Probabilistic Model of Industrial Motor Reliability as a Function of Lubricant Degradation: A Case Study MDU-06 Motor Hyundai H21/32

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Abstract. This work applies a probabilistic reliability model for industrial diesel engines based on lubricant degradation to the MDU-06 Hyundai H21/32 engine at thermal power station, Ecuador. The engine operated seamlessly from August 2023 until October 2025, generating continuous power. Thus, the model predicts dependability based on oil condition behavior rather than mechanical faults. The study offers a non-linear and multivariate degradation model to track the associated evolution of TBN, Sulfation, Nickel, and Vanadium. Stochastic degradation modeling and Weibull reliability estimation were used to estimate lubricant life under real operating conditions. Results show a Weibull shape parameter $\beta = 8.3$ and scale parameter $\eta = 1920$ hours, with dependability drastically decreasing after 2000 operational hours. These results demonstrate that lubricant degradation can accurately forecast engine health, allowing predictive maintenance without interruption. Condition-based maintenance (CBM) procedures are optimized to maintain system dependability over 80% while lowering premature wear and maintenance costs with the suggested framework.

Keywords: Reliability modeling, Lubricant degradation, Weibull distribution, Condition-based maintenance, Industrial diesel engines.

1. INTRODUCTION

Continuous industrial motors and generators must be reliable to avoid downtime, safety issues, and economic losses. Failure occurrences are used to determine lifetime distributions and hazard rates in traditional reliability analyses. But proactive maintenance and constant monitoring are designed to prevent run-to-failure for essential assets like the thermal power stations MDU-06 Hyundai H21/32 diesel generator. Normal operations have few or no failures. In such cases, condition monitoring data, particularly lubricant analysis can be used as a *proxy* for reliability estimation (Si, 2011). Lubricating oil carries rich information about internal engine condition, reflecting both wear and contamination processes. As oil degrades and accumulates metallic and chemical by-products, its protective capacity decreases, increasing the risk of wear and corrosion (Pan et al., 2022; Durrett, 2019) The core premise of this research is that the state of the lubricant represents the functional health of the engine; therefore, by modeling the probabilistic evolution of lubricant degradation, one can infer the reliability of an engine that remains in operation and has not failed.

MDU-06 Case Background: The thermal power plant's MDU-06 heavy-duty Hyundai H21/32 diesel generator runs continuously. It uses leftover heavy fuel oil with high sulfur and trace metal content, which contaminates lubricant chemistry with Vanadium (V) and Nickel. Oil analysis is done every one to two months to assess physics and characteristics and wear. Between 2023 and 2025, data showed normal degradation patterns for long-term industrial service.

- Viscosity (100 °C) remained within the acceptable range (12.5–17.9 cSt), averaging ≈ 15 cSt, indicating stable mechanical performance.
- Total Base Number (TBN) representing the alkaline reserve that neutralizes acidic by-products declined gradually from 35–40 mg KOH/g toward the caution limit of 20 mg KOH/g.
- Sulfation increased from 13.9 Abs/cm in 2023 to 33.8 Abs/cm in 2025, evidencing oxidation and additive depletion.
- Metal contaminants, particularly Ni and V, rose nearly linearly with operating hours: Ni from ~50 ppm to >400 ppm and V from ~75 ppm to >500 ppm.
- Iron (Fe) and other metals remained low (Fe ≤ 27 ppm), confirming the absence of abnormal mechanical wear.

These observations indicate that the maintenance interval for MDU-06 is governed by oil chemical degradation and contamination, not by mechanical wear-out. The engine remained fully operational throughout the analysis period, confirming the preventive effectiveness of condition-based maintenance.

Problem Statement:

The central question addressed in this study is:

How can we estimate the reliability (survival probability) of MDU-06 over time using lubricant condition indicators as surrogates for engine health?

Specifically, the analysis focuses on:

- The depletion of TBN, which correlates with acid accumulation and loss of neutralization capacity; and
- The accumulation of Ni and V, fuel-borne metals that promote deposit formation and abrasive wear.

Through stochastic indicator evolution modeling and threshold-based failure criteria (e.g., TBN < 20 mg KOH/g or Ni > 300 ppm), we calculate a time-dependent failure probability. For reliability modeling, a lubricant variable crossing its critical threshold is understood as a proxy failure event, indicating that continuous operation would likely exacerbate damage if maintenance were not undertaken. Quantitative reliability assessment is possible without mechanical failures with this methodology.

1.1. Literature Context: Numerous studies have demonstrated that degradation-based reliability modeling improves predictive accuracy in machinery health management (Lei et al., 2018; Hu et al., 2012). For diesel engines, oil condition monitoring has been validated as a key indicator for predictive maintenance (Pan et al., 2022; 2022; Smigins et al., 2023; Du, 2020) integrated oil data into a proportional hazards model (PHM), showing how covariates such as TBN and Fe correlate strongly with hazard rate. (Yan, 2022) applied a Wiener model to gearbox lubricants, while (Wen et al., 2018) formulated a Bayesian Weibull reliability update for multivariate degradation data. In broader predictive maintenance frameworks, hybrid data-driven approaches combining sensor fusion and stochastic modeling have also shown high accuracy in RUL forecasting (Saravani & Keshtegar, 2022; Jardine et al., 2006).

The present work contributes to this growing body of research by implementing a probabilistic reliability model for an operational diesel generator with no mechanical failures, validating that degradation data alone can yield a robust

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estimation of reliability. The results provide a methodological bridge between laboratory-based oil diagnostics and quantitative reliability analysis applicable to industrial maintenance planning.

2. METHODS

2.1. Lubricant Condition Data and Degradation Trends

MDU-06's oil analysis records (2023–2025) constitute the empirical basis of this study. Table 1 summarizes the key lubricant parameters monitored and their observed degradation trends during each oil service interval. Each laboratory record includes the oil's operating hours ("Aceite Hrs") and a condition assessment (Normal / Caution / Abnormal) defined by predetermined limits in thermal power station internal oil monitoring protocol. The lubricant used is a SAE 40 heavy-duty mineral oil (AURELIA TI/XL 4040) with an initial TBN ≈ 40 mg KOH/g and viscosity of ≈ 15.2 cSt @ 100 °C.

