Uniosun Journal of Engineering and Environmental Sciences (UJEES), Vol. 8 No. 2, Sept., 2026
DOI: 10.64980/ujees.v8i2.018 **Ojuola et al.**
Published: September 30, 2026

COMPARATIVE BEHAVIOUR OF PRESSURE RATIO, THERMAL DIFFERENTIAL AND VIBRATION SIGNATURES ACROSS MULTIPLE INDUSTRIAL GAS TURBINE UNITS

Bosede Mayowa OJUOLA[1*], Titus Oluwasuji AJEWOLE[2], Abdulsemiu A. OLAWUYI[3], Olubunmi Folashade ATILOLA[4], Opeyemi ONARINDE[5]

[1,2,3]*Department of Electrical and Electronic Engineering, Osun State University, Osogbo, Nigeria*

[4]*Department of Electrical and Electronic Engineering, Redeemer's University, Ede, Nigeria*

[5]*Elektron Energy Development Strategies Limited, Egbin Power Plant, Ikorodu.*

[*]*Corresponding Author: bosede.ojuola@uniosun.edu.ng*

Abstract
Industrial power gas turbines suffer performance loss and these effects appear in their thermodynamics and mechanical variables. In this paper, the correlation of the Pressure ratio (PR) , the temperature differential and the vibration signatures of four industrial gas turbines (GT1, GT3, GT4 and GT5) was compared along an 8 months inspection period (1,818 hourly points recorded). A comprehensive study was performed to analyze the relationships between these indicators and the failure patterns. Pressure ratio and temperature differential were considered thermodynamic derived variables, and vibration amplitude was measured following the ISO 10816-4 recommendation for industrial gas turbine units on fluid film bearings. Vibration amplitude had the highest correlation to the occurrence of fault among the original sensors, r = 0.497. Temperature differential higher than 330^0C had a high correlation with thermal degradation faults and the pressure ratio had a non-linear relationship with the probability of failure. Filter differential pressure showed a strong negative correlation to the pressure ratio 24 hour rolling mean (r = 0.618), demonstrating its effect over the overall compressor performance in the long term. The research provides a base on multi-parameter health monitoring methods for industrial gas turbines and also helps build prediction maintenance systems where the thermodynamic and mechanical properties can be fused.

Keywords
gas turbine condition monitoring, pressure ratio, temperature differential, vibration analysis, predictive maintenance, compressor performance degradation

1. INTRODUCTION

Industrial gas turbines are critical power generation assets that provide high efficiency, flexible operation, and fast dynamic responses in power generation, marine propulsion, and aerospace applications [1]. Their ability to deliver baseload power while rapidly responding to demand variations has made them indispensable in the modern global energy landscape. Consequently, gas turbine reliability is paramount to the operational and economic viability of power generation systems, and the monitoring of machine health is of considerable interest to power plant operators and maintenance engineers.

Gas turbines are, however, susceptible to fouling, wear, and blade erosion because contaminants such as dust and salt enter the multi-stage compressor from the inlet stream [2]. Performance degradation is often evidenced by wear, thermal stressing, vibrational anomalies, and compressor fouling. Each degradation mechanism produces different signatures within measurable operating parameters [3], and the accumulation of these processes over time leads to reduced efficiency, increased fuel consumption, lower power output, and eventually unexpected machine failure with potentially catastrophic consequences. Among these mechanisms, compressor fouling has historically been identified as the most significant contributor to performance loss in industrial gas turbines, accounting for an estimated 70–85% of total operational performance degradation [6]. Inlet filter restriction, quantified by filter differential pressure (Filter_DP), is also closely linked to compressor fouling and long-term performance deterioration.

Two thermodynamic indicators are central to compressor health assessment. The pressure ratio (PR) is defined as the ratio of compressor discharge pressure (CDP) to compressor inlet pressure (CIP) as represented is Equation (1).

$$PR = \frac{CDP}{CIP} \quad (1)$$

It measures the compression achieved by the compressor stage and is a primary thermodynamic performance metric [5]. As the compressor deteriorates through fouling, erosion, or mechanical wear, the pressure ratio decreases. Because PR normalises discharge pressure by inlet pressure, it removes the influence of ambient pressure variations and is therefore valuable for condition monitoring. The temperature differential (ΔT) is the difference between compressor discharge temperature (CDT) and compressor inlet temperature (CIT) as represented in Equation (2)

$$\Delta T = CDT - CIT \quad (2)$$

It acts as a complementary metric to PR because an increasing ΔT at a fixed pressure ratio indicates reduced compressor efficiency [7]. A less efficient compressor must consume more work to compress the incoming air to the same pressure ratio, which raises the outlet temperature.

