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Engine Failure Assessment Using Economic Risk Priority Number (ERPN) Approach

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Abstract

Heavy equipment in aluminum smelters operates under harsh thermal and mechanical conditions, leading to increased risks of vehicle failure and unplanned downtime. This study proposes an Economic Risk Priority Number (ERPN) approach to overcome the limitations of the conventional Risk Priority Number (RPN) used in Failure Mode and Effects Analysis (FMEA). A five-year maintenance dataset (2019–2024), comprising 2,303 corrective work orders across 58 units, was analyzed. The classical RPN is approach prioritized failure modes primarily based on frequency, identifying wheels and hydraulic systems as the most critical subsystems. However, the proposed ERPN model incorporates economic impact, including maintenance cost, labor cost, and production loss, leading to a re-prioritization of the engine subsystem as the highest-risk component. The most severe engine failure resulted in a financial loss of approximately USD 1.92 million due to extended downtime and repair costs. Root cause analysis identified coolant loss, low oil pressure, and excessive vibration as primary contributors to failure, supported by diagnostic data and repeated alarm patterns. Statistical validation using the Kruskal–Wallis test confirmed significant differences among subsystem risk rankings for both RPN ($\chi^2 = 846.07$, df = 4, $p < 0.0001$) and ERPN ($\chi^2 = 131.69$, df = 4, $p < 0.0001$). The results demonstrate that ERPN provides a more realistic and economically aligned framework for maintenance prioritization in heavy industrial operations. The proposed approach enhances decision-making by integrating reliability analysis with economic impact, offering a practical tool for improving maintenance strategies and reducing operational risk in aluminum smelter fleets.

Keywords: failure mode and effects analysis (FMEA); aluminum smelters; engine failure assessment; risk assessment; Economic Risk Priority Number (ERPN)

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1. Introduction

The reliability of engines in transport fleets used in aluminum smelters is stressed by the requirement of continuous production flow, with minimal operating expenses, keeping safety at an appropriate level during the service.(Ciancio et al., 2020) According to Majid et al. (2015), the harsh environment where the maintenance activity is carried out is harmful especially for the mechanical and electrical systems of complex units due to heat generated by high ambient temperature, dust, and mainly electromagnetic interference in the aluminum smelter (Schmitz, 2007). Although some attempts to transport the reliability analysis methods to a mining fleet or construction fleet have been reported (Deulgaonkar et al., 2021). The endeavor in this work is to study patterns of fleet failure in

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aluminum plant vehicles in a more rigorous way using maintenance records and formal risk prioritization.

The reliability of these equipment's is assessed by statistical metrics that capture the failure phenomena and system availability as a function of time. In the case of heavy-duty vehicles, these indicators are related to maintenance performance, since breakdowns and recovery times significantly influence fleet availability and production flow (Wang et al., 2018; Daya, 2024). There is an urgent demand for methodical, data-driven techniques to systematically discover primary failure modes and their root causes, based on actual operational data (Hu et al., 2026) to avoid the delay of the logistics of operating molten metal transport and entail hazards and lost productivity (Odeyar et al., 2022).

Gong et al. (2020) used the Failure Modes, Effects, and Criticality Analysis (FMECA) model which is used to evaluate the behavior of vehicle failure events. This methodology allows for systematic identification, evaluation, and ranking of vehicles failure modes in terms of their risk exposure, supporting focused maintenance planning and enhanced reliability under harsh industrial scenarios (Filz et al., 2021). The Risk Priority Number (RPN) system also arranges the failure modes in terms of priority by assessing and categorizing them according to their overall hazard, which is determined by the byproduct of their severity, occurrence, and detectability (Hwang et al., 2024). The Risk Priority Number (RPN) is a number is used to quantify the risk associated with each failure mode. It is calculated as.

$$RPN = S \times O \times D \quad \text{(Eq. 1)}$$

where S is Severity, O is Occurrence, and D is Detection, (Hwang et al., 2024). The higher the RPN, the more critical and difficult it is to address the failure mode that needs to be fixed immediately. But this simple product of scores has come under close examination. It is the result of a combination of subjective and ordinal scales that can lead to equivalent or deceptive ranks (Liu et al., 2023; Liu et al., 2013). However, the conventional RPN fails to account for significant factors, including economic expense or downtime due to failure. A low-cost common failure could have the same RPN as a high-cost rare failure and ruin maintenance policy. In practice, a low-cost frequent failure with many correction methods can have similar risk priority numbers (RPN) to those of high-cost rare failures.

