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Implementing OSA-CBM Architecture for Operational Readiness Assessment of Aging Motor Grader Engines

Nova Pangastuti [1,*], Muhammad Ilham Muslimin [1], and Sepriandi Parningotan [2]

[1]Department of Industrial Engineering, Binus Online University, Jakarta 11480, Indonesia
[2]Department of Mechanical Engineering, Politeknik Negeri Jakarta, Depok 16424, Indonesia
*Corresponding Author: nova.pangastuti@binus.ac.id (NP)

Abstract

Traditional interval-based maintenance policies for diesel engines often rely on fixed overhaul schedules recommended by Original Equipment Manufacturers (OEM), which may not accurately reflect the actual health status of aging heavy equipment in harsh mining environments. Such static approaches risk either premature, costly overhauls or catastrophic, unexpected failures. This study proposes a robust methodology by integrating Interquartile Range (IQR)-based statistical control limits within the Open System Architecture for Condition-Based Maintenance (OSA-CBM) framework to evaluate the operational readiness of an aging motor grader engine. Historical oil analysis data from May 2024 to November 2025, covering an extended operational period from 13,515 to 19,755 hours, were examined to identify wear behavior and lubricant degradation.The implementation of the seven functional layers of OSA-CBM, from data acquisition to advisory generation, ensures a structured and traceable diagnostic process. The results indicate that primary wear metal parameters, specifically iron (Fe) and chromium (Cr), remained stable with Risk Index (RI) values below unity (RI < 1), signifying a steady-state wear condition despite the engine operating far beyond typical overhaul intervals. Although a significant isolated spike in aluminum (Al) was detected with a Risk Index of 3.20, the absence of correlated increases in Fe or Cr suggests episodic contamination or a transient event rather than progressive mechanical wear. Furthermore, lubricant condition indicators, including kinematic viscosity and Total Base Number (TBN), consistently complied with SAE 15W-40 specifications. These findings demonstrate that embedding unit-specific statistical boundaries within the OSA-CBM architecture provides reliable, data-driven decision support, enabling justified operational life extension and optimized maintenance strategies for aging heavy-duty engines.

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1. Introduction

In large-scale mining operations, the operational continuity of heavy equipment plays a critical role in maintaining productivity, operational efficiency, and safety performance. Among supporting assets, motor graders are essential for haul road maintenance, where engine reliability becomes crucial due to harsh working environments involving high loads, abrasive contaminants, and long operational duty cycles. Traditionally, maintenance strategies for diesel engines rely on preventive maintenance policies based on fixed overhaul intervals recommended by Original Equipment Manufacturers (OEM). However, interval-based maintenance policies may not always reflect the actual condition of the equipment during operation. Recent studies emphasize that condition-based maintenance (CBM) approaches can provide more reliable maintenance decision support by utilizing real-time or historical condition monitoring data [1], [2].

Oil analysis has been widely recognized as an effective diagnostic tool for monitoring the health condition of internal combustion engines. By analyzing wear metals, contamination levels, and lubricant degradation indicators, oil analysis enables early detection of abnormal wear mechanisms and lubricant deterioration [3], [4]. Several studies have also demonstrated that oil analysis data can be used to estimate lubricant remaining useful life (RUL) and support predictive maintenance strategies for heavy-duty engines [5], [6]. In mining and heavy equipment applications, analytical models based on oil monitoring have been successfully applied to evaluate wear behavior and identify potential component degradation [7].

To facilitate the transformation of condition monitoring data into actionable maintenance decisions, standardized architectures for condition-based maintenance have been developed. One of the most widely recognized frameworks is the Open System Architecture for Condition-Based Maintenance (OSA-CBM), originally formalized through the MIMOSA specification and subsequently standardized within the ISO 13374 series. The framework consists of seven functional layers, namely Data Acquisition, Data Manipulation, State Detection, Health Assessment, Prognostic Assessment, Decision Support, and Presentation, which collectively support the conversion of raw monitoring data into maintenance recommendations.[8]. Recent research has also integrated risk-based maintenance modeling and advanced diagnostic approaches to enhance decision reliability in lubrication systems [9]. Despite the increasing adoption of oil condition monitoring, most previous studies have primarily focused on developing diagnostic models, machine learning algorithms, or lubricant degradation prediction methods [6–10]. However, these studies generally rely on generalized threshold values or population-based models that may not accurately represent the operating behavior of individual machines. In practice, heavy-duty equipment operating under different environmental and loading conditions often exhibits unique wear characteristics that cannot be adequately captured using generic thresholds.

In addition to traditional oil laboratory analysis, modern research has explored advanced sensing and diagnostic technologies to improve wear detection capability. Techniques such as hyperspectral analysis, laser-induced breakdown spectroscopy, and tribological correlation methods have demonstrated promising results in identifying wear particles and lubricant degradation characteristics[10], [11], [12]. Furthermore, machine learning and data-driven models have increasingly been applied to oil condition monitoring to improve predictive capability and anomaly detection in industrial machinery [13], [14], [15]. On the other hand, the Open System Architecture for Condition-Based Maintenance (OSA-CBM) has been widely recognized as a standardized framework for transforming condition monitoring data into maintenance decisions. Although numerous studies have discussed the conceptual implementation of OSA-CBM and ISO 13374, most applications remain focused on system architecture and information flow design rather than on the development of practical decision-making mechanisms within the Health Assessment and Decision Support layers. In particular, limited research has investigated how unit-specific statistical thresholds can be embedded into OSA-CBM to support maintenance decisions for aging industrial assets.