Vibration measurement remains one of the most direct methods for assessing the mechanical health of rotating machinery. The ISO 10816-4 standard defines vibration severity zones for gas turbine sets with fluid-film bearings [4]. Zone A represents good, newly commissioned machines; Zone B is satisfactory for long-term operation; Zone C represents machines in unsatisfactory condition that require attention; and Zone D indicates a potential for imminent damage. The boundary between Zone B and Zone C is commonly set at 8 mm/s. Vibration amplitude is typically expressed as root-mean-square (RMS) velocity in mm/s, which provides a measure of the energy content of the vibration signal. With advances in micro-electromechanical systems (MEMS) technology, sensitive and high-bandwidth piezoelectric accelerometers have been developed for measuring combustion-induced vibrations in gas turbine engines [7, 8]. MEMS devices also offer potential for integration with complementary metal-oxide-semiconductor (CMOS) processes, enabling size reduction, increased integration, and greater resistance to adverse operating environments [10]. Other non-contact techniques, such as blade tip timing, optical measurement, and casing wall pressure measurement, have been developed to overcome some limitations of traditional methods such as strain-gauge-based vibration measurement. However, many of these techniques are largely limited to individual turbines, and little comparative research has been performed across multiple turbines even under identical operational conditions, owing to variations in installation and operating parameters.

Most existing literature on gas turbine degradation is based either on a single turbine or on simulation studies. This paper addresses that gap by presenting a comparative analysis of the behaviour of pressure ratio, temperature differential, and vibration signatures across four industrial gas turbine units GT1, GT3, GT4, and GT5 and by examining how these indicators relate to the occurrence of faults. The operational data were recorded at hourly intervals over an eight-month inspection period from July 2025 to February 2026, resulting in 1,818 observations across 17 variables. The study also considers filter differential pressure as an operational parameter because inlet filter restriction can influence overall compressor performance in the long term.

The specific objectives of the study are to characterise the distinct signature profiles exhibited by each turbine unit, to quantify the correlations between health indicators and fault occurrence, to identify which parameters provide the earliest and most reliable warning of impending faults, and to establish a priority ranking for maintenance intervention based on multi-parameter health assessment. By integrating thermodynamic indicators such as PR and ΔT with mechanical indicators such as vibration and operational parameters such as Filter_DP, the study provides a quantitative basis for multi-parameter health monitoring and for the development of predictive maintenance systems in which thermodynamic and mechanical properties can be fused.

2. MATERIALS AND METHOD

2.1. Dataset Description

The operational data used in this study were obtained from the condition monitoring system of a power generation facility and cover four industrial gas turbines: GT1, GT3, GT4, and GT5. These units constitute a representative sample from the facility's operating fleet and differ in terms of operating age, historical maintenance, and service life cycles. Data were recorded at hourly intervals over an eight-month study period from July 2025 to February 2026, resulting in a total of 1,818 observations and 17 variables. The dataset therefore provides a substantial record of thermodynamic, mechanical, and operational behaviour under real industrial operating conditions. The following parameters were selected as features: compressor inlet pressure (CIP, kPa), compressor inlet temperature (CIT, °C), compressor discharge pressure (CDP, bar), compressor discharge temperature (CDT, °C), turbine vibration (VIB, mm/s RMS), and filter differential pressure (Filter_DP, kPa). In addition, the dataset includes inlet guide vane position (IGV Position), gas turbine speed (GT Speed), turbine load (Load), and the currently active fault state (Fault Current) as determined by the facility's monitoring system. Fault Current is a binary variable, where 1 indicates that any sensor value has crossed a predefined alarm threshold and 0 indicates normal operation. Figure 1 illustrates the temporal coverage of the dataset across the four turbine units.

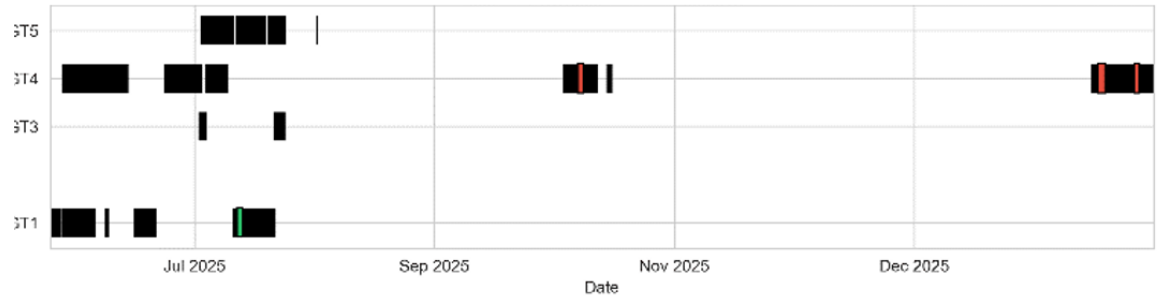


Figure 1: Data Availability Timeline

The distribution of available data is not uniform across the four units. GT4 has the largest share, with 1,032 observations over seven months, accounting for approximately 52% of all measurements. GT1 contains 515 observations over two months, representing nearly 25.6% of the data. GT5 contributes 382 observations over one month, constituting 19% of the dataset. GT3 has the smallest sample, with 81 observations over one month, accounting for only 4% of the dataset. This uneven distribution should be considered when interpreting comparative results, because GT4 and GT1 have been monitored for longer periods and under more varied operating conditions than GT3 and GT5. The difference in sample sizes may introduce bias in cross-turbine comparisons, and the results for GT3 and GT5 should therefore be treated with appropriate caution.

