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Operational Factor Analysis for Predictive Maintenance in Mining Fleets: A Correlation-Based Approach



Malihe Goli, Thanos Kontogiannis, Nick Eleftheroglou, and Masoud S.Shishvan

Abstract Technical failures in truck operations within the mining industry can lead to significant profit losses and disruptions across interconnected processes such as hauling, processing, storage, and material transportation. These disruptions can lead to reduced efficiency and increased costs. Hence, a comprehensive understanding of the critical operational factors that contribute to technical failures and disruptions is essential for reducing downtime, improving reliability, and optimizing maintenance schedules. Several studies have highlighted the importance of understanding machine failure patterns and operational disruptions in industrial contexts, particularly in high-cost sectors like mining. Most existing research focuses on individual component reliability or general maintenance strategies, but few works examine the interplay between operational factors and maintenance scheduling, in a holistic manner. For example, studies on condition-based maintenance (CBM) and predictive maintenance (PdM) emphasize the role of real-time monitoring of single-component wear but often fail to address the role of broader operational factors—such as fleet utilization and environmental conditions—in predicting and preventing breakdowns. This study bridges this gap by analyzing performance metrics, event logs and failure data to pinpoint high-risk components based on

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frequency of failure and severity. Following this, a correlation analysis is performed on real-world operation and utilization data to identify which factors contribute to specific failures. The findings are presented through a correlation matrix heatmap that visualizes these relationships and provides actionable insights. The insights from this study can assist mining companies in refining both long-term and short-term maintenance schedules, minimizing unplanned downtimes and improving operational efficiency.

Keywords Predictive maintenance · Mining fleets · Operational factors · Correlation analysis · Technical failures · Reliability

1 Introduction

In the mining industry, operational efficiency is crucial due to the high costs and interdependencies across processes such as hauling, processing, and material transport. Technical failures in mining trucks can lead to substantial disruptions, directly impacting productivity and profitability while posing significant safety risks [1]. Unplanned downtime and inefficient maintenance practices create additional challenges, as these processes rely heavily on optimal equipment performance for continuity [2].

Traditional maintenance strategies—such as time-based or reactive approaches—have been employed to reduce equipment failures, yet these methods often lack the precision to predict failures in complex, high-stress mining environments [3]. In response, predictive maintenance (PdM) and condition-based maintenance (CBM) approaches have emerged, leveraging real-time data to monitor component health and forecast failures. Despite these advances, existing predictive models largely focus on individual machine metrics and often neglect broader operational variables, such as fleet utilization rates and environmental stressors, which significantly influence machine reliability [4].

Recent studies emphasize the impact of environmental and operational factors, such as dust exposure, extreme temperatures, and utilization patterns, on equipment reliability. Kalbayevich [5] demonstrated that environmental factors play a critical role in machine performance, yet the interaction between operational variables and PdM frameworks remains underexplored. The absence of this integration limits the ability to prevent failures comprehensively across mining fleets [5].

Correlation analysis is a vital tool in predictive maintenance, offering insights into the relationships between operational variables and equipment failures. It helps uncover both direct and indirect factors influencing system reliability and supports the development of robust maintenance strategies. Pearson correlation, a widely used technique for measuring linear dependencies, has proven effective in identifying key performance drivers. Baek [6] demonstrated its utility by revealing strong positive correlations between operation-end times and ore production in mining, while Wu et al. [7] used it to identify ventilation facilities as a significant

factor influencing highway tunnel maintenance costs. These applications highlight its value in optimizing maintenance operations based on measurable linear relationships.

Expanding beyond linearity, Spearman's rank correlation evaluates monotonic relationships, making it ideal for non-linear datasets. Rymarz et al. [8] employed this method to rank downtime causes in bus fleets, linking unavailability to downtime categories rather than vehicle age. Similarly, Hernández-Chover et al. [9] confirmed a strong positive correlation between preventive maintenance levels and plant efficiency, underscoring its relevance in evaluating maintenance impacts in non-linear contexts. For more complex systems, partial correlation isolates the influence of confounding variables to clarify direct relationships. Wu et al. [7] leveraged this technique in their hierarchical regression analysis of tunnel maintenance data, revealing unambiguous effects of factors like traffic volume on maintenance costs. This approach enhances understanding in scenarios with multiple interacting variables, where traditional correlation might obscure key insights. Finally, cross-correlation captures time-lagged interactions, crucial for analysing delayed effects of operational stressors. Fumagali et al. [10] employs cross-correlation analysis to examine how different arrangements of maintenance interventions over time impact the reliability of a mechanical system. By analysing the relationship between the timing of these interventions and system reliability, the study aims to identify optimal maintenance strategies that enhance overall system performance. West et al. [11] applied it to maintenance metrics, showing how proactive efforts could paradoxically increase downtime while reducing failures. These studies illustrate its significance in time-sensitive predictive maintenance planning.