This limitation is particularly critical in heavy industrial environments. For example, a small problem such as a flat tire can happen with high frequency (high O) and not be detected early (high D), resulting in a high RPN, while an expensive catastrophic engine failure may occur infrequently (low O), but the consequences are very severe and might have a lower RPN precisely due to that infrequency. The classic RPN would have been to place the focus tire issue over engine failure. At least in business, this contradicts practical operational expectations, where engine failures are considered critical events. For instance, Rhee and Ishii (2003) identified some significant limitations of the RPN as a ranking mechanism and proposed an LCC-based Failure Mode and Effect Analysis (FMEA) that orders risk according to the future costs of failures. Their approach overcame several shortcomings of the traditional FMEA by trading severity for money and considering failure probabilities. This made it easier to sort out risks by how much they would impact on the business. The objective of this study is to enhance the classical FMEA approach by introducing an Economic Risk Priority Number (ERPN), which considers how the failures will impact the economy. The proposed ERPN approach is used to compare the traditional RPN with a set of maintenance data from industrial vehicles in an aluminum smelter. The new ERPN more accurately sorts the failure modes based on the importance ratings of components and their relative cost influences, ensuring that reliable data obtained for maintenance decisions. This research extends the early work in engine failures, recalibrates risk priorities under ERPN, and assesses which improvement may be expected for the ranking of critical components.

To scale the classical formulation with equal weight constraint, normalized formulations, and rescaled scores to a range of [0,100] was identified. This approach enables us to study all the possible failure modes and their consequences thus that problems can be prevented from happening. A data-

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driven FMEA can use operational and historical information to dynamically rank component specific probabilities of failure, which will lead to increased accuracy in maintenance scheduling and decision-making (Filz et al., 2021; Jin et al., 2026). Furthermore, this technique is an advanced approach over the traditional preventive maintenance strategy maneuvered in practice, which is unexpectedly not efficient and can be used to design optimized reliability-based maintenance strategies (Tripathi & Prasad, 2024; Yuan et al., 2026). The purpose of this paper is to work on the integration of the conventional FMEA analysis and modern predictive analysis applied to heavy vehicles failures in aluminum smelters thus that a generic framework for evaluating engine failures can be proposed.

This paper proposes a technique that is based on both FMEA experience and the best new data driven techniques to aid in the identification and classification of aluminum manufacturing engine failure modes (Payette et al., 2025). This structured approach provides a reliable basis for the evaluation of the relevance of different failure modes and assists in developing focused maintenance plans as well as enhancing overall reliability. The FMEA technique, applied to a vast variety of fields, is a systematic process for identifying potential failures and their associated causes and effects. This provides the backdrop for repair (Grabill et al., 2024). It transforms raw maintenance data into actionable information that can be used to predict when maintenance will be needed and minimize unplanned downtime (Ma et al., 2021). This study addresses this gap by integrating economic impact into FMEA through the proposed ERPN framework.

2. Methodology

2.1. Maintenance Data Collection

An extensive set of maintenance records was extracted from the SAP enterprise asset management system to assess the reliability of aluminum smelter transport fleets. The dataset was collected over a five-year period (2019–2024) and includes 2,303 corrective maintenance work orders recorded for 58 heavy equipment units. The data collection and processing flow is shown in Figure 1.

Figure 1. Data collection flow.

