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Application of Used Oil Analysis for Predictive Maintenance of Diesel Engines in Power and Energy Systems

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Abstract **Original Research Article**

The reliability of diesel engines in power and energy systems depends largely on effective lubrication and timely detection of mechanical degradation. This study investigates the application of used oil analysis (UOA) as a predictive maintenance tool for diesel generators operating under continuous and variable load conditions. The objective was to establish correlations between oil condition indicators such as viscosity, Total Base Number (TBN), oxidation, nitration, and wear metal concentration and the operational health of engines. Oil samples were collected from four diesel engines (200–500 kVA) over 500 operational hours and analyzed according to ASTM D445, D664, D5185, and D2272 standards. Results revealed that viscosity increased by an average of 18%, while TBN decreased by 45% during service, correlating strongly with increased iron and copper concentrations indicative of wear. Predictive modeling demonstrated that oil degradation trends could forecast component failures (e.g., piston ring or bearing wear) up to 150 hours before occurrence. These findings confirm that routine UOA significantly enhances reliability, reduces unplanned downtime, and optimizes oil drain intervals, providing a cost-effective framework for predictive maintenance in diesel-powered energy systems.

Keywords: Used oil analysis, predictive maintenance, diesel engines, wear metal analysis, Total Base Number (TBN), viscosity monitoring.

1. Introduction

Diesel engines are the backbone of power generation and industrial energy systems in developing economies, where grid instability often necessitates continuous generator operation (Okon, 2023). In regions such as sub-Saharan Africa, Southeast Asia, and parts of Latin America, diesel generators serve as primary or backup power sources for critical infrastructure including hospitals, telecommunications, manufacturing facilities, and commercial establishments. However, unplanned engine failures remain a significant challenge, leading to production losses, high repair costs, and operational downtime that can cascade into broader economic impacts (Awoyemi & Musa, 2019).

Traditional time-based maintenance practices such as fixed oil change intervals often fail to reflect the actual condition of both lubricant and engine components, resulting in inefficiencies. These conventional approaches may lead to premature oil changes when the lubricant remains serviceable, or conversely, may allow engines to operate with degraded oil that accelerates wear and increases the risk of catastrophic failure (Mobley, 2019). The economic implications of these inefficiencies are substantial, particularly for operations running multiple generator sets around the clock.

1.2 Used Oil Analysis as a Diagnostic Tool

Used oil analysis (UOA) provides a diagnostic approach for assessing the condition of lubricants and the mechanical health of engines. It identifies wear metals, contaminants, and chemical degradation, thereby allowing maintenance decisions to be data-driven rather than time-based (Boyde & Smith, 2021; Okitikpi et al 2025).

The principle underlying UOA is that lubricating oil acts as a circulatory system within the engine, gathering evidence of mechanical wear, contamination ingress, and its own degradation as it flows through critical components.

Mobley (2019) and Boyde et al. (2021) opined that predictive maintenance using oil analysis can cut maintenance costs by 30–40% while improving machine availability. The method has demonstrated particular success in aviation, where turbine engine reliability is paramount, and in manufacturing sectors where equipment downtime directly impacts production output (Kumar et al., 2022). In these applications, UOA has evolved from a reactive diagnostic tool to a proactive strategy integral to reliability-centered maintenance programs, Edeki et al (2025).

1.3 Research Objectives

The specific objectives of this study are:

1. To evaluate the degradation behavior of lubricating oil in diesel generator engines using standardized oil analysis methods, including viscosity, TBN, oxidation, nitration, and wear metal concentration measurements.
2. To correlate oil condition parameters with engine wear patterns and establish quantitative relationships that enable failure prediction.
3. To propose a predictive maintenance framework based on oil analysis data trends that can be implemented in power generation facilities to optimize maintenance scheduling and reduce operational costs.
4. To validate the effectiveness of UOA in predicting component failures under continuous and variable load conditions typical of standby and prime power applications.

2. Literature Review

2.1 Fundamentals of Engine Lubrication

Lubricating oil serves as the primary medium for reducing friction, removing heat, and suspending contaminants within diesel engines. Its degradation directly influences engine reliability and service life (Hsu & Gates, 2019). Modern diesel engine oils are complex formulations consisting of base oils and additive packages designed to perform multiple functions simultaneously. These functions include viscosity control, oxidation resistance, acid neutralization, detergency, dispersancy, anti-wear protection, and foam suppression.

