvement in engine maintenance.

2.6.2.5 Risk Level Distribution

Figure 7 presents a pie chart showing the proportion of breakdown events classified by risk level. The distribution

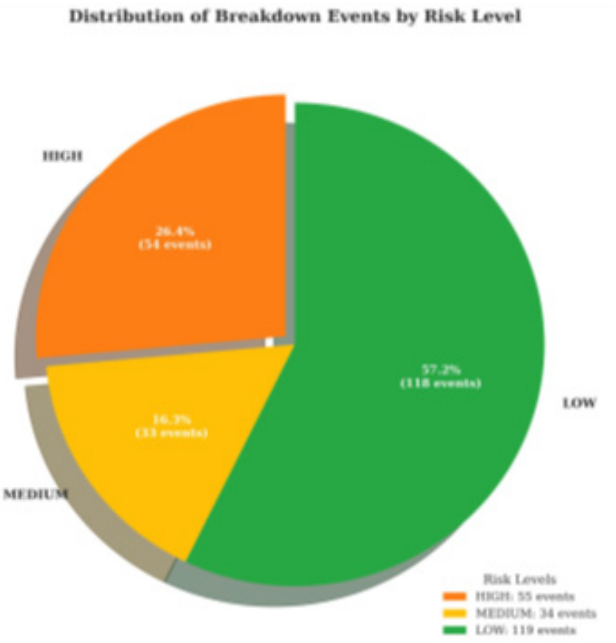


Figure 7. Distribution of breakdown events by risk level.

of risk levels indicates that the majority of events fall within the low-risk category, accounting for 119 cases (57.2%), which lie in the green zone and can be managed through routine maintenance practices. A smaller proportion, 34 events (16.3%), are classified as medium risk, falling in the yellow zone and requiring scheduled improvements to prevent escalation. Notably, 55 events (26.4%) are categorized as high risk, representing the orange zone and demanding immediate priority action. This distribution highlights that while most failures are manageable, a significant share requires focused intervention to enhance system reliability and safety.

Significance: Over a quarter of all breakdown events fall into the HIGH risk category, all of which are attributable to engine failures. This concentration of risk in a single category presents both challenges and an opportunity.

Outcome: Addressing engine reliability would eliminate all HIGH risk events from the fleet, dramatically improving the overall risk profile. This single-point focus enables efficient resource allocation for a maximum impact.

2.6.2.6 Breakdown Duration vs. RPN Relationship

Figure 8 explores the correlation between the breakdown duration (repair time) and RPN values. Each point represents a breakdown event, color-coded by failure category.

The analysis indicates that the correlation coefficient (r) is weak, suggesting that the Risk Priority Number (RPN) is not directly dependent on repair duration. This is further supported by the behaviour of engine-related failures, which, despite having a high RPN of 240, exhibit a wide variation in repair times ranging from 2 to 24 hours. Additionally, certain low-RPN failures, particularly in suspension systems, are associated with relatively long repair durations, highlighting that lower risk does not necessarily imply quicker resolution. Tyre-related issues, on the other hand, show a more consistent pattern, clustering around an RPN value of 96 with moderate repair times. Overall, these observations demonstrate that repair duration and risk priority are not strongly correlated and should be considered as independent factors in maintenance planning.

Significance: The weak correlation confirms that the RPN captures risk factors beyond downtime. A failure can be high-risk because of frequency or detection difficulty, even if the individual repair times are short.

Outcome: Maintenance planning should not rely solely on historical repair durations to prioritize work. The RPN metric provides a more comprehensive risk assessment that considers multiple factors.