1. Filtering and Tagging: Work orders were filtered by functional location, equipment hierarchy codes, and corresponding assemblies of Metal Transport Vehicles (MTV), Anode Pallet Transport Vehicles (APTV), Bath Tapping Vehicles (BTV), and other specialized fleets. This allowed the data to be organized by subsystem (engine, hydraulic, electrical, etc.) for subsequent analysis.

2. Normalization: Failure descriptions, cost entries, and maintenance comments were standardized to eliminate duplicates caused by inconsistent naming conventions or technician shortcuts.

3. Data Integration: Cost, frequency, and downtime fields from the maintenance modules were merged into a single reliability dataset for statistical analysis.

After data cleaning and integration, a master dataset was developed containing failure events with fields for (a) affected component (subsystem); (b) failure mode description; (c) maintenance cost in parts & materials; and (d) labor costs incurred. Production loss due to downtime was calculated using known production loss rates for each vehicle type. To maintain uniformity, costs were converted to US dollars. In addition, each failure event was assigned RPN scores for severity (S), occurrence (O), and detection (D), based on expert judgment and data analysis.

2.2. Risk Prioritization Using RPN

FMEA was then applied to the integrated database to rank vehicle-related failure modes using the traditional Risk Priority Number (RPN). RPN was calculated as the product of severity (S), occurrence (O), and detection (D).

$$\mathrm{RPN} = S \times O \times D \quad \text{(Eq. 1)}$$

where S represents the severity of the failure effect, O represents the occurrence frequency of the failure mode, and D represents the detectability of the failure before occurrence. Each parameter was evaluated using a rating scale derived from maintenance history and expert assessment.

2.3. Economic Risk Priority Number (ERPN) Formulation

To overcome the shortcomings of conventional RPN, an Economic Risk Priority Number (ERPN) is proposed to incorporate the financial consequences of failures into the prioritization process. A dimensionless Cost Factor (C_f) was defined for each failure record on a 0–100 scale according to the total cost of the failure incident relative to the most expensive incident in the dataset. If is the total cost of incident C_i and C_{max} is the maximum total cost among all incidents, the Cost Factor was calculated as:

$$C_f(\mathrm{i}) = \frac{C_i}{C_{max}} \times 100 \quad \text{(Eq. 2)}$$

Where C_i is the total cost of failure event *i*, calculated as:

$$C_i = C_1 + C_2 + C_3 \quad \text{(Eq. 3)}$$

With:

- $C_1 =$ Maintenance cost (It represents the cost of spare parts which used, external services done externally)
- $C_2 =$ Manpower cost (It represent the wage rate per hour multiplied by labor hours on the maintenance)
- $C_3 =$ Production loss cost (It represents the production loss rate per hour multiplied by equipment hours downtime)

$C_{max} =$ It is the highest total cost among all failure events.

In this formula, the most expensive failure event is weighted 100, and all other events are numerically rated by how costly. The idea is to give more weight to failure modes that cost more money; a higher $C_f(i)$ means a more expensive failure. For example, the most expensive single failure event in the dataset was an engine overhaul, which resulted in a total cost of approximately USD 1.92 million due to repair cost and production downtime.

The Economic Risk Priority Number (ERPN) for each failure event was calculated by combining the traditional RPN with the cost factor as follows:

$$ERPN = Classic\ RPN \times C_f \quad \text{(Eq. 4)}$$

3. Results

3.1. RPN-Based Risk Analysis

Figure 2 presents the cumulative subsystem-level RPN distribution across the vehicle systems.