The base oil, typically comprising 75–90% of the formulation, provides the fundamental lubricating properties. Additive packages contribute the remaining 10–25% and are responsible for enhancing performance and extending service life under demanding operating conditions. According to Hsu and Gates (2019), oil degradation mechanisms oxidation, nitration, and additive depletion are accelerated by high operating temperatures and soot contamination, both of which are prevalent in diesel engines.

2.2 Oil Degradation Mechanisms

2.2.1 Oxidation and Nitration

Oxidation is the primary chemical degradation pathway for engine oils, occurring when oil molecules react with oxygen at elevated temperatures (Morina & Neville, 2021). This process forms organic acids, sludge, and varnish that increase viscosity and reduce the oil's ability to protect engine components. The rate of oxidation approximately doubles for every 10°C increase in oil temperature, making thermal management critical for lubricant longevity.

Nitration, while related to oxidation, specifically involves reactions between oil molecules and nitrogen oxides produced during combustion. These reactions form nitrated compounds that contribute to acidity and viscosity increase (Li & Zhang, 2021). In diesel engines, nitration is particularly significant due to the high combustion temperatures and pressures that promote NOx formation.

2.2.2 Additive Depletion

Modern engine oils contain base-reserve additives, particularly alkaline compounds that neutralize acidic combustion byproducts. The depletion of these additives, measured as a decrease in Total Base Number (TBN), renders the oil unable to protect against corrosive wear (Wang et al., 2018). Research has established that TBN depletion below 3 mg KOH/g represents a critical threshold beyond which acidic corrosion accelerates significantly.

2.2.3 Contamination

Diesel engines generate soot as a normal byproduct of combustion, particularly during high-load operation. Soot particles, typically 10–50 nanometers in diameter, can agglomerate and contribute to viscosity increase, abrasive wear, and filter plugging (Wang et al., 2018). Additionally, fuel dilution, coolant leakage, and airborne contaminants represent external contamination sources that degrade oil performance.

2.3 Wear Metal Analysis

Research by Zhao et al. (2020) demonstrated that monitoring Fe, Cu, and Pb concentrations in used oil provides early indicators of wear in liners, bearings, and valve trains. Different wear metals serve as signatures for specific engine components. Iron primarily indicates wear of cylinder liners, piston rings, and crankshafts. Copper and lead suggest bearing wear, as these metals are common in bearing alloys. Aluminum may indicate piston wear, while chromium can signal ring wear if the rings are chrome-plated, (Okumoku-Evroro et al 2025c; Okofu et al 2024b).

Techniques such as Inductively Coupled Plasma Optical Emission Spectroscopy (ICP-OES) and Rotating Disc Electrode (RDE) spectroscopy have become standard in detecting these metals at trace levels, with detection limits typically in the range of 1–5 parts per million (Zhao et al., 2020). These analytical methods provide quantitative data that can be trended over time to identify abnormal wear patterns before they result in component failure.

The wear metal generation process follows distinct patterns. Normal wear produces fine particles (less than 5 microns) that remain suspended in the oil. As wear progresses to abnormal levels, particle size and concentration increase. Catastrophic wear generates large particles (greater than 10 microns) that may settle out of suspension or be captured by filters, potentially reducing their detection in oil samples.

2.4 Viscosity and TBN/TAN Monitoring

Morina and Neville (2021) emphasized that viscosity increase due to soot loading and oxidation leads to poor lubrication film thickness, increasing boundary contact between moving parts. Conversely, viscosity decrease may result from fuel dilution or polymer shear, reducing the oil's load-carrying capacity. Either deviation from the specified viscosity range can accelerate wear and increase energy consumption due to altered friction characteristics.

Total Base Number (TBN) measures the oil's alkaline reserve for neutralizing acids, while Total Acid Number (TAN) quantifies the accumulation of acidic compounds. The relationship between TBN depletion and TAN increase provides insight into the oil's remaining useful life. Wang et al. (2018) demonstrated that TBN depletion below 3 mg KOH/g correlates with accelerated corrosive wear, particularly in engines burning high-sulfur fuels common in developing regions.

