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Accounting for sahelian environmental conditions in operational reliability analysis: The case of diesel generator sets in Burkina Faso

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ABSTRACT: In Sahelian countries, diesel thermal power plants remain the primary means of electricity generation. However, their performance is significantly affected by thermal and hygrometric stresses (high ambient temperatures and extreme relative humidity) as well as by heterogeneous maintenance practices. This study analyzes the operational reliability of a fleet of seven diesel generator units at the Komsilga thermal power plant in Burkina Faso using field data collected between 2022 and 2025 (12,500 operating hours, 248 maintenance interventions, hourly environmental measurements, and historical records of failures and component replacements).

The methodological approach combines (i) parametric survival modeling based on the Weibull distribution, extended through an Accelerated Failure Time (AFT) model integrating temperature (T) and humidity (H) as covariates, and (ii) a machine learning approach using a Random Forest model for short-term failure risk prediction (72-hour horizon).

The results reveal a strong negative correlation between temperature and MTBF ($r = -0.72$) and between temperature and reliability ($r = -0.75$), with an amplifying effect of humidity ($r = -0.58$ with MTBF). The Weibull-AFT model highlights an exponential decrease in the scale parameter η as temperature and humidity increase, indicating accelerated equipment aging under severe environmental conditions. Under critical operating conditions ($T > 40$ °C and $H > 70$ %), MTBF decreases by approximately 55% compared with nominal conditions. The predictive Random Forest model achieves an AUC-ROC of 0.92 and identifies temperature as the most influential variable, followed by humidity and time since the last maintenance operation. A predictive maintenance strategy based on a risk score could reduce unplanned downtime by an estimated 20–30% according to simulation results.

KEYWORDS: Reliability, Diesel generator sets, Weibull-AFT model, Sahelian climate, Predictive maintenance, SONABEL.

1 INTRODUCTION

Electric power systems in Sahelian countries still rely heavily on diesel thermal power plants to ensure the balance between electricity supply and demand. However, the intermittency of renewable energy sources such as solar photovoltaic and wind power limits the guarantee of firm power. In this context, an accurate understanding of the operational reliability of diesel generator units becomes a key determinant of: (i) fleet availability, (ii) electricity production costs, and (iii) the continuity of power supply.

In Burkina Faso, diesel generators operate under severe environmental conditions characterized by ambient temperatures that can reach 49 °C, relative humidity exceeding 75%, and frequent dust episodes. These environmental stresses accelerate lubricant degradation, increase thermal constraints, and promote corrosion and electrical faults. In parallel, the variability of maintenance practices such as maintenance quality, intervention frequency, and spare parts availability acts as a confounding factor. Consequently, a reliability model that is useful for operational management must integrate both environmental stress factors and operational maintenance indicators.

Furthermore, the rapid growth in energy demand resulting from demographic expansion requires strategies aimed at reducing dependence on petroleum products. In addition, the depletion of natural resources reinforces the urgency of sustainable energy transition policies in Sahelian countries [1]. In Burkina Faso, electricity demand has been increasing by more than 10% annually, mainly due to the expansion of the industrial production sector. Currently, two main types of electricity generation technologies are predominantly used by the national electricity company: solar photovoltaic power plants and diesel thermal power plants. Several projects involving these generation technologies are currently under development, with a predominance of diesel-based generation.

According to Toktarova et al. (2025), renewable energy technologies have experienced rapid progress over the past decade, leading to substantial cost reductions and improved cost competitiveness compared to fossil fuel and nuclear technologies (Toktarova et al., 2025). However, fossil fuels are expected to continue supplying nearly 80% of global energy demand by 2040, while also contributing significantly to greenhouse gas emissions [3]. Nevertheless, diesel thermal power plants will continue to play a crucial role in the global energy landscape because they provide reliable, stable, and flexible electricity generation solutions.

In Africa, approximately 80% of electricity production still relies on non-renewable energy sources, including natural gas, oil, and coal [4]. In Burkina Faso, according to the latest figures published in 2025, diesel thermal power plants represent 36% of the installed capacity, solar photovoltaic plants 11.5%, hydroelectric power plants 3.5%, while 49% corresponds to electricity imports within the national electricity company SONABEL [5].