Despite these advancements, many industrial maintenance practices still rely on static OEM thresholds or generalized population averages when interpreting oil analysis results. Such static limits may fail to capture unit-specific operational behavior and may trigger premature overhaul decisions or false failure indications. Recent studies highlight the importance of utilizing historical operational data and dynamic statistical boundaries to improve the reliability of condition monitoring interpretation [16], [17], [18]. In particular, machine learning and statistical anomaly detection techniques have shown potential in identifying abnormal lubricant behavior and wear mechanisms based on historical monitoring data [19], [20]. Therefore, three important research gaps can be identified. First, existing oil analysis studies generally employ static thresholds that do not account for unit-specific operating characteristics. Second, previous OSA-CBM implementations rarely integrate statistical anomaly detection methods directly into the Health Assessment and Decision Support layers. Third, limited studies have investigated maintenance decision support for aging heavy-duty equipment operating beyond OEM-recommended overhaul intervals using sparse historical monitoring data.

To address these gaps, this study proposes an integrated framework that combines Interquartile Range (IQR)-based dynamic control limits with the OSA-CBM architecture for operational readiness assessment of aging motor grader engines. Unlike conventional approaches that rely on fixed thresholds, the proposed framework establishes unit-specific statistical boundaries derived from historical oil analysis data and embeds them directly into the Health Assessment and Decision Support layers of OSA-CBM. The proposed methodology provides a practical and interpretable mechanism for supporting maintenance decisions under limited data conditions and enables justified life-extension assessments for aging heavy-duty equipment.

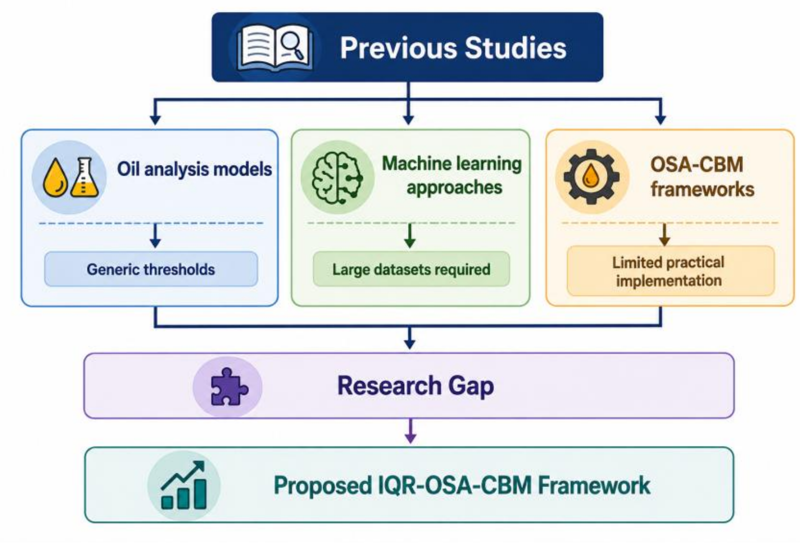

Figure 1. Identification of research gaps and positioning of the proposed framework.

As illustrated in Figure 1, previous studies have generally focused on either oil condition monitoring techniques or OSA-CBM implementation independently. Limited studies have integrated unit-specific statistical anomaly detection with OSA-CBM to support maintenance decision-making for aging heavy-duty engines operating under sparse historical data conditions. This gap motivates the development of the proposed framework.

2. Methods

This study adopts a CBM approach by integrating oil analysis techniques within the Open System Architecture for Condition-Based Maintenance (OSA-CBM) framework, as standardized in ISO 13374. The methodology is designed to ensure a structured and traceable process, starting from raw data acquisition to maintenance decision support, enabling objective evaluation of engine condition for aging equipment operating beyond OEM-recommended service life.

2.1. OSA-CBM framework architecture

The proposed methodology follows the seven functional layers of the OSA-CBM architecture to transform oil analysis data into actionable maintenance decisions, as shown in Figure 2.