The lack of integration between operational factors and maintenance schedules represents a significant gap in existing predictive maintenance strategies. Current research often falls short of examining the combined impact of operational parameters on equipment reliability, particularly in the context of mining trucks. While researchers like [12] emphasize the importance of data-driven maintenance planning that incorporates fleet utilization rates, environmental conditions, and operational metrics, few studies have systematically addressed these variables in a cohesive framework. Moreover, no prior research has comprehensively employed Pearson, Spearman, and cross-correlation techniques within a single study to capture both direct/indirect and time-lagged relationships between operational conditions and maintenance outcomes. This limitation constrains the industry's ability to accurately predict failures and optimize resource allocation effectively. To bridge this gap, this study introduces a novel approach that integrates all three correlation analysis techniques to analyze mining truck performance and downtime. Pearson correlation uncovers linear relationships, Spearman's rank correlation identifies monotonic dependencies, and cross-correlation captures time-lagged effects, providing a complete understanding of how operational parameters (e.g., travel distance, load duration, and utilization patterns) influence fault occurrences. This methodology enables the identification of both immediate and delayed impacts of operational stressors on equipment reliability.

The study applies this framework to a real-world case study of a small mining fleet, leveraging operational and fault data to analyze disruption risks at the vehicle level. Visual tools, such as correlation matrix heatmaps, enhance the interpretability of results, highlighting critical factors influencing downtime. This integrated approach not only fills the gap in linking operational data with maintenance strategies but also paves the way for advanced predictive models to refine maintenance scheduling further. By aligning maintenance activities with operational realities, this study aims to minimize unplanned downtimes, optimize resource usage, and enhance safety and efficiency in mining operations.

The remainder of this paper is structured as follows: Sect. 2 outlines the research methodology, variable definitions, and the application of correlation techniques. Section 3 details the data collection and preprocessing steps, presents the findings, including visualizations of the results and an in-depth discussion of their implications. Finally, Sect. 4 summarizes the key insights, discusses theoretical and managerial contributions, and proposes directions for future research.

2 Methodology

This section outlines the methodology used in this study, emphasizing the identification of high-risk components in mining trucks based on failure frequency and severity. It then discusses the application of various correlation analysis techniques to achieve the research objectives. The methods employed include Pearson correlation, Spearman's rank correlation, and cross-correlation analysis. Together, these techniques provide a robust analytical framework for uncovering linear, non-linear, and time-lagged relationships between operational metrics (independent variables) and fault or failure events (dependent variables).

2.1 Critical Component Analysis

To identify critical components in mining trucks, a weighted approach was applied, integrating both the frequency and severity of failure events. The analysis employs a Severity-Adjusted Critical Event Ratio (CER) to prioritize components based on their operational impact. This ratio provides a normalized measure of how often critical events occur relative to working hours, weighted by the importance of the failure type.

The Severity-Adjusted CER is calculated as follows:

$$Severity - Adjusted\ CER = \frac{\sum (\text{Event Count for Severity } i \times \text{Weight for Severity } i)}{\text{Working Time (hr)}} \tag{1}$$

Table 1 Severity weighting

Severity category	Description	Weight
1 (Alarm/Warning)	Non-critical	1
2 (Driver action needed)	Moderate impact	5
3 (Critical maintenance)	High impact	10

Where *i* represents each severity category and:

- Event Count for Severity *i*: The number of occurrences of failure events within each severity category (*i*)
- Weight for Severity *i*: A predefined factor representing the criticality of each severity category (e.g., downtime impact or repair cost).
- Working Time (hr): The total number of active working hours for the equipment.