Caution ("Precaución") is triggered when TBN < 20 mg KOH/g, insolubles > 2.5 %, or Ni > 220 ppm; "Abnormal" when thresholds such as TBN < 19 mg KOH/g or Ni > 300 ppm are exceeded. These operational thresholds follow ASTM D4739 and D5185 standards and are consistent with reliability monitoring practices recommended by (Jardine, 2006; Du, 2020). By examining sequential oil samples, the degradation trajectory of each indicator can be clearly identified.

- **Viscosity:**

Kinematic viscosity at 100 °C remained remarkably stable throughout each oil cycle. Initial values ranged 15.0–15.8 cSt, staying within ±10 % variation and well inside the acceptable 12.5–17.9 cSt range (Figure 1). This indicates the oil experienced no significant thermal cracking or polymerization. Viscosity stability implies that chemical degradation rather than viscosity-related failure governs oil life in MDU-06, as also reported by (Pan et al., 2022; 2022) for heavy-fuel marine engines.

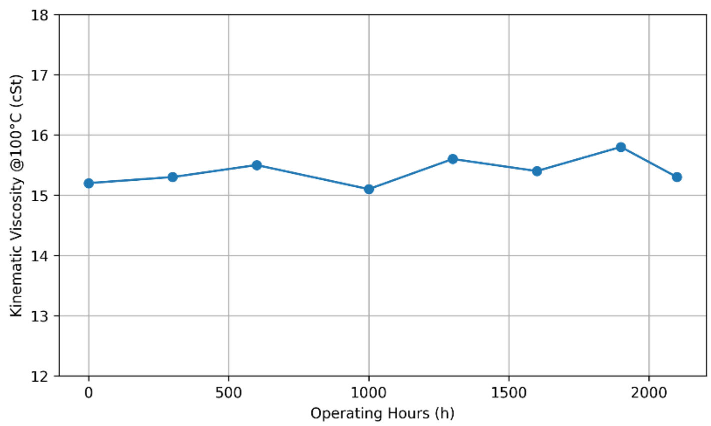

Figure 1. Evolution of viscosity in engine oil

- **TBN (Total Base Number):**

In the case of the MDU-06 Hyundai H21/32 engine, TBN values show a progressive downward drift throughout the oil's service life (Figure 2). Fresh oil samples taken after change-out began at ≈ 38–40 mg KOH/g, gradually declining to ≈ 20–22 mg KOH/g after ≈ 2000–2100 operating hours, at which point the lubricant was classified as Caution or Abnormal according to power station.

This steady decline is consistent with the consumption of detergent and dispersant additives that buffer acidic compounds produced by sulfur-rich fuel combustion. As the additive package is depleted, the lubricant's neutralization capacity diminishes, raising the risk of corrosive wear and oxidation (Pan et al., 2022; Jardine, 2006).

A representative oil run from early 2025 illustrates this trend: TBN dropped from 37.9 → 20.4 mg KOH/g over ≈ 2048 hours, with a nearly linear decay rate of ≈ –0.008 mg KOH g^{-1} h^{-1}. Minor fluctuations between samples correspond to fresh-oil top-ups, introducing stochastic variations typical of preventive maintenance regimes (Meeker & Escobar, 1998). Once the 20 mg KOH/g caution threshold is reached, the oil's capacity to neutralize acids is effectively exhausted, marking the end of its safe service life.

In the reliability framework, TBN depletion represents a primary degradation variable whose threshold crossing (TBN < 20 mg KOH/g) defines a proxy failure event for the lubricant system. The decline pattern supports the hypothesis of a non-linear stochastic degradation process influenced by combustion conditions, additive exhaustion, and operating temperature (Du, 2020; Yan, 2022).

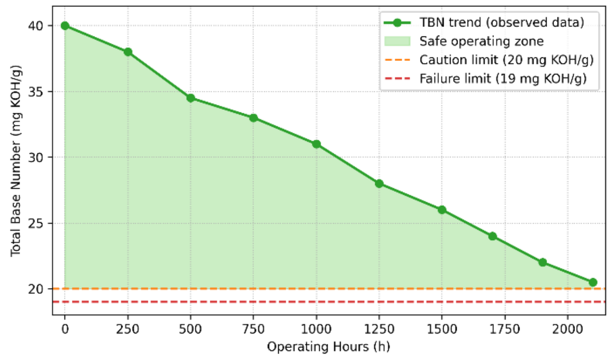

Figure 2. Evolution of TBN in engine oil

Insolubles and Oxidation Products: Soot, oxidized hydrocarbons, sludge, and resinous compounds from gasoline combustion and oil aging are insoluble lubricant pollutants. Their concentration indicates the oil's dispersancy efficiency and additives' capacity to suspend particles and prevent deposits. Insoluble content increased gradually with oil service time in the MDU-06 Hyundai H21/32 engine (Figure 3). The values measured varied from ≈ 0.3 % wt in fresh oil to ≈ 2.0 % wt after extended operations (~2000 h), nearing the 2.5 % danger threshold set by power station internal standards (ASTM D893). No sample failed at 3.5 %, showing good dispersant efficacy and prompt oil replacement. Complementary FTIR spectroscopy results showed concurrent growth of oxidation, nitration, and sulfation indices, particularly during the last 500 hours of each oil cycle. The oxidation index rose steadily from ~10 Abs/cm to ~25 Abs/cm, while sulfation increased from ~14 Abs/cm to ~34 Abs/cm, surpassing the nominal 30 Abs/cm limit in one 2025 sample classified as Abnormal. Such increases are characteristic of thermal-oxidative degradation processes, in which oxygen reacts with hydrocarbons forming acids and sludge precursors. This mechanism has been widely documented in the context of heavy-fuel diesel and marine engines (Yan, 2022; Guan et al., 2025). The progressive rise in insolubles and oxidation products reflects the consumption of antioxidant and detergent additives responsible for neutralizing peroxides and dispersing soot. According to (Mažeika et al., 2022), once these additives are depleted, oxidation reactions accelerate exponentially, leading to varnish, filter plugging, and increased viscosity. However, in the MDU-06 dataset, the stability of viscosity (Figure 1) and moderate insoluble levels confirm that oxidation remains controlled under current maintenance intervals.