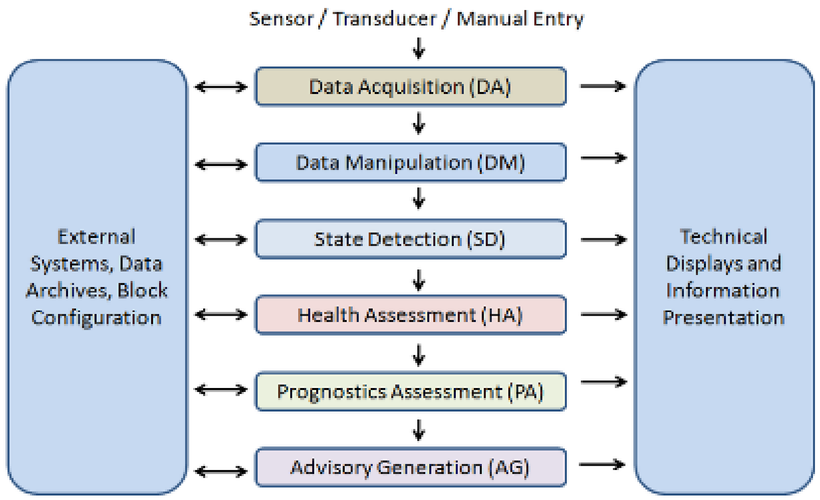

Figure 2. Study paths of machine condition assessment data processing and information flow basics based on ISO 13374 Standard.

2.2. Data sources and collection procedure

Oil samples were collected periodically from the engine lubrication system during normal operation. Laboratory oil analysis provided quantitative data on wear metals and lubricant condition parameters.

- Oil Analysis Dataset Description: The dataset used in this study consists of historical oil analysis records collected from a motor grader engine operating in a mining environment. A total of seven oil samples were analyzed, covering an operational period from May 2024 to November 2025. The engine operating hours during this period ranged from 13,515 hours to 19,755 hours, representing an aging engine operating beyond typical overhaul intervals. Oil samples were obtained periodically during scheduled maintenance intervals with an approximate sampling frequency of 400–500 operating hours. Each oil sample was analyzed in a laboratory to determine the concentration of key wear metals and lubricant condition parameters. The dataset therefore provides a time-series representation of wear behavior and lubricant condition throughout the monitoring period.
- Data Manipulation: Raw laboratory results were standardized and organized based on sampling intervals. Data preprocessing included normalization of concentration values and alignment with operating hours to ensure consistency for trend evaluation.
- State Detection: Initial condition assessment was conducted by comparing current oil analysis results with historical values to detect deviations from normal operating behavior.
- Health Assessment: Statistical evaluation was performed using trend analysis and the IQR method to classify parameter conditions into normal, warning, or abnormal states based on unit-specific historical data.
- Prognostic Assessment: Trend slopes of key wear metal parameters were analyzed to evaluate wear progression and short-term stability, providing insight into the likelihood of accelerated wear or impending failure.
- Decision Support: Maintenance decisions were derived by integrating wear metal behavior, lubricant condition, and statistical risk levels to determine whether engine overhaul could be safely deferred.
- Presentation Layer: The oil analysis dataset consists of seven historical observations collected during the available monitoring period.

A temporal gap exists between July 2024 and August 2025 because complete laboratory oil analysis records were not available for this interval. The absence of intermediate records reflects data availability limitations rather than equipment inactivity. Consequently, the dataset should be interpreted as a collection of historical condition snapshots rather than a continuous high-frequency monitoring series.

Results were summarized using trend graphs, control limits, and decision matrices to support clear interpretation by maintenance engineers and decision-makers. Although the dataset consists of only seven oil analysis observations, the objective of this study is not to establish population-level statistical inference but to evaluate the applicability of an OSA-CBM decision framework in a real industrial case. Similar condition monitoring studies on critical mining assets frequently rely on limited observations due to the high cost of laboratory analysis and long sampling intervals associated with heavy-duty equipment operation. Therefore, the dataset is treated as a longitudinal case-study dataset rather than a large-sample statistical population.

2.3. Wear rate calculation

To evaluate the severity and progression of component wear, wear rate was calculated to account for differences in oil sampling intervals. The wear rate for each metal parameter was determined using Equation (1).

$$WR = \frac{C_n - C_{n-1}}{\Delta H} \tag{1}$$

where C_n is the current wear metal concentration (ppm) C_{n-1} is the previous concentration (ppm), and ΔH represents the operating hours between two consecutive oil samples. This calculation allows wear behavior to be interpreted as a function of time rather than absolute concentration values, improving comparability across samples.

2.4. IQR for dynamic control limits

The IQR method was selected because it is a non-parametric statistical technique that does not require assumptions regarding data normality and is relatively robust to isolated extreme observations. Previous studies have demonstrated that quartile-based approaches can provide stable anomaly detection performance under limited-sample conditions where conventional mean-based statistical methods may become unreliable. Therefore, the IQR approach was considered appropriate for exploratory condition assessment within the context of industrial oil analysis datasets characterized by sparse observations and long sampling intervals.

