

# OIL DEGRADATION MECHANISMS AND ROOT CAUSE ANALYSIS FOR ENHANCED MACHINERY RELIABILITY

**Karunanithi Thanaraj**

**Research Scholar, Department of Mechanical Engineering, Kennedy University**

**Registration No.: KUSLS20220144313**

## **Abstract**

*Lubricating oil degradation represents one of the foremost contributors to premature machinery failure in industrial systems. This study investigates the physicochemical and tribological mechanisms underlying oil degradation and applies root cause analysis (RCA) to enhance machinery reliability. The objectives were to quantify oil quality deterioration through kinematic viscosity, total acid number (TAN), total base number (TBN), and wear metal concentrations, and to identify the primary root causes of lubrication-related machinery failures. A systematic secondary data analysis design was employed, integrating peer-reviewed field studies and laboratory investigations published between 2019 and 2025. The hypothesis posits that progressive oil degradation driven by oxidation, thermal stress, additive depletion, and contamination is the principal root cause of unplanned machinery downtime. Results reveal that friction increases up to 9% while wear rates surge over 420% within a 20,000 km service cycle; iron concentrations average 23.72 ppm across diesel engine fleets; and AI-based predictive monitoring systems achieve 96.67% fault detection accuracy. These findings collectively support the adoption of condition-based maintenance frameworks for improved reliability engineering.*

**Keywords:** *oil degradation<sup>1</sup>, tribology<sup>2</sup>, root cause analysis<sup>3</sup>, machinery reliability<sup>4</sup>, condition-based maintenance<sup>5</sup>.*

## **1. Introduction**

The reliability of industrial machinery is fundamentally governed by the integrity of its lubrication system. Lubricating oils serve as the primary interface between metal surfaces, providing film separation, heat dissipation, and protection against corrosion and wear. However, oils are not static they undergo complex physicochemical degradation over their service life, progressively losing their protective capacity and exposing machinery components to accelerated deterioration (Johns-Rahnejat et al., 2023). The consequences of inadequately managed lubrication are severe: unplanned downtime, catastrophic component failure, and substantial economic losses across all sectors of industrial operation. Research has established that approximately 23% of total global energy consumption is attributable to tribological contacts, with 87% of that energy expended solely in overcoming friction (Duran et al., 2023). In the context of rotating machinery encompassing turbines, compressors, gearboxes, and hydraulic systems lubrication failure is a leading cause of equipment breakdown. Industry-wide surveys place lubrication-related failures among the top causes of bearing damage, accounting for 40–90% of rotating machinery failures across industrial sectors (Hou et al., 2022).

Oil degradation is not a singular event but a multifactorial, threshold-dependent process. Oxidation, thermal decomposition, mechanical shear, contamination by water and particulate matter, and additive depletion all contribute to oil quality deterioration over time (Agocs et al., 2022). The progressive decline in viscosity stability, acid neutralization capacity, and anti-wear additive concentration creates a cascade of tribological consequences increased boundary friction, elevated wear rates, and varnish formation on critical machine surfaces (Martini et al., 2018). Critically, early-stage rheological changes often mask escalating subsurface damage risk, making routine parameter-based monitoring insufficient without systematic analytical interpretation (Gupta & Muzakkir, 2023). Root cause analysis (RCA) is an essential diagnostic methodology for understanding the underlying drivers of machinery failure. In lubrication engineering, RCA enables maintenance engineers to trace observable failure symptoms bearing damage, excessive heat generation, or elevated wear metal concentrations back to specific oil degradation pathways. Without systematic RCA, organizations tend to address symptoms rather than root causes, resulting in recurring failures and escalating maintenance costs (Gao et al., 2023). A widely cited case study documented how turbine bearing failure, superficially attributed to product defect, was in reality caused by a sequence beginning with management-driven cost-cutting that delayed oil analysis and allowed oxidation products to form varnish deposits that progressively starved bearings of lubrication flow. Despite extensive research on individual degradation mechanisms, there remains a need for integrated studies connecting specific oil degradation pathways to machinery failure modes and monitoring strategies. This paper addresses that gap by examining established oil degradation mechanisms, applying RCA frameworks to failure data, and evaluating condition monitoring technologies for improving machinery reliability.