Despite the high potential for both renewable and non-renewable energy resources, Sahelian countries still face significant energy deficits due to limited investment and harsh environmental conditions. Assessing the photovoltaic (PV) solar potential in these countries is therefore essential to evaluate the feasibility of solar energy systems and to support the planning and implementation of solar-based electrification projects [6].

However, electricity generation based solely on renewable energy sources presents several drawbacks. First, the initial investment costs remain relatively high. According to the IEA-PVPS T9-13 report, the installation cost of a diesel thermal power plant ranges between 400 and 800 USD/kW, whereas photovoltaic solar plants require 900 to 1500 USD/kW [7]. Second, electricity supply from renewable sources is not always reliable due to their intermittent and uncertain nature [14].

In Burkina Faso, as in most Sahelian countries, both diesel and photovoltaic power plants are widely used for electricity generation [8]. Unfortunately, these facilities frequently experience equipment failures and performance degradation caused by severe environmental conditions, including high temperatures, humidity levels up to 75%, and significant airborne dust pollution during certain periods of the year [9].

These constraints result in high electricity production costs characterized by increased specific fuel consumption, reduced load capacity, premature generator failures, and decreased efficiency of solar panels. For instance, a study conducted in Nigeria reported an overall reliability of 55.73% for a diesel thermal power plant composed of six generator units. The low reliability was attributed to environmental constraints and maintenance practices based solely on manufacturer recommendations [10].

Diesel thermal power plants are essential for maintaining stable electricity supply, but they are also associated with high operating costs and potential economic losses caused by equipment failures [11]. In addition, the Nigerian energy sector faces numerous production challenges due to insufficient capacity and gas supply issues. Frequent grid disturbances, including generator trips, significantly increase maintenance requirements and operational costs [12].

Electricity production from diesel power plants also depends on the availability of spare parts required for generator operation and maintenance. Power plant operators generally follow manufacturer recommendations to avoid major failures, even though this often leads to excessive spare parts inventories [13]. Maintenance planning typically determines generator shutdown periods for safety inspections over one- or two-year intervals. However, this planning has become an increasingly complex optimization problem. Insufficient maintenance interventions may lead to excessive costly failures, whereas overly frequent maintenance may reduce power system reliability and significantly increase maintenance and operating costs [14].

The objective of this study is to analyze the operational reliability of a fleet of seven diesel generators at the Komsilga thermal power plant in Burkina Faso, in order to develop a predictive maintenance strategy based on a risk score and operational recommendations. Specifically, this study aims to:

- quantify the impact of temperature and humidity on reliability indicators (β, η, MTBF, R (t), λ (t));
- propose a parametric survival model (Weibull-AFT) to predict reliability under environmental covariates;
- enhance predictive maintenance using a Random Forest model for early failure detection.

In this context, a critical review of the scientific literature is necessary to identify existing approaches, their limitations, and the research perspectives that justify the present study.

2 LITERATURE REVIEW

Several studies have demonstrated the importance of environmental factors in the reliability analysis of engineering systems. Zhang et al. (2024) showed the significant impact of temperature on the degradation of mechanical systems, while Chen and Li (2025) developed accelerated aging models incorporating humidity as an acceleration factor [15], [16].

Kumar et al. (2024) validated the use of the Weibull distribution for analyzing diesel engine failures in tropical environments with climatic conditions similar to those observed in Burkina Faso [17]. Earlier research by Mishra et al. (2020) pioneered the analysis of combined temperature-humidity effects on energy system reliability, establishing significant correlations between environmental conditions and equipment failure rates.

Zhang and Li (2021) developed accelerated aging models experimentally validated on medium-power generator sets [18]. Similarly, Garcia et al. (2023) demonstrated the effectiveness of Weibull analysis for predictive maintenance in tropical environments. Chen and Watanabe (2024) further introduced advanced approaches for integrating environmental covariates into reliability models [19], [20].

Smith and Johnson (2020) pioneered the integration of environmental covariates into Weibull reliability models for critical equipment. Their approach improved failure prediction accuracy by approximately 30% compared with traditional models [21]. Zhang et al. (2021) also proposed an environmental accelerated reliability analysis framework establishing quantitative relationships between temperature, humidity, and failure rates for diesel engines [22].

