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DEVELOPING A CONDITION-BASED PROGNOSTIC MAINTENANCE FRAMEWORK FOR A FLEET OF HAUL TRUCKS IN A SURFACE MINE ENVIRONMENT

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A B S T R A C T

This study presents a Condition-Based Prognostic Maintenance (CBPM) framework designed to enhance the reliability and maintainability of haul trucks within surface mining operations. To overcome the inherent limitations of reactive and time-based maintenance strategies, the proposed framework integrates historical maintenance data, Failure Modes, Effects, and Criticality Analysis (FMECA), and data-driven prognostic techniques. The framework is validated through a comprehensive case study conducted at Mining Site R, utilizing three years of operational data. Analysis revealed significant performance deficiencies, with Mean Time Between Failures ranging from 22 to 59 hours (against a target of ≥50 hours) and Mean Time To Repair spanning 3 to 7 hours (against a target of ≤2 hours). The FMECA identified engine blow-by and tyre punctures as the most critical failure modes. A polynomial regression model, applied to crankcase-pressure-based health indicators, achieved a predictive accuracy of 93.8%, offering a 19-week lead time for proactive maintenance intervention. The proposed CBPM framework provides a scalable, data-driven solution for predictive maintenance in mining, with the potential to substantially reduce downtime, extend equipment service life, and improve overall operational profitability.

1. INTRODUCTION

Haul trucks are indispensable to surface-mining operations, serving as the primary mode of material transport. Their reliability and availability directly affect production throughput and cost efficiency. However, the harsh environmental and operational conditions of open-pit mining such as extreme temperatures, high dust concentration, vibration, and remote locations with long parts-supply lead times accelerate component degradation and increase the frequency of unscheduled failures Galatia (2020). As emphasized by (Rojas et al., 2025), the high capital intensity of mining trucks means that maintenance effectiveness has a direct and substantial influence on productivity and profitability (Werbinska-Wojciechowska & Rogowski, 2025).

Traditional maintenance strategies, such as run-to-failure and preventive time-based maintenance (TBM), are increasingly inadequate in this context. Maintenance expenditures in mining typically consume 30 - 50 % of

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total operating costs (Topal et al., 2010) and BS EN 13306 (2010). In response, the industry has progressively shifted toward Condition-Based Maintenance (CBM), in which maintenance interventions are determined by the actual health condition of equipment derived from in-service monitoring (Dalzochio et al., 2020; Shamim, 2025). More recently, Condition-Based Prognostic Maintenance (CBPM) has emerged as an advanced paradigm that leverages real-time and historical data to predict failures before they occur, optimizing maintenance schedules and minimizing downtime (Yadav et al., 2020: Sai et al., 2019).

Despite its demonstrated success in manufacturing and aerospace, the adoption of CBPM in mining remains limited. Most existing frameworks are generic, designed for stationary assets, and fail to account for the operational and environmental complexity of mobile mining equipment such as haul trucks. Furthermore, within current research, prognostics, the ability to estimate Remaining Useful Life (RUL) is less developed than diagnostics, particularly in mining applications (Bousdekis et al., 2015).

Broadly, the existing CBPM/CBM frameworks found in the literature fall into three patterns: (i) data-centric models, which emphasize data acquisition and feature extraction but often lack integrated prognostics elements; (ii) life-cycle approaches, which combine FMECA and reliability modelling yet are seldom tailored to mining's dynamic duty cycles (More et al., 2023); and (iii) business-integrated systems, which link health assessment to enterprise decisions but remain overly generic and difficult to deploy in field conditions.

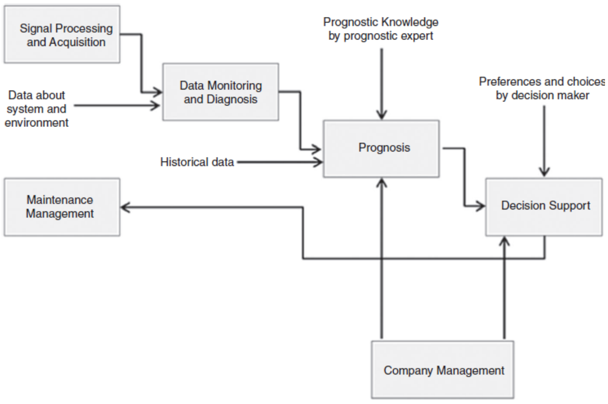

Figure 1. Generic Condition-Based Maintenance conceptual framework.

A representative conceptual structure of a generic CBM system is shown in Figure 1, comprising three modules: data acquisition, diagnostics/prognostics, and decision support. However, such frameworks typically lack mining-specific customization for dominant failure modes such as engine blow-by, hydraulic leakage, or tyre failure, which exhibit complex degradation dynamics under variable loads.

To bridge these gaps, this study (i) identifies and prioritizes critical haul-truck failure modes through FMECA (clarifying what fails and why), (ii) develops data-driven prognostic models using regression analysis to characterize degradation trajectories and predict failure progression (how it fails), and (iii) integrates these elements into a mining-specific CBPM framework, demonstrating how to implement predictive maintenance practically at the fleet level.