## 2. Literature Review

Scientific investigation of lubricating oil degradation has advanced considerably over the past decade, with field-based studies providing increasingly granular insights into real-world oil behavior. Dörr et al. (2019) conducted one of the first comprehensive chemical assessments of engine oil degradation across a full 20,000 km passenger car service cycle, demonstrating systematic deterioration in zinc dialkyl dithiophosphate (ZDDP) antiwear additive concentration alongside measurable increases in oxidation and nitration products. This foundational work was expanded by Agocs et al. (2022), who reported a 9% increase in friction coefficient and over 420% increase in wear rate in the same vehicle platform, establishing that tribological deterioration is disproportionate to observable rheological changes and confirming that standard viscosity-based alarm limits are insufficient for protecting machinery in late oil service life. Transmission oil degradation, comparatively less studied than engine oil, was investigated by Duran et al. (2023) through analysis of field-collected gear transmission oils from agricultural tractors. Their study identified viscosity drop and additive depletion as predominant degradation mechanisms and demonstrated that transmission oil evolution differs significantly from engine oil due to distinct thermal and mechanical loading profiles. The study reinforced that oil degradation is system-specific and cannot be characterized by universal thresholds alone. Besser et al. (2022) furthered this mechanistic understanding by showing that nitration processes must be explicitly incorporated into laboratory ageing simulations to achieve results representative of real field conditions a finding critical for validating artificial ageing protocols used in accelerated testing programs.

The quantitative prediction of oil degradation trajectories has been advanced through machine learning. Nazari et al. (2022) employed Gaussian Process Regression (GPR) to model kinematic viscosity degradation in industrial machinery, achieving an  $R^2$  of 0.618 and RMSE of 0.971 mm<sup>2</sup>/s, with a predicted maximum oil age of 31.9 months. Their Mahalanobis-Taguchi Gram-Schmidt analysis identified kinematic viscosity at 40°C and TAN as the most diagnostically significant parameters findings corroborated by Gupta and Muzakkir (2023), who demonstrated through online gearbox monitoring that TAN values exceeding 0.1 mg KOH/g reliably signal advanced additive breakdown and imminent surface damage. Extended oil drain intervals represent a major

reliability risk in fleet operations. Gołębiowski et al. (2024) evaluated oil degradation across two consecutive operational intervals in a real-world bus fleet, finding that phosphate anti-wear additive depletion correlated directly with mileage exceedance, while Wojciechowski et al. (2025) established a Spearman correlation of  $r = -0.810$  between sulfur content and wear scar diameter in the same fleet context, validating elemental analysis as a reliable diagnostic tool. Zhao et al. (2024) extended this diagnostic approach by demonstrating that engine oil chemical fingerprinting could identify impending cooling system failures in urban public transport, with copper concentrations reaching 274 ppm in buses that subsequently experienced engine failure. These fleet-scale studies collectively confirm that individualized oil analysis, rather than fixed-interval replacement, is necessary for reliable maintenance decision-making.

Wear metal monitoring through debris analysis has received substantial research attention. Sun et al. (2021) reviewed more than three decades of oil debris monitoring literature, concluding that real-time particle counting remains the most reliable early warning technology for bearing degradation, particularly for detecting incipient spalling and pitting before vibration signatures emerge. Advances in multi-sensor fusion, reported by Wang et al. (2025), demonstrate that deep learning frameworks achieve 96.67% fault detection accuracy with zero false alarms a transformative improvement over conventional single-parameter monitoring. Spikes (2025) provided updated mechanistic analysis of ZDDP tribofilm formation, clarifying competitive adsorption and decomposition pathways critical to anti-wear film longevity, while Raposo et al. (2019) confirmed that oil analysis data successfully predict equipment condition and optimize maintenance intervals in industrial case studies. Padgurskas et al. (2023) and Chokelarb et al. (2024) further demonstrated that integrating physical oil quality metrics with performance indicators substantially extends the predictive horizon for remaining useful life estimation, providing the quantitative basis for condition-based maintenance programs. The collective body of literature establishes oil degradation as a tractable, quantifiable phenomenon amenable to systematic RCA and predictive maintenance intervention.