The IQR method was selected to establish dynamic control limits because of its robustness in handling small datasets and its resistance to extreme outliers. Unlike mean-based statistical approaches such as standard deviation control charts, which may be significantly influenced by extreme values, the IQR method relies on quartile distribution and therefore provides a more stable representation of the central tendency of the data. This characteristic is particularly important in oil analysis datasets where occasional transient spikes may occur due to contamination events or operational disturbances. By using quartile-based boundaries, the IQR method allows abnormal conditions to be detected without allowing isolated extreme values to distort the statistical limits. Furthermore, the IQR approach is computationally simple and suitable for practical industrial applications where rapid interpretation of oil analysis results is required in engine condition monitoring. The IQR is defined as Equation (2).

$$IQR = Q_3 - Q_1 \tag{2}$$

Where Q_1 and Q_3 are the first and third quartiles of the historical dataset, respectively. Based on this method, Statistical boundaries were defined as:

$$\begin{gathered} Upper\ limit = Q_3 + 1.5\ x\ IQR \\ Lower\ limit = Q_1 - 1.5\ x\ IQR \\ UCL = Q_3 + k(IQR) \end{gathered} \tag{3}$$

In this study, a multiplier value of k = 1.5 was adopted according to Tukey's criterion for outlier detection. This value is widely used in exploratory data analysis because it provides a practical balance between sensitivity and robustness when identifying abnormal observations. Compared with larger multiplier values such as k = 3.0, the k = 1.5 criterion is more sensitive to early deviations while still minimizing the influence of random fluctuations. The selection of k = 1.5 was based on established statistical literature rather than empirical calibration or engine-specific wear mechanisms. Therefore, the resulting control limits should be interpreted as statistical indicators supporting engineering judgment rather than absolute failure thresholds.

Although no universally accepted minimum sample size exists for IQR-based anomaly detection, statistical literature generally recommends larger datasets when population-level inference is required. In the present study, the objective is not statistical generalization but condition assessment of a specific asset. Consequently, the available dataset is treated as an engineering case-study dataset, and the resulting control limits should be interpreted as unit-specific indicators rather than universally applicable thresholds.

2.5. Risk index and condition classification

To support decision-making within the OSA-CBM framework, The Risk Index (RI) was defined as a normalized IQR-based deviation metric, representing the relative distance of a measured value from its statistical reference range, as defined on Equation (4). Based on RI values, engine condition was classified into three categories:

$$RI = \frac{X_{obs}}{UCL} \tag{4}$$

where X_{obs} is the observed parameter value and UCL is the upper control limit derived from the historical dataset.

- Normal (Green): RI < 1
- Warning (Yellow): RI ≈ 1
- Abnormal (Red): RI > 1

This classification provides a clear and consistent basis for evaluating operational risk and determining appropriate maintenance actions.

2.6. Decision-oriented maintenance evaluation

The final output of the methodology is a condition-based maintenance recommendation derived from the OSA-CBM decision-support layer. By combining wear rate trends, IQR-based control limits, and risk index classification, the methodology enables an objective assessment of whether the engine remains in stable operating condition or requires immediate corrective action. This approach supports justified life extension decisions for aging equipment while maintaining acceptable operational risk levels.

3. Results and Discussion

This section presents the results of oil analysis and discusses their implications for engine condition assessment and maintenance decision-making. The evaluation focuses on wear metal behavior and lubricant condition, interpreted using trend analysis and statistical boundaries derived from the IQR method. The discussion emphasizes engineering judgment rather than raw data reporting, in accordance with condition-based maintenance principles.

3.1. Wear metal trend analysis

The primary wear metal parameters evaluated in this study are iron (Fe), chromium (Cr), and aluminum (Al), which represent wear mechanisms associated with critical engine components such as cylinder liners, piston rings, and piston assemblies as shown in Table 1 and Figure 3. These parameters were analyzed using historical trend data to assess wear progression and identify abnormal behavior.

Table 1. Representatives wear metal data.

Sampling Date	Hours Meter (h)	Fe (ppm)	Cr (ppm)	Al (ppm)
1-May-24	13,515	24	1	2
7-Jun-24	14,019	18	1	1
10-Jul-24	14,495	18	1	0
1-Aug-25	18,534	11	1	1
10-Sep-25	19,028	14	0	1
28-Oct-25	19,549	24	1	8
13-Nov-25	19,755	6	0	0

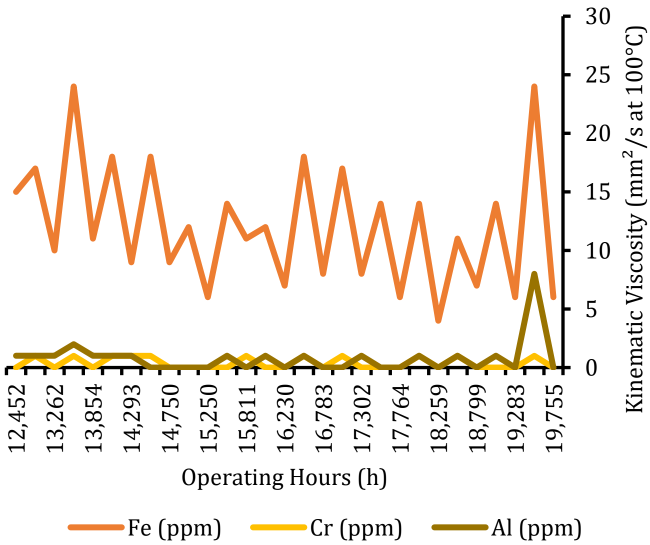

Figure 3. Trend of Fe, Cr, and Al (all Samples).