More recently, Chen and Martinez (2023) introduced time-varying Weibull parameter models capable of capturing seasonal variations in failure patterns influenced by climatic conditions [23]. Kumar et al. (2024) conducted a comprehensive study on the impact of thermal stress on generator lifetime in tropical environments, experimentally validating theoretical reliability models. Taiwo and Li (2025), in their recent meta-analysis, confirmed the robustness of Weibull-based approaches for reliability modeling under multiple environmental constraints.

Diesel generators are complex socio-technical systems composed of multiple interacting subsystems including diesel engines, alternators, auxiliary circuits, control systems, cooling systems, lubrication systems, and fuel supply circuits. Recent literature emphasizes that reliability depends not only on thermo-mechanical components (overheating, fatigue, wear) but also on electrotechnical failures (insulation degradation, connection faults, corrosion) and operational conditions such as load variations, start-stop cycles, and fuel quality.

Case studies on industrial and marine diesel engines have widely applied Weibull-based methods to estimate reliability indicators such as reliability function R (t), failure rate λ (t), and mean time between failures (MTBF) [25]. These studies highlight the combined effects of temperature, humidity, and dust exposure, which contribute to accelerated wear, corrosion, and cooling constraints, emphasizing the need to incorporate environmental stress factors into reliability and performance models [26].

According to Shahriaria et al. (2024), the Weibull distribution remains the dominant statistical model in reliability analysis due to its interpretability and its compatibility with key reliability indicators such as R (t), λ (t), MTBF, and the Weibull parameters β (failure regime) and η (scale parameter). Recent studies continue to propose methodological advances in Weibull-based reliability inference [27].

Wang et al. (2021) proposed statistical inference methods for accelerated degradation tests involving multiple stresses and dependent competing failure processes. Their findings demonstrate that reliability decreases significantly under higher temperature, humidity, and random shock conditions, as the average wear rate increases with higher stress levels, leading to higher degradation and lower system reliability [28].

More recently, Yang and Wang (2025) applied the Random Forest algorithm to predict machine failures and evaluate predictive performance. Several performance metrics were used, including accuracy, precision, recall, F1-score, and ROC-AUC.

Among all tested models, the Random Forest model achieved the best performance, reaching a classification accuracy of 99.5% while maintaining a balanced trade-off between recall and precision [29].

3 MATERIALS AND METHODS

3.1 GENERATOR SET FLEET OF THE KOMSILGA DIESEL THERMAL POWER PLANT

The Komsilga thermal power plant has seven (07) MAN B&W and CATERPILAR brand generators, with ratings ranging from 12.5 to 18.9 MW, as shown in table 1 below. It has an installed capacity of more than 90 MW and contributes to more than 30% of the total thermal production of the National Electricity Company of Burkina Faso (SONABEL) [30]. These generators also ensure the production of electrical energy at any time and in any season for the benefit of the National Interconnected Network (NIN) of SONABEL.

Table 1. Generator set fleet of the Komsilga diesel thermal power plant

N°	Brand & type	Nominal power (MW)	Engine speed (RPM)	Year of operation
1	MAN 18V48/60	18,9	500 ~ 514	2013
2	Caterpillar 16CM43C	12,527	500 ~ 514	2012
3	Caterpillar 16CM43C	12,527	500 ~ 514	2012
4	Caterpillar 16CM43C	12,527	500 ~ 514	2012
5	Caterpillar 16CM43C	12,527	500 ~ 514	2014
6	Caterpillar 16CM43C	12,527	500 ~ 514	2014
7	Caterpillar 16CM43C	12,527	500 ~ 514	2014

3.2 DATA AND PREPARATION

The data covers 2022 to 2025 and includes:

3.3 HOURS OF OPERATION;

- 248 maintenance interventions;
- hourly environmental measurements (ambient temperature, machine room temperature and relative humidity);
- failure history and replacement of spare parts.

Before modeling, the series are synchronized on time, missing values are imputed (short interpolation method and seasonal median), and events are encoded in runtime between failures. Censored observations (periods without observed failure until end of follow-up) are retained to avoid selection bias.

