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A multi-indicator predictive maintenance framework for industrial equipment under Sahelian climatic and technical constraints: Case of diesel generator sets in a diesel thermal power plant

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Abstract

Industrial equipment used in agri-food processing, mining, power generation, and agricultural mechanization across Sahelian countries is exposed to severe environmental stressors. In Burkina Faso, the commissioning of new diesel thermal power plants highlights the growing importance of diesel generator sets in ensuring energy supply. However, their operation remains strongly constrained by harsh environmental conditions. High ambient temperatures, heavy dust loads, and strong hygrometric variability - further aggravated by climate change - accelerate equipment degradation, impair performance, and reduce the effectiveness of conventional maintenance strategies.

This study proposes a predictive maintenance framework tailored to the Sahelian context, based on the exploitation of real operational data from the National Electricity Company of Burkina Faso (SONABEL). Statistical methods combined with advanced algorithmic approaches were used to identify failure patterns and develop novel predictive indicators. In particular, a Thermal Stress Index (TSI) was formulated by integrating ambient temperature, machine-room temperature, and applied load. The results indicate that ambient temperature is among the most influential factors associated with the occurrence of failures.

To the best of our knowledge, this study is among the first to investigate the operational reliability of diesel generator sets under Sahelian operating conditions. The findings provide practical insights for implementing predictive maintenance strategies based on composite indicators, thereby strengthening the resilience and long-term sustainability of industrial equipment in tropical developing countries.

Keywords: Predictive maintenance; Diesel generator sets; Sahelian countries; Industrial equipment reliability; Thermal Stress Index; SONABEL

1. Introduction

Maintenance of industrial equipment in Sahelian countries - including Burkina Faso, Mali, Niger, Senegal, and Chad - has become a major technical and economic challenge. In agri-food processing plants, environmental constraints such as temperature, humidity, dust, and seasonal climatic variations exert significant stress on industrial assets, accelerate wear mechanisms, and reduce operational lifetime. Integrating these environmental factors into equipment design,

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maintenance planning, and asset management is therefore essential for improving reliability and optimizing operating costs [1].

Similarly, in the mining sector, the extreme environmental conditions prevailing in many Sahelian countries generate both technical and organizational challenges, making maintenance particularly complex. In such contexts, maintenance is a key lever for ensuring productivity, safety, reliability, and long-term equipment sustainability [2]. Among all these sectors, however, the energy sector remains the fundamental enabler of the economic activities mentioned above. It powers mechanized agriculture, mining facilities, manufacturing industries, small and medium-sized enterprises, and processing zones. Without reliable and affordable energy, the productivity of these sectors cannot grow sustainably [3].

As a result, electricity supply has become a strategic issue for the economic and social development of Sahelian countries. In a context characterized by rapid population growth, sustained urbanization, and rapidly increasing energy demand, the stability and reliability of power generation equipment directly condition economic competitiveness, industrial expansion, and the quality of life of local populations [4].

Burkina Faso provides a particularly relevant case study. As a landlocked Sahelian country, it faces multiple constraints related to industrial equipment maintenance. The National Electricity Company of Burkina Faso (SONABEL), which is responsible for electricity generation, transmission, and distribution, frequently relies on diesel generator sets to support production and compensate for structural shortcomings in the interconnected grid. These units play a crucial role, particularly in covering peak demand periods and maintaining supply continuity during regional interconnection failures. However, their operation is subject to particularly severe environmental constraints.

Under a Sahelian climate characterized by ambient temperatures often exceeding 40 C, highly variable humidity across seasons, heavy dust concentrations, and fluctuating fuel quality, diesel generator sets operate far from the nominal conditions for which they were originally designed [5]. These environmental deviations have direct consequences for equipment reliability and durability. Diesel engines exposed to harsh conditions experience accelerated degradation, premature wear of critical components, and increased risk of unexpected failures. Such failures do not merely result in service interruptions; they also generate high maintenance costs, additional expenses associated with spare-part imports, and substantial economic losses for the utility [6].

In a country where financial and technical margins for securing electricity supply remain limited, every failure represents a critical risk to service continuity and economic development. Against this background, the question of which maintenance strategy should be adopted becomes central. Historically, corrective maintenance - intervening only after a failure occurs - has dominated operational practices. While such an approach may appear pragmatic in the short term, it becomes particularly costly and inefficient in contexts where equipment availability is essential [7]. Preventive maintenance based on fixed maintenance schedules constitutes an improvement, but it may still be suboptimal because it does not account for the actual condition of the machines [8].

In this context, condition-based and predictive maintenance emerges as a relevant and promising approach. It relies on the use of operational data collected in real time to anticipate failures and schedule interventions at the most appropriate moment - neither too early, which would waste resources, nor too late, which would expose the system to breakdowns [9]. The literature has extensively demonstrated the effectiveness of predictive maintenance approaches, particularly through the integration of connected sensors, advanced statistical models, and artificial intelligence techniques. These methods have significantly reduced maintenance costs and improved equipment availability in a variety of industrial sectors [10].

However, most of these studies have been conducted in standard industrial environments - typically temperate climates with robust infrastructure and sufficient financial resources to deploy advanced sensing and AI solutions. Very few studies have addressed the specific context of Sahelian countries. Yet the singularity of these environments - extreme temperatures, dust, irregular fuel quality, logistical constraints, and limited financial resources - requires specific methodological and practical adaptations [11].

This article addresses this scientific and operational gap by proposing an in-depth analysis of operational data from SONABEL diesel generator sets. The objectives are threefold: (i) to identify the main factors influencing failure occurrence in a tropical Sahelian environment; (ii) to develop relevant indicators capable of supporting condition-based and predictive maintenance decisions; and (iii) to assess the potential impact of these indicators on cost reduction and equipment availability improvement.

By providing empirical evidence from a still underexplored context, this work contributes to the scientific literature on predictive maintenance and opens practical perspectives for strengthening the reliability of power infrastructures in developing countries. Through the example of Burkina Faso, the study also demonstrates how context-adapted intelligent maintenance approaches can support the resilience of Sahelian power systems under environmental and economic constraints.

The novelty of this study is articulated around four main contributions: the proposal of a frugal and contextualized predictive maintenance framework for diesel generator sets operating in hot and constrained environments; the formulation of an interpretable Thermal Stress Index (TSI) designed as a thermo-mechanical proxy for failure risk; the local calibration of alert thresholds based on observed distributions from the studied generator fleet; and the incremental and comparative validation of the developed indicators within a predictive and decision-support pipeline. In other words, the novelty of the study does not rely solely on the geographical case study, but rather on the combination of physical contextualization, instrumental frugality, interpretability, validation, and operational usefulness.

2. Literature Review

2.1. Evolution of Maintenance Strategies in the Context of Sahelian Countries

Historically, maintenance of power-generation equipment in West Africa - and particularly in Burkina Faso - has long relied on a corrective approach, i.e., intervening only after a failure has occurred. This practice remains common in several African public utilities due to budget constraints, the limited availability of advanced diagnostic tools, and insufficient training in predictive maintenance [5]. Although pragmatic in the short term, this strategy generates frequent downtime and high repair costs, which is especially problematic in countries where access to electricity remains limited, particularly in rural areas [4].

The adoption of planned preventive maintenance, based on fixed service intervals (e.g., oil changes every 500 operating hours), has partially improved reliability. However, in the Burkinabe context, this method faces several limitations. Extreme climatic conditions reduce the effectiveness of standard maintenance intervals defined by manufacturers, variability in fuel quality modifies maintenance cycles, and spare-part import delays often extend downtime [7]. As a result, condition-based and predictive maintenance appears to be a promising pathway for SONABEL, as it enables failure anticipation based on the actual condition of equipment.

Several international studies have demonstrated the effectiveness of this approach through sensor-based data acquisition and algorithmic analysis [8-10]. However, these works mainly concern stable industrial environments, and their direct transferability to Sahelian contexts remains limited [11].