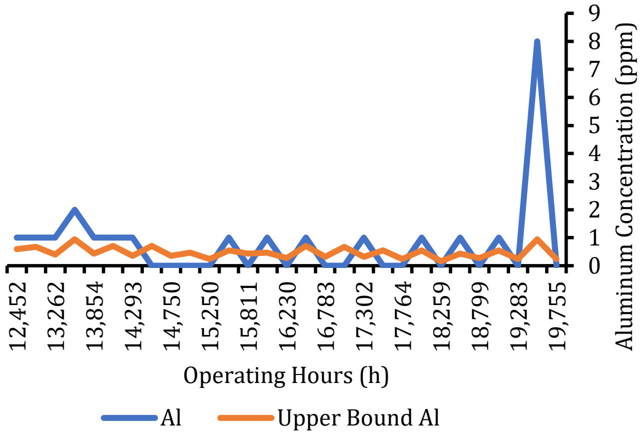

Figure 4. Aluminum concentration trend with IQR-based control limits.

The representative data indicate that Fe exhibits the highest absolute concentration among the analyzed wear metals, which is expected due to its dominance as a structural material in engine components. However, despite fluctuations, Fe does not show a sustained upward trend across the monitoring period. Cr remains consistently low, indicating minimal wear associated with piston rings and cylinder liners.

The combined trend visualization confirms that Fe and Cr remain relatively stable even as the engine approaches 20,000 operating hours, as shown in Figure 3. This behavior suggests a steady-state wear condition rather than accelerated or runaway wear typically associated with end-of-life engine operation. The observed stability of Fe and Cr concentrations is consistent with the findings reported by [5], who demonstrated that steady wear metal concentrations indicate a stable tribological condition in heavy-duty mining equipment. Similarly, [10], [11], [12] reported that engines operating under normal wear conditions generally exhibit low variability in primary wear metals even during extended service intervals. The present findings therefore suggest that the motor grader engine remains in a steady-state wear regime despite exceeding the OEM-recommended overhaul interval.

3.2. Aluminum anomaly and episodic wear interpretation

While Fe and Cr demonstrate stable behavior, Al exhibits a significant spike at one sampling interval, reaching its maximum observed concentration within the dataset. Based on the IQR-based statistical evaluation, this condition results in a Risk Index (RI) exceeding unity, categorizing the parameter within the abnormal zone, as shown on Figure 4.

A deeper engineering interpretation indicates that this aluminum anomaly is not accompanied by a proportional increase in iron (Fe) or chromium (Cr). From a tribological standpoint, structural wear of aluminum-based components such as pistons would normally induce secondary wear on mating components, leading to concurrent increases in Fe and Cr. The absence of such correlated behavior strongly suggests that the aluminum spike represents episodic wear rather than progressive structural damage.

This episodic behavior may be attributed to transient external contamination, short-term abnormal operating conditions, or localized particle ingress, rather than a sustained mechanical failure mechanism. Consequently, reliance on a single-parameter threshold without multi-parameter validation could lead to false failure indications. The isolated aluminum excursion differs from the progressive wear patterns reported by [19], [20], where piston degradation resulted in simultaneous increases in aluminum, iron, and chromium concentrations. In contrast, the absence of correlated increases in Fe and Cr observed in the present study strongly suggests that the detected anomaly represents a transient event rather than an active wear propagation mechanism.

To further investigate whether the observed aluminum excursion was associated with progressive wear mechanisms, correlation analyses were performed between aluminum (Al) and the primary wear metals iron (Fe) and chromium (Cr), as shown in Figure 5. The results indicate weak relationships, with coefficients of determination (R^2) below 0.30 for both comparisons, as shown in Table 2.

The scatter plots show that elevated aluminum concentrations were not accompanied by proportional increases in Fe or Cr. From a tribological perspective, progressive piston or

Table 2. Correlation analysis between aluminum and other wear metals

Relationship	Correlation Coefficient (r)	R^2	Interpretation
Al vs Fe	0.47	0.22	Weak correlation
Al vs Cr	0.31	0.10	Very weak correlation

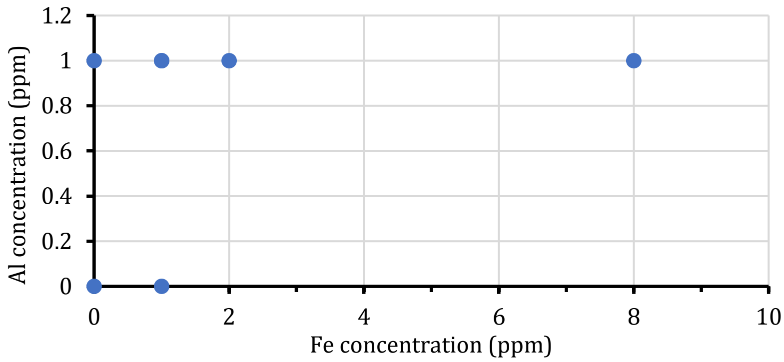

Figure 5. Relationship between aluminum and iron concentration.

liner wear would normally generate correlated increases across multiple wear metal species. The absence of such behavior suggests that the aluminum excursion represents an isolated and episodic event rather than a sustained wear mechanism.