2.2 Measurement Equations

Three key derived parameters were computed from the raw sensor measurements to capture thermodynamic relationships and temporal degradation patterns:

2.2.1 Pressure ratio

The pressure ratio as illustrated in Equation (1) represents the compression achieved by the compressor stage. A decrease in PR over time indicates compressor performance degradation due to fouling, erosion, or mechanical wear [5]. This dimensionless parameter is a fundamental indicator of compressor health that has been widely used in gas turbine condition monitoring literature. The pressure ratio is particularly valuable because it normalises discharge pressure by inlet pressure, removing the effects of ambient pressure variations.

2.2.2 Temperature differential

The temperature differential also illustrated in Equation (2), represents the temperature rise across the compressor. An increase in ΔT for a given pressure ratio indicates reduced compressor efficiency [7]. This parameter captures the thermal consequences of compressor degradation, where fouled or damaged blades require more work to achieve the same compression, resulting in higher discharge temperatures. The temperature differential is expressed in degrees Celsius.

2.2.3 24-Hour rolling mean for pressure ratio

Rolling statistics capture medium-term degradation trends that individual point readings cannot reveal, smoothing short-term fluctuations caused by load changes and ambient conditions [9]. The 24-hour rolling mean as shown in equation (3) provides a stable estimate of average pressure ratio over the preceding day, reducing the influence of transient operating conditions. This feature is essential for identifying gradual degradation that may not be apparent from instantaneous readings.

$$\overline{PR_{24t}}(t) = \frac{1}{24}\sum_{i=0}^{23}(PR(t-i)) \quad (3)$$

Vibration amplitude was measured using accelerometers mounted on the turbine bearing housings, expressed as root-mean-square (RMS) velocity in mm/s following ISO 10816-4 standards for gas turbine sets with fluid-film bearings [1]. The standard establishes evaluation zone boundaries for vibration of non-rotating parts, with zones A (good), B (satisfactory), C (unsatisfactory), and D (unacceptable) defined for gas turbine sets operating under steady-state conditions. The RMS vibration velocity is the preferred measurement parameter for machine condition monitoring because it provides a measure of the energy content of the vibration signal.

2.3 Data Preprocessing

The following preprocessing procedures were applied to ensure data quality and consistency:

2.3.1 Data cleaning

Duplicated records were identified and removed to prevent data redundancy from skewing statistical analyses. Timestamps were converted to a uniform format (YYYY-MM-DD HH:MM:SS) to enable proper time-series analysis. Outlier verification was performed to identify any data points that fell outside physically

plausible ranges, which could indicate sensor malfunction or data transmission errors. Data consistency checks were conducted to ensure that derived relationships (such as PR and ΔT) were internally consistent with their constituent measurements.

2.3.2 Missing value treatment

Missing values were replaced using mode imputation, which preserves the discrete nature of fault indicators and is robust to outliers in skewed distributions. Mode imputation was selected over mean or median imputation because industrial datasets often contain periodic gaps in sensor readings, and the mode provides a reasonable estimate of the most likely value based on the data distribution.

2.3.3 Feature engineering

Derived variables were computed using Equations 1-3 to capture thermodynamic relationships and temporal degradation patterns. These engineered features transform raw sensor data into predictive indicators that reflect both instantaneous operating conditions and longer-term degradation trends. The feature engineering process is critical because individual point readings may not capture the gradual performance decay that precedes faults.

2.3.4 Correlation analysis

Correlation analysis was performed using Pearson correlation coefficients to examine relationships between all input variables and fault occurrence. The Pearson correlation coefficient is defined as:

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \cdot \sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

where x_i and y_i are the individual sample points,

$\bar{x}$ and $\bar{y}$ are the sample means, and n is the number of samples.

The coefficient r ranges from -1 to +1, where +1 indicates perfect positive linear correlation, -1 indicates perfect negative linear correlation, and 0 indicates no linear correlation. This metric was chosen for its interpretability and sensitivity to linear relationships between sensor readings and fault labels.

This metric measures the linear relationship between two variables, with values ranging from -1 (perfect negative correlation) to +1 (perfect positive correlation). The correlation analysis was essential for identifying which features are most strongly associated with fault occurrence and revealing multicollinearity among variables.