2. LITERATURE REVIEW

2.1 Prognostic Maintenance as a Driver of Proactive Strategies

Prognostic maintenance represents the most advanced stage of condition-based maintenance, wherein the time-to-failure and associated probability of failure are estimated using mathematical or data-driven models (Jardine et al., 2006). It fuses condition monitoring with predictive analytics, enabling maintenance interventions to be executed proactively rather than reactively (Lei et al., 2018).

Prognostic techniques are generally classified into two categories:

- Physics-based models: which describe the physical degradation process through analytical or mechanistic equations. Although highly accurate, these models require deep knowledge of failure mechanisms and they are costly and time-consuming to develop for complex systems like haul trucks (Tobon-Mejia et al., 2012).
- Data-driven models: which rely on historical or real-time operational data to capture degradation patterns through statistical or machine-learning techniques. These methods including regression, neural networks, and probabilistic models are effective when the physical failure mechanisms are difficult to model explicitly Mobley (2019).

For systems with abundant operational data but limited physics-of-failure information, data-driven prognostics provide a practical and scalable solution. Figure 2 (adapted from De Jonge & Scarf, 2020; Cao et al., 2025) illustrates the general workflow of a prognostic maintenance system, comprising data acquisition, feature extraction, model training, and Remaining Useful Life (RUL) estimation.

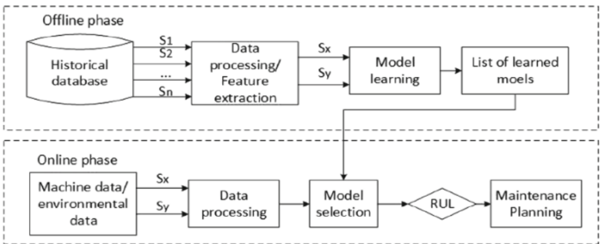

Figure 2. Schematic representation of a prognostic maintenance system (De Jonge & Scarf, 2020).

This research advances existing work by validating a hybrid framework that combines FMECA-based prioritization with regression-driven prognostic modelling, applied to real operational data from a mining haul-truck fleet.

2.2 Maintenance Challenges in Surface Mining

The surface-mining environment imposes distinctive challenges on equipment maintenance. Haul trucks operate under cyclic loading, variable gradients, and abrasive conditions, leading to accelerated wear and stochastic failure behaviour. Traditional OEM-prescribed time-based maintenance intervals often fail to reflect true operating stress and degradation rates. Consequently, unscheduled breakdowns significantly disrupt production and escalate operating costs, with maintenance expenses for haul trucks representing up to half of total haulage costs (Topal & Ramazan, 2012). Most prior studies have focused on improving truck utilization through operational optimization such as dispatching or haul-road design while paying limited attention to predictive maintenance optimization (Rojas et al., 2025). As a result, persistent problems such as unforeseen major component failures, ineffective maintenance planning, and high maintenance costs remain prevalent. This underscores the need for a prognostics-driven maintenance strategy that is contextually adapted to mining.

2.3 Research Gap: The Need for a Mining-Specific CBPM Framework

Although the literature strongly supports the potential of CBM and prognostics to optimize maintenance outcomes, a substantial gap between theory and industrial implementation remains. As highlighted by Bousdekis et al. (2015) and Sai et al. (2019), the development of structured, field-validated CBPM frameworks for heavy mining equipment is still in its infancy. This lack of sector-specific research limits both the credibility and adoption of prognostic maintenance in the mining industry. Therefore, this study seeks to develop and validate a scalable, data-driven CBPM framework tailored to the operational realities of surface mining. The framework integrates performance assessment, systematic failure analysis, and prognostic modelling to transform haul-truck maintenance from a reactive cost centre into a predictive, reliability-driven asset-management function.

3. METHODOLOGY

This study adopted a three-phase mixed-methods approach to develop and validate a Condition-Based Prognostic Maintenance (CBPM) framework for surface mining haul trucks. The approach integrates quantitative reliability assessment, expert-driven failure mode analysis, and data-driven prognostic modelling. The case study was conducted at a mining Site R utilizing purposively selected fleet of haul trucks monitored over a three-year operational period. The methodology is schematically presented in Figure 3. As it is illustrated, the methodology follows a structured data-driven sequence. Training and testing datasets are first processed to construct health indicators representing the degradation state of haul-truck components. These indicators are stored in a centralized database for subsequent analysis. The workflow then proceeds through three analytical stages: correlation analysis, regression analysis, and mathematical model formulation. The resulting predictive model estimates the Estimated Time to Failure (ETTF), which serves as the basis for prognostic maintenance decision-making within the CBPM framework.

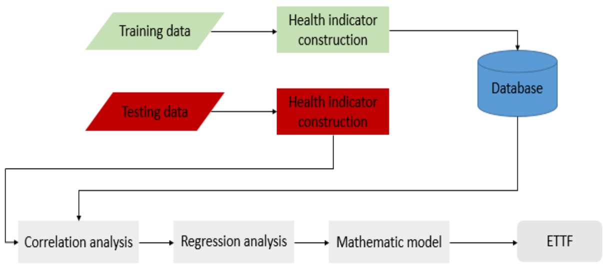

Figure 3. Methodological flow for developing the CBPM framework

To ensure a logical and systematic progression from problem identification to framework validation, the methodology was implemented in three sequential phases including, Performance Assessment and Failure-Mode Identification; Prognostic Model Development, and Framework Integration and Validation. Each phase is described in detail in the following subsections.