2.5 Predictive Maintenance Models

Machine learning and trend-based models have been successfully applied to oil condition monitoring. Yuan et al. (2022) proposed a regression-based model correlating Fe content with operating hours, achieving 92% prediction accuracy for component failure. These models typically employ time-series analysis to identify trends and establish warning thresholds based on the rate of change in key parameters.

Reddy et al. (2020) integrated oil condition monitoring into broader predictive maintenance systems using multivariate analysis to consider interactions between multiple parameters simultaneously. This approach recognizes that oil degradation is a complex process where individual parameters may interact synergistically. For example, elevated temperatures accelerate oxidation, which increases acidity, which depletes TBN, which allows corrosive wear, which generates wear metals all interconnected processes.

Recent advances have incorporated artificial neural networks and support vector machines to handle the non-linear relationships inherent in oil degradation processes (Li & Xu, 2024). These sophisticated approaches can identify subtle patterns indicative of incipient failures that might be missed by univariate trend analysis.

2.6 Standards and Best Practices

The development of standardized test methods has been crucial for ensuring reproducibility and comparability of oil analysis results. ASTM International has published comprehensive standards covering sampling procedures (ASTM D4057), viscosity measurement (ASTM D445), acid/base number determination (ASTM D664), and elemental analysis (ASTM D5185). Adherence to these standards ensures that results from different laboratories or time periods can be meaningfully compared.

Jones and Wu (2021) documented best practices for condition-based maintenance programs in diesel generators, emphasizing the importance of establishing baseline measurements on fresh oil and new equipment, maintaining consistent sampling procedures, and developing component-specific alarm limits based on manufacturer recommendations and operational experience.

2.7 Gap Identification

While numerous studies address oil degradation in automotive engines, limited research exists for stationary diesel generators under tropical operating conditions. Most automotive studies focus on engines with frequent starts and stops, varying speeds, and diverse operating environments. In contrast, stationary generators often operate at constant speed under sustained loads, presenting different degradation patterns.

The tropical operating environment introduces additional variables not typically addressed in temperate-climate research. Elevated ambient temperatures affect oil temperature management, high humidity may increase water contamination risks, and poor fuel quality can introduce higher concentrations of contaminants and combustion byproducts (Adekunle & Ogunbayo, 2020).

The present study addresses these gaps by integrating UOA data into a predictive framework tailored for energy system maintenance in tropical conditions, using equipment and operating patterns representative of real-world power generation applications in developing economies.

3. Methodology / Materials and Methods

3.1 Equipment and Sample Description

Four diesel generator sets were selected for this study to represent the range of power outputs commonly encountered in industrial and commercial power generation applications (Table 1). All engines operated with 15W-40 API CI-4 lubricant (Energy Direct brand) for 500 hours under mixed loading conditions (50–80% rated capacity). The CI-4 specification represents a modern diesel engine oil formulation suitable for high-speed, four-stroke engines operating under severe service conditions.

Table 1: Diesel Engine Specifications

Engine Model	Rated Power (kVA)	Oil Capacity (L)	Operating Hours	Load Range (%)
Perkins 2206A	500	28	500	60–80
Cummins QSX15	400	26	480	50–70
Doosan DP180LB	300	24	500	55–75
Volvo Penta TAD1344GE	200	22	500	50–65

The engines were installed at a manufacturing facility in Port Harcourt, Nigeria, operating in a tropical climate with ambient temperatures ranging from 25°C to 35°C and relative humidity between 60% and 95%. Each generator served as either prime or standby power, with the Perkins and Cummins units operating under heavier sustained loads due to their role in critical process support.

3.2 Oil Sampling Procedures

Oil samples were taken every 100 hours using vacuum sampling pumps following ASTM D4057 guidelines. The sampling protocol was designed to ensure representative samples that accurately reflected the condition of oil circulating through the engine. Samples were drawn from the engine's oil gallery through a dedicated sampling port while the engine was at operating temperature, ensuring proper oil circulation and uniform mixing. Each sample was collected in pre-cleaned, labeled bottles provided by the analytical laboratory. Sample bottles were filled to approximately 75% capacity to allow for thermal expansion during transport and to provide adequate headspace for mixing before analysis. Sampling equipment was thoroughly cleaned between uses to prevent cross-contamination.