These findings provide additional statistical support for the interpretation derived from the IQR-based anomaly assessment and strengthen the maintenance recommendation that immediate overhaul is not required.

A sensitivity analysis was conducted by varying the IQR multiplier (k = 1.5, 2.0, and 3.0), as shown in Table 3. Although the upper control limit changed with the multiplier value, the observed aluminum peak remained above all calculated thresholds. Therefore, the engineering interpretation and maintenance recommendation remained unchanged, demonstrating the robustness of the proposed framework.

3.3. Oil condition evaluation

In addition to wear metals, lubricant condition parameters were evaluated to determine whether the oil remained capable of protecting internal engine components during extended service life. Kinematic viscosity and Total Base Number (TBN) were used as primary indicators of lubricant degradation, oxidation, and acid-neutralizing capability, as shown in Figure 6.

The results show that kinematic viscosity remains within the operational range for SAE 15W-40 lubricants, indicating the absence of excessive oxidation or fuel dilution. Furthermore, TBN values remain within the green zone, demonstrating sufficient alkaline reserve to neutralize acidic by-products of combustion. These findings confirm that, despite the engine operating far beyond the OEM-recommended overhaul interval, lubricant performance remains adequate. The stable viscosity and TBN values further support the interpretation that the lubrication system remains in a healthy condition. Similar observations were reported by [17] who demonstrated that lubricant properties could remain within acceptable limits even during extended service periods when wear generation remains controlled.

Table 3. Sensitivity analysis of IQR multiplier

k Value	UCL Al (ppm)	Classification
1.5	2.5	Abnormal
2.0	3.0	Abnormal
3.0	4.0	Abnormal

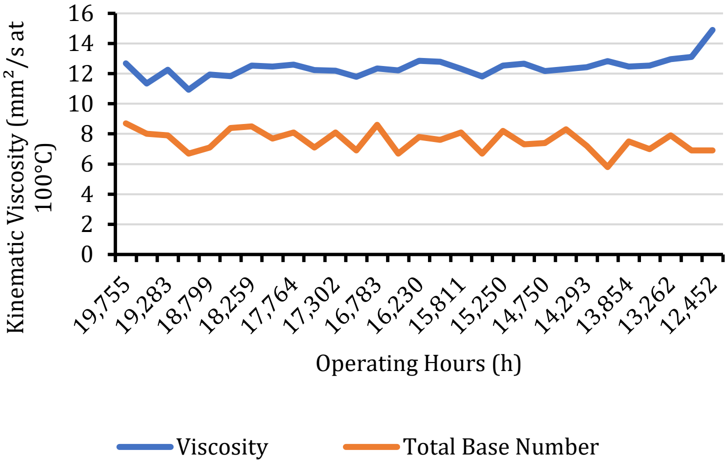

Figure 6. Trends of kinematic viscosity and TBN during the monitoring period.

3.4. Integrated condition assessment and maintenance implications

By integrating wear metal trends, lubricant condition parameters, and IQR-based risk classification within the OSA-CBM framework, the engine condition can be categorized as stable but require increased monitoring. Although aluminum exhibits an episodic anomaly, the absence of supporting evidence from Fe and Cr trends, combined with stable lubricant properties, indicates that the engine has not entered a rapid wear phase, as shown in Table 4.

IQR-based indices for viscosity and TBN are used solely as deviation indicators and do not represent oil condemnation thresholds.

3.5. Benchmark comparison with alternative methods

To evaluate the robustness of the proposed IQR-based approach, the results were compared with two commonly used statistical monitoring techniques: Z-score analysis and Shewhart 3-sigma control limits, as shown in Table 5. All methods consistently identified Fe and Cr as operating within acceptable conditions. However, the aluminum excursion was detected more clearly by the IQR-based method due to its robustness against skewed distributions and small sample sizes. The comparison suggests that the proposed approach provides a more conservative and interpretable anomaly detection mechanism for limited oil analysis datasets. The benchmark values presented in Table 5 are intended to provide practical engi-

Table 4. Risk and deviation index classification of key oil analysis parameters.

Parameter	Method	Representative Index Value	Criterion	Status
Iron (Fe)	IQR-based Risk Index	0.94	RI < 1	Green
Chromium (Cr)	IQR-based Risk Index	0.40	RI < 1	Green
Aluminum (Al)	IQR-based Risk Index	3.20	Isolated spike	Yellow (Watch)
Viscosity (V100)	IQR-based Deviation Index	1.11	Within SAE 15W-40	Green
TBN	IQR-based Deviation Index	0.89	> 50% fresh TBN	Green

Table 5. Benchmark comparison with alternative methods.

Parameter	IQR	Z-score	3 Sigma
Fe	Normal	Normal	Normal
Cr	Normal	Normal	Normal
Al	Abnormal	Warning	Normal

neering context for interpreting the observed oil analysis results. These reference values were compiled from established lubricant analysis literature and industry guidelines and are not intended to function as universal failure thresholds. Consequently, the final maintenance recommendation is based on the integrated OSA-CBM assessment framework rather than on any single benchmark value.