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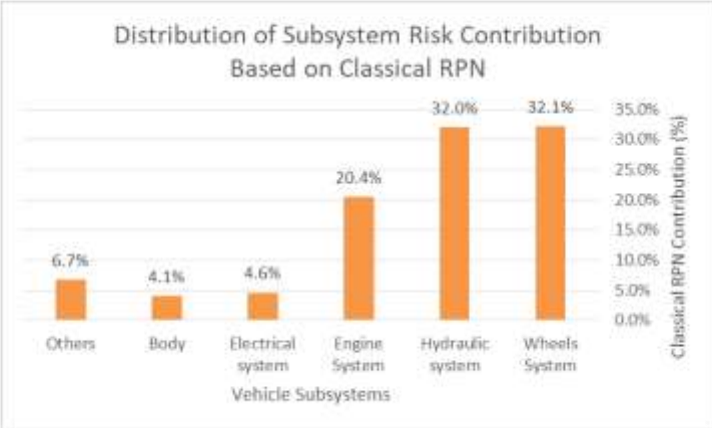

Figure 2. Subsystem Risk Contribution (%) for Classical RPN.

The traditional RPN analysis identified the wheel and hydraulic systems as having the highest RPN scores, mainly due to frequent failures of moderate severity, such as tire punctures and hydraulic line leaks. The engine, which is an operationally significant subsystem, ranked lower in RPN because the catastrophic failure frequency of the engine is low compared to its severity. This indicates that the classical RPN approach does not adequately capture the economic impact of rare but high-consequence failures.

To further examine the distributional behavior of subsystem risks under the classical RPN method, a box plot representation was constructed as shown in Figure 3.

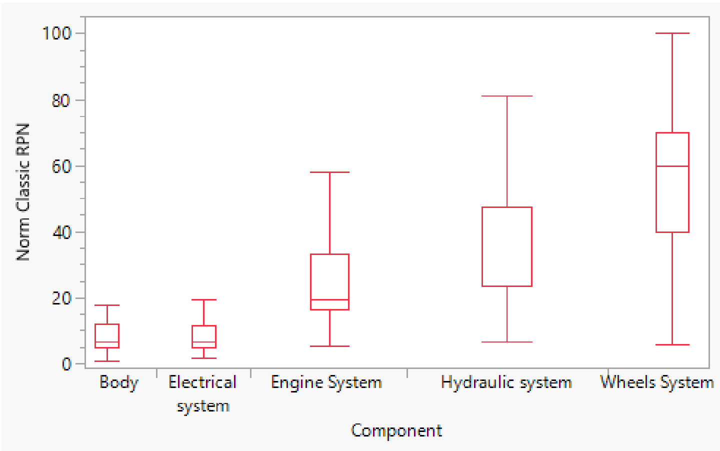

Figure 3. Box Plot of Normalized Classical RPN by component (Subsystem).

Figure 3 illustrates the dispersion and median differences of normalized classical RPN values across subsystems. These results show that the wheel and hydraulic systems have the highest median values and variability, reflecting their frequency driven dominance in the traditional FMEA framework.

The normalized RPN values were non-normal and positively skewed; therefore, the Kruskal–Wallis nonparametric test was applied to assess differences among subsystems. The results indicated significant differences ($\chi^2 = 846.07$, df = 4, $p < 0.0001$).

3.2. ERPN Based Risk Analysis

Accordingly, a failure event with both a high RPN and a high-cost factor will yield a high ERPN, indicating that it is both technically critical and financially significant. The new algorithm keeps its logical meaning: an incident with a high RPN and a high-cost factor will have an extremely high ERPN, which means it is both technically risky and financially costly. On the other hand, an incident

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with a high RPN and a low cost might have its ERPN drop a lot, while an incident with a low RPN and a remarkably high cost will have its ERPN go up. Subsystem level prioritization using ERPN is shown in Figure 4.

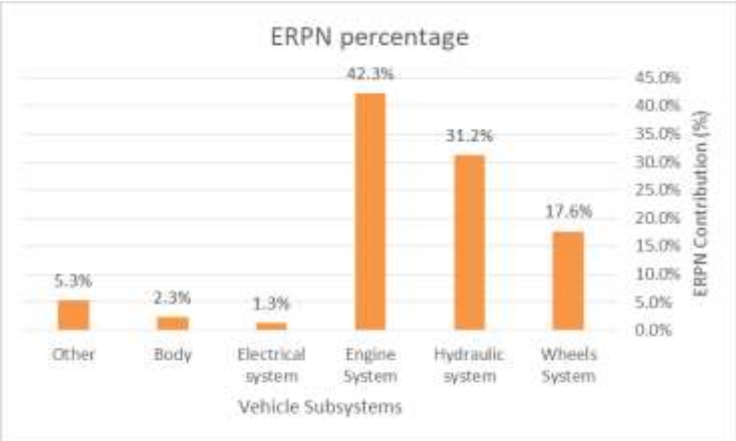

Figure 4. Subsystem Risk Contribution (%) for ERPN.