3.4 PARAMÈTRES DE LA DISTRIBUTION DE WEIBULL ET EXTENSION À COVARIABLES

Weibull's distribution method is used to develop models in devices with a decline, stable, or increasing failure rates. The versatility of this method is one reason for its wide use in reliability analysis. The Weibull distribution is generally described by shape, scale and threshold parameters. These parameters are known as the three (03) parameter Weibull distribution (Nnaji et al., 2020). Moreover, it is one of the most efficient mathematical models to describe the reliability of technical systems throughout their life cycle. The main advantage of Weibull analysis lies in its ability to model different phases of a component's life cycle using the shape parameter β. When β < 1, the distribution describes the infant mortality failure phase, often caused by manufacturing defects or incorrect break-in procedures. When β = 1, failures occur randomly at a constant rate, typical of systems without significant wear. When β > 1, the intensity of failures increases over time due to wear mechanisms [32]. Thus, the parameters necessary for measuring reliability are (Nnaji et al., 2020): Probability density f (t), representing the probability of failure in a time interval (t) [34].

$$f(t) = \frac{\beta}{\eta}\left(\frac{t-\gamma}{\eta}\right)^{\beta-1} e^{-\left(\frac{t-\gamma}{\eta}\right)^{\beta}} \qquad (1)$$

With γ: Positional parameter;

η: Scale parameter;
β: Shape parameter.

- The Mean Time Between two Failures (MTBF) is an arithmetic value and an average over a long period of time with a large number of units. It is given by the following formulas:

$$\text{MTBF} = \int_0^{+\infty} R(t)dt \tag{2}$$

$$\text{MTBF} = \frac{Uptime}{number\ of\ breakdowns} \tag{3}$$

If λ is constant: MTBF = $\frac{1}{\lambda}$
If λ is not constant, MTBF + Aη + γ

- The reliability function R (t) characterizes the probability that an equipment will not fail until a given moment (t). It is given by the following formula:

$$R(t) = e^{-(\frac{t}{\eta})^{\beta}} \tag{4}$$

- The distribution function F (t) is the general notation of the probability of failure in the time interval [0, t]. It is obtained by:

$$F(t) = 1 - e^{-(\frac{t-\gamma}{\eta})^{\beta}} \tag{5}$$

- The failure rate λ (t) is the probability of failure at the moment (t+dt), knowing that the device was good at the moment t. Also called the failure rate, it depends on the performance time, with the rate varying over the life cycle of an equipment. It is expressed as:

$$\lambda(t) = \frac{\beta}{\eta}(\frac{t}{\eta})^{\beta-1} \tag{6}$$

or:

$$\lambda(t) = \frac{F(t)}{R(t)} \tag{7}$$

Pour intégrer l'environnement, nous adoptons une formulation Accelerated Failure Time (AFT) avec une échelle dépendante des covariables:

$$\eta(x) = \exp(\alpha_0 + \alpha_1 \cdot T + \alpha_2 \cdot H + \alpha_3 \cdot T\_{salle}) \tag{8}$$

With:

- T: ambient temperature (°C)
- H: relative humidity (%)
- T_{salle}: machine room temperature (°C)

In this writing, an increase of T or H can decrease η, thus accelerating the appearance of breakdowns (accelerated aging).

4 Results And Discussion

4.1 Environmental Statistics

The measurements show an average temperature of 42.3 °C (4.7 °C), a temperature range of 32 to 49 °C, and an average relative humidity of 65 % (8 %). Critical periods are generally from March to June with a temperature T > 45 °C and humidity H > 70 %.

4.2 Weibull Parameters By Generator Group And Interpretation

Except for G4 (β < 1), the other generator groups exhibit β > 1, indicating a wear-out phase characterized by an increasing failure rate. Generator G4 shows the best reliability at 100 h (0.82) and a relatively high MTBF, although improvements are still possible.

Table 2 below presents the Weibull parameters and the reliability indicators derived from field data.

Table 2. Weibull parameters and reliability indicators (derived from field data)

Generator	β	η (h)	MTBF (h)	R(100h)
G1	1.15	285	267	0.72
G2	1.08	310	295	0.74
G3	1.25	240	225	0.68
G4	0.92	420	378	0.82
G6	1.42	380	350	0.78

Furthermore, **Figure 1** below illustrates the **Weibull reliability curves for each generator group based on the estimated parameters β and η**.