To capture the varying significance of failure events, a Severity Weight is assigned to each category:

- Category 1 (Alarm/Warning, Weight = 1): Low-impact events, such as alerts or warnings that do not disrupt operations.
- Category 2 (Driver Action Needed, Weight = 5): Moderate-impact events requiring operator intervention but not immediate maintenance.
- Category 3 (Critical Maintenance, Weight = 10): High-impact events necessitating immediate action, such as engine failures, where the vehicle must stop for repairs.

Table 1 provides the severity weighting system of this study.

For each truck, the Severity-Adjusted Critical Event Ratio (CER) is calculated individually for each type of failure, considering both the frequency and severity of occurrences. For example, if a truck experiences Payload Overload Limit Exceeded faults 400 times, all classified as severity level 1, over 4000 h of operation, the CER for this failure is 0.1. Similarly, if the same truck records Low Brake Accumulator Pressure faults 300 times at severity level 3 and 50 times at severity level 2 within just 1000 h, the CER for this failure is 3.25. This means that, on average, 3.25 brake accumulator pressure failures occur per operating hour, compared to 0.1 for payload overload faults. Such comparisons help prioritize high-risk failures, enabling maintenance teams to focus on the most critical issues and allocate resources effectively.

2.2 Correlation Analysis

This subsection describes the application of correlation analysis techniques used to uncover relationships between operational parameters (independent variables) and critical failure events (dependent variables). The methods employed include Pearson correlation, Spearman's rank correlation, and cross-correlation analysis, forming a robust analytical framework to explore linear, monotonic, and time-lagged

dependencies. The results are summarized in a comprehensive correlation matrix, which visualizes these relationships across all variables.

2.2.1 Pearson Correlation

Pearson correlation measures the linear relationship between two variables. The Pearson correlation coefficient (r) is computed as:

$$r_{X,Y} = \frac{Cov\ (X, Y)}{\sigma_X \sigma_Y} \tag{2}$$

Where:

- $Cov\ (X, Y) = \frac{1}{n-1} \sum_{i=1}^{n} \left(X_i - \overline{X}\right) \left(Y_i - \overline{Y}\right)$ is the covariance between variables X (operational parameter) and Y (Failure event).

σ_X and σ_Y are the standard deviations of X and Y, respectively.

This method is ideal for identifying direct linear dependencies between variables.

2.2.2 Spearman's Rank Correlation

Spearman's rank correlation is a non-parametric measure of monotonic relationships between two variables. It assesses how well the relationship between two variables can be described by a monotonic function. The Spearman correlation coefficient ρ is given by [8]:

$$\rho = 1 - \frac{6 \sum d_i^2}{n\left(n^2 - 1\right)} \tag{3}$$

Where:

- d_i: Difference between the ranks of corresponding values in the datasets.
- n: Number of observations.

This method is especially suitable for datasets that do not meet the assumptions of linearity or normality.

2.2.3 Cross-Correlation Analysis

Cross-correlation identifies time-lagged relationships between two variables, making it particularly useful in understanding delayed dependencies. This study uses cross-correlation to analyse how operational parameters (e.g., truck load, engine hours) influence critical failure event at different time lags.

The normalized cross-correlation function $R_{xy}(k)$ at lag k is given by [13]:

$$R_{xy}(k) = \frac{\sum_t (x_t - \overline{x})\ (y_{t+k} - \overline{y}\ )}{\sqrt{\sum_t (x_t - \overline{x})^2 \sum_t (y_{t+k} - \overline{y}\ )^2}} \tag{4}$$

Where:

- k: Time lag (positive or negative),
- x_t, y_t: Observed values of variables.

The time lag k with the highest correlation reveals significant dependencies, providing insights into how operational metrics influence downtime over time.

2.2.4 Correlation Matrix Construction

A correlation matrix is constructed to provide a comprehensive view of the relationships between operational parameters and downtime. This matrix can be generated using any of the above-mentioned correlation methods—Pearson, Spearman, or cross-correlation. The general form of the correlation matrix is:

$$Correlation\ Matrix = \begin{bmatrix} rX_1, X_1 & \cdots & rX_1, Y \\ \vdots & \ddots & \vdots \\ rX_n, X_1 & \cdots & rX_n, Y \end{bmatrix} \tag{5}$$

Where:

- rX_i, X_j:Correlation coefficient between operational parameters X_i and X_j
- rX_i, Y: Correlation coefficient between operational parameter X_i and failure event Y.