2.2. Environmental Constraints and Their Impact on the Operational Reliability of Equipment

The Sahelian environment presents unique challenges for the operation of diesel generator sets that remain insufficiently addressed in the existing literature. Extreme temperatures regularly exceed 40 C during dry seasons, while strong seasonal humidity variations create corrosive operating conditions [12]. Harmattan winds transport large amounts of dust that rapidly clog air filters and degrade combustion efficiency [13]. In addition, inconsistencies in fuel quality due to importation and storage challenges accelerate engine fouling and increase failure rates [5].

Recent studies have begun to quantify some of these environmental impacts. Fetene et al. [6] showed that tropical operating conditions may reduce the mean time between failures (MTBF) of diesel generator sets by up to 40% compared with temperate climates. However, their analysis was limited to the Ethiopian highlands and may not fully represent Sahelian operating conditions. Abdelrahman et al. [11] proposed a predictive maintenance framework for harsh environments, but their work focused mainly on offshore applications rather than land-based tropical conditions.

2.3. Advanced Maintenance Indicators for Predictive Maintenance

Beyond conventional maintenance metrics, recent literature has proposed advanced key performance indicators that are better suited to critical operating environments. For SONABEL, several of these indicators are particularly relevant because they integrate climatic conditions, fuel quality, and the economic consequences of failures. Table 1 summarizes the main advanced KPIs and their potential relevance for diesel generator sets.

Table 1 Advanced KPIs and their usefulness for generators

Indicator	Definition	Scientific/industrial utility	Relevance for SONABEL
RUL (Remaining Useful Life)	Estimated remaining lifetime	Enables optimal planning of interventions [5]	Essential for maintenance planning in remote areas
Health Index (HI)	Multi-parameter health score	Overall view of engine condition [6]	Can integrate dust, overheating, and fuel quality
Probability of Failure (PF)	Probability of failure within a given horizon	Proactive risk management	Prioritize interventions on critical units
Degradation Rate (DR)	Speed of parameter wear	Measures degradation evolution	E.g., rapid increase in engine temp. in hot season
SFOC (Specific Fuel Oil Consumption)	Energy efficiency (g/kWh)	Increase indicates fouling or poor fuel	Crucial as Burkinabe diesel is heterogeneous
Thermal Stress Index (TSI)	Combined temperature-load factor	New indicator for tropical conditions	Integrates ambient and operational thermal stress

2.4. Gaps in the Literature and Research Opportunities

The literature consistently highlights the benefits of predictive maintenance in stable industrial environments [8–10]. However, three major limitations remain when considering the Burkinabe case.

First, there is a lack of contextualized indicators that explicitly account for dust, variable diesel quality, or the alternation between dry and wet seasons. Second, there is a significant lack of African operational data, since most predictive models have been calibrated using datasets from Asia, Europe, or North America. Third, the economic consequences of failures remain insufficiently integrated into maintenance studies, particularly in Africa, where indicators such as the cost of unserved energy are rarely used despite their relevance.

More broadly, four additional research gaps can be identified:

- Few studies specifically address diesel generator sets in diesel thermal power plants operating under Sahelian or similar environmental conditions, despite their strategic importance in electricity generation in these countries.
- Existing studies rarely investigate predictive maintenance from the perspective of instrumental frugality, i.e., using a limited number of variables that are actually available in thermal power plants in developing countries.
- The indicators proposed in the literature are often either too generic or insufficiently contextualized to local thermal, environmental, and logistical constraints.
- Comparative evidence regarding the performance of contextualized indicators relative to raw variables, as well as their translation into operational and economic benefits, remains limited.

Accordingly, the present study positions itself precisely within this scientific space. It does not merely seek to confirm that high temperatures degrade the reliability of diesel generator sets a fact already widely acknowledged but rather to provide a methodological response to a more operational and original question: how can thermal stress in diesel generator sets operating under Sahelian conditions be quantified in a simple and useful way, how can credible local thresholds be calibrated, and how can these elements be integrated into a reproducible predictive and decision-support framework?

This articulation between physical contextualization, statistical validation, algorithmic comparison, and operational interpretability constitutes the core contribution of the study.

3. Materials and Methods

3.1. Study Context and Equipment Under Analysis

3.1.1. Diesel Generator Fleet at the SONABEL Komsilga Thermal Power Plant

This study is based on the analysis of five diesel generator sets operated by SONABEL (G1, G2, G3, G4, and G6), with nominal capacities ranging from 12.5 MW to 18.9 MW. These units fulfill three essential functions within the national electricity system: peak-load coverage, supply security in the event of regional interconnection failures or structural generation shortfalls, and frequency support and grid stability in a relatively small power system where each additional megawatt remains operationally significant.

The studied units differ in terms of operating conditions, machine-room ventilation, equipment age, load profiles, and maintenance practices. These inter-unit differences justify a differentiated analysis rather than a simple pooled aggregation.

3.1.2. Sahelian Constraints and Expected Effects

The studied generators operate under severe environmental conditions that are characteristic of the Sahelian region :

- High ambient temperatures (> 40°C) : these reduce intake-air density, increase cooling-system stress, and may induce a power derating estimated at approximately 3–5% per additional 10°C above reference conditions [19].
- Strong hygrometric variability (≤ 20% in the dry season ; ≥ 80% during the rainy season) : such fluctuations promote corrosion of metallic components and condensation within intake-air circuits.
- Dust exposure associated with Harmattan winds : concentrations may exceed 1000 µg/m^3, leading to rapid air-filter clogging, reduced combustion quality, and accelerated abrasive wear.
- Variable quality of imported diesel fuel : fluctuations in density, sulfur content, and thermal stability affect combustion performance and may accelerate engine degradation.

These environmental constraints, specific to the Sahelian context, make it necessary to develop **contextualized indicators** that complement conventional reliability KPIs.

3.2. Data and Data Collection Strategy

Two datasets were used in this study. The first consists of environmental and operational data (n = 115 snapshots), each including a standardized timestamp, generator-set identifier, elapsed operating hours since the last oil change, load factor, local humidity rate, ambient temperature, and machine-room temperature. The second consists of reliability and performance data (n = 67 observation periods) covering intervals ranging from several days to several months, including total operating time, required operating time, recorded failure events, and specific fuel consumption (SFC, g/kWh).

These variables were used to characterize the local thermal gradient and the operating environment of each generator.

3.3. Standard Reliability Indicators

To characterize operational performance, standard reliability indicators were first computed:

$$\text{Availability (\%)} = \text{Operating Time} / \text{Required Time} \times 100 \quad (1)$$

$$\text{MTBF} = \text{Total Operating Time} / \text{Number of Failures} \quad (2)$$

$$\text{MTTR} = \text{Total Downtime} / \text{Number of Failures} \quad (3)$$

In reliability engineering, failure occurrence is often approximated using an exponential model, leading to the expression

$$P(t) = 1 - \exp(-t/\text{MTBF}) \quad (4)$$

MTTR is particularly sensitive to logistical constraints and measures the efficiency of maintenance processes. In the Burkinabe context, MTTR is strongly influenced by spare-part availability, import delays, and organizational response capacity [19].

3.4. Analytical Pipeline and Reproducibility

The study was structured around an explicit analytical pipeline, from raw-data consolidation to final predictive model comparison. This pipeline was designed to provide full traceability of the operations performed on environmental, operational, and reliability data from the studied generator fleet.

After consolidation and temporal alignment of data from multiple sources, the dataset was subjected to quality control and preprocessing. Low-level missing values were imputed using within-generator median imputation when appropriate, while observations with missing values in several critical variables were excluded from the modeling subset. Extreme values were retained when physically plausible, because they may correspond to genuinely severe operating conditions.

Derived variables were then constructed, including standard reliability indicators, the Thermal Stress Index (TSI), the Adverse Conditions Count (ACC), and the Aging Index (AI). An exploratory data analysis was performed to characterize distributions, identify patterns, and examine inter-variable relationships. Explanatory variables were selected on the basis of both engineering relevance and statistical relevance.

Three families of predictive models were considered : Logistic Regression, Random Forest, and XGBoost. Validation relied on time-aware procedures whenever feasible, and performance was assessed using Accuracy, Precision, Recall, F1-score, AUC-ROC, and confusion matrices. Incremental validation and ablation analysis were used to assess the additional contribution of contextualized indicators beyond raw variables.