3. RESULTS AND DISCUSSION

3.1 Comparative Signature Analysis

Figure 2 shows a comparison of signatures of all the four turbine units with respect to health parameters. GT1 shows the best signature with minimum vibration, steady pressure ratio and modest temperature difference whereas both GT3 and GT5 have the most severe signatures with degraded health indicators as indicated by their much higher fault rates.

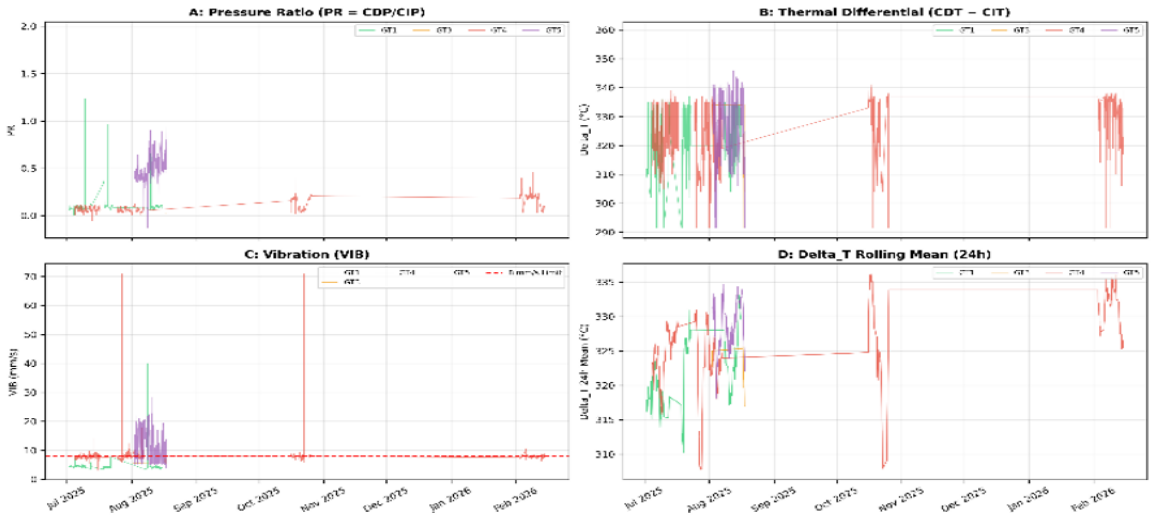


Fig 2: Comparative Signature Analysis

Table 1 lists some statistical properties of the most significant health indicators for all the four units. GT3 has the lowest mean pressure ratio of 0.029 and the highest temperature difference of 319.7^{0}C. Also the vibration is the second highest (5.88 mm/s). This corresponds to a 100% fault rate for GT3 although one needs to be

careful in analyzing this figure since the sample size of GT3 is the smallest one (81 records). The mechanical signature of GT5 is the most deteriorated, with the highest vibration amplitude of 11.35 mm/s and the largest temperature difference of 328.2^0C, matching its 62.0% fault rate. GT1 with the least fault rate of 4.9% exhibits the best thermodynamic conditions of PR=0.099 and T=321.6^0C. GT4 falls in between other turbines in terms of all health parameters according to its 44.3% fault rate.

Table 1: Comparative Signature Statistics by Turbine Unit

Turbine	Rows	Faults	Fault%	PR (mean)	ΔT (°C) (mean)	VIB (mm/s) (mean)	Filter_DP (kPa) (mean)
GT1	515	25	4.9%	0.099	321.6	4.48	0.82
GT3	81	81	100%	0.029	319.7	5.88	1.56
GT4	1032	457	44.3%	0.102	325.9	7.95	0.94
GT5	382	237	62.0%	0.502	328.2	11.35	1.31

The filter differential pressure showed consistent correlation with performance degradation. GT3 exhibited the highest Filter_DP (1.56 kPa) alongside the lowest PR, confirming the relationship between inlet filter restriction and compressor performance degradation [6]. The progressive increase in Filter_DP from GT1 (0.82 kPa) to GT5 (1.31 kPa) to GT3 (1.56 kPa) correlates with declining pressure ratio values, establishing a clear inverse relationship between filter condition and compressor performance. This relationship has important practical implications, as inlet filter maintenance represents one of the most cost-effective interventions for maintaining compressor performance.

The comparative study shows the degradation levels clearly among the turbines. A 100% fault rate for GT3 must be treated with significant caution: it was represented by only 81 rows of data as compared to 1032 data for GT4-more than a 10 fold factor! This implies that a 100% fault rate for this single turbine might as well signify a single anomalous event that lasted for some very limited time: it is not an anomaly indicative of degradation across the turbine or to fleet level behavior-it might as well be something simple like sensor offset or data artifact.