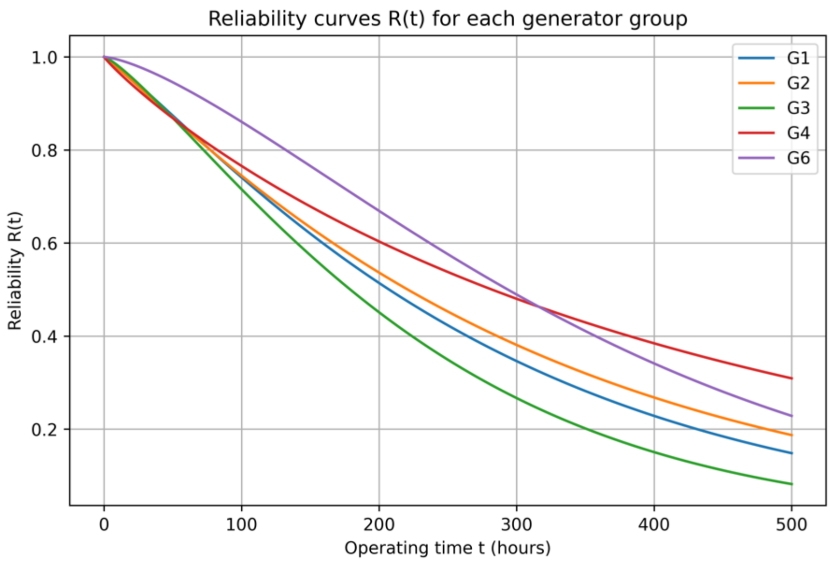

Fig. 1. Reliability curves R (t) for each generator group

Interpretation

All reliability curves decrease over time. In other words, as operating time increases, the probability of remaining operational decreases, reflecting the progressive increase in failure probability. This behavior is typical of diesel generators subjected to wear processes.

For G1, G2, G3, and G6, where β > 1, the curves show a steep downward trend, corresponding to an increasing failure rate and progressive wear-out regime.

Conversely, G4 exhibits a smoother slope, associated with a decreasing failure rate, indicating behavior closer to that of a stable system. This suggests that the unit is either better maintained or less heavily utilized.

These results confirm that the reliability of the generator fleet is heterogeneous, despite the units having similar technical characteristics.

Overall, it can be concluded that the power plant operates predominantly in a wear-out regime, with different degradation rates across the generator units.

4.3 CORRELATIONS AND QUANTIFICATION OF ENVIRONMENTAL IMPACT

The correlation matrix highlights the following relationships:

- Temperature and MTBF (**r = −0.72**)
- Temperature and Reliability (**r = − 0.75**)
- Humidity and MTBF (**r = − 0.58**)
- Humidity and Reliability (**r = − 0.62**)
- Temperature and Failure Rate (**r = 0.78**)

These relationships support a coherent causal mechanism: $T\uparrow \rightarrow \eta\downarrow \rightarrow MTBF\downarrow \rightarrow R\ (t)\ \downarrow \rightarrow \lambda\ (t)\ \uparrow T\uparrow$

with humidity acting as an amplifying factor.

Thus, the relationship between MTBF and temperature is illustrated in Figure 2.