4. Results: Performance Analysis and Operational Characteristics

4.1. Differential characterization of generator performance

4.1.1. Fundamental reliability metrics

The analysis of the 67 reliability records collected over the 2022–2025 period enabled a comparative assessment of the operational behavior of the five generator sets. Boxplots of availability and specific fuel consumption (SFC), together with scatter plots relating availability to SFC and MTBF to MTTR, were used to characterize inter-generator differences (Fig. 1).

The comparative analysis reveals substantial heterogeneity in reliability performance across the fleet.

- **G1** exhibits a high dispersion in availability despite periods of satisfactory performance, suggesting unstable operating behavior and irregular reliability.
- **G2** also shows noticeable variability, but with better overall stability than G1 and a median availability close to **80%**.
- **G3** displays relatively good average availability but with very large dispersion, indicating the presence of prolonged downtime episodes and potentially severe failure events.
- **G4** presents a lower median availability than G2 and G3, suggesting a higher sensitivity to failures and weaker operational robustness.
- **G6** emerges as the most stable unit, with high availability and relatively low dispersion, indicating more robust reliability performance.

A similar differentiation appears when examining **specific fuel consumption**

- SFC values are globally concentrated within the **200–215 g/kWh** range.
- **G3** shows comparatively lower and more stable SFC, suggesting better combustion efficiency and more stable operating conditions.
- **G2** and **G6** exhibit slightly higher but relatively consistent SFC values.
- **G1** and **G4** display the greatest dispersion in SFC, pointing to less predictable efficiency and more variable operating conditions.

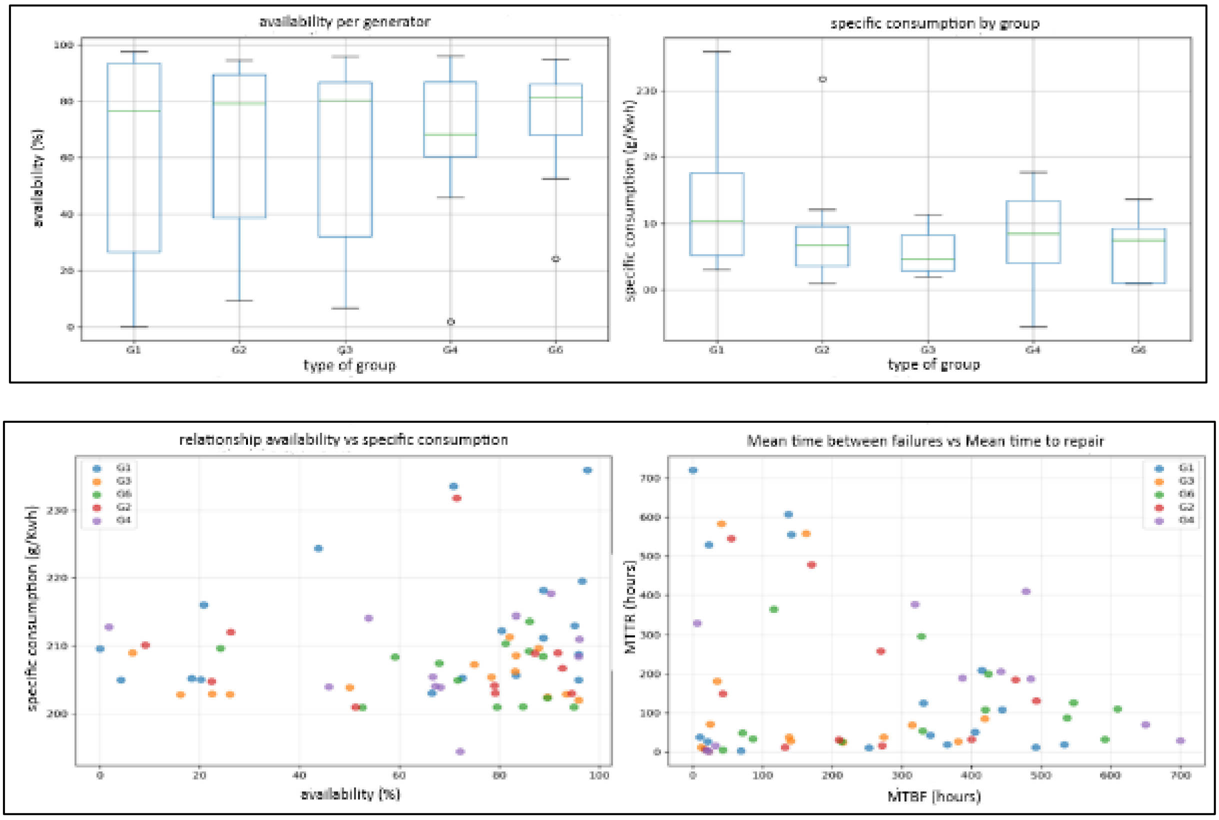


Figure 1 Comparative Reliability Analysis by Generator Set

The scatter plot relating availability and SFC does not reveal a strong direct linear relationship. However, units with the best availability levels (typically >70%) tend to cluster around SFC values between 200 and 210 g/kWh, whereas low-availability states are associated with a more dispersed SFC pattern. This suggests that availability alone is insufficient to characterize thermodynamic performance, and that energy efficiency must be interpreted jointly with reliability metrics.

The MTBF–MTTR relationship further highlights operational contrasts :

- **G6** shows the most favorable combination (**high MTBF + low MTTR**), indicating both strong intrinsic reliability and effective maintainability.
- **G2** and **G3** also demonstrate acceptable maintenance performance, with relatively good MTBF and moderate MTTR.
- **G1** exhibits highly dispersed behavior, suggesting unstable reliability and maintenance outcomes.
- **G4** is clearly disadvantaged by **high MTTR values**, indicating either more severe failures, longer repair processes, or stronger logistical constraints.

Overall, these results confirm that the generator fleet cannot be treated as homogeneous and that **unit-specific maintenance prioritization** is justified.

4.2. Environmental and Operating Conditions: Quantifying Sahelian Stress

The analysis of the **115 environmental measurements** provides a first quantitative characterization of the severity of the operating conditions to which the generator sets are exposed. Table 2 summarizes the descriptive statistics of the environmental and operational variables.

Table 2 Statistical characterization of environmental and operating conditions

Parameter	Mean	Standard deviation	Minimum	Maximum	Median	95th Percentile
Ambient temperature (°C)	37.9	4.0	23.0	44.0	38.5	43.8
Machine-Room Temperature (°C)	43.5	4.1	37.7	49.1	44.2	49.0
Ambient humidity (%)	46.8	20.0	17.0	81.0	45.0	73.0
Load factor (%)	75.2	13.8	0.0	91.3	78.0	88.9
Thermal Stress Index (TSI)	4.2	3.1	0.0	10.8	3.8	10.3

Several findings emerge from these statistics.

- First, the **mean ambient temperature of 37.9°C** confirms that the generators routinely operate under hot conditions, with upper values reaching **44°C**.
- Second, the **mean machine-room temperature of 43.5°C** and the **95th percentile of 49.0°C** indicate that the local thermal environment around the machines is frequently more severe than the external ambient environment. This supports the hypothesis that internal heat accumulation and imperfect ventilation play a significant role in operational stress.
- Third, humidity exhibits very strong variability (**17–81%**), reflecting the pronounced alternation between dry and rainy seasons in the Sahelian climate. Such variability is operationally relevant because it may amplify corrosion risk, condensation effects, and the sensitivity of control systems and electrical components.
- Fourth, the **mean load factor of 75.2%** is close to the commonly recommended operating range for diesel generator sets, but the upper tail (**95th percentile = 88.9%**) indicates recurrent periods of high mechanical and thermal demand.
- Finally, the **TSI distribution** confirms the presence of non-negligible thermal stress, with a maximum of **10.8** and a **95th percentile of 10.3**, suggesting the existence of distinct high-stress regimes that may be critical for maintenance decision-making.

The multidimensional visualization of environmental conditions (Fig. 2) further refines the interpretation of these operating constraints.