Therefore, these "extremes" for GT3 for example their PR (0.029) and Filter_DP (1.56 kPa) are considered with care and not regarded to be directly interpretable physical degradation signs.

3.2 Vibration Behaviour

Fig. 3 displays the vibration amplitude trends with the ISO 10816-4 alarm threshold (8 mm/s, dashed red line). This figure is arguably the most important diagnostic tool in the study, as it provides an immediate visual assessment of which turbines are operating in alarm territory. Vibration amplitude demonstrated a clear positive relationship with fault occurrence across all turbine units.

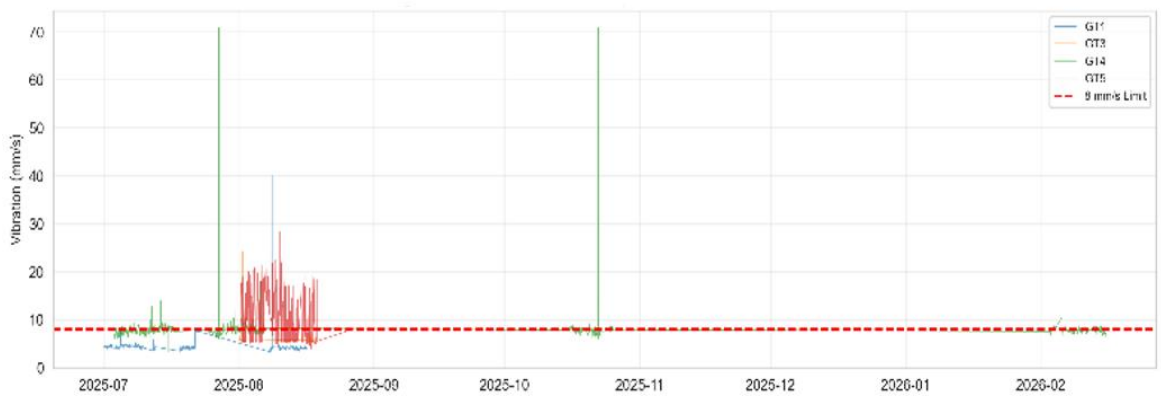


Figure 3: Vibration Trend Comparison

GT5 exhibits the most concerning vibration behaviour. With a mean vibration amplitude of 11.35 mm/s, the turbine operates 41.9% above the 8 mm/s alarm threshold. Furthermore, 60.8% of all readings from GT5 exceed the 8 mm/s limit, indicating that the turbine is in a chronic alarm state. This sustained operation above the ISO 10816-4 Zone B limit suggests progressive mechanical degradation, possibly due to bearing wear, rotor imbalance, or blade damage. The high vibration levels in GT5 are consistent with its 62.0% fault rate and indicate that this turbine should be the highest priority for maintenance intervention.

GT4 presents an equally concerning but slightly less severe vibration profile. With a mean vibration amplitude of 7.95 mm/s, the turbine operates at 99.4% of the 8 mm/s alarm threshold. Over one-third of all readings (36.5%) exceed the threshold, indicating that GT4 frequently enters the alarm zone. The high frequency of alarm events, combined with the long monitoring period (7 months), suggests progressive

degradation rather than transient anomalies. GT4's vibration profile, together with its 44.3% fault rate, identifies it as the second-highest priority for maintenance.

GT3 shows moderate vibration levels with a mean of 5.88 mm/s and no readings exceeding the 8 mm/s threshold. However, this turbine has a 100% fault rate driven by other parameters (likely Filter_DP or CIP anomalies). The vibration data indicate that GT3's faults are not mechanically driven, suggesting that the root cause lies in the inlet system, control system, or sensor issues rather than rotating machinery degradation.

GT1 demonstrates the healthiest vibration profile with a mean of 4.48 mm/s and only 0.2% of readings exceeding the 8 mm/s threshold. This turbine operates comfortably within ISO 10816-4 Zone B (satisfactory) and shows no evidence of progressive mechanical degradation. The low vibration levels are consistent with GT1's low fault rate (4.9%).

The graduated pattern of vibration exceedance across the four turbines correlates directly with fault rates, confirming vibration as the most direct and reliable indicator of mechanical degradation. The ISO 10816-4 evaluation zones provide a structured framework for interpreting these vibration measurements, with exceedance of zone boundaries triggering alert signals and prompting maintenance investigations.

3.3 Correlation Analysis

Fig. 4 presents the correlation matrix of all input features, revealing interrelationships among the monitoring variables.

The strongest correlation with fault occurrence is observed for vibration amplitude (r = 0.497), confirming its primacy as an early degradation indicator. This finding aligns with established condition monitoring literature where vibration analysis serves as the primary mechanical health assessment tool for turbomachinery [4]. The positive correlation indicates that higher vibration levels are associated with increased fault probability.