### 3. Objectives

1. To quantify the progression of key physicochemical oil degradation parameters kinematic viscosity, TAN, TBN, and wear metal concentrations across different machinery service intervals and identify threshold conditions that precede component failure.
2. To identify and classify the primary root causes of lubrication-related machinery failures through systematic degradation-linked failure data analysis, and to evaluate the comparative effectiveness of condition monitoring technologies in reducing unplanned downtime.

### 4. Methodology

This study adopted a systematic secondary data analysis design, integrating peer-reviewed field investigations and laboratory-based tribological studies published between 2019 and 2025. The research design followed a convergent mixed-methods approach in which quantitative physicochemical data kinematic viscosity, TAN, TBN, wear metal concentrations, friction coefficients, and wear rates were extracted from verified empirical sources and synthesized into comparative analytical frameworks aligned with the study objectives. The data sample comprised six major empirical studies involving diesel and gasoline engine oils, gear transmission oils, and industrial hydraulic fluids. Operational samples spanned service intervals from fresh oil to extended drain conditions exceeding 80,000 km in fleet vehicles and up to 31.9 months in industrial rotating machinery. Oil types included SAE 5W-30, SAE 10W-40, and SAE 15W-40 grades assessed across passenger cars, commercial bus fleets, and agricultural transmission systems operating under real-world field conditions. Primary analytical tools and protocols used in the source studies included inductively coupled plasma optical emission

spectrometry (ICP-OES) for wear metal quantification, Fourier Transform Infrared (FTIR) spectroscopy for oxidation, nitration, and additive depletion assessment, Stabinger viscometer (Anton Paar SVM 3001) and Ubbelohde capillary viscometers for kinematic viscosity measurement, and acid-base titration for TAN and TBN determination following ASTM D445, ASTM E2412, and ASTM D2896 standard protocols. Tribological testing was conducted using the High Frequency Reciprocating Rig (HFRR) and Mini Traction Machine (MTM) for friction and wear evaluation. Root cause analysis was conducted using the Five-Why methodology and Fault Tree Analysis (FTA), applied to failure case data across source studies. Statistical relationships between degradation parameters and tribological outcomes were evaluated using Pearson and Spearman rank correlation coefficients. Condition monitoring methods were compared using fault detection accuracy, false alarm rate, and lead time before failure as standardized performance metrics.

## 5. Results

**Table 1: Physicochemical Properties of SAE 5W-30 Engine Oil Over 20,000 km Service Life**

Parameter	Fresh Oil	5,000 km	10,000 km	15,000 km	20,000 km
KV at 40°C (cSt)	68.2	71.4	76.8	82.3	89.7
KV at 100°C (cSt)	11.1	11.3	11.6	12.0	12.6
TAN (mg KOH/g)	0.80	1.20	2.10	3.40	4.90
TBN (mg KOH/g)	8.50	7.80	6.30	4.70	2.90
Viscosity Index	167	164	161	158	152

(Source: Agocs et al., 2022)

Table 1 documents the progressive deterioration of SAE 5W-30 engine oil over a 20,000 km passenger car service cycle. Kinematic viscosity at 40°C increased by 31.5% from 68.2 to 89.7 cSt indicating oxidative thickening consistent with accumulated insoluble degradation products. TAN rose from 0.80 to 4.90 mg KOH/g while TBN declined sharply from 8.50 to 2.90 mg KOH/g, reflecting progressive depletion of alkaline reserve. The declining viscosity index from 167 to 152 confirms shear-induced polymer degradation in viscosity modifiers, indicating that multigrade oil performance is substantially compromised before conventional drain limits are reached (Agocs et al., 2022).

**Table 2: Wear Metal Concentrations (ppm) in Diesel Engine Oil — Fleet Analysis (n = 555 Reports)**

Metal	Mean (ppm)	Q1 (ppm)	Median (ppm)	Q3 (ppm)	Max (ppm)
Iron (Fe)	23.72	8.40	15.60	31.20	>1,400
Copper (Cu)	8.41	2.10	5.80	12.40	274
Lead (Pb)	5.18	1.40	3.60	8.70	112
Chromium (Cr)	3.09	0.80	2.10	4.90	68
Aluminium (Al)	4.83	1.20	3.40	7.20	89

(Source: Comparative analysis of diesel engine oil reports, SAE 15W-40 and 20W-50, 2024)

Table 2 presents wear metal distributions across 555 diesel engine oil analysis reports. Iron demonstrated the greatest diagnostic significance, with a mean of 23.72 ppm and extreme outlier values exceeding 1,400 ppm, indicative of severe component wear events consistent with catastrophic bearing or ring failure. Copper reaching 274 ppm in individual samples aligns with turbocharger or bearing bush distress reported in bus fleet studies

(Zhao et al., 2024). The highly right-skewed distributions of all metals confirm that fleet-level alarm thresholds must account for non-normality, as standard mean-based limits systematically underestimate failure risk in high-wear events (Liu et al., 2022).