For Pearson and Spearman correlations, statistical significance is assessed using the t -statistic [14]:

$$t = r\sqrt{\frac{n-2}{1-r^2}} \tag{6}$$

Where:

- r: Correlation coefficient.
- n:Number of observations.

The t-distribution's degrees of freedom is (n-2) because estimating the correlation requires calculating the means of both variables, reducing the independent data points available for variability assessment [15]. The calculated t -value is compared

against the critical value from the t -distribution with $(n - 2)$ degrees of freedom to determine the confidence level of the observed correlation.

For cross-correlation, the significance of time-lagged relationships can be evaluated by examining peaks in the cross-correlation function $R_{xy}(k)$ and comparing them against thresholds derived from historical data or randomized null models.

By using a unified structure, the correlation matrix enables comparative analysis across methods, offering a detailed perspective on both direct and complex relationships between operational metrics and failure events.

3 Results and Discussion

This section presents the findings of the study, focusing on identifying high-risk components and analysing their relationships with operational factors through correlation analyses.

3.1 Data Collection and Preprocessing

Data for this study was collected from a real-world mining fleet consisting of eight mining trucks. The dataset spanned one year and included operational, utilization, and maintenance logs, capturing variables such as working hours, distance travelled, overload duration, non-overload duration, fuel usage, and fault occurrences.

Preprocessing involved handling missing values through interpolation and mean imputation, detecting and removing outliers using statistical methods, and standardizing variable units for consistency. Noise in highly variable parameters was reduced through smoothing techniques, and categorical data was numerically encoded where necessary.

Challenges included missing and incomplete data, high variability in operational parameters, and unit inconsistencies. These were addressed by applying appropriate imputation, smoothing, and standardization techniques to ensure the dataset's reliability for computing the Severity-Adjusted CER and performing correlation analyses.

3.2 Critical Components and Failure Patterns

The Severity-Adjusted CER was calculated for each fault event and mining truck using the fault history dataset, which included details such as equipment ID, model, fault code description and ID, severity level, fault date, working hours, mileage, and fault source. This analysis helped identify high-risk faults and their associated components. Figure 1 highlights the CER for individual trucks, with Truck 3

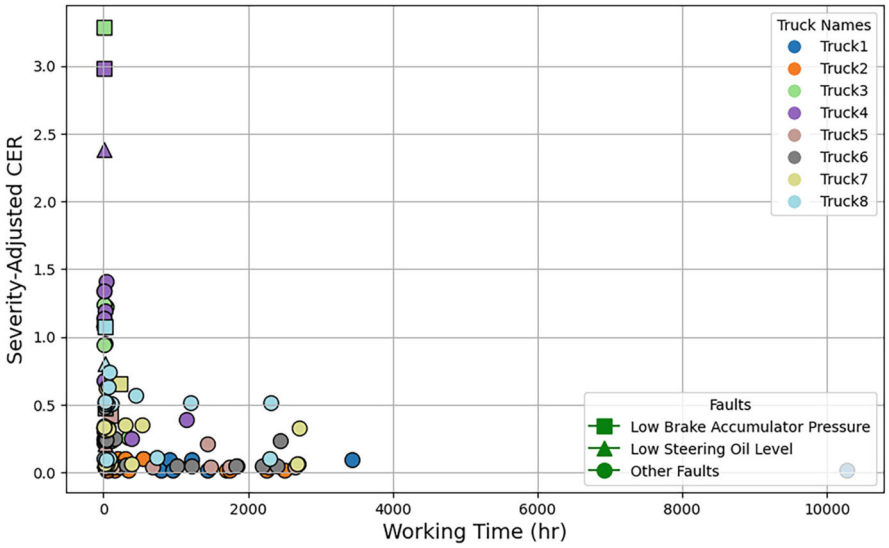


Fig. 1 Scatter plot of severity-adjusted CER vs. Working time for different trucks

and Truck 4 exhibiting the highest Severity-Adjusted CERs, at 3.288 and 2.98, respectively. Both trucks had frequent occurrences of the "Low Brake Accumulator Pressure" fault, indicating significant operational vulnerabilities.