The filter differential pressure shows a strong negative correlation with the 24-hour rolling mean pressure ratio (r = −0.618). This indicates that as filter restriction increases (higher Filter_DP), the long-term pressure ratio performance degrades (lower PR_Rolling_Mean_24h). This relationship has important practical implications, as it suggests that inlet filter maintenance can significantly impact compressor performance. The negative correlation confirms the physical expectation that filter degradation reduces the available inlet pressure, forcing the compressor to work harder to achieve the required discharge pressure.

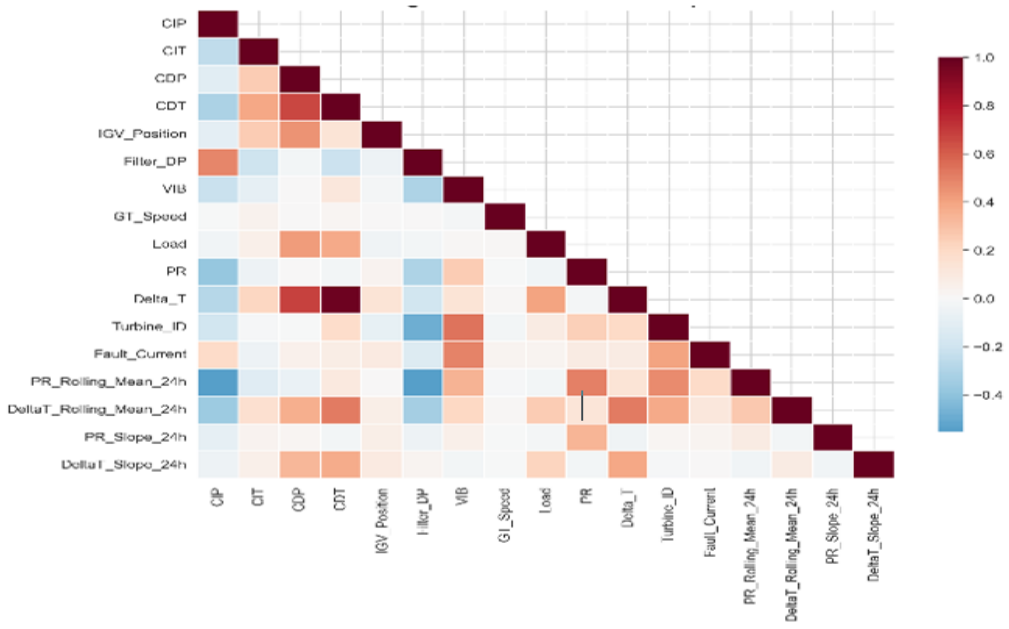


Figure 4: Correlation Analysis heatmap

The correlation between CIT and IGV Position (r = 0.713) reflects the control system's response to ambient temperature variations. As ambient temperature increases, the inlet guide vanes adjust to maintain optimal compressor operation by varying the angle of the inlet guide vanes. This control response is expected and indicates that the dataset captures normal operational variations across different ambient conditions.

The near-perfect correlations observed between CDT and Delta_T (r = 0.994) and between CDP and PR (r = 0.843) are expected mathematically, as Delta_T is directly derived from CDT and CIT, and PR is derived from CDP and CIP. These high correlations indicate mathematical redundancy between these features, which should be considered in feature selection for predictive modelling. However, the derived features (PR and Delta_T) are still valuable because they provide physically meaningful interpretations of the raw measurements.

3.4 Pressure Ratio and Temperature Differential Behaviour

Fig. 5 presents boxplots comparing normal and fault conditions for vibration, pressure ratio, and temperature differential. The boxplots provide a visual assessment of which parameters effectively discriminate between normal and fault operating conditions.

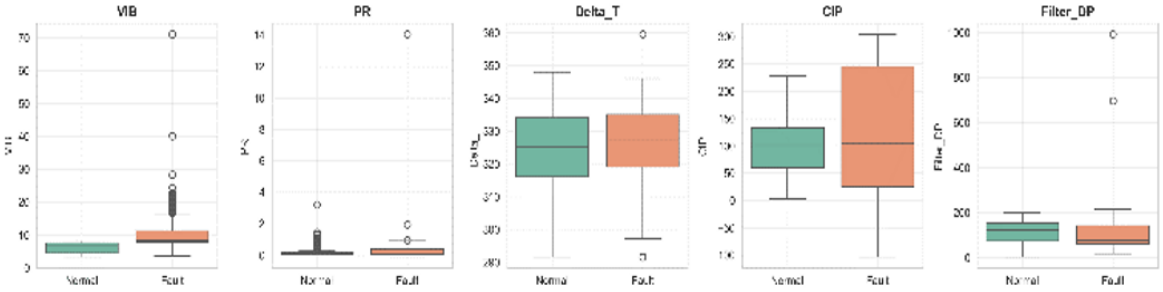


Figure 5: Pressure Ratio and Temperature Differential Behaviour

Vibration exhibits the strongest separation between normal and fault conditions. The normal distribution shows a median of 6.70 mm/s with the third quartile at 7.50 mm/s. The fault distribution shows a median of 8.40 mm/s with the first quartile at 7.90 mm/s. This means the boxes barely overlap, and the fault median sits exactly at the 8 mm/s alarm threshold. The clear separation confirms that vibration is the most reliable single indicator of impending faults.