3.1. Phase 1: Performance Assessment and Critical Failure Mode Identification

The first phase aimed to establish the baseline maintenance performance and to identify failure modes with the highest operational criticality by addressing Quantitative performance benchmarking and Failure Mode, Effects, and Criticality Analysis (FMECA).

3.1.1. Quantitative Performance Benchmarking

Operational data were extracted from the mine's Computerized Maintenance Management System (CMMS), including work orders, failure logs, and repair histories. The complete dataset used for performance benchmarking and reliability analysis is provided in Appendix A (Haul truck historical data from MMRS). Key performance indicators (KPIs), Availability, Mean Time Between Failures (MTBF), and Mean Time to Repair (MTTR) were computed to benchmark fleet performance against internal targets:

$$Availability = MTBF \,/\, MTBF + MTTR \quad (1)$$

$$MTBF = Total\ Operating\ Time \,/\, Number\ of\ Failures \quad (2)$$

$$MTTR = Total\ Downtime \,/\, Number\ of\ Repairs \quad (3)$$

These indicators were analyzed following the reliability engineering framework outlined in ISO 13381-1 (2015) and recent mining applications by Yadav et al. (2020). The analysis revealed MTBF values between 22-59 hours and MTTR values between 3-7 hours, indicating substantial deviation from targets and highlighting existing maintenance inefficiencies.

3.1.2. Failure Mode, Effects, and Criticality Analysis (FMECA)

A structured FMECA was performed with a multidisciplinary panel of maintenance engineers, focusing on the operational realities of mining fleets. Failure criticality was assessed across four dimensions: Cost Impact, Production Loss, Safety Impact, and Environmental Consequence. The Risk Priority Number (RPN) was computed as:

$$RPN = S \times O \times D \tag{4}$$

where S, O, and D represent *Severity*, *Occurrence*, and *Detectability*, respectively.

The process was guided by the dynamic FMEA approach proposed by (Gomaa, 2025), which allows periodic updating of criticality scores as new data become available. The analysis identified engine blow-by (RPN = 420), engine overheating (RPN = 385), and tyre punctures (RPN = 360) as the most critical failure modes. Among these, engine blow-by was selected for prognostic model development due to its high operational impact and data richness

3.2. Phase 2: Data-Driven Prognostic Model Development

The second phase involved developing a quantitative prognostic model to predict the Remaining Useful Life (RUL) of critical components associated with engine blow-by. This was accomplished by constructing a Health Indicator (HI) from crankcase-pressure data and modelling its degradation trajectory using regression-based approaches.

3.2.1. Health Indicator (HI) Formulation

The Health Indicator (HI) was derived from the correlation between pressure signals of a reference (healthy) truck and a degrading truck using Pearson's correlation coefficient r (Lei et al., 2018):

$$HI = r = \frac{\sum_{i=1}^{N}(x_i-\bar{x})\ (y_i-\bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i-\bar{x})^2}\sqrt{\sum_{i=1}^{N}(y_i-\bar{y})^2}} \tag{5}$$

where x_i and y_i represent the pressure sample readings from the healthy (HT94) and degrading (HT104) engines, respectively,

$\bar{x}, \bar{y}$ = sample means, and N is the number of data samples.

A value of HI = r ϵ [-1, 1] indicates perfect health, whereas HI→0 corresponds to total degradation.

Noise smoothing (moving average of window m):

To mitigate signal noise and enhance data fidelity, a moving average smoothing technique was applied, as recommended by (Lei et al., 2018) and (Deng et al., 2023), followed by temporal resampling to ensure uniform sampling intervals across all datasets.

$$\tilde{x}_k = \frac{1}{m}\sum_{i=0}^{m-1} x_{k-i} \tag{6}$$

Where $\tilde{x}_k$= smoothed sample at time index k, and m = window length

3.2.2. Mathematical formulation of degradation models

Three candidate models were formulated to represent the degradation trajectory of the HI over time (t), based on established regression principles and physical degradation assumptions. These models are widely applied in prognostic and health management (PHM) literatures.

(a) Linear degradation model

Assuming a constant degradation rate:

$\frac{dHI}{dt} = k$, Integrating over time results

$$HI(t) = a_1 t + b \tag{7}$$

where a_i is the degradation rate and b is the initial health value.