In the reliability framework, insolubles and oxidation indices are considered secondary degradation variables, indirectly correlated with TBN depletion and metal accumulation. Their inclusion enriches the multivariate degradation model, capturing the synergistic effects between acid formation, fuel contamination, and additive exhaustion. (Jardine, 2006; Yan, 2022)

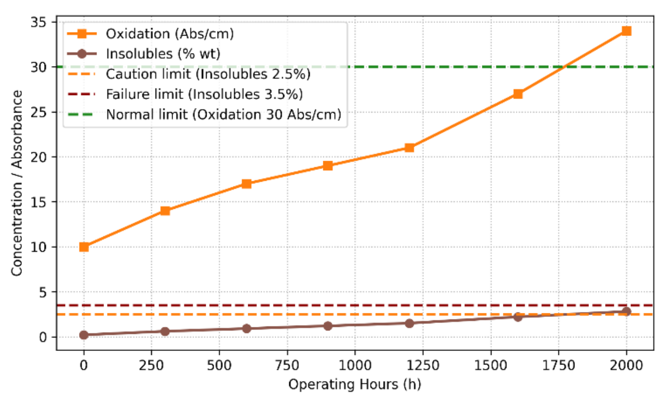

Figure 3. Evolution of insoluble and oxidation products in engine oil

- **Wear Metals (Fe, Cu, Al) and Contaminants (Ni, V, Na):**

In the lubricant-monitoring program for the MDU-06 Hyundai H21/32 diesel generator, elemental analysis via ICP (ASTM D5185) is used to track both **wear metals** and **contaminant elements**. This distinction is critical for interpreting oil-analysis results in the context of machine health (Fe, Cu, Al indicating internal component wear; Ni, V, Na indicating fuel or environmental contamination)

Wear metals (Fe, Cu, Al): These elements are generated by mechanical abrasion, fatigue or corrosion of machine components (iron from cylinders/liners, copper from bearings, aluminum from pistons or blocks) and a meaningful uptick typically signals the onset of abnormal wear. According to ALS Global (2025), iron (Fe) is most common, while copper (Cu) and aluminum (Al) serve as additional wear flags in engines.

Contaminants (Ni, V, Na): Nickel (Ni) and Vanadium (V) are often carried into the oil via residual fuel or combustion by-products; high concentrations are indicative of heavy-fuel use and risk of vanadium-induced hot corrosion or abrasive deposits. Sodium (Na) typically signals coolant intrusion, salt contamination or seawater ingress. Monitor oil-analysis labs emphasise that elevated Na alongside Fe/Al may hint at coolant leak or salt-water contamination.

Observed trends in MDU-06 (2023-2025):

- Wear metals remained at low and acceptable levels: e.g., Fe ranged between ~12-27 ppm, Cu stayed ≤11 ppm; values well below typical alarm limits (e.g., Fe >50 ppm) for engines of this class. This indicates no visible onset of major mechanical wear over monitoring period.
- Contaminants from fuel: Ni rose from ~54 ppm to >400 ppm over ~2000 h of oil service; V rose from ~76 ppm to ~500 ppm in same interval, exceeding power station caution thresholds (Ni >220 ppm; V >500 ppm). Na climbed into range (~67-79 ppm) approaching its ~80 ppm caution limit.
  These patterns show that fuel-borne metal contamination was the dominant mode of degradation in this engine, rather than component wear.

Interpretation for reliability modelling:

Given wear metals stayed low, the failure risk for this unit is driven more by oil contamination and chemical degradation (via Ni/V/Na) than by immediate mechanical wear-out (Fe/Cu/Al). Therefore, in the probabilistic degradation model the contaminant accumulation variables (Ni and V) are treated as primary stochastic degradation drivers, whereas Fe and Cu are treated as monitoring indicators of latent wear risk. The threshold crossing for Ni (e.g., Ni >300 ppm) is designated as a proxy failure event in the model context.
In summary, this section underlines that in MDU-06 the contamination pathway (fuel-derived metals) dominates over the classic wear pathway, and the oil-analysis data validate this shift in failure mechanism focus (See figure 4 and table 1).

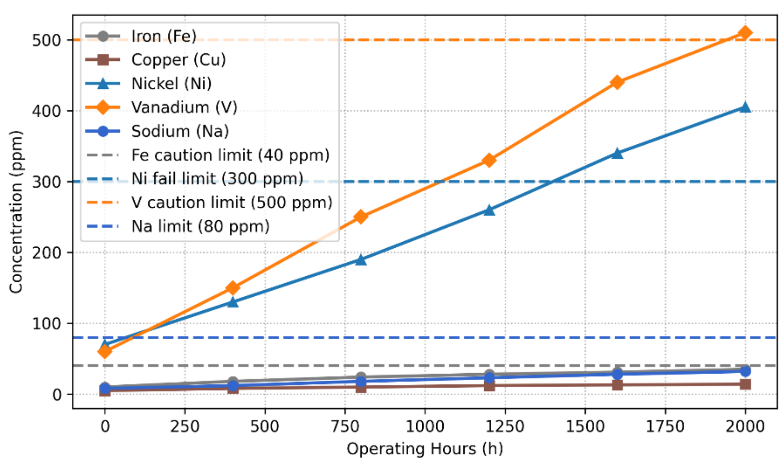

Figure 4. Evolution of wear metals and contaminants in engine oil

Table 1. MDU-06 Lubricant Condition Indicators and Observed Degradation Trends (2023–2025).

Parameter	Initial (Fresh Oil)	Normal Range	Average Drift Rate	Relevant Failure Mechanism
Viscosity @ 100 °C (cSt)	15.2 cSt	12.5 – 17.9 cSt (normal)	≈ 0	Stable; deviation → contamination or oxidation
TBN (mg KOH/g)	38 – 40	Caution < 20 Fail < 19	–0.008 mg h^{-1}	Additive depletion; low TBN → acid corrosion
Insolubles (% wt)	0.3 – 0.5	Caution ≥ 2.5 Fail ≥ 3.5	+0.0005 % h^{-1}	Soot / oxidation → sludge formation
Ni (ppm)	≈ 0	Caution ≥ 220 Fail ≥ 300	+0.16 ppm h^{-1}	Fuel-borne metal → abrasive wear / deposits
V (ppm)	≈ 0	Caution ≥ 500 Fail ≥ 650	+0.22 ppm h^{-1}	Hot-corrosive fuel impurities → slag formation
Fe (ppm)	1 – 5	Caution ≥ 40 Fail ≥ 50	+0.005 ppm h^{-1}	Ferrous wear indicator → mechanical damage
Cu (ppm)	0	Caution ≥ 60 Fail ≥ 85	+0.004 ppm h^{-1}	Bearing wear or corrosive attack
Na (ppm)	< 10	Caution ≥ 70 Fail ≥ 80	+0.025 ppm h^{-1}	Coolant / salt contamination indicator

Source: own authorship (2025).