The **histogram distributions** reveal climate-specific patterns:

- Ambient temperature appears **slightly bimodal**, likely reflecting seasonal alternation between relatively milder and extremely hot periods.
- Humidity displays a broad spread (**15-90%**), consistent with strong seasonal variability.
- Very high humidity levels (**>80%**) remain relatively infrequent but represent potentially critical conditions when combined with elevated temperatures.
- The **bivariate scatter plots** suggest the presence of **threshold effects**. In particular, when **machine-room temperature exceeds approximately 45°C**, the dispersion of other variables increases markedly, which may indicate the onset of nonlinear degradation mechanisms or unstable operating regimes.

The relationship between **ambient temperature and machine-room temperature** is clearly positive, but with substantial scatter. This suggests that while external climate strongly influences the internal thermal environment, machine-room conditions are also modulated by local factors such as ventilation efficiency, heat recirculation, and operational load.

Taken together, these results confirm that the studied generators operate under **multi-factor environmental stress**, where external climate alone does not fully explain the thermal conditions experienced by the equipment.

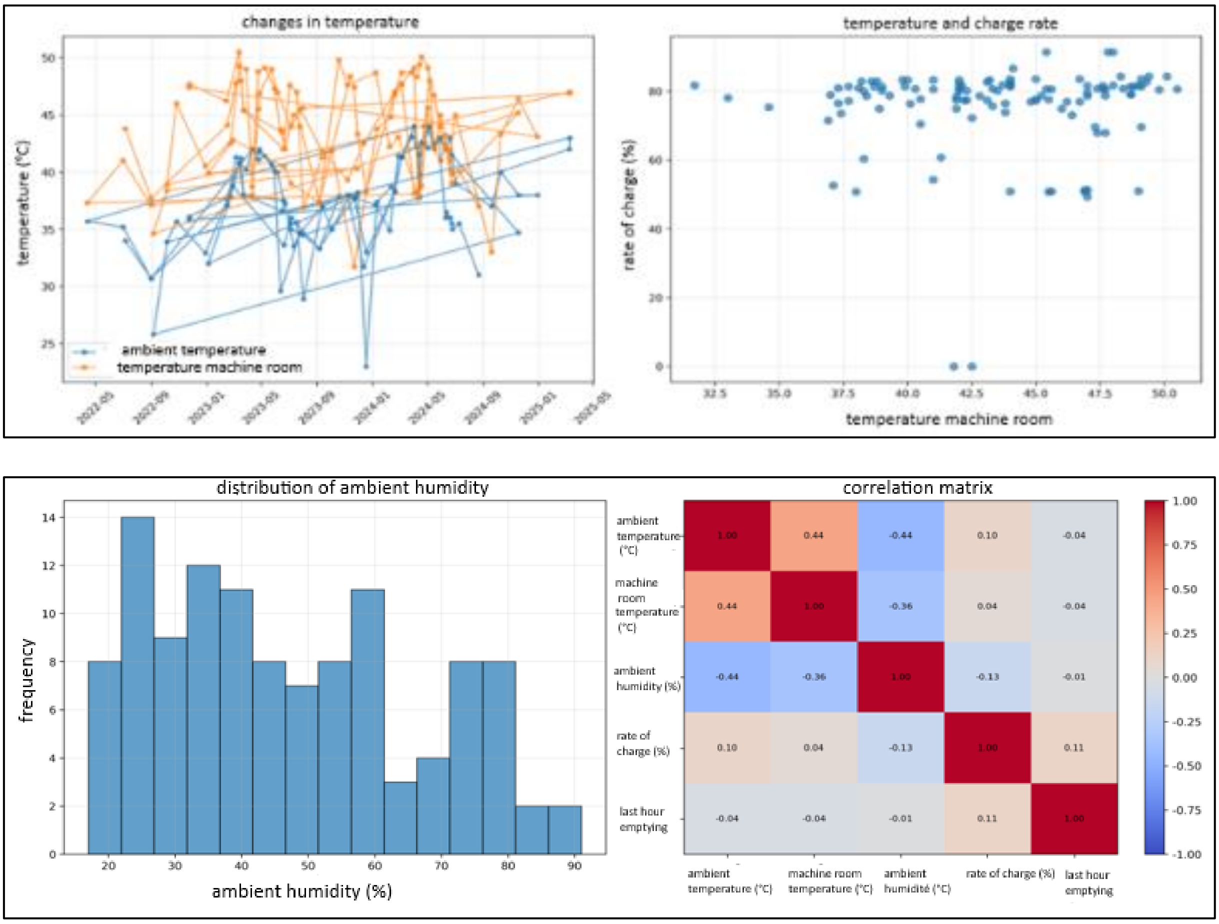


Figure 2 Distribution of environmental conditions and bivariate relationships

4.3. Development and Validation of Composite Indicators

4.3.1. Thermal Stress Index (TSI)

A central objective of this study was to develop a synthetic indicator capable of translating the actual thermal constraint experienced by an operating diesel generator set into a form that is directly usable for maintenance decision-making. In the Sahelian context, thermal stress does not depend on a single factor, but rather on the interaction between:

- The external environment
- The local thermal conditions inside the machine room
- The operating intensity of the generator.

A simple interpretation based only on ambient temperature or only on load is therefore insufficient to characterize the true operational risk. For this reason, the Thermal Stress Index was introduced.

The TSI is not a simple empirical aggregation ; it is intended as a simplified thermo-mechanical proxy of the stress experienced by the generator set. Its rationale is based on three principles :

The term ($T_{room} - T_{ambient}$) represents the internal-to-external thermal gradient, which indirectly reflects the difficulty of heat dissipation.

The load factor represents the operating intensity and, therefore, the rate of heat generation.

Their combination expresses a thermo-operational stress level that is physically consistent with expected degradation mechanisms in diesel generator sets operating in hot environments.

In diesel thermal power plants operating under hot Sahelian climates, a reference machine-room temperature of approximately 30°C may be considered desirable, with a normal operating range of 25-35°C. Above 40°C, the risks of hot-air recirculation, cooling degradation, and power derating increase significantly. Furthermore, installation guidelines generally recommend that generator intake-air temperature should not exceed ambient temperature by more than 3-6°C. In parallel, to avoid prolonged low-load operation (and the associated risk of wet stacking) while preserving thermodynamic efficiency, a reference load factor of approximately 75% of nominal power is often recommended, with an optimal range of 70-85%.

Accordingly, the TSI was defined as:

$$TSI = (T_{room} - T_{ambient}) \times \frac{Load\ Factor}{100} \quad (5)$$

with :

(Troom−Tambient) : thermal gradient to be dissipated

Load Factor/100 : operating intensity multiplier

TSI : normalized thermal stress proxy

4.4. Empirical validation

The TSI showed strong and operationally meaningful associations with other variables

TSI ↔ Load Factor : $r = 0.756$, $p < 0.01$

TSI ↔ Specific Fuel Consumption : $r = 0.523$

Locally calibrated thresholds were identified as follows :

Attention threshold: 7.71

Critical threshold: 10.34

Application Example: Generator G4

For a representative critical operating condition of **G4**

$T_{room} = 48.5$ °C

$T_{ambient} = 42.0$ °C

Load Factor = 87%

$TSI = (48{,}5 - 42.0) \times \frac{87}{100}$

TSI = 6.5×0.87 = **5.66**

This value corresponds to moderate thermal stress, remaining below the attention threshold of 7.71.

Importantly, the TSI should be interpreted as a relative thermal over-stress indicator. A high TSI may result from :

- High operating load,
- Local thermal confinement,
- Insufficient ventilation,
- Cooling-system drift,
- Or a combination of these factors.

The value of the TSI lies precisely in the fact that it does not merely signal a hot environment; it identifies a contextualized thermal stress level that is consistent with actual operating conditions. Thus, two situations with identical ambient temperature may generate very different TSI values depending on machine-room conditions and load factor. This property makes the TSI more useful for maintenance than isolated temperature readings.

Within a monitoring framework, the TSI can be used

- As an explanatory variable in predictive models,
- As an alert indicator in maintenance dashboards,
- As a criterion for prioritizing inspections or cooling-related corrective actions.