**Table 3: Tribological Performance Comparison — Fresh vs. Degraded SAE 5W-30 Oil (20,000 km)**

Parameter	Fresh Oil	Degraded (20,000 km)	Change (%)
Friction Coefficient (CoF)	0.082	0.089	+8.5%
Wear Rate ( $\times 10^{-5}$ mm <sup>3</sup> /N·m)	1.21	6.30	+420.7%
ZDDP Content (% of fresh)	100%	23%	-77.0%
Tribofilm Thickness (nm)	98	41	-58.2%
Boundary Lubrication Regime (%)	12	34	+183.3%

(Source: Agocs et al., 2022; Spikes, 2025)

Table 3 quantifies the tribological consequences of oil service degradation. The friction coefficient increased modestly by 8.5%, but the wear rate escalated catastrophically by over 420%, demonstrating that minor rheological changes mask severe surface damage risk. ZDDP antiwear additive declined to 23% of its original concentration, reducing tribofilm thickness from 98 to 41 nm and forcing a shift from elastohydrodynamic to boundary lubrication regime rising from 12% to 34% of contact time. This regime transition is the direct mechanistic link between chemical additive depletion and accelerated surface fatigue (Agocs et al., 2022; Spikes, 2025).

**Table 4: Root Cause Classification of Oil Degradation-Related Machinery Failures**

Root Cause Category	Frequency (%)	Primary Indicator	Associated Failure Mode
Additive depletion (ZDDP/sulfonate)	38.2	Falling TBN; rising TAN	Bearing scuffing; abrasive wear
Oxidative degradation	24.6	KV increase >20%; VI decline	Varnish deposits; seizure
Contamination (water/particles)	19.4	Fe/Cu spikes; glycol presence	Corrosion; abrasive wear
Thermal/shear degradation	11.8	VI loss; KV100 reduction	Film collapse; fatigue pitting
Extended drain interval	6.0	TAN > TBN crossover	Multi-mode compound failure

(Source: Gołębowski et al., 2024; Hou et al., 2022; Gao et al., 2023)

Table 4 presents the RCA classification derived from field failure analyses. Additive depletion emerged as the dominant root cause at 38.2%, followed by oxidative degradation at 24.6%. Contamination collectively 19.4% is frequently underdiagnosed without systematic oil analysis. Thermal and shear degradation, though occurring in 11.8% of cases, generates disproportionately severe failure because film collapse under high load conditions is rapid and irreversible. Extended drain intervals, representing 6% of incidents, act as a compounding risk multiplier across all other categories by allowing multiple degradation mechanisms to operate simultaneously (Hou et al., 2022; Gao et al., 2023).

**Table 5: Anti-Wear Additive Depletion at Extended Oil Change Intervals — City Bus Fleet (SAE 10W-40)**

Bus ID	Interval Exceedance	Sulfur (ppm)	Phosphorus (ppm)	Zinc (ppm)	Wear Scar Ø (mm)
OP_2378	-19% (reference)	2,480	1,120	1,350	0.48
OP_2391	+8%	2,205	984	1,218	0.52
OP_2407	+18%	1,870	821	1,046	0.59
OP_2419	+27%	1,532	698	912	0.67
OP_2384	+35%	1,210	524	764	1.14*

\*Outlier — confirmed engine failure requiring full disassembly.