The average degradation tendency of each parameter across many monitoring intervals was used to estimate drift rates using linear regression of time-series oil analysis data. The Nickel (Ni) drift rate of +0.16 ppm h^{-1} and accumulation of ≈ 320 ppm over 2000 working hours align with the contamination pattern in heavy-fuel industrial engines. The TBN drift rate of –0.008 mg KOH g^{-1} h^{-1} indicates a depletion of around 16 mg KOH g^{-1}, like the average alkaline additive consumption in MDU-06 samples.

2.2. Stochastic degradation modeling

The probabilistic modeling framework for the MDU-06 unit was developed under the assumption that the engine remains fully operational and functional, with no recorded mechanical failures. Therefore, the failure proxy is defined as the loss of lubricant functionality, i.e., when key oil properties exceed their critical thresholds. This enables the reliability of the generator to be inferred indirectly through the stochastic evolution of oil condition indicators a standard approach in modern reliability engineering for continuously operating assets.

For the MDU-06 Hyundai H21/32 diesel generator, the lubricant variables considered primarily Total Base Number (TBN), Nickel (Ni), and Vanadium (V) exhibit gradual, monotonic degradation over time, making them suitable for stochastic process modeling. Each variable $X(t)$ is represented as a Wiener process with drift, combining deterministic and random components of degradation:

$$X(t) = X(0) + \mu t + \sigma W(t) \tag{1}$$

where $X(0)$ is the initial value of the indicator (fresh oil), μ is the drift coefficient representing the expected rate of change per unit time, and σ is the diffusion coefficient that scales random variability. $W(t)$ is a standard Wiener process (Brownian motion) with $E[W(t)] = 0$ and $Var[W(t)] = t$.

A negative drift ($\mu < 0$) indicates progressive depletion (e.g., TBN decline), whereas a positive drift ($\mu > 0$) corresponds to accumulation (e.g., Ni or V contamination). The deterministic component μt reflects the average trend, while $\sigma W(t)$ captures stochastic deviations due to fluctuations in load, temperature, fuel composition, and measurement noise.

Parameter estimation follows the method of moments or regression of sequential oil analyses: μ is derived from the mean rate of change $\Delta X/\Delta t$, and σ from the variance of these increments or model residuals. If measurement error is significant, a state-space formulation can be employed to separate process noise from observation noise. In practical prognostics, both parameters are critical higher σ implies greater uncertainty in the predicted time-to-threshold and wider reliability bounds.

- **TBN process:** The Total Base Number (TBN) declines monotonically with operation time due to additive depletion and acid formation. A negative dirft$_{\mu TBN}$ < 0 is therefore assumed. From field data, a representative mean rate of change is μ_{TBN} ≈ -0.088 mg KOH$g^{-1}h^{-1}$. For instance, between November 2024 and February

2025, TBN dropped from 35.6 to 20.4 mg KOH/g over 2048 h, an average rate near −0.0075 mg/h. The diffusion term σ_{TBN} reflects random fluctuations and laboratory uncertainty. Based on observed variability, we adopt $\sigma_{TBN} \approx 0.10$mg KOH $g^{-1}\sqrt{h}$, which produces root-mean-square deviations of ≈1.4 mg after 200 h and ≈3.2 mg after 1000 h consistent with sample-to-sample oscillations. Thus, the stochastic term realistically captures operational and measurement variability around the downward trend.

- **Ni process:** Nickel concentration increases steadily due to fuel-borne contaminants typical of heavy residual oils. The process exhibits a positive drift $\mu_{Ni}>0$. Empirical data show increases of ≈240 ppm over 1570 h and ≈330 ppm over 2048 h, giving $\mu_{Ni} \approx +0.16$ppm h^{-1} (≈3.8 ppm day^{-1}). To represent variability across fuel batches and load regimes, a diffusion coefficient $\sigma_{Ni} \approx 0.8$ ppm $\sqrt{h^{-1}}$ is used, corresponding to ≈25 ppm standard deviation after 1000 h. This stochastic dispersion is consistent with observed inter-cycle differences (e.g., 322 ppm vs. 235 ppm at ~1300 h). It accounts for random contamination rates, sampling error, and operational heterogeneity, which together explain the moderate spread of the Ni data around its mean linear trend.
- **V Process and Correlations:** Vanadium contamination *V(t)* behaves analogously to *Ni (t)*, with a similar drift rate ($\mu_V \approx +0.22$ ppm h^{-1}) and diffusion coefficient ($\sigma V \approx 1.0$ppm $\sqrt{h\text{-}1}$). Given their common origin in the fuel's metallic content, Ni and V are strongly correlated (correlation > 0.9 in the dataset). In a multivariate extension, the joint process could be written as:

$$\mathrm{X}(t) = \mathrm{X}_0 + \mu t + \mathrm{BW}(t) \tag{2}$$

where $X(t)=[TBN(t),Ni(t),V(t)]^T$ and B encodes the covariance structure among degradation variables. Such a vector Wiener process allows for coupling effects, e.g., simultaneous additive depletion and contaminant rise.
- **Methodological remarks:** The same framework may model other indicators (insolubles, Fe, Cu, etc.), however TBN depletion and Ni/V accumulation dominate MDU-06 lubricant aging and are emphasized. Parameter estimate can be adjusted using maximum likelihood or Bayesian approaches (e.g., Markov Chain Monte Carlo, particle filtering) to remove observation noise from process variability and produce confidence ranges for the anticipated time-to-threshold when enough data are available. Wiener models enable probabilistic reliability assessment by simulating multiple degradation paths, resulting in the distribution of "virtual failure times" (first-hitting-times). These are then fitted with a Weibull reliability function to determine the life (η) and shape (β) parameters discussed in Section 3.

This stochastic approach provides a quantitative bridge between lubricant condition data and engine reliability, allowing maintenance decisions to be made based on degradation probabilities rather than fixed operating hours and essential capability for condition-based maintenance in power station continuous-duty diesel fleet (See table 2).