Thus, the TSI is not merely an empirical temperature indicator, but a contextualized decision-support tool linking thermal environment, real operating conditions, and predictive maintenance logic.

4.4.1. Adverse Conditions Count (ACC)

The Adverse Conditions Count quantifies the number of stress factors simultaneously present at a given observation point. This approach is motivated by the fact that environmental constraints are not purely additive ; rather, their combined occurrence may produce synergistic effects on degradation and failure risk.

The ACC was defined using the following logic

+1 if machine-room temperature > 45.0 °C

+1 if humidity >70.0%

+1 if load factor > 85.0%

+1 if TSI > 6.0

This yields an integer indicator ranging from **0 to 4**.

Table 3 Interpretation and observed distribution of the ACC

Algorithm Interpretation	Observed SONABEL Distribution
ACC = 0 : Normal conditions	ACC = 0 : 45% of observations
ACC = 1 : One stress factor	ACC = 1 : 32% of observations
ACC = 2 : Unfavorable conditions	ACC = 2 : 18% of observations
ACC = 3 : Critical conditions	ACC ≥ 3 : 5% of observations
ACC = 4 : Extreme conditions	Rare / extreme cases

The observed distribution shows that:

- **45%** of observations correspond to normal operating conditions,
- **32%** correspond to a single stress factor,
- **18%** correspond to multiple unfavorable conditions,
- approximately **5%** correspond to **critical multi-factor stress**.

This confirms that the most severe conditions are relatively infrequent, but not negligible. From an operational perspective, these rare but high-risk states are precisely the situations where predictive maintenance adds the greatest value.

4.4.2. Aging Index (AI)

Equipment wear generally follows a **nonlinear progression** rather than a strictly linear trend. To capture this progressive degradation, an **Aging Index (AI)** was introduced.

The AI was defined as :

$$AI = \log\left(\frac{H}{168} + 1\right) \quad (6)$$

where :

- H = elapsed operating hours since the last reference maintenance action,
- **168 hours** corresponds to one week.
- This formulation was chosen for three reasons :
- the **logarithmic form** reflects diminishing marginal degradation accumulation over time ;
- **weekly normalization** improves interpretability for maintenance practitioners ;
- the indicator can support **adaptive thresholds** depending on maintenance type or fleet characteristics.

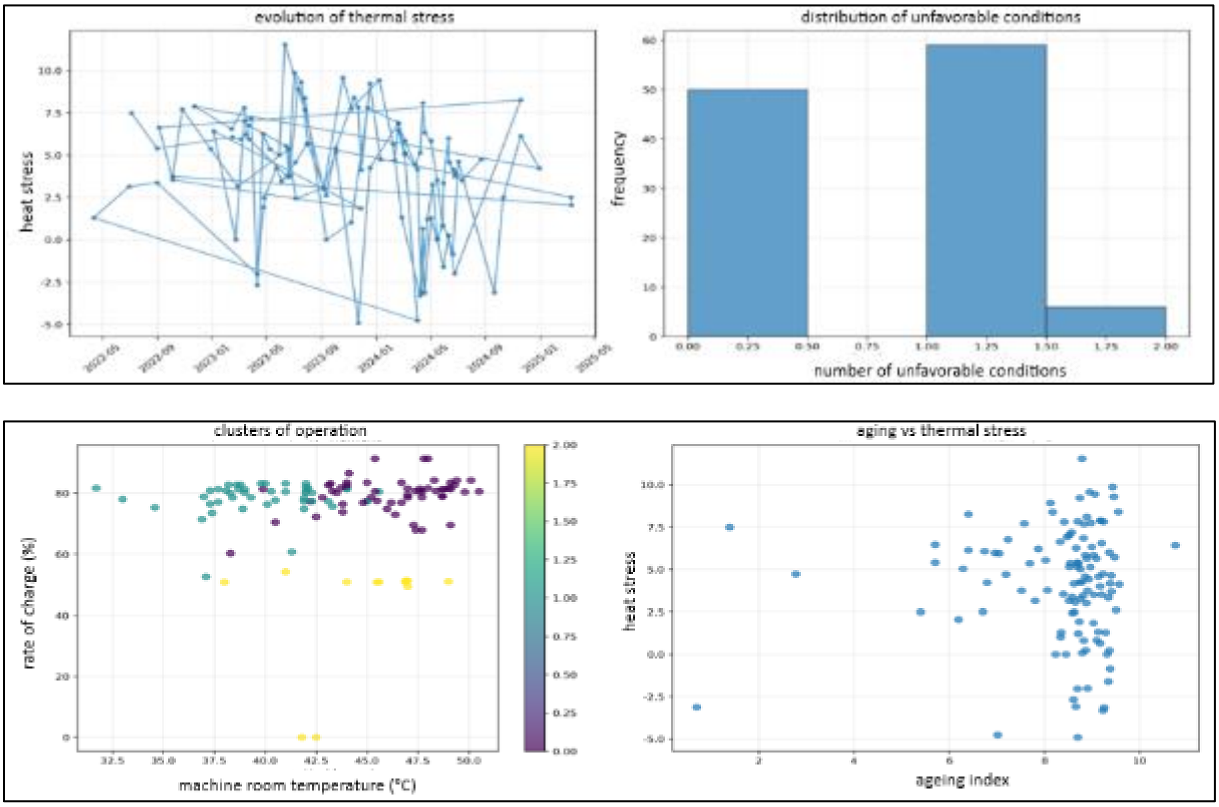


Figure 3 Evolution of the aging index as a function of time

The theoretical degradation curve (Fig. 3) clearly shows a nonlinear increase in AI over time. This supports the idea that maintenance decisions should not rely solely on raw elapsed time, but on an indicator that better reflects the progressive accumulation of wear.

4.4.3. Composite Risk Score

To synthesize the information contained in the various indicators, a Composite Risk Score (CRS) was constructed. The objective was to combine thermal, environmental, operational, and aging-related factors into a single decision-support indicator.

The score was defined as:

$$CRS = \sum_i (wi \times Ii, normalized) + \text{aging factor} \quad (7)$$

With:

wi denotes the weight associated with indicator i ;

$I_{i,normalized}$ is the normalized value of indicator i.

Optimized weights

The weighting scheme was based on the relative importance identified during the statistical analysis :

- Machine-room temperature : **25%**
- TSI : **20%**
- Load factor : **18%**
- Humidity : **15%**
- Ambient temperature : **12%**
- ACC : **10%**

Indicator Normalization

Each indicator was normalized to the [0,1] interval according to its operational range.

Illustrative Example for G4

- For a representative high-stress operating condition of **G4** :
- Machine-room temperature = **48.5°C** → normalized = **0.79**
- TSI = **8.2** → normalized = **0.53**
- Load factor = **87%** → normalized = **0.74**
- Humidity = **76%** → normalized = **0.74**
- Ambient temperature = **42°C** → normalized = **0.86**
- ACC = **4** → normalized = **1.00**

The resulting score is :

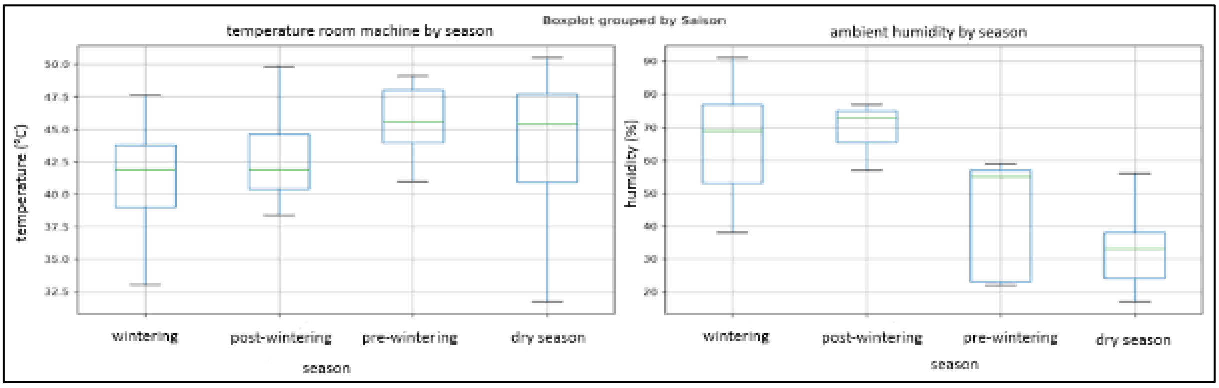
CRS = 0.25(0.79) + 0.20(0.53) +0.18(0.74) + 0.15(0.74) + 0.12(0.86) + 0.10(1.00)

CRS = 0.198 + 0.106 + 0.133 + 0.111+ 0.103 + 0.100 = 0.751

This corresponds to a **high-risk condition (75.1%)**.