Pressure ratio shows weaker separation between normal and fault conditions. The normal median (0.09) and fault median (0.10) are nearly identical, but the fault distribution shows a much wider spread (Q1 = 0.04, Q3 = 0.38) compared to the normal distribution (Q1 = 0.07, Q3 = 0.18). This indicates that faults are associated with both abnormally low and abnormally high pressure ratios, suggesting a non-monotonic relationship. The wide spread in the fault distribution confirms that pressure ratio alone is insufficient to discriminate faults and supports the need for nonlinear analytical approaches.

Temperature differential shows moderate separation. The normal median (325°C) and fault median (328°C) differ by only 3°C, but the fault distribution shows a slight elevation (Q3 = 335°C compared to 334°C for normal). The overlap between distributions indicates that temperature differential alone does not provide strong fault discrimination, but it can contribute additional information when combined with other indicators.

The pressure ratio demonstrated a non-monotonic relationship with fault probability across the dataset. Both very low PR (<0.05) and very high PR (>0.40) increased fault probability, while PR values in the 0.10–0.20 range were associated with normal operation. This U-shaped risk profile explains why linear correlations between PR and faults were near-zero and supports the use of nonlinear analytical approaches for gas turbine health monitoring [12]. The non-monotonic behaviour suggests that faults can arise from both excessive pressure losses (low PR) and abnormal operating conditions causing elevated PR.

GT5's mean PR (0.502) is 5.1× higher than GT1 and GT4, indicating a fundamentally different operating regime or sensor scaling. This elevated pressure ratio, combined with high vibration and high temperature differential, suggests that GT5 operates at a different operating point compared to the other turbines. This may be due to different load conditions, control settings, or instrument calibration.

Temperature differential values exceeding 330°C showed strong association with fault occurrence. GT5 exhibited the highest mean ΔT (328.2°C) with 62% fault rate, while GT1 maintained 321.6°C with only 4.9% faults. This confirms thermodynamic intuition: a hotter discharge relative to inlet indicates the compressor is performing more work for the same pressure rise, which is a signature of efficiency loss [7]. The temperature differential is a valuable indicator of compressor fouling or other forms of efficiency degradation.

3.5 Integrated Signature Analysis And Maintenance Priority Ranking

Table **2** provides a comprehensive cross-turbine comparison integrating all key operational and fault parameters with a prioritised maintenance ranking. This integrated view enables ranking of maintenance priority based on multiple health indicators, providing plant operators with a clear action plan.

GT5 is identified as the highest priority for maintenance intervention based on the following indicators: highest vibration amplitude (11.35 mm/s, 41.9% above alarm threshold), highest temperature differential (328.2°C), elevated pressure ratio (0.502), and 62.0% fault rate. The chronic vibration exceedance (60.8% of readings), combined with elevated thermal stress, indicates progressive mechanical degradation requiring immediate investigation. The recommended action is an urgent mechanical inspection focusing on bearings, rotor assembly, and comprehensive vibration analysis to identify the root cause. GT4 is the second-highest priority with 44.3% faults, mean vibration approaching the 8 mm/s threshold (7.95 mm/s), and the longest monitoring period (7 months). The gradual increase in faults over time, combined with the high frequency of vibration threshold exceedance (36.5% of readings), suggests progressive degradation that, if unaddressed, may lead to catastrophic failure. The large dataset (1,032 rows) provides confidence in the statistical

significance of these findings. The recommended action is intensified vibration monitoring and preparation for scheduled maintenance within 1-2 weeks. GT3 presents an interesting anomaly with 100% fault rate but only 81 observations, low vibration (5.88 mm/s), and moderate temperature differential (319.7°C). The high fault rate appears to be driven by other parameters, likely the highest Filter_DP (1.56 kPa) or CIP anomalies, rather than mechanical or thermal degradation. The small sample size suggests a single persistent anomaly rather than a broader degradation trend. GT3 should be investigated for inlet system issues, filter condition, or sensor calibration problems. The recommended action is a focused investigation of the inlet filter system and CIP sensor calibration. GT1 demonstrates the healthiest profile with only 4.9% faults, lowest vibration (4.48 mm/s), stable pressure ratio (0.099), moderate temperature differential (321.6°C), and lowest filter differential pressure (0.82 kPa). This turbine shows no evidence of progressive degradation and can serve as a baseline for "healthy" operation against which the other turbines can be compared. The recommended action is routine monitoring with continuation of the current maintenance schedule. The integration of multiple signatures in Table 2 provides a more comprehensive assessment of gas turbine health than any single parameter alone. The strong correlation between filter differential pressure and rolling mean pressure ratio ($r = -0.618$) suggests that inlet filter maintenance may represent one of the most cost-effective interventions for preventing performance degradation across all units. The differentiated signature profiles across turbine units suggest that unit-specific baselines and trend analysis are essential for effective condition monitoring. The maintenance priority ranking derived from this analysis provides plant operators with a clear, actionable plan for resource allocation and intervention scheduling.