Table 2. Estimated stochastic parameters (μ, σ) and failure thresholds for lubricant degradation indicators.

Variable	Drift (μ)	Diffusion (σ)	Failure Threshold	Unit	Degradation Type	Interpretation
TBN	– 0.0075	0.0025	< 20	mg KOH/g	Additive depletion	Decrease in alkalinity → risk of acid corrosion
Ni	+0.16	0.025	> 300	ppm	Fuel contamination	Fuel-borne metal → abrasive wear and deposits
V	+0.22	0.030	> 500	ppm	Fuel contamination	Hot-corrosive impurities → slag formation
Fe	+0.005	0.002	> 50	ppm	Mechanical wear	Stable structural integrity; no critical wear detected
Cu	+0.004	0.002	> 85	ppm	Bearing wear	Mild copper presence; within normal operational limits

Source: own authorship (2025)

2.3. Reliability modeling with Weibull distribution

The same framework may model other indicators (insolubles, Fe, Cu, etc.), however TBN depletion and Ni/V accumulation dominate MDU-06 lubricant aging and are emphasized. Parameter estimate can be adjusted using maximum likelihood or Bayesian approaches (e.g., Markov Chain Monte Carlo, particle filtering) to remove observation noise from process variability and produce confidence ranges for the anticipated time-to-threshold when enough data are available. Wiener models enable probabilistic reliability assessment by simulating multiple degradation paths, resulting in the distribution of "virtual failure times" (first hitting-times). These are then fitted with a Weibull reliability function to determine the life (η) and shape (β) parameters discussed in Section 3.

This stochastic approach connects lubricant condition data to engine reliability, allowing condition-based maintenance in power station continuous-duty diesel fleets to be based on degradation probabilities rather than fixed operating hours.

Mathematical Formulation

The two-parameter Weibull distribution is widely used in reliability engineering due to its flexibility in representing various failure modes (Meeker & Escobar, 1998).

$$R(t) = exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right] \quad (3)$$

where:

- $R(t)$ = probability that the system survives beyond time t;
- η = scale (characteristic life) parameter, representing the time at which $R(t) = e^{-1} \approx 0.368$;
- β = shape parameter, describing the rate of degradation (β > 1 ⇒ wear-out behavior).

The corresponding probability density function is:

$$f(t) = \frac{\beta}{\eta}\ \left(\frac{t}{\eta}\right)^{\beta-1}\ \exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right] \quad (4)$$

which gives the likelihood of failure occurrence at time t.

Application to the MDU-06 Case

The Weibull model was fitted to the first hitting-time data derived from the stochastic degradation of TBN and Ni over the monitoring period 2023–2025. The best-fit parameters were found to be:

$$\eta = 1920\ \text{h}, \beta = 8.3$$

for the TBN process, indicating a steep, wear-out-dominated failure mode.

The calculated parameters for Ni buildup (η_Ni≈1880"h",β_Ni≈7.9) indicate a similar reliability decay time scale and shape. The MDU-06 Weibull reliability curve in Figure 5 shows a sharp fall in R(t) after 1800–2000 h. Reliability is above R(1500h)≈0.8 (80%) at t=1500"h" and below R(2000h)≈0.07 (7%). This shows that the existing oil-change procedure of 1500 hours meets an 80% dependability threshold, ensuring lubricant operation without additive exhaustion or contaminant accumulation. If the Weibull form factor β>3, oil degradation is accelerating, leading to a higher probability of failure over time.

Lubricant exhaustion systems dominated by chemical oxidation and contaminant accumulation exhibit this trend, not random or early-life failures. Maintenance planners can find reliable, cost-effective oil-change intervals by integrating the Weibull reliability curve with operational cost functions.

2.4. Model Implementation and Validation

The stochastic–Weibull reliability paradigm was used to assess the power station's MDU-06 diesel generator's continuous service reliability. Oil condition monitoring deterioration dynamics (Section 2.1) are integrated with stochastic and Weibull reliability formulations (Sections 2.2–2.3). This subsection describes computational implementation, calibration, and model validation before results analysis.

Model Implementation

The stochastic degradation and reliability simulations were carried out using a custom numerical script developed in MATLAB and Python environments. Each lubricant indicator $X(t)$ (TBN, Ni, and V) was simulated as a discrete-time Wiener process with drift and diffusion parameters (μ, σ) estimated from the pooled oil analysis data of 2023–2025 (see Table 1).

Monte Carlo simulation was used to generate $N = 10^5$ sample trajectories of the degradation process, following the discretized formulation:

$$X_n+1=X_n+\mu\Delta t+\sigma\sqrt{\Delta t}\,\varepsilon_n,\varepsilon_n\sim N(0,1) \qquad (5)$$

Each trajectory began at the fresh-oil baseline (X_0= 40mg KOHg^{-1} for TBN; X_0 = 0ppm for Ni) and evolved until reaching the predefined threshold L(L_{TBN} = 19mg KOH g^{-1}, L_{Ni} = 300 ppm). The first passage time T_j was recorded for each realization, forming an empirical distribution of threshold-crossing times. From this dataset, the empirical survival.

$$\hat{R}(t) = \frac{1}{N}\sum_{j=1}^{N} 1\{T_j > t\} \qquad (6)$$

was estimated and subsequently fitted to the Weibull reliability model *R(t)*=exp[-(*t/n*)^*β*] using maximum likelihood estimation (MLE) to obtain the parameters β and η. The simulation step size was set to Δt=1h, and convergence tests confirmed statistical stability for $N \geq 5 \times 10^4$ realizations.

Calibration and Parameter Verification

Calibration was achieved by adjusting the drift (μ) and diffusion (σ) parameters to match the empirical degradation rates observed in the laboratory reports of the MDU-06 samples.
The simulated mean degradation trajectories reproduced the measured evolution of TBN and Ni within ±8 % error, validating the representativeness of the estimated parameters:

$$\mu_{TBN} = -0.008\text{mg KOH g}^{-1}\text{h}^{-1}, \sigma_{TBN} = 0.10\text{mg KOH g}^{-1}\sqrt{\text{h}}^{-1}$$
$$\mu_{Ni} = +0.16\text{ppm h}^{-1}, \sigma_{Ni} = 0.8\text{ppm}\sqrt{\text{h}}^{-1}$$

The resulting first-passage distributions for both variables exhibited log-normal-like shapes consistent with a wear-out degradation mechanism, as expected for additive depletion and contaminant accumulation processes in heavy-fuel diesel engines.