This section compares the subsystem risk rankings obtained using the classical RPN and the proposed ERPN approach. This section compares subsystem risk rankings using classical RPN and ERPN approaches for main vehicle subsystems under both prioritization methods began by studying overall risk profiles. The traditional RPN analysis indicated that the wheel and hydraulic systems were the most critical subsystems, primarily due to the high frequency of failures such as tire punctures and hydraulic leaks. This was largely because issues with tires and hydraulic leaks both occur frequently, with moderate severity and detection ratings. The engine subsystem was ranked lower under the RPN method despite its critical operational importance. Major engine failures, after all, occurred less frequently than wheel and hydraulic problems even though an engine failure is a more critical occurrence. The cumulative RPN values for each subsystem further support this observation. The wheel system recorded the highest cumulative RPN (≈ 15327), followed closely by the hydraulic system (≈ 15254), while the engine subsystem showed a significantly lower cumulative RPN (≈ 9751). Based on this result, the classical FMEA approach would prioritize wheel and hydraulic failures over engine-related failures.

However, when economic impact is incorporated through the ERPN approach, the subsystem prioritization changes significantly. The cumulative ERPN values indicate a clear shift in prioritization, where the engine subsystem exhibits the highest total ERPN (≈ 2028), followed by the hydraulic system (≈ 1498) and the wheel system (≈ 846). In other words, although the wheel subsystem experienced the highest number of failures, these events were associated with relatively low economic impact. In contrast, engine failures, despite their lower frequency, resulted in significantly higher costs and extended downtime. This demonstrates that the ERPN approach provides a more realistic representation of subsystem criticality by incorporating both technical risk and economic impact. Figure 5 demonstrates that the engine subsystem exhibits higher dispersion.

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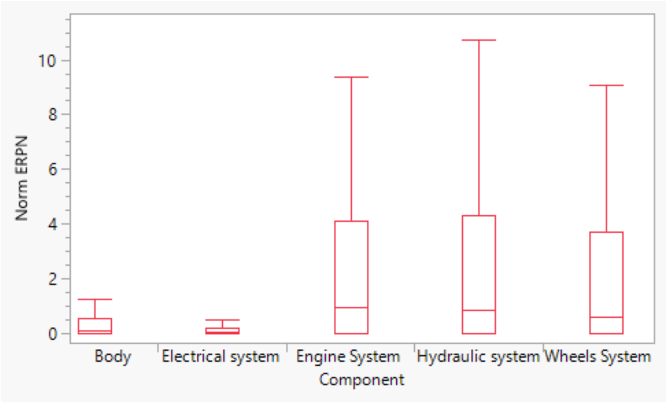

Figure 5. Box Plot of Normalized ERPN by component (Subsystem).

Figure 5 demonstrates that the engine subsystem exhibits higher dispersion and upper quartile values compared to the classical RPN results, reflecting the influence of economic weighting on subsystem risk ranking. The Kruskal Walli's test confirmed statistically significant differences in ERPN distributions across subsystems ($\chi^2 = 131.69$, df = 4, $p < 0.0001$).

Preliminary analysis indicated that both normalized RPN and ERPN values exhibited non-normal distributions with positive skewness. Therefore, nonparametric statistical testing (Kruskal–Wallis) was selected to evaluate subsystem-level differences.