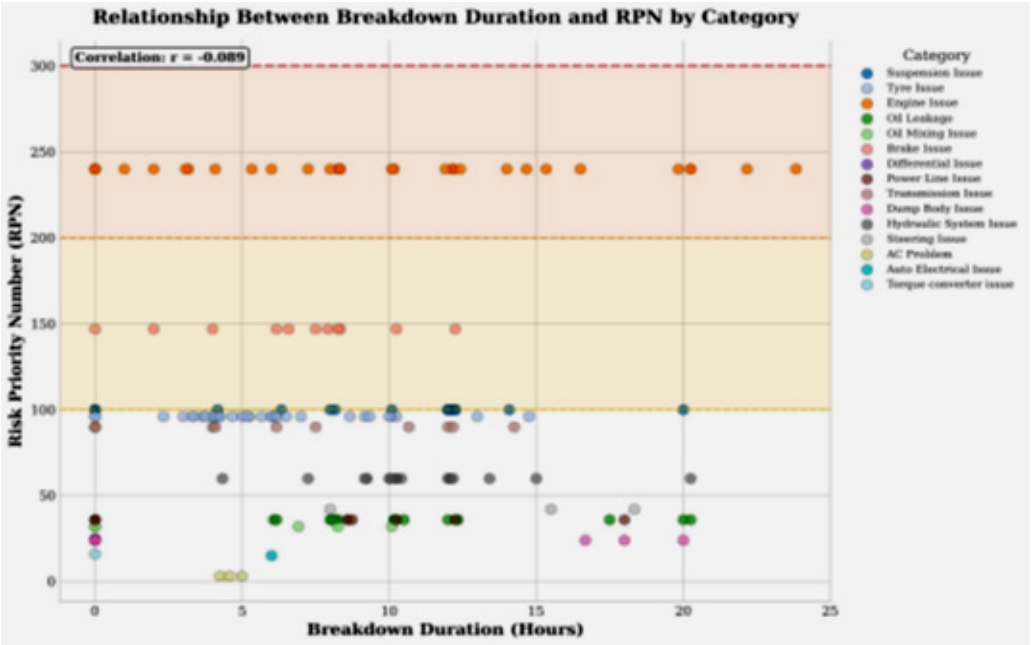


Figure 8. Relationship between breakdown duration and RPN by category

2.6.2.7 S-O-D Component Heatmap

Figure 9 presents a heatmap visualization of the S-O-D scores for all 15 failure categories. Darker colors indicate higher scores (greater concerns). This matrix view enables simultaneous pattern recognition across multiple categories.

Key Patterns:

- High Occurrence Column: Engine issues stand out with a score of 10.
- High Detection Row: Tyre (8) and brake (7) issues have poor detectability.
- High Severity Row: Brake (7) and steering (7) issues are the most severe.
- Balanced Scores: The suspension issue showed moderate scores across all three components.

Significance: The heatmap enables the identification of systemic patterns. Categories with multiple dark cells require comprehensive interventions, whereas those with single dark cells require targeted solutions.

Outcome: The visualization supports strategic decision-making by revealing which combination

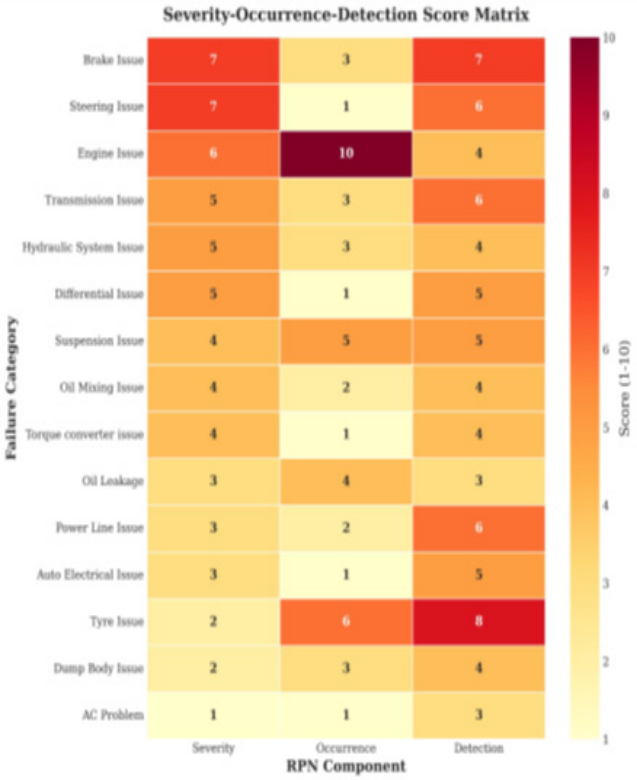


Figure 9. Severity-occurrence-detection score matrix.

of factors creates a risk for each failure type, guiding appropriate mitigation strategies.

2.6.2.8 Pareto Analysis

Figure 10 combines a bar chart of failure counts with a cumulative percentage line (Pareto chart). The 80% threshold line identifies the vital categories that drive most breakdowns.

Key Finding: The top 5 categories (engine, tyre, suspension, oil leakage, and transmission/hydraulic tie) accounted for approximately 80% of all breakdown events.