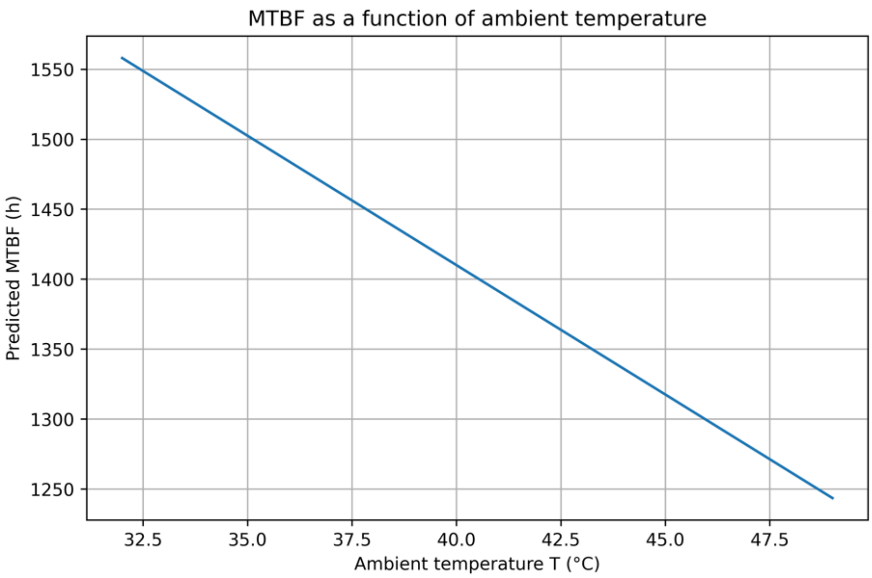

Fig. 2. MTBF as a function of temperature (linear regression model)

INTERPRETATION

The results show that MTBF decreases as temperature increases.

More specifically, an increase of 1°C leads to an average MTBF reduction of approximately 18.5 hours.

Temperature therefore acts as an accelerating factor of equipment aging, particularly through:

- faster degradation of lubricants
- increased mechanical stress
- reduced thermal efficiency
- overheating of electrical components

This figure ultimately indicates that ambient temperature is the primary driver of generator fleet degradation.

Furthermore, Figure 3 illustrates how MTBF varies with humidity when temperature remains constant.

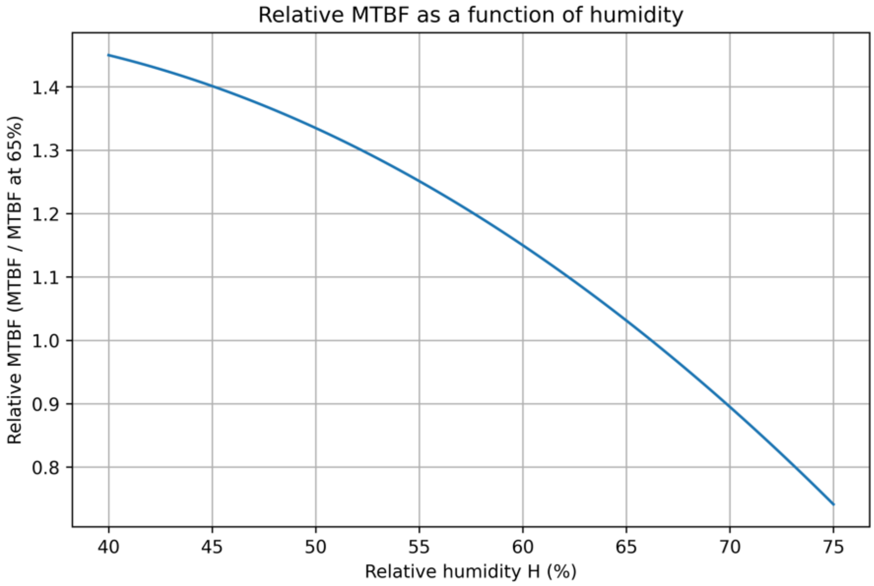

Fig. 3. Relative MTBF surface (T, H): visualization of performance zones

INTERPRETATION

When humidity increases, MTBF decreases even at constant temperature.

Humidity alone does not fully explain the degradation process. Its impact is weaker than that of temperature, but it amplifies thermal stress effects.

Therefore, humidity does not independently trigger failures, but it significantly accelerates degradation mechanisms already induced by heat. **Figure 4** illustrates the relative MTBF as a function of both temperature (T) and humidity (H).