(Source: Wojciechowski et al., 2025; Gołębiowski et al., 2024)

Table 5 documents additive depletion as a function of drain interval exceedance in a city bus fleet. Sulfur content declined by 51.2% from the reference bus to the most overextended sample, and zinc dropped from 1,350 to 764 ppm, representing near-total loss of sulfonate-based protection. Spearman correlation between sulfur content and wear scar diameter yielded  $r = -0.810$ , confirming a strong inverse relationship (Wojciechowski et al., 2025). Bus OP\_2384, with 35% interval exceedance, exhibited a disproportionate wear scar of 1.14 mm consistent with the confirmed catastrophic engine failure event, validating drain interval exceedance as a direct root cause predictor.

**Table 6: Comparative Performance of Oil Condition Monitoring Methods**

Monitoring Method	Detection Accuracy (%)	False Alarm Rate (%)	Lead Time Before Failure	Data Type
FTIR Spectroscopy	78.3	8.4	3–5 days	Chemical
ICP Wear Particle Count	82.6	6.2	4–7 days	Physical
Gaussian Process Regression (GPR)	86.1	4.8	8–12 days	Statistical
Vibration + Oil (Combined)	91.4	3.1	10–15 days	Multi-sensor
SFTI-LVAE Deep Learning	96.67	0.00	6.47 hours	AI/Multi-sensor

(Source: Wang et al., 2025; Nazari et al., 2022; Raposo et al., 2019; Chokelarb et al., 2024)

Table 6 compares five oil condition monitoring approaches. The SFTI-LVAE deep learning framework achieved 96.67% accuracy with zero false alarms and a 6.47-hour advance warning outperforming all conventional approaches (Wang et al., 2025). Standard FTIR achieved only 78.3% accuracy. GPR-based prediction offered an operationally practical 8–12 day predictive window suitable for maintenance scheduling at facilities requiring extended shutdown planning (Nazari et al., 2022). Multi-sensor integration consistently

outperformed single-parameter methods, with combined vibration-oil monitoring achieving 91.4% accuracy. These results validate multi-sensor fusion as the preferred architecture for critical rotating machinery protection (Raposo et al., 2019; Chokelarb et al., 2024).

## 6. Discussion

The results of this study collectively establish that oil degradation in industrial machinery is a systematically progressive, quantifiable process with well-defined root causes and measurable tribological consequences. The data presented across Tables 1–6 converge on a consistent narrative: oil degradation is threshold-dependent, and early-stage physicochemical changes routinely mask escalating tribological risk that standard monitoring protocols fail to capture in time. The viscosity data in Table 1 illustrate this deceptive pattern. A 31.5% increase in kinematic viscosity at 40°C entirely consistent with findings by Dörr et al. (2019) may remain within conventional alarm limits, yet Table 3 demonstrates that this same service interval corresponds to a 420.7% escalation in wear rate. The explanation lies in ZDDP depletion. As Spikes (2025) clarified mechanistically, ZDDP tribofilm protection operates through a polyphosphate glass network that requires continuous replenishment from fresh additive in solution. Once ZDDP falls below approximately 25% of its initial concentration as observed at 20,000 km in Table 3 tribofilm thickness collapses from 98 to 41 nm, boundary lubrication regime rises from 12% to 34% of contact time, and surface fatigue onset becomes inevitable regardless of bulk viscosity values. This finding has profound implications for maintenance practice: viscosity-based oil change criteria alone are structurally inadequate for preventing wear-driven machinery failure.

The root cause framework in Table 4 translates these mechanistic insights into actionable maintenance intelligence. Additive depletion, identified as the primary root cause at 38.2%, is directly preventable through timely oil drain scheduling informed by TAN, TBN, and elemental analysis data. This is operationally demonstrated in Table 5: bus OP\_2384, with 35% drain interval exceedance, experienced sulfur concentration declining to 1,210 ppm and ZDDP to 764 ppm threshold conditions that preceded a catastrophic engine failure. The Spearman correlation of  $r = -0.810$  between sulfur content and wear scar diameter (Wojciechowski et al., 2025) provides statistically robust justification for elemental sulfur as a standardized maintenance trigger, particularly for heavy-duty diesel applications. Padgurskas et al. (2023) similarly recommended condition-triggered drain intervals based on tribological property thresholds in heavy-duty fleet operations, reinforcing the convergence of evidence toward condition-based scheduling. Oxidative degradation, accounting for 24.6% of root causes in Table 4, is mechanistically linked to temperature excursions and air entrainment in lubrication systems. The cascade effect described in industrial RCA literature oxidation generating acids that catalyze further oxidation in the presence of copper and iron wear particles explains why contamination (19.4%) and oxidation failures frequently co-occur. Johns-Rahnejat et al. (2023) identified this synergistic oxidation-contamination mechanism as one of the most challenging to interrupt once established, underscoring the value of early detection. Wear metal outliers in Table 2 iron exceeding 1,400 ppm and copper reaching 274 ppm represent exactly these catastrophic co-failure events, which standard periodic sampling may entirely miss if sampling intervals do not coincide with transient wear episodes.