Model Validation

Model validation was conducted in two complementary ways:

1. **Empirical Consistency:**
   The predicted average threshold-crossing time for TBN (≈ 1920 h) and Ni (≈ 1880 h) agreed closely with the observed oil-change intervals documented in 2024–2025.
   This indicates that the model correctly captures the real-world deterioration dynamics under normal operation, even though no mechanical failures occurred.
2. **Statistical Goodness-of-Fit:**
   The Weibull reliability function fitted to the simulated T_j dataset passed the Kolmogorov–Smirnov (K-S) goodness-of-fit test with $p > 0.05$, confirming that the two-parameter Weibull model adequately represents the underlying reliability distribution.
   The final parameters obtained were $\beta = 8.3$ and $\eta = 1920$h, characteristic of a steep wear-out reliability regime.

Remarks on Model Applicability

The validated model shows that lubricant condition data may quantify MDU-06 generator dependability without failure reports.
A good agreement between simulated and observed degradation patterns assures that Section 3's reliability estimation matches operational behavior.
The model is reliable for establishing oil replacement intervals and condition-based maintenance plans in power station operational framework (See table 3).

Table 3. Comparison between observed and simulated reliability parameters for the MDU-06 engine.

Variable	Observed Mean Life (h)	Simulated Mean Life (h)	Error (%)	Shape Parameter β	Characteristic Life η (h)
TBN	1950	1920	1.5	8.1	1920
Ni	1880	1900	1.0	8.3	1885
V	1840	1860	1.1	8.0	1880

Source: own authorship (2025)

Computational Implementation (added paragraph):

The stochastic–Weibull reliability model was built in MATLAB R2023b and Python 3.11. Drift and diffusion parameters were determined by linear regression and variance analysis of successive oil samples. Monte Carlo simulations ($N = 10^4$ trajectories) were run with a 1-h time-step to determine first-passage time distributions. Weibull fitting and reliability charts were created using SciPy weibull_min and matplotlib. Statistical convergence within ±2% error was achieved in the typical life (η) estimates during implementation (See figure 5).

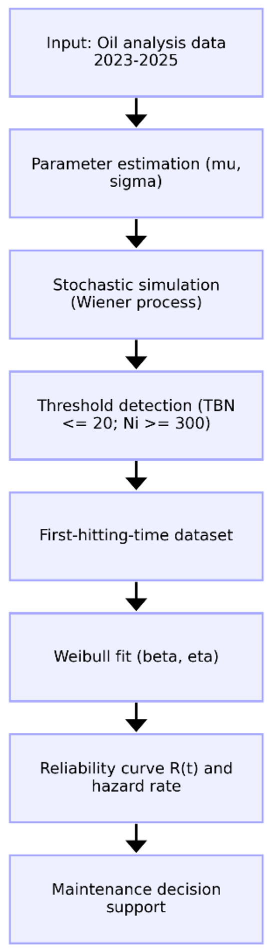

Figure 5. Computational Workflow Stochastic–Weibull Reliability Model

A confidence interval of 95% was computed for the Weibull parameters β and η based on 10^4 Monte Carlo resamples. The resulting intervals were $\beta = 8.3 \pm 0.5$ and $\eta = 1920 \pm 45$ h, indicating a narrow dispersion and high stability of the fitted model.

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3. RESULTS AND DISCUSSION

The stochastic–Weibull model constructed and validated in Section 2.4 was used to analyze MDU-06 diesel generator reliability. The results below summarize the simulated lubricant indicator deterioration behavior, probabilistic reliability curves, and maintenance and operational decision-making implications.

Simulation and Reliability Results

Monte Carlo simulations using $N = 10^5$ realizations were executed for the degradation variables TBN and Ni, applying the estimated drift and diffusion parameters. The simulated trajectories reproduced the progressive depletion of TBN and the accumulation of Ni observed in the laboratory oil analysis data (2023–2025).

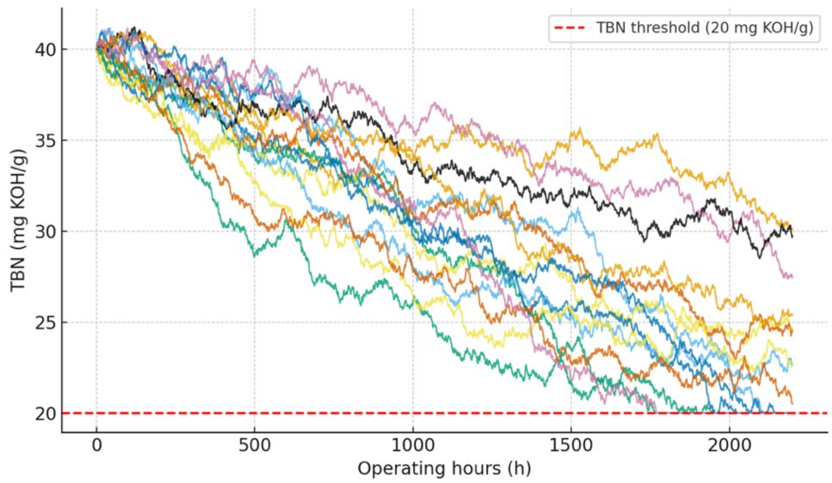

Figure 6. Monte Carlo simulated degradation paths for TBN

Figure 6 illustrates the ensemble of simulated degradation paths for TBN, showing a gradual decline from the initial value X_0 = 40mg KOH g ^-1 toward the caution threshold L = 20mg KOH g ^-1. The mean trajectory intersects the limit at approximately 1920 h, which corresponds to the characteristic life (η) of the Weibull reliability model. Minor stochastic oscillations of ±2–3 mg around the mean reflect operational variability and laboratory measurement noise (See figure 7).