The practical interest of the CRS lies in its ability to aggregate multiple weak or moderate signals into a single operationally interpretable risk level. This makes it particularly useful for:

- Maintenance prioritization
- Alarm ranking
- Intervention scheduling
- Resource allocation under constrained operational conditions.



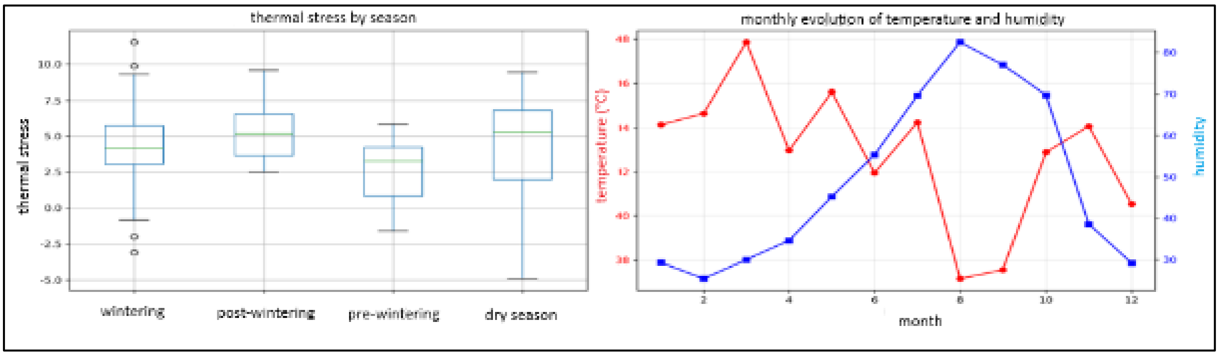


Figure 4 Temporal évolution of predictive indicators and maintenance events

The temporal analysis of predictive indicators reveals several noteworthy patterns.

First, **thermal stress fluctuates substantially over time**, with values ranging approximately from **-5 to +12** in the original visualization scale. Most observations lie within the **2-8** range, suggesting recurrent but mostly moderate stress levels, punctuated by sharper peaks corresponding to combinations of :

- High machine-room temperature
- Elevated load
- Unfavorable environmental conditions.

Second, the distribution of adverse conditions confirms that critical states are episodic rather than permanent, which is consistent with the observed TSI peaks.

Third, the clustering results indicate that the generators operate predominantly under loaded regimes, with a non-negligible share of operation under thermally severe conditions.

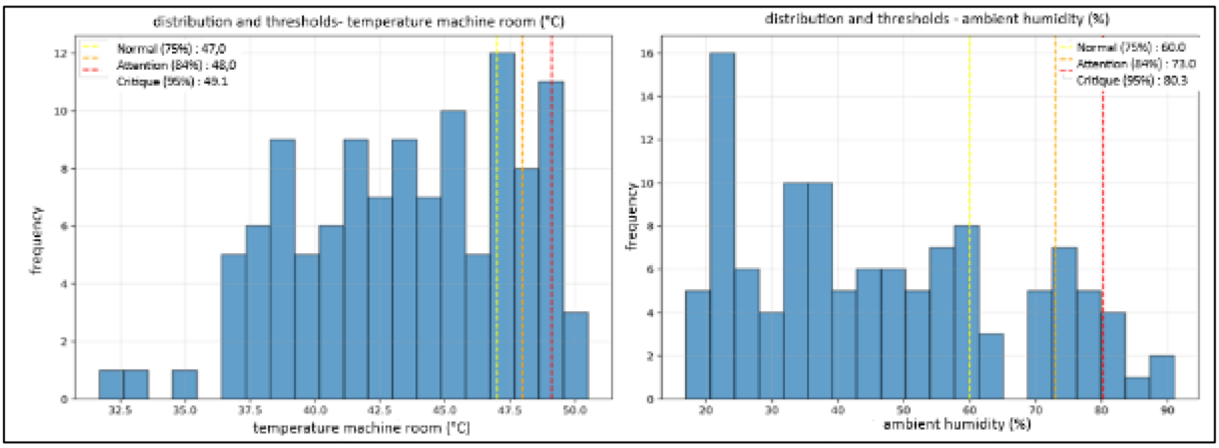
Most importantly, the joint analysis of aging and thermal stress suggests that aging amplifies sensitivity to thermal stress, thereby increasing failure susceptibility in older maintenance cycles.

A particularly important operational result is that TSI peaks systematically preceded maintenance interventions by approximately 2-3 weeks. This temporal lead supports the predictive relevance of the indicator and suggests that it may provide a practical planning window for preventive intervention.

In addition, the TSI exhibits a clear seasonal cyclicity, with the highest values occurring during the pre-rainy season (April-May), identified as the most critical period for the studied fleet.

4.4.4. Establishment of critical thresholds : A data-driven approach

To support predictive maintenance decisions, alert thresholds were established for key variables using a percentile-based statistical approach. The resulting thresholds are illustrated in Fig. 5 and summarized in Table 4.



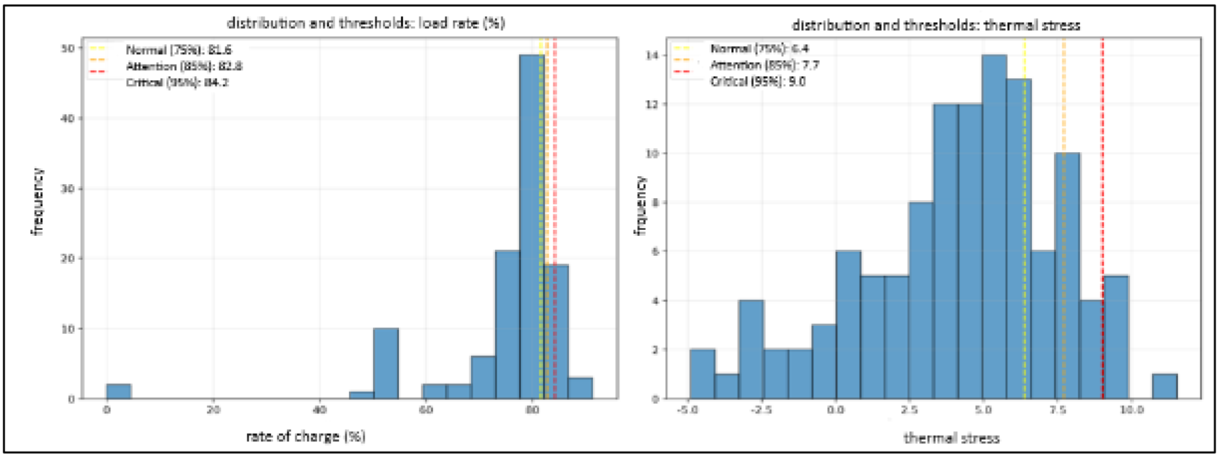


Figure 5 Distribution of variables and positioning of alert thresholds

The threshold analysis highlights three major findings :

- **Empirical validation of thresholds:** The selected thresholds correspond to the tails of the observed distributions, capturing exceptional conditions without generating excessive false alarms.
- **Adaptation to local operating conditions:** The locally derived thresholds differ substantially from manufacturer recommendations (typically **40-42°C** for machine-room thermal conditions), highlighting the inadequacy of generic international standards in Sahelian contexts.
- **Operationally balanced calibration:** The exceedance frequencies associated with the attention and critical thresholds are consistent with realistic monitoring objectives, allowing risk detection without excessive alert overload.