At the fleet level, the total CER for each fault type, as shown in Fig. 2, reveals that Low Brake Accumulator Pressure has the highest CER and is also one of the most frequent faults, occurring 240 times. This combination of severity and frequency makes it the most critical fault across the fleet, requiring immediate attention to prevent severe operational disruptions. Other notable findings include the "Low Steering Oil Level" fault, which, despite being less frequent, has a high CER, indicating a significant impact when it occurs. In contrast, faults such as "Transmission Abuse Warning" and "Engine Overspeed Warning" have very low CER values (approximately 0.0199), making them less critical for immediate action as they are less severe or infrequent.

These findings emphasize that Low Brake Accumulator Pressure is the most critical fault, both in terms of severity and frequency, while certain less frequent faults with high CERs, such as Low Steering Oil Level, also warrant monitoring. Conversely, faults with low CERs can be deprioritized for immediate intervention.

The next section will focus on correlation analyses for the braking system fault, examining its relationship with operational and utilization parameters. This will provide insights into contributing factors and inform strategies to optimize maintenance and reduce unplanned downtimes.

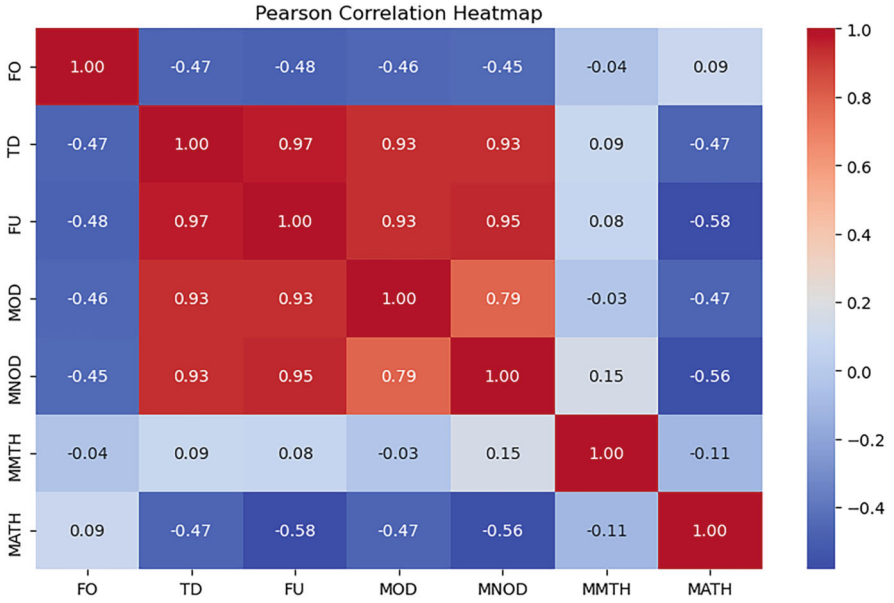


Fig. 2 Pearson correlation heatmap of fault occurrences with key operational variables

3.3 Correlation Analysis Result

This section presents the findings from Pearson, Spearman, and cross-correlation analyses, focusing on relationships between operational parameters and brake fault occurrences. Key operational parameters include:

- FO: Fault Occurrences
- TD: Travel Distance (km)
- FU: Fuel Used (L)
- MOD: Monthly Overload Duration (hr)
- MNOD: Monthly Non-Overload Duration (hr)
- MMTH: Monthly Max Travel Height (m)
- MATH: Monthly Avg. Travel Height (m)

Metrics are aggregated per truck (by Name) and per month to reflect cumulative operational performance over the period. Durational metrics (e.g., Overload Duration) are converted to hours, and binary overload indicators are aggregated to compute the monthly overload duration. Missing values and outliers are handled appropriately to ensure data consistency and accuracy.

3.3.1 Pearson Correlation

The Pearson correlation analysis explored linear relationships between operational parameters and brake fault occurrences. A heatmap is used to visualize Pearson correlation coefficients which provide an intuitive visualization of the strength and direction of correlations, ranging from -1 to 1, between variable pairs. Red shades indicate positive correlations (values closer to 1), meaning that as one variable increases, the other tends to increase as well. Blue shades indicate negative correlations (values closer to -1), meaning that as one variable increases, the other tends to decrease. White indicates little to no correlation (values around 0). The results, visualized in Fig. 2, reveal key insights:

- Fuel Used ($r = 0.48$) showed the strongest correlation with fault occurrences, indicating that higher fuel consumption is moderately associated with increased faults — possibly due to extended operational time and cumulative mechanical stress.
- Travel Distance ($r = 0.47$) also demonstrated a moderate positive correlation, suggesting that covering longer distances may increase the likelihood of faults, likely as a result of prolonged usage.
- Monthly Overload Duration ($r = 0.46$) and Non-Overload Duration ($r = 0.45$) exhibited similar correlation levels. This similarity suggests that total operational hours, regardless of load condition, may be more indicative of fault risk than the load status itself.
- Max Travel Height ($r = 0.04$) and Average Travel Height ($r = 0.09$) showed very weak correlations with fault occurrences, indicating minimal linear relationships between elevation and failures.

Operational interdependencies were also observed, with Travel Distance and Fuel Used showing a very strong correlation ($r = 0.97$), reflecting their proportional relationship. Similarly, Monthly Overload and Non-Overload Duration strongly correlated with Travel Distance ($r = 0.93$), aligning with the operational pattern of longer trips under non-overload conditions.

The Pearson correlation analysis indicates that Fuel Used and Travel Distance are the most relevant factors influencing fault occurrences, both showing moderate positive correlations. Overload and Non-Overload Duration also exhibit similar correlation levels, suggesting that total operational time—rather than load conditions alone—may contribute to fault risk. In contrast, other parameters such as Travel Height show very weak linear relationships. These results suggest that operational patterns alone may not fully explain the occurrence of brake faults, highlighting the need for further analysis using non-linear or time-lagged methods, such as Spearman's rank and cross-correlation, to uncover additional insights.

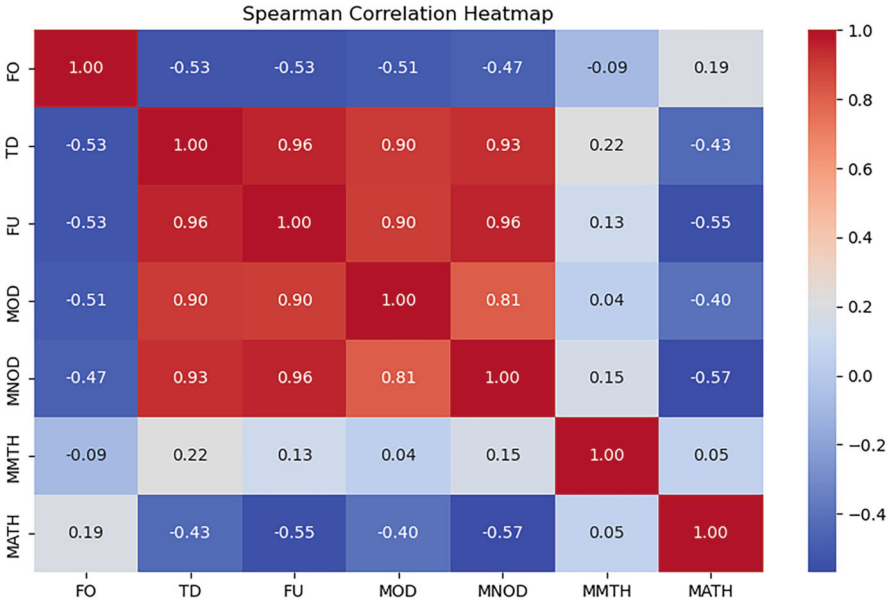


Fig. 3 Spearman correlation heatmap of operational variables with fault occurrences

3.3.2 Spearman's Rank Correlation

Spearman's rank correlation examined monotonic relationships between operational parameters and fault occurrences. This approach identifies non-linear dependencies, offering insights beyond the linear relationships explored in Pearson correlation.

The heatmap in Fig. 3 visualizes the results of Spearman's rank correlation:

- Fuel Used ($\rho = -0.5323$) and Travel Distance ($\rho = -0.5276$) showed moderate negative correlations, indicating that longer trips, which consume more fuel, may lead to fewer faults, possibly due to smoother operations during extended trips.
- Monthly Overload Duration ($\rho = -0.5082$) and Non-Overload Duration ($\rho = -0.4739$) also exhibited moderate negative correlations, suggesting that extended operational hours under both conditions are weakly associated with reduced faults.
- Max ($\rho = -0.0917$) and Avg Travel Height ($\rho = 0.1853$) displayed very weak correlations, reaffirming their limited relevance in fault prediction.