3.3. Engine Failure Analysis

Following the data collection stage, a detailed technical investigation of engine failures was conducted for vehicles operating in aluminum smelter environments. The objective was to identify the dominant engine failure modes contributing to unplanned downtime and to investigate their root causes using maintenance records, inspection reports, and physical failure evidence.

1. SAP Maintenance Logs: This indicated when an engine was overhauled, what parts were replaced, and how long it was down.

2. OEM Site Inspection Reports (Cummins/UES): Provided technical source feedback, diagnostic trouble codes (DTCs), and service comments for each vehicle

3. Evidence of Field Failure: Disassembly and examination of field-failed engines documented damage to parts by photographs and metallurgical sections.

To ensure that the data was traceable and accurate, every failure report was cross-checked with the engine serial number and number of hours accumulated. The analysis concentrated on the Cummins QSB6.7 and QSB5.6 engine models utilized in Anode Pallet Transport Vehicles (APTV) and Bath Tapping Vehicles (BTV), the two fleets exhibiting the highest incidence of engine related failures.

3.3.1. Engine Block Failures

Several vehicles had cracks and breaks in the engine block, especially near the crankcase (Figures 6 and 7). There was visual evidence that mechanical damage was thus severe, it would cause abrupt failure of internal components. Root cause tracing revealed that these failures were triggered by the loss and overheating of coolant, which resulted in a decrease in strength for the cylinder block structure and gradual deterioration of the material structure weaker and caused the material to wear out over time.

Figure 6. Engine block damage.

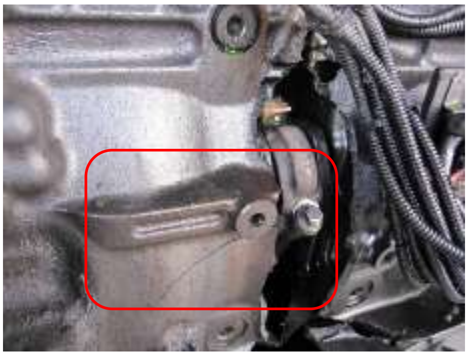

Figure 7. Crack in engine block.

3.3.2. Deformation of the Push Rod and Valve Train

Several cases showed bent push rods and valve train parts (Figure 8). The problems were caused by valves that weren't set up right, hydraulic lifters that didn't work, and overheating that made the valves expand and hit the pistons. The bending messed up the timing of the valves, which led to a bad misfire and low compression.

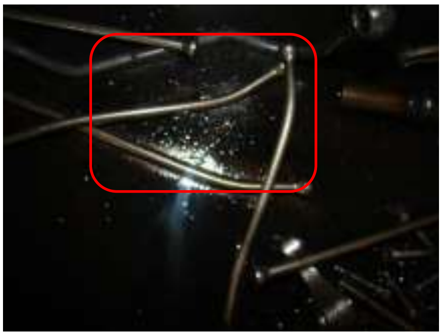

Figure 8. Push rods bend.

3.3.3. Breakage of the Piston and Connecting Rod

Engine tear down examinations (Figure 9) confirmed that the pistons and connecting rods were broken. A metallurgical analysis indicated that oil starvation and thermal shock were the primary causes. In most cases when lubrication was lost, the crankshaft continued to rotate for a short time, during which fatigue cracks developed and propagated until one rod broke.

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Figure 9. Piston and connecting rod damage.

3.3.4. Oil Leaking and Seals Breaking Down

The patterns of oil leaking also appeared around turbo return lines and crankcase vents as shown (Figure 10).The leaks increased because it was had been exposed to high temperatures and conductive dust for an extended period, which lead the seals to harden and the pressure in the container to decrease. The oil did not stop leaking, thus low oil pressure fault codes and engine history were logged in the ECM.

Figure 10. Engine oil leak.

3.3.5. Electronic Diagnostic Evidence

The ECM logs (Figsures 11–13) validated what was identified by the physical inspection. Several data inputs displayed high coolant temperature (107.7°C) and low coolant level alarms that occurred multiple times during several operating cycles prior to system failure. Inactive fault histories demonstrated that early warnings were issued but not heeded appropriately, indicating a problem with condition monitoring. For low coolant level, there are multiple dormant faults (512–803 counts), which strongly indicates that a systemic issue with the cooling system is leading to the mechanical failures observed.