Model parameters are estimated using Ordinary Least Squares (OLS):

$$\hat{\theta} = (X^T X)^{-1} X^T y, \quad X = \begin{bmatrix} t_1 & 1 \\ t_2 & 1 \\ \vdots & \vdots \\ t_n & 1 \end{bmatrix}, \qquad \theta = \begin{bmatrix} a_1 \\ b \end{bmatrix},$$

$$y = \begin{bmatrix} HI_1 \\ HI_2 \\ \vdots \\ HI_n \end{bmatrix} \tag{8}$$

Where t = time, a_1= slope (degradation rate), and b = the intercept

(b) Exponential model

When the degradation rate is proportional to the deviation from an asymptotic baseline c:

$\frac{d(HI-c)}{dt} = k(HI - c)$, Integration yields: $HI(t) = ae^{bt} + c$ (9)

This nonlinear model was estimated using nonlinear least-squares optimization (Levenberg -Marquardt algorithm) to minimize the Sum of Squared Errors (SSE):

$$\min_{a,b,c} SSE(a,b,c) = \sum_{i=1}^{N}(HI_i - [ae^{bt_i} + c])^2 \tag{10}$$

Where:

HI_i : the observed Health Indicator at time t_i ;

$ae^{bt_i} + c$: model-predicted value of the Health Indicator at the same time t_i ;

a, b, c: parameters to be estimated, c= asymptotic floor; and

N: total number of observations

Such exponential decay patterns are commonly observed in mechanical wear, corrosion, and seal degradation phenomena Tobon-Mejia et al. (2012) and Yao et al. (2023).

(c) Polynomial models

For systems exhibiting non-linear degradation behaviour, the degradation trajectory can be expressed using a Taylor series expansion:

$$HI(t) = a_3t^3 + a_2t^2 + a_1t + b \qquad (11)$$

Truncation to the second-order term yields the quadratic form:

$$HI(t) = a_2t^2 + a_1t + b \qquad (12)$$

Coefficients were estimated using OLS, consistent with the approaches of (Liao & Köttig, 2016) and (Katreddi et al., 2022), who emphasize the suitability of low-order polynomials for early-life degradation modelling.

3.2.3. Model evaluation and validation

After model formulation, each regression model was evaluated to determine its predictive accuracy and suitability for representing the degradation behaviour of the haul-truck components. Each regression model was evaluated based on:

- Coefficient of determination (R^2),
- Root Mean Square Error (RMSE), and
- Residual distribution analysis.

Physical interpretability of the degradation pattern was also considered, following recommendations by Jardine et al. (2006). The second-order polynomial model demonstrated the best predictive performance with R2 = 0.938, effectively capturing the non-linear, accelerating trend of engine blow-by degradation:

$$HI(t) = 0.005t^2 - 0.203t + 0.8344 \qquad (13)$$

where t represents time in weeks.

3.2.4. Remaining Useful Life (RUL) estimation

After identifying the optimal polynomial regression model, the next step involved estimating the Remaining Useful Life (RUL) of the critical component using the model's degradation trend. The Estimated Time to Failure (ETTF) was defined as the point where HI(t) reached the failure threshold (HI = 0). From Eq. (13):

$HI(t_{final}) = 0 \Rightarrow$

t_{final} = root of $(-0.005t^2 - 0.203t + 0.834 = 0)$ (14)

The RUL at any current inspection time ($t_{current}$) is computed as:

$$ETTF = t_{final} - t_{current} \qquad (15)$$

For this case study, the predicted ETTF=19.1 weeks with a deviation of ±5.8 % from observed failure, validating the model's field applicability.

3.3. Phase 3: Integrated CBPM Framework Design

Phase 3: Integrated CBPM Framework Design

Insights from Phases 1 and 2 were synthesized into an operational CBPM framework, depicted in Figure 4, designed to support continuous improvement in reliability-centered maintenance within surface-mining operations. The proposed framework comprises three interdependent functional modules that collectively enable proactive maintenance planning and data-driven decision-making:

1. Performance Assessment Module: Continuously monitors key performance indicators (KPIs) such as availability, Mean Time Between Failures (MTBF), and Mean Time to Repair (MTTR). Deviations from target thresholds automatically trigger maintenance reviews and root-cause analyses, providing the basis for initiating corrective actions.
2. FMECA-Driven Prioritization Module: dynamically updates the ranking of critical failure modes through recalculation of the Risk Priority Number (RPN) values, in accordance with the adaptive maintenance planning principles proposed by (Barberá et al., 2012). This ensures that maintenance priorities remain aligned with evolving equipment-health trends and operational realities.
3. Prognostics and Decision Support Module: implements data-driven degradation models (Eq. 13) to predict Estimated Time to Failure (ETTF) and Remaining Useful Life (RUL). The resulting forecasts guide optimal maintenance scheduling, spare-parts procurement, and resource-allocation decisions, enabling a shift from reactive to predictive maintenance.

A closed-loop feedback mechanism links the three modules, ensuring continuous refinement of FMECA scores, model parameters, and KPI baselines as new operational and sensor data become available. This adaptive feedback process underpins the framework's long-term robustness and alignment with Mining 4.0 and Industrial IoT paradigms (Alabadi et al., 2021). The structure and data-flow logic are consistent with recent digital predictive-maintenance implementations in mining operations and hybrid Prognostics and Health Management (PHM) architectures that integrate model-based and data-driven reasoning.