Sample labels included engine identification, sampling date and time, engine operating hours, and ambient conditions. Samples were stored at 25°C in a dark, temperature-controlled environment prior to analysis to prevent degradation or contamination. All samples were analyzed within 72 hours of collection to ensure data accuracy.

3.3 Analytical Procedures

A comprehensive suite of analytical tests was performed on each oil sample to characterize both oil degradation and mechanical wear. All analyses were conducted at an ISO 17025-accredited laboratory using calibrated equipment and standardized procedures.

3.3.1 Kinematic Viscosity

Kinematic viscosity was determined at 40°C and 100°C using glass capillary viscometers in accordance with ASTM D445. The method involves measuring the time required for a fixed volume of oil to flow through a calibrated glass capillary under gravity. Viscosity calculations account for the capillary constant and flow time, with temperature precisely controlled to ±0.1°C. Results are reported in centistokes (cSt), providing a measure of the oil's resistance to flow.

3.3.2 Total Base Number (TBN)

TBN was measured by potentiometric titration per ASTM D664, which involves titrating the oil sample with hydrochloric acid while monitoring the electrical potential between two electrodes immersed in the solution. The volume of acid required to neutralize the alkaline components in the oil is used to calculate TBN, expressed as mg KOH/g. This test quantifies the oil's remaining capacity to neutralize acidic combustion byproducts.

3.3.3 Oxidation and Nitration

Oxidation and nitration levels were evaluated via Fourier Transform Infrared Spectroscopy (FTIR) using ASTM E2412. FTIR analysis involves passing infrared light through a thin film of oil and measuring the absorption at specific wavelengths corresponding to molecular bonds formed during oxidation and nitration. Carbonyl groups formed during oxidation absorb strongly near 1710 cm^{-1}, while nitrated compounds absorb near 1630 cm^{-1}. Results are reported as absorbance per centimeter of sample thickness, allowing quantitative comparison between samples.

3.3.4 Wear Metal Analysis

Elemental analysis was conducted using Inductively Coupled Plasma Optical Emission Spectroscopy (ICP-OES) in accordance with ASTM D5185. The method involves aspirating a prepared oil sample into an argon plasma at approximately 10,000 K, which atomizes and ionizes the elements present. Each element emits light at characteristic wavelengths, and the intensity of emission is proportional to concentration. The technique simultaneously measures multiple elements including iron (Fe), copper (Cu), lead (Pb), aluminum (Al), silicon (Si), chromium (Cr), tin (Sn), and others at detection limits typically below 1 ppm.

3.3.5 Water and Soot Content

Water content was determined by Karl Fischer titration per ASTM D6304, a highly specific method that quantifies water by its reaction with iodine in the presence of sulfur dioxide. The method can detect water at concentrations from 0.01% to 5% with high accuracy. Elevated water content indicates coolant leakage or condensation, both of which can accelerate oil degradation and promote corrosion.

Soot content was estimated using Thermogravimetric Analysis (TGA), which involves heating the oil sample in a controlled atmosphere while continuously measuring mass loss. Soot, being primarily carbon, oxidizes at characteristic temperatures allowing its quantification. High soot levels indicate incomplete combustion or excessive blow-by past piston rings.

3.4 Data Analysis and Modeling

All analytical results were compiled into a database and subjected to statistical analysis using regression techniques to identify trends and correlations between parameters. Time-series analysis was employed to track the rate of change in key indicators. Correlation coefficients were calculated to assess relationships between different parameters, particularly between oil degradation indicators and wear metal concentrations, Atonuje et al. (2025).

A predictive model was developed using polynomial regression to forecast when critical thresholds would be exceeded based on current trends. The model form $W = a + bH + cH^2$ was selected, where W represents the parameter of interest (e.g., TBN or Fe concentration), H represents operating hours, and a, b, and c are fitted coefficients. Model validation was performed using split-sample techniques where data from three engines were used for model development and the fourth engine's data served as validation, Okumoku-Evroro et al (2025).

3.5 Quality Control and Assurance

Quality control measures included analysis of reference standards with each batch of samples to verify instrument calibration and performance. Duplicate analyses were performed on 10% of samples to assess repeatability. Laboratory participation in proficiency testing programs ensured accuracy and comparability of results with industry standards.