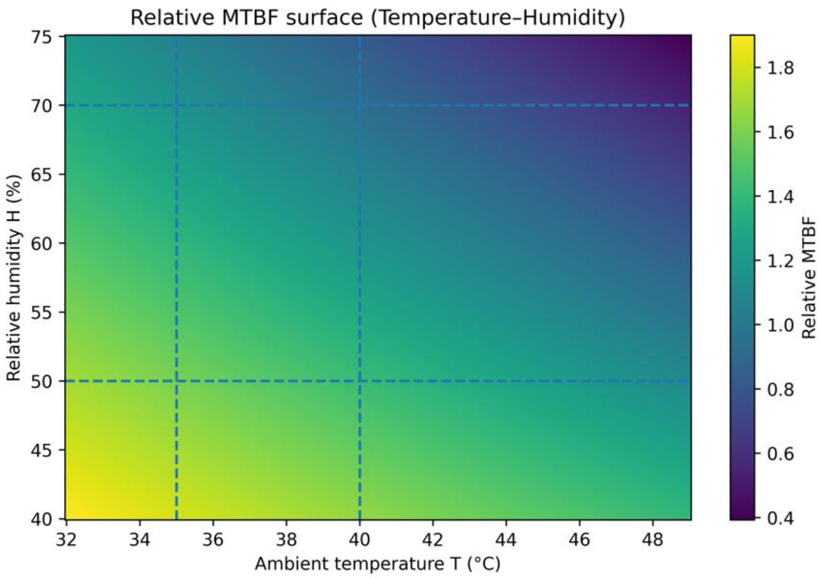

Fig. 4. Relative MTBF surface (Temperature–Humidity)

INTERPRETATION

Two main operating zones can be identified:

High-performance zone (green/high region)

- Moderate temperature
- Low to moderate humidity
- Corresponds to optimal operating conditions.

Critical zone (T > 40°C and H > 70%)

- MTBF drops sharply
- MTBF reduction reaches approximately 55%.

This indicates that environmental effects are not simply additive, but involve nonlinear interactions between temperature and humidity.

This figure therefore validates the use of the Weibull-AFT model and the accelerated aging hypothesis under climatic stress.

It also demonstrates that reliability depends on environmental coupling rather than on a single factor.

In conclusion, Sahelian climatic conditions create a combined stress zone in which reliability declines sharply.

Overall, the figures demonstrate that the reliability of diesel generators operating in Sahelian environments is governed by an accelerated aging process induced by thermo-hygrometric coupling. Temperature acts as the primary driver of wear acceleration, while humidity amplifies electrochemical and thermal degradation mechanisms, leading to a nonlinear reduction of MTBF under extreme conditions.

5 Predictive Reliability Analysis Using Random Forest

The Weibull-AFT model provides an explanatory reading and a medium/long term projection (η, MTBF, R functions and λ). For the operational decision (trigger an action within 24–72 h), we introduce a Random Forest that learns non-linear relationships and interactions (thermal/hygrometric thresholds, effect of time since the last maintenance). Thus, explanatory variables such as ambient temperature, machine room temperature, number of operating hours, time since last maintenance, number of historical breakdowns, and seasonal indicator have emerged. What led to the identification of a target variable: failure in the next 72 hours (binary classification).

To avoid over-estimation of performance (time leaks), the evaluation should prioritize a time validation (train on previous periods, test on later periods) and a class balancing if the failure is rare. Beyond AUC-ROC, we recommend reporting: (i) PR-AUC (rare class), (ii) confusion matrix at the chosen threshold, (iii) Brier score / calibration curve for probabilistic quality of alerts, and (iv) stability analysis of variable importances.

The results obtained after the test games gave the following performances:

- Accuracy = 88.4%,
- Accuracy = 85,7 %,
- Reminder = 90,1 %,
- F1-score = 87.8%,
- AUC-ROC = 92%.

Ambient temperature (~34.6%) and humidity (~21.8%) dominate the feature importance ranking, confirming the survival analysis results.

The Random Forest model provides not only a binary decision (failure/no failure) but also an instantaneous probability of failure.

A **risk score** is therefore defined:

R_{RF} (t) = P (défaillance | X (t)) (9)

with: X (t) representing the set of operational and environmental variables observed at time t namely: ambient temperature, relative humidity, temperature machine_room, time since last maintenance, cumulative operating time, history of breakdowns and seasonal indicator. Thus, three (03) zones are proposed:

- low (< 0.3): normal operation;
- moderate (0.3 - 0.6): enhanced surveillance;
- high (0.6): priority maintenance.

In simulation, 78% of outages are detected 48 hours in advance, with an estimated reduction of 20 to 30% of unplanned stops.