Significance: The Pareto principle (80/20 rule) was confirmed in this dataset. Focusing improvement efforts on these five categories will address most of the maintenance burden.

Outcome: Resource allocation should prioritize the five categories. A targeted improvement program addressing engine, tyre, suspension, oil leakage, and hydraulic/transmission issues would provide the highest return on investment.

2.6.2.9 Top 5 Priority Categories Deep Dive

Figure 11 provides a detailed view of the top 5 priority categories. The left panel shows the absolute RPN values with risk-level colouring. The right panel shows the stacked contributions of the S, O, and D components.

Component Breakdown Analysis:

The analysis of the top five high-risk categories, as illustrated in Figure 11, highlights the contribution of Severity (S), Occurrence (O), and Detection (D) to the overall Risk Priority Number (RPN). Each category exhibits a distinct risk profile, requiring targeted intervention strategies.

Firstly, *Engine Issues* (RPN = 240) are predominantly driven by a very high occurrence value (O = 10), contributing nearly 50% of the total component influence. This indicates that frequent failures are the primary concern, and therefore, efforts should focus on reducing failure frequency through improved preventive maintenance and reliability enhancement measures.

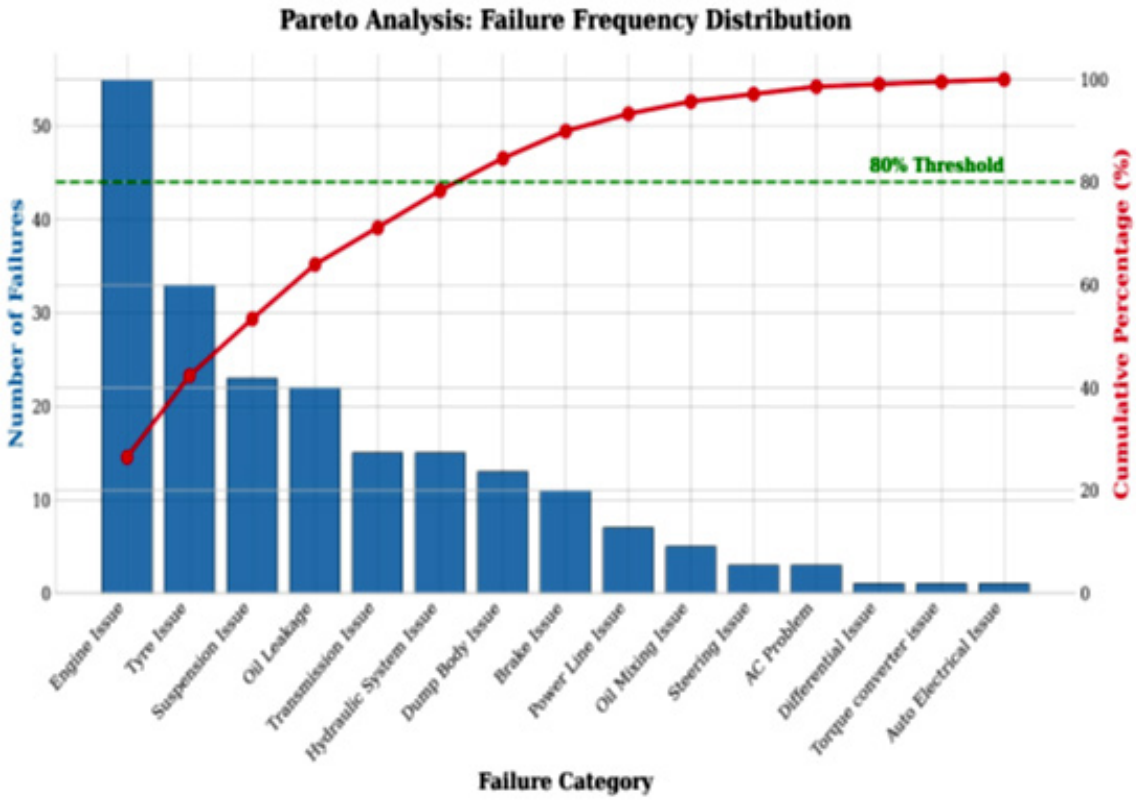


Figure 10. Pareto analysis: failure frequency distribution.