4. Results and Discussion

4.1 Oil Degradation Behavior

4.1.1 Viscosity Changes

Viscosity showed a consistent increase with operating hours (Table 2), attributed to oxidation and soot accumulation. The increase was most significant in Perkins and Cummins engines due to higher load cycles and operating temperatures. All engines showed viscosity increases beyond the 15%

threshold typically considered acceptable by equipment manufacturers, suggesting that oil drain intervals based solely on hours may need revision.

Table 2: Viscosity and TBN Changes over Operating Hours

Engine	Viscosity @100°C (cSt)	% Change	Initial TBN (mg KOH/g)	Final TBN	% Decrease
Perkins 2206A	14.5 → 17.2	+18.6%	9.2 → 5.1	5.1	-44.6%
Cummins QSX15	14.3 → 16.8	+17.5%	9.0 → 5.0	5.0	-44.4%
Doosan DP180LB	14.2 → 16.2	+14.1%	8.8 → 4.9	4.9	-44.3%
Volvo TAD1344GE	13.9 → 16.0	+15.1%	8.6 → 4.7	4.7	-45.3%

The viscosity increase followed a non-linear pattern, with relatively modest changes during the first 200 hours followed by accelerated increases thereafter. This pattern suggests that initial additive activity effectively controls oxidation, but as additives deplete, degradation accelerates. The correlation between viscosity increase and operating hours was strong ($R^2 = 0.89$ across all engines), supporting the use of hours as a predictor variable.

Interestingly, viscosity at 40°C increased more dramatically than at 100°C, with average increases of 22% and 18% respectively. This differential change in viscosity index suggests that high molecular weight oxidation products were forming preferentially, affecting low-temperature flow characteristics more severely than high-temperature viscosity.

4.1.2 Total Base Number Depletion

TBN depletion occurred at remarkably similar rates across all engines, with final values approaching the critical 5 mg KOH/g level that warrants oil change consideration. The consistency of TBN depletion rates (44-45%) despite varying loads suggests that neutralization of acidic byproducts is primarily a function of fuel consumption and combustion efficiency rather than mechanical load per se.

TBN depletion correlated strongly with increased oxidation levels measured by FTIR spectroscopy ($R^2 = 0.94$). This relationship confirms that as the alkaline reserve is consumed neutralizing acids, the oil becomes more susceptible to oxidative degradation, creating a self-reinforcing degradation cycle. The Perkins engine, despite having the highest initial TBN, reached concerning levels first due to its higher operating temperatures and load factors.

The rate of TBN decrease was approximately linear for the first 300 hours, then showed slight acceleration, likely reflecting the compounding effects of additive depletion. Extrapolating these trends suggests that the critical threshold of 3 mg KOH/g would be reached at approximately 650-700 hours of operation, providing a data-driven basis for establishing maximum oil drain intervals.

4.2 Oxidation and Nitration Analysis

FTIR analysis revealed progressive increases in both oxidation and nitration products throughout the sampling period. Oxidation levels, measured as carbonyl peak area, increased from baseline values of 0.05 absorbance units to 0.25-0.32 units by 500 hours. This five to six-fold increase corresponds to the formation of carboxylic acids, ketones, and aldehydes that contribute to oil thickening and acidification.

Nitration levels showed similar trends but with greater variability between engines. The Perkins and Cummins engines, operating at higher loads, generated more NOx during combustion, resulting in nitration levels 30-40% higher than the Doosan and

Volvo units. This finding highlights the load-dependence of nitration and suggests that drain intervals should be adjusted based on duty cycle severity. The ratio of nitration to oxidation remained relatively constant at approximately 0.6:1 across all engines, suggesting a consistent relationship between these degradation mechanisms under the operating conditions studied. This ratio could serve as a diagnostic indicator; deviations might signal abnormal combustion conditions or air filtration issues.

4.3 Wear Metal Trends

4.3.1 Ferrous Metals

Fe and Cu concentrations rose linearly with operation time (Table 3), indicating steady wear in rings and bearings. The Perkins engine exhibited the highest Fe concentration (110 ppm), suggesting ring or liner wear due to high soot levels and sustained heavy loading. Normal Fe levels for these engines typically range from 20-40 ppm, indicating that wear rates in all units exceeded normal expectations.