Table 4 Alert thresholds established for Predictive Maintenance

Parameter	Normal Range	Attention Threshold (85th percentile)	Critical Threshold (95th percentile)	Exceedance Frequency
Machine-Room Temperature (°C)	< 47.0	48.0	49.0	15.7% / 5.2%
Ambient Humidity (%)	< 60.0	73.0	81.0	13.0% / 4.3%
Load Factor (%)	< 81.6	82.8	88.9	13.9% / 5.2%
Thermal Stress Index (TSI)	< 6.37	7.71	10.34	15.7% / 5.2%

These thresholds provide a locally calibrated operational basis for transitioning from generic maintenance rules toward context-aware predictive maintenance.

4.5. Predictive model performance: Validation of the Machine Learning Approach

The comparative evaluation of the three machine-learning algorithms shows that **Random Forest** achieved the best overall balance between predictive performance and operational interpretability in the present dataset.

Table 5 Comparative performance of predictive models

Model	Precision	Recall (Sensitivity)	Specificity	F1-Score	AUC-ROC	Training Time
Random Forest	0.847	0.789	0.823	0.806	0.891	2.3 s
XGBoost	0.831	0.812	0.798	0.805	0.876	4.7 s
Logistic Regression	0.742	0.695	0.718	0.706	0.798	0.8 s

Several observations can be drawn from these results.

- **Random Forest** provides the highest Precision (0.847) and AUC-ROC (0.891), indicating strong global discriminative ability and more reliable alert generation.
- **XGBoost** slightly outperforms Random Forest in Recall (0.812 vs. 0.789), which may be advantageous when minimizing missed failures is the primary objective.
- However, Random Forest achieves a more balanced trade-off between precision, specificity, and overall discriminative power, while also requiring less training time than XGBoost.
- **Logistic Regression** remains useful as a transparent baseline but shows clearly lower predictive performance, suggesting that nonlinear relationships and interactions play a meaningful role in the failure process.
- From an operational perspective, these results support the use of **Random Forest as the preferred deployment model**, especially in a context where interpretability, robustness, and computational simplicity are all important.

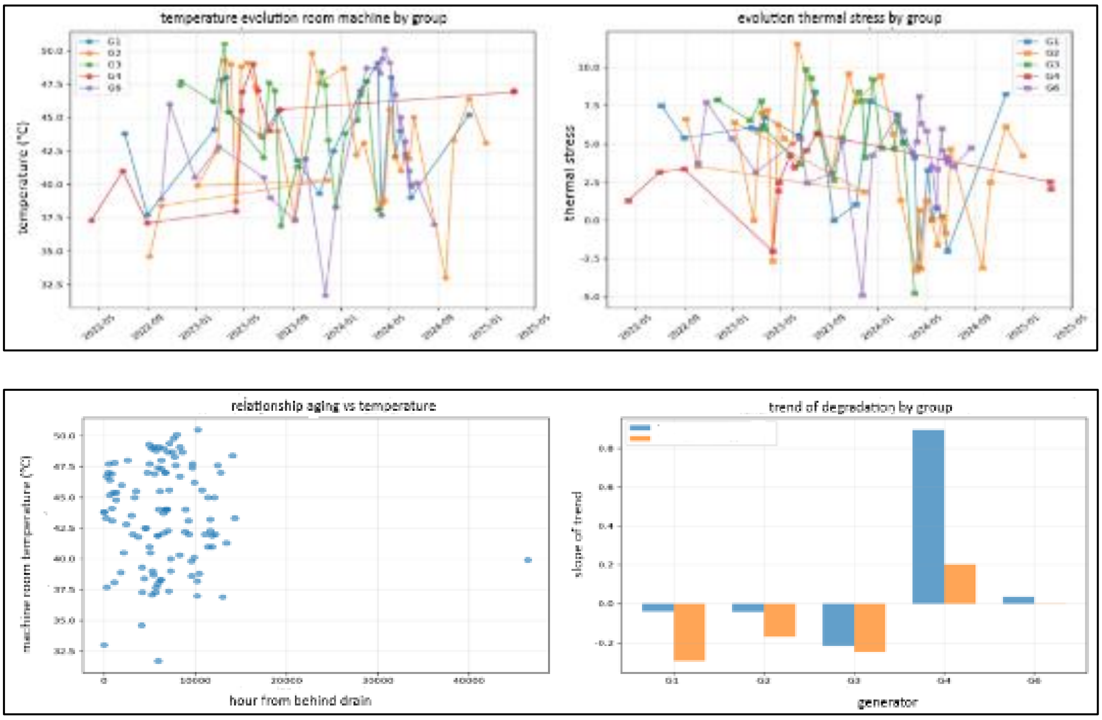


Figure 6 Hierarchy of Predictive Variable Importance (Random Forest Model)

The variable-importance analysis provides strong support for the proposed methodological framework.

The most important predictor is the Thermal Stress Index (TSI), accounting for 32.1% of total importance. This dominant ranking strongly supports the methodological relevance of the TSI as a contextualized composite indicator.

The next most influential variables are :

- **Machine-room temperature : 28.7%**
- **Hours since maintenance : 21.4%**
- **Ambient temperature : 12.3%**

Together, TSI + machine-room temperature + ambient temperature account for more than 70% of the predictive signal, underscoring the central role of thermal stress in the failure dynamics of the studied fleet.

Several implications follow

Validation of the TSI concept: The fact that the TSI ranks above all raw variables confirms that combining thermal gradient and load captures information that isolated measurements fail to represent.

Thermal factors are dominant: The strong cumulative importance of thermal variables confirms that overheating is not a secondary issue, but a central reliability driver in the Sahelian operating context.

Time since maintenance remains relevant: The significant importance of elapsed hours since maintenance confirms that conventional maintenance-cycle logic still matters, but should be complemented by contextualized environmental indicators.

Sensor and monitoring prioritization: This hierarchy provides practical guidance for prioritizing instrumentation investments, suggesting that machine-room thermal monitoring and contextualized thermal indicators offer the best cost-to-value ratio.

4.6. Scenario-based techno-economic evaluation

- A scenario-based comparative analysis was conducted to assess the practical value of the proposed predictive maintenance strategy relative to two alternative approaches.
- Compared with the **current maintenance strategy** (corrective + fixed preventive), the **fixed-threshold strategy** already reduces the number of residual failures, but at the cost of a higher number of preventive interventions. It therefore improves reactivity, but remains relatively coarse and may generate unnecessary interventions.
- By contrast, the **proposed strategy**, based on a composite score integrating **TSI, ACC, and AI**, provides the best compromise between intervention targeting and reduction of unexpected failures.

Under the illustrative scenario considered :

- The proposed strategy would prevent approximately **9 additional failures** compared with the current practice ;
- It would do so while triggering **fewer interventions than the fixed-threshold strategy**
- It would therefore improve selectivity rather than merely increasing maintenance intensity.

Table 6 Conceptual comparison of maintenance strategy

Strategy	Triggering Logic	Sensitivity to Sahelian Constraints	Estimated Number of Interventions	Estimated Failures Avoided	Maintenance Cost	Residual Failure Cost	Estimated Total Cost	Comment
Current SONABEL strategy	Corrective + fixed preventive	Low	Medium	Baseline (0)	Moderate	High	High	Late response to thermal drifts
Fixed-threshold strategy	Trigger when a simple threshold is exceeded	Medium	Medium to high	Moderate	Medium	Medium	Intermediate	More reactive but mono-indicator
Proposed strategy	Composite score (TSI + ACC + AI)	High	Targeted / optimized	High	Controlled	Low	Lowest	Best cost-risk trade-off

Table 7 Illustrative quantified comparison of the three strategy (per 100 Risk Episodes)

Strategy	Triggered Interventions	Estimated Residual Failures	Failures Avoided (vs.current)	Maintenance Cost (FCFA)	Failure Cost (FCFA)	Estimated Total Cost (FCFA)
Current SONABEL strategy	18	14	0	5,400,000	35,000,000	40,400,000
Fixed-threshold strategy	26	9	5	7,800,000	22,500,000	30,300,000
Proposed strategy (TSI + ACC + AI)	22	5	9	6,600,000	12,500,000	19,100,000

These estimates suggest a substantial economic benefit associated with the proposed approach.