Based on the integrated evaluation of wear metal trends, viscosity behavior, and TBN depletion, the overall condition of the engine lubrication system is classified as stable with monitoring requirement. The majority of wear-related parameters, including iron (Fe) and chromium (Cr), exhibited consistently low and stable risk index values, indicating normal wear behavior throughout the monitoring period. An isolated aluminum (Al) excursion exceeding the IQR-based upper limit was observed; however, the absence of persistence and the lack of correlation with other wear metals suggest a non-progressive and episodic event rather than an active wear mechanism. Furthermore, viscosity values remained within the SAE 15W-40 specification range, and TBN levels stayed above the defined condemning threshold, confirming that the lubricant retained adequate physical and chemical properties. Therefore, the observed condition does not indicate imminent failure, but continued monitoring is recommended to detect any potential trend escalation

In the present study, wear metal trends remained stable despite the engine operating beyond the conventional OEM overhaul interval. This observation supports the argument that maintenance decisions should be based on actual equipment condition rather than fixed operating-hour thresholds alone. From a tribological perspective, progressive wear mechanisms are typically characterized by correlated increases in multiple wear metals originating from interacting mechanical surfaces. For example, accelerated piston wear would normally produce elevated aluminum concentrations together with increased iron and chromium levels due to secondary wear of cylinder liners and piston rings. However, the observed aluminum excursion was not accompanied by corresponding increases in Fe or Cr concentrations. This behavior suggests that the aluminum anomaly was more likely associated with transient contamination, localized particle ingress, or a short-duration operating disturbance rather than an active wear propagation mechanism. Therefore, interpreting the aluminum spike as evidence of imminent failure would likely result in a false-positive maintenance decision.

The results also demonstrate the practical advantages of using IQR-based statistical boundaries for industrial oil analysis datasets. Unlike conventional mean-based approaches, the IQR method is less sensitive to isolated extreme values and therefore provides more robust anomaly detection when monitoring records are limited. This characteristic is particularly important in mining applications where oil sampling frequency is relatively low and historical datasets are often sparse. A key contribution of this study lies in the integration of dynamic statistical control limits within the OSA-CBM architecture. While previous studies have focused either on oil condition monitoring or on the implementation of OSA-CBM frameworks separately, limited research has demonstrated how unit-specific statistical thresholds can be embedded directly into the Health Assessment and Decision Support layers of OSA-CBM. By combining engineering-based lubricant evaluation criteria with IQR-derived statistical boundaries, the proposed framework provides a practical mechanism for reducing unnecessary overhaul actions while maintaining acceptable operational risk levels for aging mining equipment.

From an engineering management perspective, the findings suggest that condition-based maintenance strategies can support safe life-extension decisions for aging heavy-duty engines. Instead of relying solely on OEM-recommended overhaul intervals, maintenance planners can utilize historical oil analysis data and dynamic statistical limits to evaluate actual equipment condition. Such an approach may reduce premature overhaul costs, improve equipment availability, and optimize maintenance resource allocation without compromising operational reliability. These benefits are particularly relevant for mining operations where equipment downtime directly affects production performance and operational profitability.

3.6. Sensitivity analysis of IQR multiplier

To evaluate the robustness of the proposed IQR-based framework, a sensitivity analysis was conducted by varying the IQR multiplier (k) used in the calculation of statistical control limits. Three commonly used values were examined: k = 1.5, k = 2.0, and k = 3.0. The objective of this analysis was to determine whether changes in the control limit formulation would significantly alter the condition assessment results and maintenance recommendations. The analysis focused on the aluminum (Al) parameter because it was the only wear metal exhibiting an excursion beyond the normal operating range.

Table 6. Sensitivity analysis of IQR multiplier.

IQR Multiplier (k)	UCL Al (ppm)	Maximum Observed Al (ppm)	Classification
1.5	2.5	8	Abnormal
2.0	3.0	8	Abnormal
3.0	4.0	8	Abnormal

Table 6 summarizes the resulting upper control limits and corresponding condition classifications.

The results indicate that the aluminum excursion remains above the calculated upper control limit for all tested multiplier values. Although increasing the multiplier widens the statistical acceptance range, the observed peak concentration of aluminum continues to be classified as an anomaly. More importantly, the overall maintenance recommendation remains unchanged across all evaluated scenarios. The anomaly continues to be interpreted as an isolated and episodic event because no corresponding increase is observed in the primary wear metals Fe and Cr, and lubricant condition indicators remain within acceptable limits. The benchmark comparison indicates that both methods produce similar interpretations for the Fe and Cr trends, which remain within acceptable operating conditions. However, the IQR-based approach is considered more appropriate for the present application because the available dataset is limited and may not satisfy the assumptions required by mean-based statistical methods.