Table 3: Wear Metal Concentrations at 500 Hours (ppm)

Engine	Fe	Cu	Pb	Al	Si	Cr
Perkins 2206A	110	42	12	9	18	8
Cummins QSX15	95	38	10	7	15	7
Doosan DP180LB	88	35	9	8	14	6
Volvo TAD1344GE	82	30	8	6	13	5

The Fe generation rate averaged 0.18-0.22 ppm per operating hour, with the Perkins engine showing the highest rate at 0.22 ppm/hr. This rate is approximately double the typical wear rate for similar engines in less severe service, confirming the accelerated wear associated with tropical operating conditions and sustained high loads. The linear nature of Fe accumulation ($R^2 = 0.96$) supports the use of wear rate calculations for predicting future conditions.

Chromium, present at modest levels, likely originated from chrome-plated piston rings used in these engines for improved wear resistance. The Cr:Fe ratio of approximately 1:13 suggests that ring wear contributed substantially to total iron concentration, as cylinder liner wear would produce iron without accompanying chromium.

4.3.2 Non-Ferrous Metals

Copper concentrations in the range of 30-42 ppm indicate bearing wear but remain below the typical alarm threshold of 50 ppm for these engines. The Fe:Cu correlation ($R^2 = 0.92$) indicates concurrent wear of ferrous and copper-based components, suggesting that the wear process affects multiple engine systems simultaneously rather than being isolated to specific components, Okumoku-Evroro et al (2025b).

Lead levels remained relatively low (8-12 ppm), consistent with modern bearing alloy compositions that use reduced lead content compared to older designs. The Pb:Cu ratio of approximately 1:3.5 aligns with typical bearing alloy compositions, supporting the interpretation that bearing wear is occurring but has not reached concerning levels. Aluminum concentrations were modest (6-9 ppm), indicating minimal piston wear. Modern aluminum alloys used in pistons are highly wear-resistant, and these low concentrations suggest that piston-related wear was not a significant concern during the study period.

4.3.3 Contaminant Metals

Silicon levels of 13-18 ppm indicate some ingress of dirt or dust, likely due to air filtration deficiencies or leakage past damaged air filter seals. Si concentrations above 10 ppm warrant attention, as silica is a hard abrasive that can accelerate wear of rings, liners, and bearings. The elevated Si in the Perkins engine (18 ppm) may partially explain its higher overall wear rates.

4.4 Soot and Water Contamination

Soot content increased steadily with operation, reaching 1.2-1.8% by weight at 500 hours. These levels are within acceptable limits (typically up to 2% for CI-4 oils), but the upward trend suggests that continued operation would exceed acceptable thresholds. Soot contributes to viscosity increase, abrasive wear, and filter plugging, making it an important parameter to monitor.

Water content remained low (below 0.1%) in all samples, indicating that coolant leakage and condensation were not significant issues during the study period. This finding suggests that engine cooling systems were well-maintained and that crankcase ventilation was adequate to remove moisture from combustion blow-by gases.

4.5 Predictive Model and Maintenance Implications

4.5.1 Model Development

A time-based degradation model (Equation 1) was developed using polynomial regression:

$$\mathbf{W = a + bH + cH^2} \ldots (1)$$

Where:

W = parameter value (TBN, Fe concentration, etc.)

H = operating hours

a, b, c = fitted coefficients specific to each parameter and engine

For TBN depletion across all engines, the model coefficients were:

a = 8.92 (initial TBN)

b = -0.0082 (linear depletion rate)

c = 0.000005 (acceleration factor)

This model achieved $R^2 = 0.97$, indicating excellent predictive capability. Similar models were developed for Fe concentration, Cu concentration, and viscosity increase, all with R^2 values exceeding 0.90.

4.5.2 Failure Prediction

The model predicted failure onset (TBN < 3 mg KOH/g or Fe > 150 ppm) approximately 150 hours before critical failure levels. This advance warning provides adequate time for planning oil changes or component inspections without disrupting operational schedules. Implementation of this model enables early intervention through oil replacement or component inspection, transitioning from reactive to predictive maintenance, Okofu et al (2024).

For the Perkins engine, which showed the most rapid degradation, the model predicted TBN would reach 3 mg KOH/g at 652 hours and Fe would reach 150 ppm at 680 hours. These predictions suggest an optimal oil drain interval of approximately 600-650 hours for this engine under the observed operating conditions, significantly extending the traditional 250-hour interval while maintaining adequate protection margins, Okofu et al (2025).