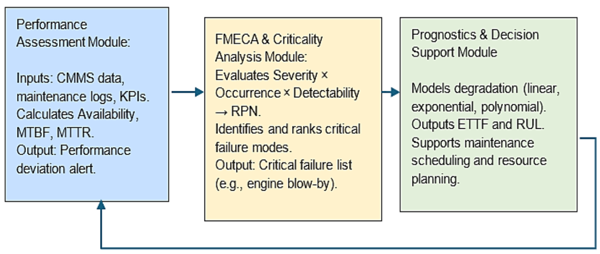

Figure 4. Proposed Condition-Based Prognostic Maintenance (CBPM) framework
Source: Authors own work

The framework integrates three interlinked modules: the Performance Assessment Module, which monitors fleet KPIs and detects deviations; the FMECA & Criticality Analysis Module, which ranks failure modes using RPN; and the Prognostics & Decision-Support Module, which models degradation and forecasts ETTF and RUL. A feedback loop continuously updates all modules, promoting adaptive, reliability-driven maintenance across the haul-truck fleet.

3.4. Validation and Generalizability

The CBPM framework was validated under constant operational and environmental conditions across the 21-truck fleet. Although demonstrated on a single engine blow-by case, the methodology is transferable to other critical components (e.g., hydraulic pumps, braking systems) and scalable to different mining sites, given adequate sensor data and maintenance records. This approach is consistent with global developments in predictive maintenance and smart mining systems (Sun et al., 2022) and (Zhou et al., 2025).

4. RESULTS AND DISCUSSION

4.1. Haul-Truck Performance Assessment: Establishing the Need for CBPM

The first phase of this research established a performance baseline for the haul-truck fleet at Site R. Analysis of three years of operational and maintenance data revealed recurring performance gaps in the key performance indicators (KPIs)- availability, reliability, and maintainability. As illustrated in Figure 5, average truck availability frequently fell below the mine's 85 % target, particularly during the second and third operational years. Figure 6 shows that the Mean Time Between Failures (MTBF) consistently underperformed relative to the 50-h reliability target, while Figure 7 indicates that the Mean Time to Repair (MTTR) regularly exceeded the 2 h maintainability threshold.

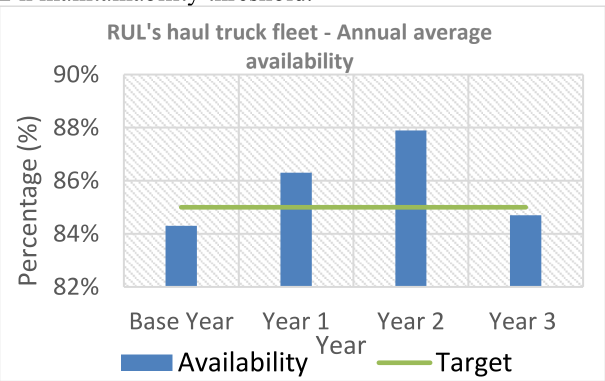

Figure 5. Annual average haul-truck availability versus target (85 %).

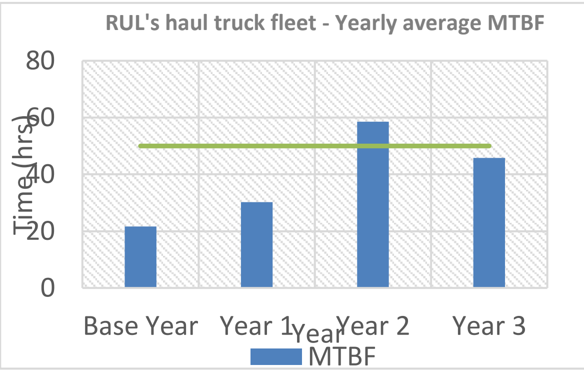

Figure 6. Annual average MTBF versus target (50 h).

These results expose the limitations of the site's existing hybrid maintenance approach—an unsystematic combination of time-based preventive maintenance, limited condition monitoring, and reactive repair practices. The persistent shortfall in MTBF and the high MTTR clearly demonstrate the absence of a predictive mechanism to anticipate failures. Comparable deficiencies have been reported in other mining fleets operating under harsh environments (Topal et al., 2012; Yadav et al., 2020). Collectively, these findings underscore the need for a Condition-Based Prognostic Maintenance (CBPM) framework capable of addressing the complex, nonlinear degradation behaviour characteristic of mining equipment.

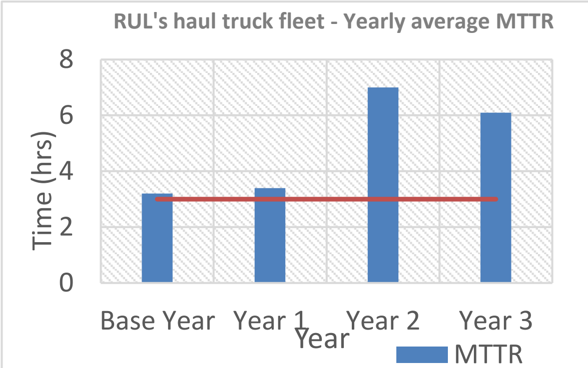

Figure 7. Annual average MTTR versus target (2 h***)***.

4.2. Identification of Critical Failure Modes via FMECA

To translate the performance gaps into actionable insights, a Failure Modes, Effects and Criticality Analysis (FMECA) was conducted with site maintenance experts. Forty-eight potential failure modes were evaluated across all major truck subsystems using the mining-specific Risk Priority Number (RPN) metric:

$$RPN = S * O * D$$

where *S*, *O*, and *D* represent *Severity*, *Occurrence*, and *Detectability*.