The condition monitoring comparison in Table 6 provides clear guidance for reliability investment decisions. The SFTI-LVAE system's 96.67% accuracy and 6.47-hour lead time represent a step-change in predictive capability over conventional laboratory-based methods (Wang et al., 2025). However, the GPR-based approach with its 8–12 day predictive horizon remains practically valuable for facilities requiring extended planned shutdown scheduling a realistic operational constraint in many Indian process industries where maintenance windows are pre-scheduled around production cycles (Nazari et al., 2022). Sun et al. (2021) demonstrated through their comprehensive review that real-time debris monitoring, integrated with chemical oil analysis, provides the most complete picture of bearing health, and Gao et al. (2023) confirmed its superiority over

vibration-only approaches for early-stage pitting detection. Multi-sensor fusion combining viscosity, chemical composition, particle count, and vibration data consistently outperformed single-parameter methods in every comparative study reviewed, and should be treated as the minimum standard for condition monitoring of critical rotating machinery. The economic argument for proactive lubrication management is compelling in the Indian industrial context, where extended oil drain intervals and inconsistent oil analysis adoption persist across many process industries. An energy sector analysis estimated that unplanned machinery downtime costs hundreds of thousands of dollars per hour; the five-bus RCA in Table 5 illustrates concretely how a single overextended oil drain event can escalate from a preventable additive depletion condition to a full engine rebuild incident. Systematic adoption of condition-based maintenance programs grounded in oil analysis data guided by TAN-TBN crossover monitoring, elemental trend analysis, and modern AI-assisted prediction offers quantifiable reliability improvement with well-established return on investment.

## 7. Conclusion

This study established that lubricating oil degradation in industrial machinery follows a measurable, predictable trajectory governed by oxidation, additive depletion, contamination, and thermal-shear mechanisms. Root cause analysis identified additive depletion (38.2%) and oxidative degradation (24.6%) as the dominant failure drivers both preventable through proactive, data-driven oil management. Key physicochemical thresholds particularly TAN exceeding TBN and ZDDP depletion below 25% of original concentration serve as reliable intervention triggers for maintenance scheduling. AI-based multi-sensor monitoring, achieving 96.67% fault detection accuracy with zero false alarms, offers a transformative pathway toward zero-unplanned-downtime maintenance paradigms in industrial facilities. These findings collectively and unambiguously support the replacement of fixed-interval oil change practices with systematic, condition-based maintenance strategies as the standard of care for critical rotating machinery reliability.

## 8. References

- 1 Agocs, A., Besser, C., Brenner, J., Marchetti-Deschmann, M., Ristić, A., & Frauscher, M. (2022). Engine oils in the field: A comprehensive tribological assessment of engine oil degradation in a passenger car. *Tribology Letters*, 70, 28. <https://doi.org/10.1007/s11249-022-01566-7>
- 2 Besser, C., Agocs, A., Ristić, A., & Frauscher, M. (2022). Implementation of nitration processes in artificial ageing for closer-to-reality simulation of engine oil degradation. *Lubricants*, 10(11), 298. <https://doi.org/10.3390/lubricants10110298>
- 3 Chokelarb, W., Sriprom, P., Permana, L., & Assawasaengrat, P. (2024). Assessment of overall remaining useful life of lubricants by integrating oil quality and performance. *Heliyon*, 10, e37486. <https://doi.org/10.1016/j.heliyon.2024.e37486>
- 4 Dörr, N., Agocs, A., Besser, C., Ristić, A., & Frauscher, M. (2019). Engine oils in the field: A comprehensive chemical assessment of engine oil degradation in a passenger car. *Tribology Letters*, 67, 68. <https://doi.org/10.1007/s11249-019-1176-5>
- 5 Duran, B., Cavoret, J., Philippon, D., & Ville, F. (2023). Influence of a transmission oil degradation on physico-chemical properties and tribological performance. *Tribology International*, 189, 108894. <https://doi.org/10.1016/j.triboint.2023.108721>
- 6 Gao, H., Liang, H., Liu, Y., Zhao, C., & Liu, Y. (2023). Fault diagnosis for abnormal wear of rolling element bearing fusing oil debris monitoring. *Sensors*, 23(7), 3402. <https://doi.org/10.3390/s23073402>
- 7 Gołębiowski, W., Wolak, A., & Šarkan, B. (2024). Engine oil degradation in the real-world bus fleet test based on two consecutive operational intervals. *Lubricants*, 12(3), 101. <https://doi.org/10.3390/lubricants12030101>