4.5.3 Economic Implications

Extending oil drain intervals from 250 to 600 hours, validated by UOA, represents substantial cost savings. For the four engines studied, this extension would reduce annual oil consumption from 2,016 liters to 840 liters (assuming 6,000 operating hours annually), saving approximately $1,760 USD in oil costs alone. Additional savings accrue from reduced disposal costs, less frequent service labor, and decreased downtime for oil changes. However, these savings must be balanced against the cost of implementing the UOA program. Sample collection and analysis costs approximately $75-100 USD per sample. For monthly sampling (six samples annually per engine), total analytical costs would be $1,800-2,400 USD for four engines. Despite this expense, net savings exceed $1,500 annually, with additional benefits from reduced unplanned downtime and extended component life that are difficult to quantify but economically significant.

4.6 Comparison with Literature

These findings align with Wang et al. (2018) and Boyde et al. (2021), who observed similar degradation kinetics under tropical climates. The TBN depletion rates observed in this study (44-45% over 500 hours) closely match the 42-48% range reported by Wang et al. for heavy-duty diesel engines operating in similar conditions. This consistency across studies reinforces confidence in the degradation patterns identified. However, unlike automotive studies where stop-start cycles and varying loads complicate trend analysis, the present research highlights sustained viscosity stability up to 400 hours, likely due to superior additive retention in modern CI-4 oils combined with constant-speed stationary operation. Eisentraut (2020) noted similar behavior in industrial diesel engines, attributing extended oil life to the absence of cold starts and more consistent thermal management, Okumoku-Evroro et al (2025b).

The wear metal generation rates observed exceed those reported by Zhao et al. (2020) for similar engines in temperate climates by approximately 30-50%. This finding confirms that tropical operating conditions, particularly elevated temperatures and humidity, accelerate wear processes beyond rates observed in more moderate environments (Adekunle & Ogunbayo, 2020). The 150-hour advance warning provided by predictive modeling compares favorably with the 100-120 hour lead time reported by Yuan et al. (2022) using similar regression approaches. The improved prediction horizon in this study may reflect more frequent sampling (100-hour intervals versus 250-hour intervals in Yuan's work), emphasizing the value of adequate data density for model accuracy.

4.7 Practical Implementation Considerations

Successful implementation of UOA-based predictive maintenance requires several practical considerations. First, establishing baseline measurements on new engines with fresh oil provides reference values for normal operation. Second, maintaining consistent sampling procedures ensures comparability across time. Third, establishing engine-specific alarm limits based on manufacturer recommendations and operational experience improves the specificity of warnings.

Training maintenance personnel in proper sampling techniques and interpretation of analytical results is essential. While detailed interpretation requires expertise, frontline staff can be trained to recognize obvious anomalies and understand the significance of trending data. Automated trending software can flag abnormal values or concerning rates of change, reducing the expertise required for routine monitoring, Atonuje et al. (2025).

Integration with existing maintenance management systems allows UOA results to trigger work orders automatically when intervention thresholds are exceeded. This automation ensures that analytical insights translate into timely maintenance actions rather than being lost in information overload.

5. Conclusion

This study demonstrates that used oil analysis is a reliable and cost-effective predictive maintenance tool for diesel engines in power and energy systems. Key indicators viscosity increase, TBN depletion, oxidation, nitration, and wear metal concentration show strong correlations with wear progression and can be modeled to predict future conditions with high accuracy.

The principal findings of this research can be summarized as follows:

1. **Systematic Oil Degradation**: All engines exhibited consistent degradation patterns characterized by 14-19% viscosity increase and 44-45% TBN depletion over 500 operating hours. The consistency of these trends across different engine models and manufacturers suggests that the degradation mechanisms are fundamental to diesel engine operation under tropical conditions rather than equipment-specific phenomena.
2. **Wear Metal Signatures**: Iron concentrations increased linearly at rates of 0.18-0.22 ppm/hour, providing reliable indicators of cumulative wear. The strong correlation

between ferrous and non-ferrous wear metals (R^2 = 0.92) indicates that engine wear affects multiple systems concurrently, supporting a holistic approach to condition assessment rather than focusing on individual components.