Table 1. Top critical failure modes identified via FMECA.

Failure Mode	Subsystem	Severity	Occurrence	Detectability	RPN
Engine Blowby	Engine	7	5	12	**420**
Engine Overheating	Engine	8	5	10	**385**
Tyre Puncture	Tyres	8	7	6	**360**
Nose Cone Mounting Failure	Frame	8	4	12	**96**
Cylinder Head Coolant Leakage	Engine	8	6	8	**96**

The outcomes, summarized in Table 1, identified engine blow-by (RPN = 420) as the dominant failure mode, followed by engine overheating (RPN = 385) and tyre punctures (RPN = 360). Engine blow-by ranked highest due to its severe impact on power generation and potential for catastrophic engine failure, compounded by low detectability under existing preventive measures. The systematic ranking provided quantitative justification for selecting engine blow-by as the pilot failure mode for prognostic modelling- an approach consistent with dynamic FMEA methods for adaptive maintenance prioritization.

4.3. Development and Validation of the Prognostic Model

With engine blow-by identified as the most critical degradation mechanism, a Health Indicator (HI) was constructed based on the correlation between the crankcase-pressure signal of a healthy truck (HT94) and that of a degrading truck (HT104) using Pearson's correlation coefficient (Eq. 4). Values of r near 1 denote healthy operation, whereas those approaching 0 signify advanced degradation.
Three regression formulations- linear, exponential, and second-order polynomial- were tested to model the temporal degradation of the HI. Among these, the polynomial model provided the most accurate fit with R2 = 0.938, outperforming both the linear (R2 = 0.931) and exponential (R2 = 0.898) models. Regression diagnostics (Table 2) confirm the polynomial model as the most statistically robust, with $R^2 = 0.9378$, an adjusted $R^2 = 0.9309$ and random residual distribution ($p < 0.05$). The complete regression-fitting outputs, including ANOVA tables and coefficient statistics for all three models, are provided in Appendix B (Regression fitting results). The negative quadratic term effectively captured the accelerating wear characteristic of mechanical components approaching end-of-life, consistent with trends described by (Zhou et al., 2023).
The optimal degradation model was expressed as:

$$HI(t) = -0.005t^2 - 0.0203t + 0.8344$$

where t is time (weeks).

Table 2. Regression performance summary for the degradation models.

Model Type	Regression Equation	R^2	Adjusted R^2	Standard Error	F-Statistic	Significance F
Linear	$HI(t) = -0.0334t - 0.8933$	0.9305	0.9269	0.0581	254.55	1.85×10^{-12}
Exponential	$HI(t) = 1.1212e^{-0.078t}$	0.8499	0.8420	0.0855	107.56	2.92×10^{-9}
Polynomial (2nd order)	$HI(t) = -0.005t^2 - 0.0203t + 0.8344$	0.9378	0.9309	0.0565	135.81	1.38×10^{-11}

The Estimated Time to Failure (ETTF) corresponds to the root of HI(t) = 0; for a current time tcurrent = 22 weeks, the model predicts tfinal = 41.1 – 22 = 19.1 weeks. The standard error of ±5.8 % validates the model's predictive accuracy. These findings demonstrate the feasibility of transitioning from reactive or scheduled-based maintenance to a data-driven prognostic regime providing a tangible 19-week lead time for scheduling engine overhaul and resource allocation.

4.4. Comparative Evaluation of Regression Models

To substantiate model selection, crankcase-pressure data were collected under equivalent duty conditions (payload ≈ 290 ± 5 t, identical engines, 1 Hz sampling). Figure 8 compares pressure waveforms from healthy and degrading engines. The degrading engine exhibited 14.3 % higher mean pressure (82.4 kPa vs 72.1 kPa), 22 % greater peak-to-peak variability, and higher waveform skewness (0.47 vs 0.09), indicating progressive compression leakage.

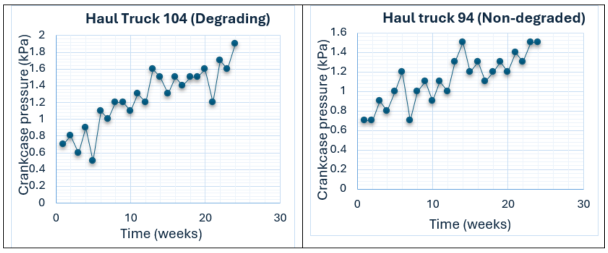

Figure 8. Crankcase-pressure signals for degrading (left) and non-degraded (right) engines. Source: Authors own work

The evolution of the correlation-based HI (Figure 9) highlights three degradation phases:

- Stage 1 (0-8 weeks): gradual decline (r = 0.92 → 0.65);
- Stage 2 (9-15 weeks): accelerated deterioration (r = 0.65 → 0.31);
- Stage 3 (>19 weeks): failure threshold ($HI < 0.2$ ± 1.1 weeks).