- Total estimated cost decreases from 40.4 million FCFA under the current strategy to 19.1 million FCFA under the proposed strategy.
- This corresponds to a potential cost reduction of approximately 52.7%.
- These values should be interpreted as decision-support estimates, consistent with the observed trends in the dataset, rather than as definitive accounting values. Nevertheless, they strongly support the practical interest of a contextualized predictive maintenance strategy in a Sahelian environment, where climatic stress, operating load, and aging interact in a nontrivial manner.

5. Discussion: Scientific and Operational Implications

5.1. Scientific Contributions and Methodological Innovations

This study provides one of the first systematic analyses of the performance and reliability of diesel generator sets operating under real Sahelian conditions, based on three years of operational observations. Several scientific and methodological contributions emerge from the results.

First, the quantitative characterization of environmental constraints highlights the severity of the local thermal environment. The observed mean thermal gradient between ambient and machine-room temperatures confirms that the generators are not only exposed to high external heat loads, but also to internal heat accumulation, which points to limits in ventilation effectiveness and thermal dissipation. This result is important because it shifts the focus from ambient temperature alone to the broader issue of **local thermal confinement**, which is more directly actionable in maintenance and operational practice.

Second, the study introduces a central methodological innovation through the Thermal Stress Index (TSI). Unlike conventional indicators based on a single variable, the TSI captures the interaction between thermal gradient and operating load, thereby providing a more realistic representation of the actual thermo-operational stress experienced by the generators. Its dominant importance in the Random Forest model supports its relevance not merely as a descriptive metric, but as a genuinely informative predictive feature. From a methodological standpoint, the TSI demonstrates the value of building interpretable composite indicators grounded in physical reasoning rather than relying exclusively on black-box predictors.

Third, the study shows that locally calibrated thresholds, derived from observed percentile distributions, are more appropriate than generic manufacturer-based thresholds for predictive maintenance in the Sahelian context. This point is particularly important. Manufacturer recommendations are generally established under standard environmental assumptions and do not necessarily reflect the real operating conditions of constrained tropical environments. By contrast, the proposed thresholds are rooted in empirical operating data and therefore provide a more credible operational basis for alert generation.

Fourth, the results show that the studied fleet does not operate under a single homogeneous regime, but rather under multiple operational states characterized by different combinations of load, thermal stress, and environmental severity. This supports the argument that predictive maintenance in such environments should not be based on fixed schedules alone, but rather on a context-sensitive maintenance logic capable of adapting to operational regime changes.

Finally, the study contributes to the broader predictive-maintenance literature by showing that a frugal data strategy, based on a limited number of accessible variables, can still yield meaningful predictive performance when indicators are carefully designed. This is particularly relevant for developing-country contexts, where the deployment of extensive sensor networks may not be immediately feasible.

5.2. Operational implications for SONABEL and regional perspectives

From an operational viewpoint, the findings suggest several directions for improving maintenance practice within SONABEL.

First, the comparative analysis of generator performance shows that the fleet should not be managed uniformly. The superior behavior of **G6**, which combines high availability with low repair times, suggests that some units already embody more effective operating and maintenance practices. Conversely, the weaker performance of **G4**, especially in terms of availability and repair burden, indicates the need for targeted corrective action. In practice, this may involve :

inspection and improvement of cooling and ventilation systems

- Reinforced monitoring of thermal drift ;
- Review of spare-parts logistics ;
- Diagnostic analysis of recurrent failure modes ;
- Prioritization of major overhaul planning.

Second, the temporal behavior of the TSI suggests that maintenance scheduling could be made more proactive by anticipating **seasonally critical periods**, especially during the pre-rainy hot season. Rather than reacting only after performance deterioration becomes visible, maintenance teams could use contextualized indicators to plan inspections and interventions ahead of high-risk windows.

Third, the proposed framework can support a more rational allocation of scarce maintenance resources. In constrained utility environments, maintenance optimization is not only a technical issue but also an economic one. By distinguishing between normal, unfavorable, and critical conditions, the framework allows interventions to be prioritized where the expected operational payoff is highest.

Fourth, the techno-economic comparison suggests that predictive maintenance based on contextualized indicators can significantly reduce the total cost of operation by limiting residual failures without proportionally increasing preventive workload. This is especially important for public utilities such as SONABEL, where maintenance decisions must reconcile service continuity, budgetary constraints, and equipment longevity.

Beyond SONABEL, the proposed methodology has potential relevance for other Sahelian and sub-Sahelian electricity systems, many of which rely heavily on diesel-based generation, backup generators, or isolated thermal units. Because the framework is based on variables that are relatively simple to obtain, it could be recalibrated and adapted to similar environments in countries such as Mali, Niger, and Chad. In that sense, the study contributes not only to a local case study, but also to the broader discussion on **context-adapted maintenance intelligence in constrained energy systems**.

5.3. Limitations and future research directions

Despite the promising results, several limitations should be acknowledged.

First, the sample size remains relatively limited, with 115 environmental observations and 67 reliability records. Although this is sufficient to reveal meaningful trends and support an exploratory predictive framework, larger datasets would improve statistical robustness and enable more advanced validation procedures.

Second, the data structure remains partially constrained by the granularity and availability of operational records. More continuous and higher-frequency monitoring would make it possible to capture transient events, detect short-lived anomalies, and build more refined prognostic models.

Third, some relevant stressors such as direct dust concentration, lubricant condition, vibration behavior, or fuel-quality variability were not explicitly modeled due to limited data availability. Their inclusion in future work could improve explanatory richness and predictive precision.

Fourth, the techno-economic evaluation remains scenario-based and illustrative. Although it is consistent with the observed patterns in the data, future work should extend this analysis using more detailed maintenance-cost accounting, downtime valuation, and uncertainty quantification.

Future research could therefore focus on :

- Extending the data-collection horizon over longer operating periods ;
- Integrating connected sensors for near-real-time monitoring ;
- Incorporating additional physical and chemical degradation markers ;
- Developing multi-objective maintenance-optimization models that jointly consider cost, availability, reliability, and environmental performance;
- Testing transferability of the proposed indicators on other thermal fleets in west africa.

These directions would help move from an interpretable predictive-maintenance framework toward a broader **digital maintenance ecosystem** for energy infrastructure in constrained tropical environments.

6. Conclusion

This research provides one of the first in-depth empirical analyses of the reliability of diesel generator sets operating under Sahelian environmental conditions. Using real operational data from SONABEL, the study proposed an original methodological framework combining contextualized indicators, statistical analysis, predictive modeling, and techno-economic interpretation.

The main contributions of the study can be summarized as follows:

- A quantitative characterization of the climatic and operational constraints specific to the Sahelian environment, showing for example a mean machine-room temperature of **43.5°C** and recurrent exceedance of critical thermal conditions ;
- The development of the **Thermal Stress Index (TSI)**, a composite indicator integrating thermal gradient and load factor, validated as one of the most informative predictors of failure risk ;
- A locally grounded threshold-calibration approach based on observed percentiles, enabling the definition of alert levels better suited to the study context than generic international standards ;
- The identification of differentiated operating regimes and the demonstration that contextualized predictive indicators can improve intervention targeting and maintenance decision support ;
- A scenario-based techno-economic comparison suggesting that the proposed strategy may substantially reduce total maintenance-related cost while lowering the number of residual failures.

Overall, the findings highlight the need for predictive maintenance strategies that are explicitly adapted to Sahelian realities and demonstrate the value of contextualized indicators for improving the availability, resilience, and long-term sustainability of industrial energy equipment.

In the longer term, extending this methodology to a broader set of SONABEL assets including other thermal power plants and possibly substations could help establish the foundations of a more integrated maintenance-intelligence framework at the national level. More broadly, the standardization and regional adaptation of such approaches could contribute to strengthening maintenance capabilities and resource optimization across West African power systems.

Compliance with ethical standards

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Disclosure of conflict of interest

No conflict of interest to be disclosed.

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