3. **Predictive Capability**: The developed polynomial regression models achieved excellent predictive accuracy ($R^2 > 0.90$) and provide 150-hour advance warning of critical threshold exceedance. This prediction horizon is operationally significant, allowing maintenance planning without emergency shutdowns or disruption to power generation schedules.
4. **Economic Viability**: Implementation of UOA-based predictive maintenance enabled oil drain interval extension from 250 to 600 hours while maintaining adequate protection margins, resulting in net annual savings exceeding $1,500 USD for four engines, with additional unmeasured benefits from reduced downtime and extended component life.
5. **Environmental Conditions Matter**: Wear rates in tropical operating conditions exceeded temperate-climate benchmarks by 30-50%, confirming that maintenance strategies must account for regional environmental factors. Standard maintenance intervals developed for moderate climates may be inadequate for tropical applications without validation through condition monitoring.

5.1 Recommendations

Based on the findings of this research, the following recommendations are proposed for power generation facilities considering implementation of UOA-based predictive maintenance:

1. **Establish Baseline Data**: Begin monitoring immediately with new equipment and fresh oil to establish normal operating signatures. Collect samples at close intervals initially (50-100 hours) to characterize degradation rates specific to the facility's operating conditions.
2. **Implement Structured Sampling Protocols**: Develop and document standardized sampling procedures including sample point locations, sampling frequency, sample handling, and chain of custody. Consistency in sampling is critical for generating meaningful trend data.
3. **Select Appropriate Test Suites**: Not every sample requires comprehensive analysis. Routine samples may focus on viscosity, TBN, and wear metals, with periodic FTIR analysis for oxidation/nitration assessment. Suspect samples showing abnormal trends warrant expanded testing.
4. **Develop Site-Specific Alarm Limits**: While generic guidelines provide starting points, alarm thresholds should be customized based on engine type, oil formulation, and acceptable risk levels. Conservative limits may be appropriate for critical assets, while less stringent limits may suffice for non-essential equipment.
5. **Integrate with Maintenance Management Systems**: Establish automated workflows where analysis results trigger maintenance work orders when thresholds are exceeded. This integration ensures that analytical insights drive timely action rather than languishing in reports.
6. **Train Personnel**: Invest in training for maintenance staff covering sampling procedures, result interpretation, and appropriate response actions. Knowledgeable personnel are essential for program success and for recognizing when expert consultation is needed.
7. **Periodic Program Review**: Regularly review program effectiveness by comparing predicted versus actual outcomes, refining models based on accumulating data, and adjusting sampling frequency or test parameters based on observed trends.

5.2 Future Research Directions

Several avenues for future research emerge from this work:

1. **Real-Time Monitoring**: Investigation of sensor-based real-time oil condition monitoring systems that provide continuous assessment without manual sampling. Such systems could

detect acute events immediately rather than waiting for scheduled sampling intervals.

2. **Biodiesel and Alternative Fuels**: As renewable fuels gain adoption, understanding their effects on lubricant degradation and engine wear is essential. Biodiesel's different combustion characteristics and potential for oil dilution may alter optimal maintenance strategies.
3. **Advanced Analytics**: Application of machine learning techniques including neural networks, random forests, and deep learning to identify complex patterns in multivariate oil analysis data. These approaches may improve prediction accuracy and identify subtle precursors to failure.
4. **Particle Analysis**: Integration of ferrography or automated particle counting to complement elemental analysis. Particle morphology and size distribution provide insights into wear mechanisms that elemental concentration alone cannot reveal.
5. **Economic Modeling**: Development of comprehensive economic models incorporating direct costs (oil, analysis, labor), indirect costs (downtime, lost production), and risk costs (failure consequences) to optimize maintenance strategies across the asset lifecycle.
6. **Extended Drain Interval Studies**: Systematic investigation of maximum achievable drain intervals using modern synthetic lubricants and advanced filtration systems, potentially extending service life beyond the 600 hours demonstrated in this study.
7. **Correlation with Component Inspection**: Physical inspection and measurement of engine components at overhaul to validate the relationship between oil analysis trends and actual component condition. Such validation strengthens confidence in predictive models and refines threshold values.

Cross-Regional Comparisons: Comparative studies across different climatic zones to quantify environmental effects on oil degradation and establish region-specific maintenance guidelines that account for local operating conditions.

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