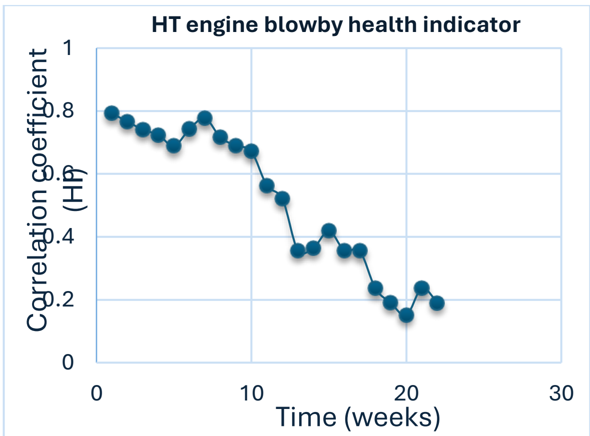

Figure 9. *Evolution of blow-by health indicator. Source: Authors own work*

The linear model (Figure 10) produced a strong correlation (R2 = 0.931):

$$HI(t) = -0.0334 - 0.8933$$

However, residual analysis revealed systematic non-random patterns which is an indicator for overestimation during early operation and underestimation in later stages, signifying model misspecification. Such behaviour verifies findings that linear degradation assumptions inadequately represent the nonlinear ageing of mechanical systems.

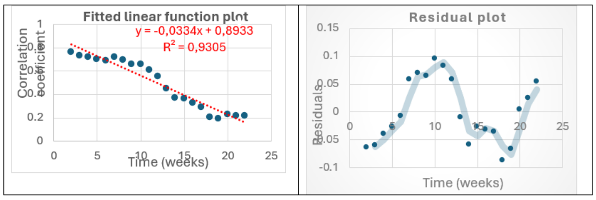

Figure 10. Linear regression fitting (left) and residuals (right). Source: Authors own work

The exponential model (Figure 11) improved late-stage prediction (R2 = 0.898):

$HI(t) = 1.1212e^{-0.078t}$

Yet periodic residual oscillations indicated persistent bias, likely caused by varying engine load and environmental stress. Similar limitations of exponential wear models under variable-load conditions have been reported by (Liao & Köttig, 2016) and (Rodriguez et al., 2025).

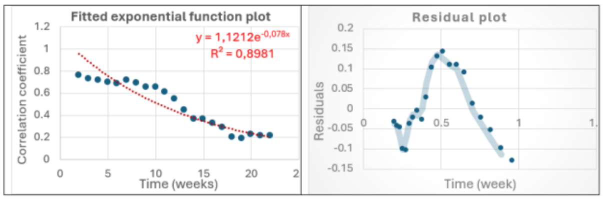

Figure 11. Exponential regression fitting (upper) and residuals (lower). Source: Authors own work

Finally, the second-order polynomial model (Figure 12) achieved the highest predictive power (R2 = 0.938) and random, pattern-free residuals, confirming its statistical adequacy.

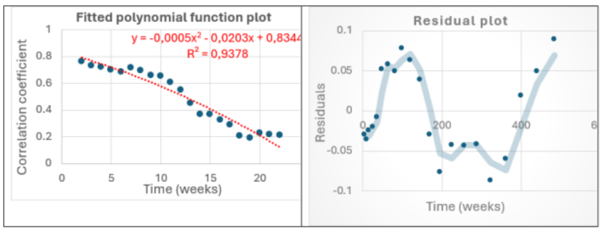

Figure 12. Polynomial regression fitting (upper) and residuals (lower). Source: Authors own work

The model accurately reproduced both the slow-wear phase and the rapid deterioration stage preceding failure. These results confirm that low-order polynomial functions can effectively capture degradation trends in heavy-equipment components where physical mechanisms are complex and operating conditions fluctuate (Yu & Tang, 2022).

4.5. Remaining Useful Life Prediction and Practical Implications

Solving Eq. (13) for HI(t) = 0 gives t_{final} = 41.1weeks, yielding:

$$ETTF = t_{final} - t_{current} = 19.1\ weeks$$

This ETTF, with ±5.8 % uncertainty, provides maintenance planners a 4-5month proactive window to schedule overhauls, procure spares, and coordinate resources, significantly reducing the risk of in-pit breakdowns and emergency repairs. The analysis assumes stable operating conditions and uniform maintenance practices across the fleet. Although these assumptions may introduce moderate uncertainty, they remain consistent with practical constraints in mining prognostics. Compared with physics-based models, the regression approach offers several advantages:

- it requires no first-principles knowledge of failure initiation,
- it dynamically estimates degradation states from field data, and
- it avoids the computational burden of high-fidelity simulations.

These strengths align with the characteristics of scalable, data-driven prognostic systems described by (Deng et al., 2023) and (Yu & Tang, 2022).

4.6. Application of the Proposed CBPM Framework

The proposed CBPM framework (Figure 13) operationalizes these analytical insights into a structured maintenance strategy comprising three interdependent modules:

- Performance-Assessment Module – Continuously monitors KPIs (availability, MTBF, MTTR) to detect deviations from baseline values and trigger maintenance reviews.
- Failure-Mode Identification and Classification Module – Employs dynamic FMECA to identify and prioritize critical subsystems based on evolving RPN values.
- Prognostics and Decision-Support Module – Applies validated regression models to compute ETTF, prioritize work orders, optimize resource allocation, and streamline spare-parts logistics.