Significant interdependencies were also observed:

- Fuel Used strongly correlated with Travel Distance ($\rho = 0.9559$), highlighting the natural relationship between longer trips and higher fuel consumption.
- Non-Overload Duration exhibited strong correlations with both Fuel Used ($\rho = 0.9570$) and Overload Duration ($\rho = 0.8131$), indicating that overall

operational hours, regardless of load, are closely tied to fuel usage and duration metrics.

Spearman's analysis confirms that Fuel Used, Travel Distance, and operational durations (overloaded and non-overloaded) are the most relevant variables for understanding fault occurrences, though their correlations are moderate. These findings suggest that optimizing operational conditions, such as fuel efficiency and travel durations, could help reduce fault frequency. On the other hand, factors like travel height appear less critical in predicting faults.

3.3.3 Cross-Correlation Analysis

The cross-correlation analysis examined **time-lagged relationships** between operational parameters and fault occurrences, identifying how past conditions influence future failures. This approach provides deeper insights beyond simple linear correlations.

As shown in Fig. 4, several significant lag periods emerge:

- Travel Distance (km): Strong correlations ($\sim \pm 0.5$) were observed at lag -2 and lag 10, indicating both early and delayed effects. Longer travel distances two months prior or ten months earlier are associated with increased fault occurrences.
- Fuel Used (L): Exhibits strong lagged correlations at lag -2 and lag 10 (both $\sim \pm 0.5$), suggesting that high fuel consumption in those periods is a strong predictor of faults, potentially due to sustained operational strain.
- Monthly Overload Duration (hr): Shows peaks at lag -1 (~ -0.5) and lag 11 (~0.5), highlighting both short-term and delayed relationships between overload exposure and fault events.
- Monthly Non-Overload Duration (hr): Correlation peaks at lag 10 (~0.6), suggesting that prolonged regular operation ten months earlier is strongly associated with increased faults, possibly due to cumulative wear.
- Monthly Max Travel Height (m): Peaks at lag 7 (~0.6), indicating that higher elevation operations seven months prior may contribute to later mechanical stress or component degradation.
- Monthly Avg. Travel Height (m): Shows moderate lagged correlations at lag -5 (-0.5) and lag $+3$ (0.5), pointing to both early and near-future associations with fault likelihood.

These findings suggest that Travel Distance and Fuel Usage are key indicators of delayed fault risk, with consistent strong correlations at multiple lag periods. The patterns observed for Overload and Non-Overload Durations highlight the potential long-term effects of both types of operation, although overload correlations are weaker—likely due to its low frequency and severity in this dataset. In contrast, Max and Avg. Travel Heights show weak correlations across most lags, likely due to the uniformity of travel heights across the fleet.