Figure 11. Engine protection setting 4 logs of low coolant.

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Figure 12. Engine protection setting 4 logs of high coolant temperature, low coolant level.

Figure 13. Engine protection shows inactive faults with high counts of low coolant level.

4. Discussion

The results obtained from both RPN and ERPN analyses provide important insights into subsystem risk prioritization in aluminum smelter fleets through the integration of past maintenance information, diagnostic results, and a systematic ranking of the risk method. The precise comparison between traditional RPN and the proposed ERPN generates insights into the limitations of the classical FMEA approach for heavy industrial fleets operating in harsh environmental conditions.

In the traditional RPN-based approach, wheels and hydraulic systems were identified as critical risk contributors due to their high failure frequency. However, this frequency-driven prioritization does not reflect the practical and economic realities of aluminum smelter operations, where high-frequency failures typically result in limited downtime, while rare engine failures lead to complete operational stoppages and significant production losses.

The ERPN method directly changed the risk ranking of subsystems by including a normalized cost value in the priority setting. For economic impact, the Engine subsystem was identified as having the highest overall contribution to risk even though it had a lower failure frequency than other subsystems. This finding indicates that financial and operational failure consequences are critical elements of the decision-making process for maintenance priorities in capital-intensive industries such as aluminum smelting. The hydraulic subsystem continued to be a high-risk contributor under ERPN in terms of relatively moderate frequency and cost, while the wheels subsystem was correctly deprioritized.

The diagnostic analysis further supports the ERPN results, identifying overheating and lubrication-related issues as the primary drivers of catastrophic engine failures. Repeated low coolant level and low oil pressure warnings were observed in ECM logs prior to failure events, indicating that early warning signals were available but not effectively utilized. This highlights the importance of timely condition monitoring and proactive maintenance response.

The statistically significant differences between subsystems confirm that failure risks are not uniformly distributed, reinforcing the need for a differentiated prioritization approach such as ERPN. From an industrial perspective, the findings highlight the importance of integrating economic impact into maintenance decision-making. In capital-intensive operations such as aluminum smelting, prioritizing failures based solely on frequency may lead to suboptimal resource allocation. The ERPN approach enables maintenance teams to focus on high cost, high impact failures, thereby improving operational availability and reducing financial losses.

5. Conclusions

This study presented a systematic, data-driven approach to evaluate engine failures in aluminum smelter transport vehicles by integrating FMEA with the proposed ERPN model. Analysis of five years of SAP maintenance records, supported by diagnostic evidence, demonstrated that traditional RPN-based prioritization is insufficient to identify failure modes with the highest economic and operational impact.

The outcomes indicated that although wheels and hydraulic systems have high failure rates compared to other systems, engine failures are considered a leading reliability risk due to their economic consequences. The adoption of ERPN provided a new weighted approach for failure mode rankings, based on costs of maintenance, manpower, and production loss, and allowed a ranking that was more in tandem with the actual consequences in an operation. The subsystem engine resulted in being the first most important contribution to overall risk due to its high cost of downtime per event.

Diagnostic analysis revealed that catastrophic engine failures were primarily associated with low coolant levels and low oil pressure, with warning signals detected prior to failure events. This highlights the importance of timely condition monitoring and effective response to early warning indicators to reduce unplanned downtime and prevent severe damage. The proposed ERPN framework provides a practical and economically aligned tool for maintenance prioritization in heavy industrial fleets operating under harsh conditions. By bridging the gap between technical reliability assessment and economic impact, the approach supports improved decision-making, enhanced operational availability, and reduced financial losses. Future research may extend this work by comparing ERPN with advanced risk prioritization models and integrating real-time condition monitoring and predictive analytics to further enhance maintenance strategies.

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