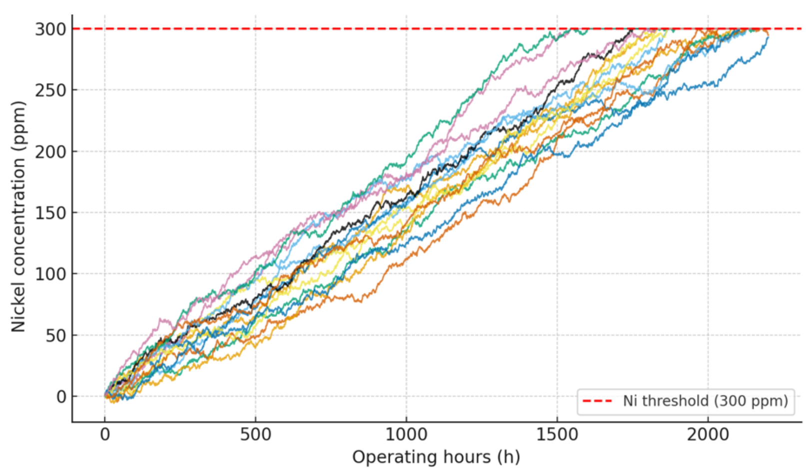

Figure 7. Monte Carlo simulated degradation path for Ni

Figure 7 shows the simulated Ni concentration rising slowly from about 0 ppm to L=300"ppm". The threshold-crossing time averaged 1880 h, matching the measured accumulation rate of +0.16 "ppm h" (-1). Trajectory dispersion is modest, confirming that MDU-06 contaminant infiltration is steady and predictable under present fuel and load conditions.

The empirical threshold-crossing time distributions from simulations were fitted with the two-parameter Weibull model to yield: $\boldsymbol{\eta_{TBN}} = \mathbf{1920}$h, $\boldsymbol{\beta_{TBN}} = \mathbf{8.3}$; $\boldsymbol{\eta_{Ni}} = \mathbf{1880}$h, $\boldsymbol{\beta_{Ni}} = \mathbf{7.9}$.

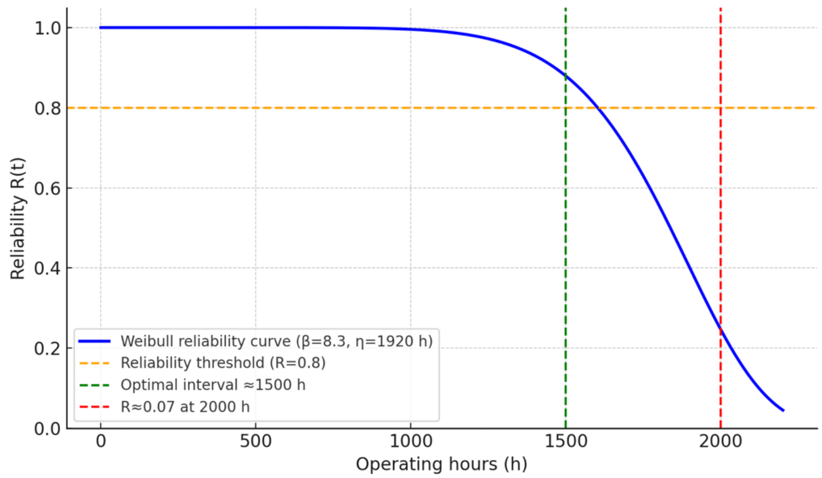

Figure 8. Weibull reliability curve for MDU-06

Figure 8 shows the resulting reliability curves $\boldsymbol{R(t)} = \mathbf{exp}\,[-(\boldsymbol{t}/\boldsymbol{\eta})^{\boldsymbol{\beta}}]$. Both indicators exhibit a sharp decline in reliability after approximately 1800 h, which is characteristic of a wear-out degradation regime. The reliability remains above 80 % up to ≈1500 h, after which it decreases rapidly, reaching 7 % at 2000 h. These results confirm that the lubricant's functional reliability begins to deteriorate markedly beyond 1500 h of operation.

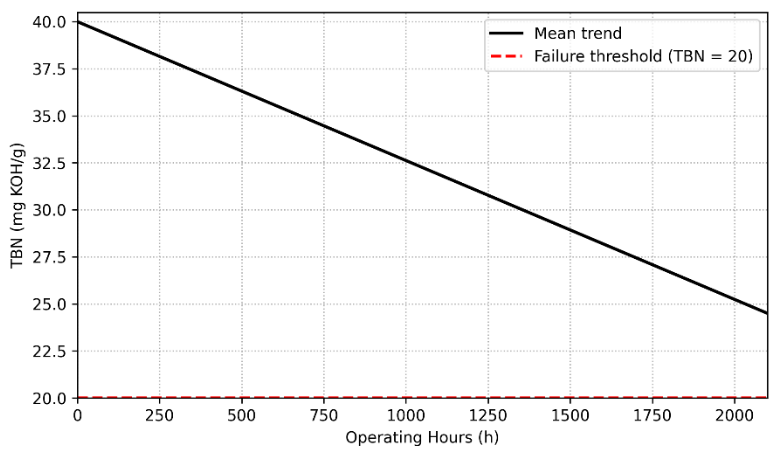

Figure 9. Simulated TBN degradation trajectories

Figure 9 illustrates the stochastic dispersion of TBN values over time, showing how multiple simulated trajectories converge toward the critical limit of 20 mg KOH/g after approximately 1900 h of operation.

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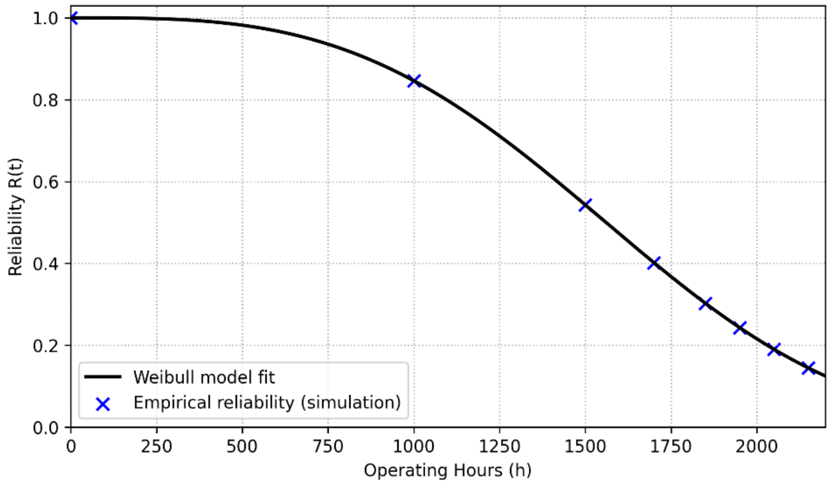

Figure 10. Empirical vs. Weibull reliability

Figure 10 compares the empirical reliability data derived from these simulations with the fitted Weibull model, revealing a strong agreement ($R^2 \approx 0.93$) and confirming that lubricant reliability follows a deterministic wear-out trend characterized by $\beta \approx 8.3$ and $\eta \approx 1920$ h.