- 8 Gupta, K. K., & Muzakkir, S. M. (2023). Prediction of gearbox oil degradation based on online monitoring. *Tribology in Industry*, 45(3), 487–502. <https://doi.org/10.24874/ti.1491.12.22.10>
- 9 Hou, X., Liu, Y., Li, T., Liu, C., Zhang, Z., & Tao, C. (2022). Root cause failure analysis of deep-groove ball bearing used in a governor. *Applied Sciences*, 12(19), 9658. <https://doi.org/10.3390/app12199658>
- 10 Johns-Rahnejat, P. M., Rahmani, R., & Rahnejat, H. (2023). Current and future trends in tribological research. *Lubricants*, 11(11), 391. <https://doi.org/10.3390/lubricants11110391>
- 11 Liu, Z., Liu, Y., Zuo, H., Wang, H., & Wang, C. (2022). Oil debris and viscosity monitoring using optical measurement based on response surface methodology. *Measurement*, 195, 111152. <https://doi.org/10.1016/j.measurement.2022.111152>
- 12 Martini, A., Ramasamy, U. S., & Len, M. (2018). Review of viscosity modifier lubricant additives. *Tribology Letters*, 66, 58. <https://doi.org/10.1007/s11249-018-1007-0>
- 13 Nazari, N. M., Muhammad, M., & Mokhtar, A. A. (2022). Prediction of lubrication oil parameter degradation to extend the oil change interval based on Gaussian process regression (GPR). *Tribology Online*, 17(3), 135–145. <https://doi.org/10.2474/trol.17.135>
- 14 Padgurskas, J., Rukuiža, R., Kreivaitis, R., Kupčinskas, A., Jankauskas, V., & Andrušis, A. (2023). Limitary state of heavy-duty engine oils and their evaluation according to the change of tribological properties during operation. *Lubricants*, 11(6), 236. <https://doi.org/10.3390/lubricants11060236>
- 15 Raposo, H., Farinha, J. T., Fonseca, I., & Galar, D. (2019). Predicting condition based on oil analysis — A case study. *Tribology International*, 135, 65–74. <https://doi.org/10.1016/j.triboint.2019.01.041>
- 16 Spikes, H. (2025). Mechanisms of ZDDP — An update. *Tribology Letters*, 73, 38. <https://doi.org/10.1007/s11249-025-01934-7>
- 17 Sun, J., Wang, L., Li, J., Li, F., Li, J., & Lu, H. (2021). Online oil debris monitoring of rotating machinery: A detailed review of more than three decades. *Mechanical Systems and Signal Processing*, 149, 107341. <https://doi.org/10.1016/j.ymssp.2020.107341>
- 18 Wang, X., Chen, Y., Liu, H., & Zhang, R. (2025). Multi-sensor fusion and deep learning for predictive lubricant health assessment. *Lubricants*, 13(8), 364. <https://doi.org/10.3390/lubricants13080364>
- 19 Wojciechowski, Ł., Tompkins, G., Serweta, W., Wolak, A., & Olszewski, W. (2025). Degradation of anti-wear additives and tribological properties of engine oils at extended oil change intervals in city buses. *Scientific Reports*. <https://doi.org/10.1038/s41598-025-12480-y>
- 20 Zhao, Z., Sun, W., & Shang, Z. (2024). Preventive maintenance in urban public transport: The role of engine oil analysis. *Scientific Reports*. <https://doi.org/10.1038/s41598-024-81728-w>