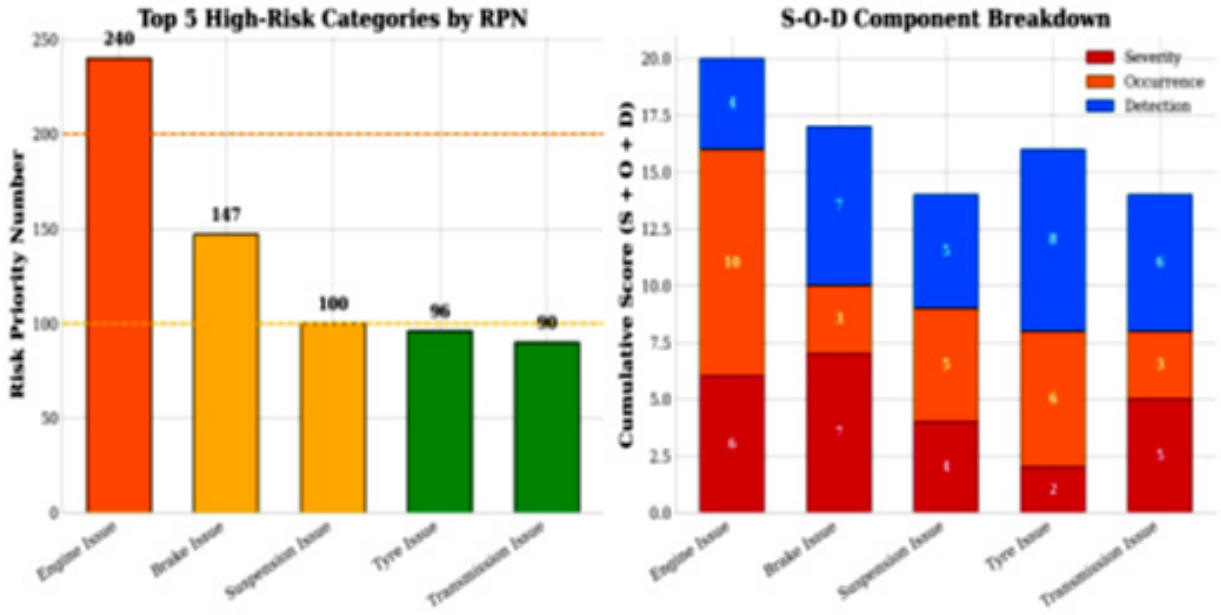


Figure 11. Top 5 high-risk categories analysis.

Secondly, *Brake Issues* (RPN = 147) demonstrate relatively high and balanced contributions from all three components (S, O, and D). This suggests that the problem is multifaceted, requiring a comprehensive approach that simultaneously addresses severity reduction, failure frequency, and detection capability.

Thirdly, *Suspension Issues* (RPN = 100) show an even distribution across all risk components. This balanced profile indicates that incremental improvements in each parameter—such as better inspection routines, material upgrades, and monitoring systems—can collectively reduce the overall risk.

In the case of *Tyre Issues* (RPN = 96), detection (D = 8) is the dominant contributing factor. This reflects limitations in early fault identification, emphasizing the need for improved inspection techniques, condition monitoring, and predictive diagnostics to enhance detectability.

Lastly, *Transmission Issues* (RPN = 90) exhibit moderate and balanced component values, suggesting that existing Preventive Maintenance (PM) strategies are reasonably effective but can be further optimized for improved reliability.

Overall, this component-wise breakdown enables a deeper understanding of risk drivers within each category. It supports the development of targeted and efficient mitigation strategies, such as occurrence reduction for engine systems, enhanced detection mechanisms for tyre-related failures, and integrated safety improvements for brake systems.

Significance: Understanding the relative contributions of each component within priority categories enables precise intervention design. Different score profiles require different mitigation strategies.

Outcome: The analysis supports targeted action plans, including occurrence-focused interventions for engines, detection improvements for tyres, and comprehensive safety protocols for brakes.

3. Result and Discussions

The developed models demonstrated high predictive performance ($R^2 > 0.96$); however, the results were interpreted cautiously considering the limited dataset size. The structured nature of the input variables contributed to consistent prediction accuracy across validation sets.

RPN-based analysis identified engine-related failures as the most critical, primarily driven by high occurrence rather than severity, indicating frequent breakdowns as

the dominant risk factor. Brake system failures, although moderate in occurrence, posed significant safety concerns due to high severity and poor detectability. Suspension failures exhibited a balanced risk profile, requiring incremental improvements across all contributing parameters.