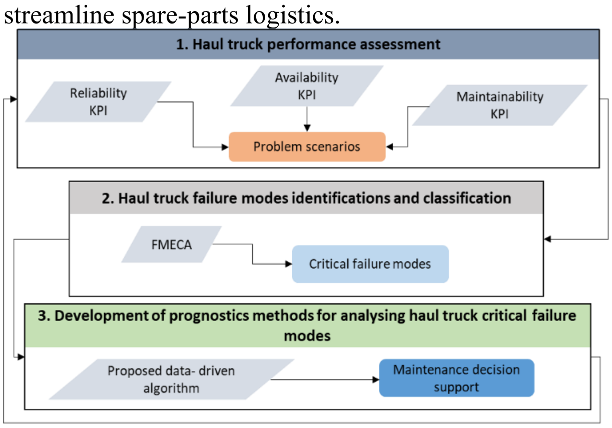

Figure 13. Proposed generic CBPM framework for haul trucks. Source: Authors own work

A closed-loop feedback mechanism continuously updates both the FMECA rankings and prognostic model parameters as new operational data become available. This adaptive intelligence enables the framework to evolve with equipment ageing and shifting operating conditions, consistent with modern Mining 4.0 and Industrial IoT paradigms (Molaei et al., 2020). The integration of prognostic analytics with decision-support functions represents a significant advancement over traditional CBM frameworks, aligning with the hybrid Prognostics and Health Management (PHM) architectures advocated by (Liao & Köttig, 2016) and the digital-twin applications demonstrated by (Zhou et al., 2023).

4.7. Discussion and Broader Implications

The validated polynomial prognostic model, embedded within the CBPM framework, demonstrates how field data can be transformed into actionable maintenance intelligence. Compared with generic CBM approaches, the proposed method:

- reduces unplanned downtime by enabling RUL-based maintenance scheduling,
- improves maintenance resource utilization, and
- establishes a repeatable, data-driven workflow adaptable to other critical components (e.g., hydraulic systems, brakes, or tyres).

These benefits align with cost-effective predictive maintenance deployments in resource-constrained environments and reinforce the global transition toward predictive, reliability-centered maintenance, echoing recent findings in smart-mining research (Zhou et al., 2023). The approach's scalability and computational simplicity make it particularly suitable for mines in developing regions, where access to advanced PHM infrastructure remains limited.

5. CONCLUSION AND FUTURE WORK

This study developed and validated a Condition-Based Prognostic Maintenance (CBPM) framework tailored to the demanding operational context of haul-truck fleets in surface mining. By integrating performance assessment, FMECA-based failure prioritization, and data-driven prognostic modelling, the framework addresses key limitations of traditional reactive and time-based maintenance strategies that often lead to high downtime, costly emergency repairs, and underutilized assets.

5.1. Conclusion

The primary contribution of this research is a practical, data-driven prognostic methodology that advances beyond conceptual discussion and demonstrates field-level applicability using real operational data from a fleet of haul trucks. Through the construction of a correlation-based Health Indicator (HI) and comparison of alternative regression models, a second-order polynomial degradation model was shown to provide accurate prediction of failure progression and Remaining Useful Life (RUL). For engine blow-by, the model yielded an Estimated Time to Failure (ETTF) of 19.1 weeks with a prediction error of ±5.8 %, offering a tangible lead time for proactive maintenance planning.

A key strength of the proposed CBPM framework is its modular and scalable architecture. Its three core modules- (i) Performance Assessment, (ii) FMECA-driven Failure Analysis, and (iii) Prognostics and Decision Support can be implemented incrementally and adapted to fleets of varying size, age, and configuration.

The closed-loop feedback mechanism ensures continuous updating of failure-criticality rankings and prognostic models as new data are collected and operating conditions evolve. This adaptability is essential for sustaining performance improvements over the full equipment lifecycle.

For mining operations seeking to transition from a reactive, cost-centre view of maintenance to a reliability-centred, strategic asset-management function, the framework provides a clear implementation pathway. It bridges the gap between advanced prognostics theory and the practical constraints of surface mining environments, yielding measurable benefits such as:

- extended component lifecycles,
- reduced unplanned downtime, and
- more efficient utilization of maintenance labor and spare parts.

Given the strong linkage between equipment reliability and production throughput, these benefits are not marginal but foundational for achieving operational excellence. Moreover, the framework's reliance on data-driven analytics establishes a future-proof foundation for integrating emerging technologies such as Industrial Internet of Things (IIoT) sensors, advanced machine learning algorithms, and digital-twin systems- without necessitating a complete redesign of maintenance infrastructure.

5.2. Future Work

Future research should extend the framework's validation to additional failure modes and equipment types to establish its broader applicability. Incorporating operational variables (e.g., payload, haul-road conditions) and exploring advanced machine-learning approaches may further enhance prediction accuracy and model robustness. A longitudinal field study quantifying the framework's economic impact particularly in terms of Total Cost of Ownership (TCO) and operational efficiency is recommended to strengthen its business justification.

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