6 DISCUSSION

The results converge towards a robust conclusion: thermal stress is the main determinant of group reliability, and humidity amplifies this stress. The identified mechanisms (overheating, oil degradation, corrosion, electrical defects) are consistent with the observed correlations and the increase of λ (t) when T and H increase. From a methodological point of view, the hybrid approach is particularly relevant: Weibull-AFT to interpret and extrapolate, Random Forest to anticipate in the short term and manage non-linearities. Methodologically, the hybrid approach proves particularly effective:

The results obtained confirm the results of [35], [36], where the advantages of proactive and predictive models to reduce the frequency of failures were highlighted. In our case, the results show that the ambient temperature is the most penalizing factor for the reliability of generators. Two elements strongly converge namely: (i) the correlations indicate a robust relationship between temperature and degradation of reliability performance: Temperature - MTBF (r = 0.72), Temperature - Reliability (r = 0.75) and Temperature - failure rate (r = 0.78)., (ii) the simple model MTBF (h) = 2150 18.5 T (R2 =0, 87) quantifies an average loss of 18.5 h of MTBF per degree Celsius, with an inflection point around 35-38°C, suggesting a regime change (limiting saturation/cooling, thermal stress rise, accelerated aging).

This sensitivity is consistent with the principles of 'rating': many electromechanical equipment is specified with a maximum reference ambient temperature around 40°C (beyond that, derating or an increase in thermal risk is expected). For example, IEC 60034-1 reminds us that the atmosphere must not exceed 40°C for the usual nominal operating conditions of rotating machines.

In our case, the observed temperature is on average 42.3°C (up to 49°C). This reinforces the plausibility of the mentioned mechanisms (overheating, oil degradation, thermal engine/alternator constraints), and justifies a seasonal operation/maintenance strategy.

The relative humidity presents a secondary, but amplifying influence. The observed correlations (H–MTBF: r = 0.58) show that even at constant temperature, an increase in humidity leads to a decrease in mean time between failures.

This result is consistent with the work of Wang et al. (2021), who demonstrate that the combination of several environmental constraints produces synergistic effects on system degradation [37]. In the case of generators, humidity contributes notably to:

- the corrosion of metal surfaces;
- the degradation of electrical insulators;
- the increase in connection faults.

The analysis of β parameters shows that the majority of groups evolve in a wear regime (β > 1), characterized by an increasing failure rate over time.

This trend confirms the results obtained in similar studies on industrial and marine diesel engines [38], [39]. The special case of the G4 group (β < 1) suggests a more stable behavior, which can be attributed to:

- a better quality of maintenance,
- a lesser solicitation,
- or a more favorable mechanical state.

These observations show that, even in an identical environment, maintenance practices play a determining role in the variability of reliability performances.

A major contribution of this study lies in the combination of two approaches:

- the Weibull-AFT model, allowing a physical interpretation of aging;
- the Random Forest, oriented towards short-term operational decision making.

The performance obtained (AUC-ROC = 0.92; recall = 90.1%) confirms the recent results of [40], which show the robustness of Random Forest models for predicting industrial failures.

This complementarity is essential:

- the survival model explains why breakdowns appear;
- the ML model indicates when to intervene.

Thus, the proposed hybrid approach exceeds the limits of classical analyses focused solely on statistical modeling.

7 Conclusion And Outlook

This study demonstrates the major impact of Sahelian environmental conditions on the operational reliability of diesel thermal power plant generators. The integration of climate variables in a Weibull-AFT model allowed quantifying the acceleration of equipment aging, highlighting a reduction in MTBF that can reach about 55% under critical thermo-hygrometric conditions.

The analysis reveals that temperature is the main factor of degradation, while humidity acts as an amplifier of thermal and electrochemical wear mechanisms. The results confirm that the reliability of generators does not only depend on their mechanical design, but also strongly on their operating environment.

Furthermore, the integration of a Random Forest prediction model effectively completes survival analysis by offering short-term anticipation capacity. The proposed probabilistic risk score allows a concrete transformation of maintenance strategies, moving from a calendar-based preventive logic to a predictive one.

This hybrid approach thus constitutes an original methodological contribution for electric power generation systems operating under severe climatic constraints and provides a directly applicable framework for diesel thermal power plants in the Sahel countries.

Outlook:

Future work could focus on:

- the integration of new operational variables (actual load, fuel quality, dust);
- multi-state or concurrent risk modeling;
- the integration of life cycle cost for overall techno-economic optimization.

Ultimately, this study establishes a robust basis for the development of intelligent maintenance strategies aimed at sustainably improving the availability of thermal power plants in the Sahelian environment.

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