Moreover, the quartile-based formulation reduces the influence of isolated observations on the calculated control limits, making the approach more suitable for exploratory anomaly detection in sparse industrial monitoring datasets. Therefore, the IQR method was selected as the primary analytical tool within the proposed OSA-CBM framework. The proposed methodology demonstrates how statistical oil analysis techniques can be systematically integrated into the OSA-CBM architecture. In particular, the IQR-based anomaly detection supports the Health Assessment layer, while the combination of correlation analysis and tribological interpretation contributes to the Prognostic Assessment process. The final maintenance recommendation is generated within the Decision Support layer by integrating statistical indicators with engineering judgment, thereby providing a practical implementation of the ISO 13374 framework. These findings demonstrate that the proposed OSA-CBM decision framework is not highly sensitive to reasonable variations in the IQR multiplier. Therefore, the resulting maintenance recommendation can be considered robust and reliable for practical industrial implementation.

3.7 Scientific implications

The findings of this study provide three important scientific implications. First, the results demonstrate that unit-specific statistical boundaries can provide more reliable condition assessment than static OEM thresholds. Second, the study shows that simple non-parametric statistical methods can be effectively integrated into the OSA-CBM architecture to support practical maintenance decision-making. Third, the findings suggest that sparse historical datasets can still provide meaningful information for operational readiness assessment when combined with engineering interpretation and multi-parameter analysis.

Compared with previous studies, the proposed framework offers several contributions. First, it embeds IQR-based anomaly detection directly into the Health Assessment and Decision Support layers of OSA-CBM. Second, the framework establishes unit-specific statistical thresholds derived from historical operating data instead of relying on generic threshold values. Third, the framework demonstrates a practical methodology for supporting life-extension decisions of aging heavy-duty equipment under limited data availability.

3.8 Future research directions

Although the proposed framework demonstrates the practical applicability of integrating IQR-based statistical control limits within the OSA-CBM architecture, several opportunities remain for further improvement. First, the present study was conducted using historical oil analysis data from a single motor grader engine; therefore, future studies should validate the proposed methodology using larger datasets collected from multiple machines, engine types, and operating environments to improve the generalizability and robustness of the findings. Second, the current assessment focused primarily on selected wear metals and lubricant condition parameters, including iron (Fe), chromium (Cr), aluminum (Al), viscosity, and TBN. Future research may incorporate additional diagnostic indicators, such as copper (Cu), lead

(Pb), particle count, oxidation, and nitration, to provide a more comprehensive evaluation of engine health. Furthermore, integrating machine learning and predictive analytics techniques could enhance anomaly detection capability and enable Remaining Useful Life (RUL) estimation for critical engine components. Finally, the integration of Industrial Internet of Things (IIoT) technologies and Digital Twin platforms could facilitate real-time condition monitoring, continuous data synchronization, and automated maintenance decision support, thereby extending the applicability of the proposed framework toward intelligent and autonomous maintenance systems for heavy-duty equipment.

4. Conclusions

This study applied an Interquartile Range (IQR)-based analytical approach combined with absolute oil condition criteria to evaluate the operational feasibility of the engine lubrication system. The results demonstrate that wear metal behavior, particularly iron (Fe) and chromium (Cr), remained within normal limits and exhibited stable trends throughout the monitoring period. Although an isolated aluminum (Al) excursion exceeded the IQR-based upper limit, the absence of persistence and cross-parameter correlation indicates a non-progressive and episodic wear event. Furthermore, viscosity values consistently complied with the SAE 15W-40 specification, and Total Base Number (TBN) levels remained above the defined condemning threshold, confirming adequate lubricant physical and chemical integrity. Overall, the engine condition is classified as stable with monitoring requirement, supporting continued operation while emphasizing the importance of routine oil analysis to detect potential trend escalation at an early stage. Although the proposed IQR-based analytical framework provides a practical approach for interpreting oil analysis data within the OSA-CBM architecture, several opportunities remain for further development. First, future research may explore the integration of machine learning models to improve predictive capability for wear progression and lubricant degradation. Data-driven models such as random forest, support vector regression, or deep learning could be used to estimate remaining useful life (RUL) of engine components based on historical oil analysis data. Second, the current study focuses primarily on key wear metals (Fe, Cr, and Al) and lubricant condition parameters (viscosity and TBN). Future studies could incorporate additional parameters such as copper (Cu), lead (Pb), particle count, oxidation, and nitration to provide a more comprehensive engine health assessment. Third, the proposed methodology was applied to a single motor grader engine operating in a mining environment. Further validation across multiple machines, different engine models, and various operational environments would help improve the generalizability and robustness of the approach. Finally, integration of real-time monitoring systems and industrial Internet of Things (IoT) platforms could enable automated condition assessment and continuous maintenance decision support within digital maintenance management systems.

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Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

The author(s) used OpenAI's ChatGPT (GPT-5.5) to assist in language editing, manuscript refinement, reviewer response preparation, and improving the organization and clarity of the scientific writing. The AI tool was used solely as a writing assistance tool and was not involved in data generation, data analysis, interpretation of results, or the final scientific decision-making process. All AI-generated content was critically reviewed, revised, and validated by the authors. The author(s) take full responsibility for the scientific accuracy, originality, and integrity of the manuscript, in accordance with the guidelines of the Committee on Publication Ethics (COPE)

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