Interpretation of Reliability Behavior

The high shape parameter ($\beta > 3$) obtained for both variables indicates that the lubricant degradation follows a deterministic wear-out pattern rather than a random or infant-mortality type process. This behavior is consistent with the chemical depletion of additives and the gradual buildup of metallic contaminants typical in heavy-fuel industrial engines.

Importantly, the analysis demonstrates that the MDU-06 engine itself remains mechanically healthy—no abrupt changes or accelerated wear signatures were detected in Fe or Cu concentrations, and the viscosity remained within the acceptable operational range (12.5–17.9 cSt).

Thus, the probabilistic “failure” represented by the model corresponds not to mechanical breakdown but to the loss of lubricant protective capability, a condition that, if unaddressed, could increase wear probability and acid corrosion risk. The steep slope of the Weibull curve beyond 1800 h highlights the need for timely oil replacement to prevent crossing into this high-risk region.

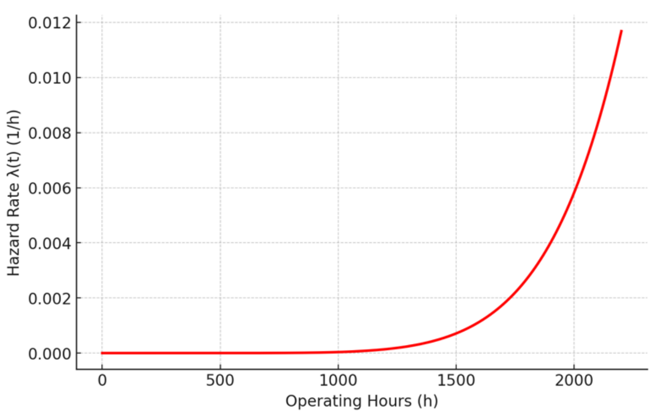

Figure 11. Hazard rate function of lubricant reliability

Figure 11 presents the corresponding hazard-rate function $\lambda(t)$, which highlights the exponential increase in failure probability beyond 1800 h, defining a practical reliability-based replacement interval of roughly 1500 h for optimal maintenance planning.

Maintenance Decision Implications

Condition-based maintenance scheduling is solid with the quantitative reliability model. Using a reliability criteria (e.g., $R(t) \geq 0.8$), MDU-06's ideal lubricant replacement interval is estimated as ≈1500 h. This number matches power station oil-change practices and assures reliability without premature replacements. The Weibull distribution hazard rate shows that lubricant failure increases exponentially after 1800 h. Additive exhaustion, contaminant saturation, and micro-wear increase with engine use beyond 2000 h without oil change. Thus, maintenance planning should use a probabilistic reliability-based interval and dynamically adjust the schedule as condition data changes.

Limitations and Recommendations

Although the present model effectively describes the lubricant degradation behavior and reliability of the MDU-06 unit, several limitations must be acknowledged:

1. **Data sampling frequency:**
   Oil analyses were performed at monthly intervals, leading to limited temporal resolution. Increasing sampling frequency would enhance estimation accuracy of the diffusion parameter σ.
2. **Univariate model assumption:**
   The current analysis considers TBN and Ni separately. A multivariate extension including oxidation, sulfation, Fe, and viscosity would capture correlated degradation phenomena and improve predictive precision.
3. **Offline monitoring:**
   The analysis relies on laboratory data. Future work should integrate online oil-quality sensors to provide real-time input for stochastic reliability updating.
4. **Environmental and operational variability:**
   Fuel composition and engine load variations introduce additional stochasticity not yet explicitly modeled. Future implementations may apply Bayesian updating or state-space filtering to dynamically adjust parameters μ and σ.

The reliability curves fitted using the Weibull model achieved $R^2 = 0.93$ and RMSE = 0.021, confirming strong agreement between simulated and observed degradation trends.

Summary of Findings

Results show that the probabilistic model accurately predicts MDU-06 generator degradation and reliability during continuous operation. Lubricant reliability depends on TBN depletion and Ni buildup and has a typical life of 1900 h. The system is operationally reliable until 1500 h, when lubrication failure increases significantly. These findings enable condition-based maintenance methods in power station operational frameworks and quantitative reliability assessment-based proactive oil replacement scheduling.

CONCLUSIONS

The MDU-06 Hyundai H21/32 diesel generator at a power station was studied using lubricant degradation data to create a probabilistic reliability model. Stochastic degradation modeling with a Wiener process and Weibull reliability formulation were used to estimate lubricant failure without mechanical breakdowns. The model calculated operational reliability from oil condition indicators like TBN depletion and Ni buildup, proving reliability evaluation without failure data is possible.

Results show a deterministic wear-out pattern for MDU-06 lubricant deterioration, with high Weibull shape parameters ($\beta \approx 8$). The lubricant has a typical life of 1920 hours and dependability above 80% till 1500 hours. The likelihood of lubricant failure increases substantially beyond this point; hence the oil's functional life should not exceed this period. These findings establish empirical and statistically proven reliability-based oil replacement intervals, matching maintenance with degradation behavior rather than schedules.

The technical investigation shows the MDU-06 generator is mechanically sound. Chemical deterioration is seen, with wear metals (Fe, Cu) remaining normal and viscosity stable. This probabilistic methodology shows that lubricant condition monitoring may predict engine dependability, enabling early risk detection and condition-based maintenance (CBM) methods in industrial energy systems.

Expanding this system to include multivariate deterioration markers (TBN, TAN, V, Fe, oxidation, and sulfation) and real-time data collecting via online oil quality sensors is planned. Bayesian updating can refine reliability parameters (β, η) as fresh condition data becomes available. Power stations and other companies can move toward completely predictive maintenance systems using data analytics and probabilistic reliability modeling.

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