The findings highlight that reliance solely on severity is insufficient for effective risk prioritization. Instead, the combined influence of occurrence and detection plays a crucial role in determining overall risk. Furthermore, the weak correlation between RPN and repair duration suggests that maintenance planning should treat risk priority and repair time as independent decision factors.

Based on these insights, a phased maintenance strategy was proposed, ranging from immediate preventive actions to long-term predictive maintenance implementation. The integration of machine learning with FMEA enables data-driven decision-making, supports proactive maintenance planning, and enhances operational reliability and safety in mining environments.

3.1 Maintenance Strategy and Implementation Framework

The proposed recommendations are structured across immediate, short-term, medium-term, and long-term implementation phases to systematically enhance equipment reliability and maintenance effectiveness.

Immediate actions within the first 30 days should focus on optimizing engine maintenance practices by reducing preventive maintenance intervals from the existing 5,000–6,000 operating hours to approximately 3,000 hours in order to mitigate high-risk failure modes. An oil analysis program should be initiated with sampling intervals of 500 hours to enable early detection of wear debris and lubricant degradation. Additionally, the installation of real-time temperature and vibration monitoring sensors is recommended to provide continuous condition assessment of critical engine components. For braking systems, the introduction of brake pad wear sensors across all dumpers will improve real-time wear monitoring, while strengthened pre-shift inspection protocols and brake fluid condition monitoring will further enhance safety and reliability. Maintenance documentation should also be updated by revising standard operating procedures based on Risk Priority Number (RPN) outcomes and developing quick-reference failure mode guides to support operator awareness and rapid response.

Short-term actions over a period of one to three months should include the implementation of a comprehensive oil analysis program covering engine oil, transmission fluid, and hydraulic systems to ensure holistic lubricant health monitoring. The deployment of a Tyre Pressure Monitoring System (TPMS) across the dumper fleet is recommended to minimize tyre-related failures and improve fuel efficiency. In addition, establishing a vibration analysis program for suspension systems will enable early detection of structural and mechanical abnormalities. A targeted operator training program should also be developed to enhance early failure recognition and encourage proactive maintenance reporting.

Medium-term initiatives within three to six months should prioritize the deployment of a centralized Internet of Things (IoT) monitoring dashboard to integrate real-time equipment health data across the fleet. The machine learning-based failure prediction system should be integrated with maintenance scheduling software to enable automated, data-driven maintenance planning. Furthermore, a systematic assessment of haul road conditions is recommended to reduce excessive tyre wear and suspension stress, thereby improving equipment lifespan. The transition from time-based to condition-based maintenance protocols should also be implemented during this phase to improve maintenance efficiency and reliability.

Long-term actions over six to twelve months should focus on the full-scale deployment of a predictive maintenance framework encompassing real-time monitoring, machine learning analytics, and automated maintenance decision-making. Integration with spare parts inventory management systems will optimize stock availability and reduce maintenance delays. Continuous retraining of prediction models using newly acquired operational data will enhance prediction accuracy over time. The predictive maintenance approach should ultimately be expanded to other equipment types within

the mining fleet to achieve enterprise-wide reliability improvement.

4. Conclusion

This study presents a data-driven framework for automating Risk Priority Number (RPN) evaluation in Failure Mode and Effects Analysis (FMEA) for heavy earth-moving machinery. The major contribution lies in integrating machine learning techniques with traditional FMEA to enable objective, consistent, and rapid risk assessment. The proposed approach reduces subjectivity in assigning Severity, Occurrence, and Detection scores while enhancing decision-making through predictive capability. Furthermore, the study demonstrates how component-wise risk decomposition can support targeted maintenance strategies, thereby improving equipment reliability, optimizing manpower utilization, and strengthening safety performance in mining operations.

The developed model not only facilitates accurate prioritization of critical failure modes but also enables proactive maintenance planning by predicting risk levels for new or unseen scenarios. This represents a significant advancement over conventional static FMEA practices, which are often time-consuming and experience-dependent.

Future work can focus on expanding the dataset to improve model generalizability across different mine environments and equipment types. Integration with real-time sensor data and IoT-based condition monitoring systems can further enhance predictive accuracy and enable dynamic risk assessment. Additionally, the incorporation of advanced techniques such as deep learning and hybrid reliability models may improve the robustness of predictions and support the development of fully autonomous maintenance decision-support systems.

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

Finally, the authors are grateful to all individuals and organizations whose contributions, directly or indirectly, have helped in the successful completion of this study.

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Author Contributions

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.