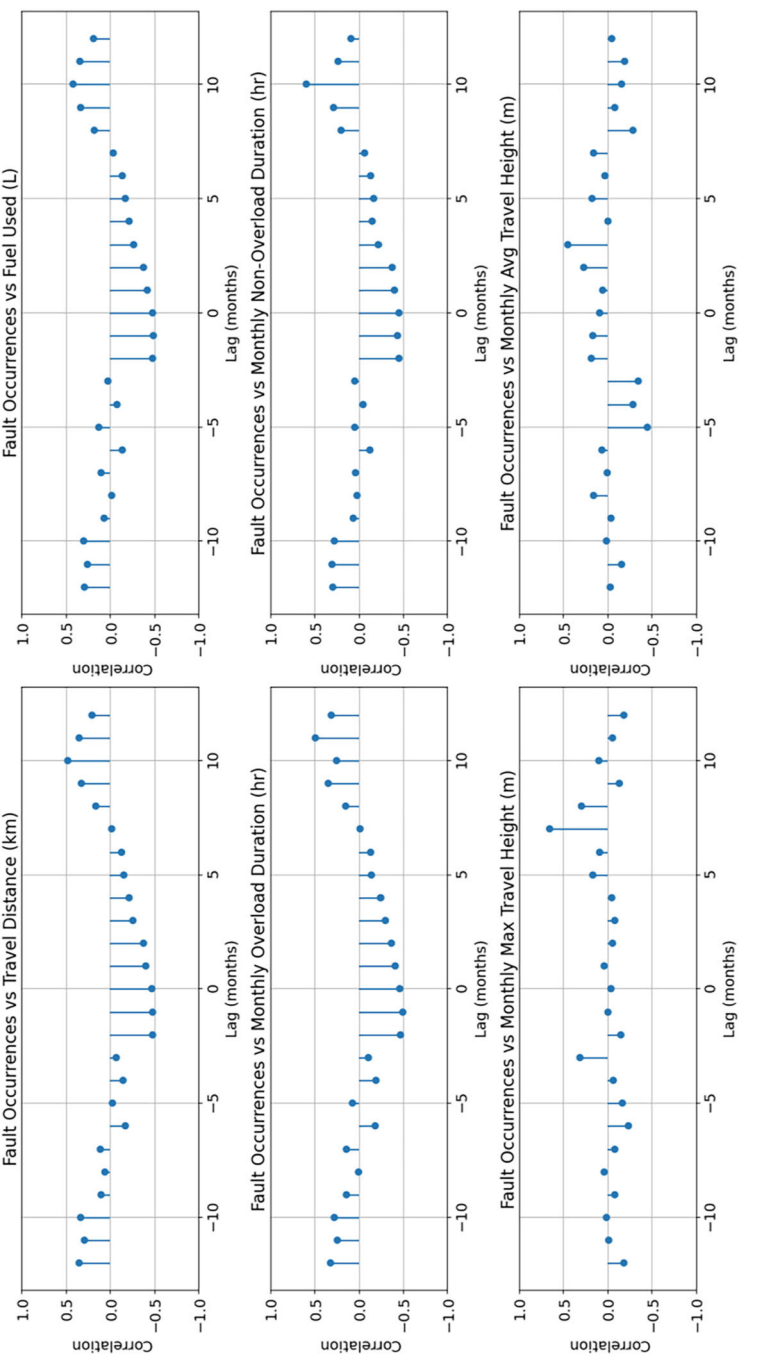


Fig. 4 Cross-correlation analysis of fault occurrences with key operational variables over time

These findings emphasize the importance of proactively managing Travel Distance and Fuel Usage to minimize future faults. While overload effects appear limited in this case study, further investigation into potential cumulative impacts of minor overloads may be beneficial. These lag-based insights highlight the importance of long-term monitoring and predictive maintenance strategies that account not only for immediate usage but also for operational patterns across preceding months.

4 Conclusion

This study addresses the critical issue of technical failures in mining truck operations by analyzing the interplay between failure patterns and operational factors. Using performance metrics, event logs, and failure data, the Severity-Adjusted CER was introduced to identify high-risk components, with the brake system emerging as the most critical. Pearson, Spearman, and cross-correlation analyses were applied to explore relationships between operational parameters—such as travel distance, fuel usage, overload duration, and non-overload duration—and fault occurrences.

The findings bridge the gap between individual component analysis and broader operational factors, demonstrating how both contribute to fault occurrences. Pearson correlation revealed weak but notable relationships between fault occurrences and non-overload duration and travel distance, suggesting that cumulative wear during these operations may lead to faults. Spearman's rank correlation identified moderate negative correlations for fuel used, travel distance, and overload duration, underscoring the importance of efficient utilization. Notably, overload durations in earlier months may contribute to increased fault occurrences, though the immediate impact weakens over time. Cross-correlation analysis provided deeper insights into time-lagged effects, highlighting how past travel distances and fuel consumption influence current fault trends. Collectively, these results emphasize the importance of managing travel distance, fuel consumption, and overload conditions to optimize maintenance scheduling and minimize downtime.

The study offers mining companies a data-driven framework for refining maintenance strategies and improving fleet reliability. By integrating CER and correlation analyses, actionable insights are provided to prioritize critical components and develop both short-term and long-term maintenance plans. However, the study is limited by the scope of operational and failure data. Environmental conditions (e.g., dust and temperature) and detailed maintenance history were not fully incorporated, which may further influence fault patterns. Future research could focus on integrating broader span real-time monitoring data, environmental factors, and advanced machine learning models to enhance fault prediction and maintenance planning. In conclusion, this study delivers a practical and scalable approach to improving maintenance strategies, reducing operational costs, and ensuring greater reliability in mining operations.

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