Table 2: Integrated Signature Analysis and Maintenance Priority Ranking

Priority	**Turbine**	**Fault%**	**VIB (mean)**	**% >8mm/s**	**PR (mean)**	**ΔT (°C) (mean)**	**Filter_DP (mean)**	**Key Observation**	**Recommended Action**
1	GT5	62.0%	**11.35**	**60.8%**	0.502	**328.2**	1.31	Chronic vibration alarm; 41.9% above 8mm/s threshold; highest thermal stress	**IMMEDIATE:** Mechanical inspection; bearing and rotor assessment; vibration analysis
2	GT4	44.3%	7.95	36.5%	0.102	325.9	0.94	Mean VIB at 99.4% of alarm threshold; progressive degradation over 7 months	**SCHEDULED:** Vibration monitoring intensification; prepare for maintenance within 1-2 weeks
3	GT3	**100%**	5.88	0.0%	**0.029**	319.7	**1.56**	Highest fault rate but mid-range VIB; likely inlet/filter issue (highest Filter_DP)	**INVESTIGATE:** Inspect inlet filter system; check CIP sensor calibration; control system review
4	GT1	**4.9%**	**4.48**	**0.2%**	0.099	321.6	**0.82**	Healthiest profile; stable parameters; no degradation indicators	**ROUTINE:** Continue normal monitoring; maintain current maintenance schedule

3.6 Comparison with Existing Literature

To benchmark the present findings, Table 3 compares the key indicators with values and trends reported in previous studies. The vibration–fault correlation obtained in this study ($r = 0.497$) is consistent with the condition-monitoring literature, where vibration is recognised as the primary mechanical health. The 8 mm/s

alarm threshold is consistent with ISO 10816-4 [3]. The strong negative correlation between filter differential pressure and 24-hour rolling mean pressure ratio ($r = -0.618$) supports previous findings that compressor fouling and inlet restriction are major contributors to gas turbine performance loss [5]. The non-monotonic relationship between pressure ratio and fault probability agrees with studies recommending nonlinear analytical approaches for gas turbine health monitoring [4, 10]. The observation that temperature differential above 330 °C is associated with fault occurrence is consistent with thermodynamic studies showing that increased discharge temperature at a given pressure ratio indicates compressor efficiency loss [5].

Table 3: Benchmark comparison with previous studies

Indicator	**Present study**	**Previous studies**	**Interpretation**
Vibration–fault correlation	$r = 0.497$	Vibration is a primary mechanical health indicator [3]	Consistent
Vibration threshold	8 mm/s	ISO 10816-4 Zone B/C boundary [3]	Validated
Filter_DP vs rolling PR	$r = -0.618$	Fouling/inlet restriction causes 70–85% performance loss [5]	Consistent
Pressure ratio	Non-monotonic	Nonlinear behaviour reported [4, 10]	Supports nonlinear monitoring
ΔT threshold	> 330 °C associated with faults	Increasing ΔT at fixed PR indicates efficiency loss [6]	Consistent

3.7 Limitations

Several limitations should be acknowledged. First, the sample sizes are unequal across the four turbines. GT4 accounts for approximately 52% of all measurements, while GT3 accounts for only 4%. This imbalance may bias cross-turbine comparisons, and the results for GT3 and GT5 should be interpreted with caution. Second, the monitoring period varies from one month for GT3 and GT5 to seven months for GT4, limiting the ability to observe long-term degradation trends for all units. Third, possible differences in sensor calibration, installation, and operating conditions across the units may influence the measured signatures. Fourth, the fault label is a binary variable derived from alarm thresholds rather than a detailed fault classification, which limits the specificity of the fault diagnosis. Fifth, the analysis does not normalise for ambient conditions, load, or other operating variables, which may confound the observed relationships. Future work should address these limitations through longer monitoring periods, balanced sample sizes, and multivariate normalisation.

4. CONCLUSION

This study has presented a comprehensive comparative analysis of pressure ratio, thermal differential, and vibration signatures across four industrial gas turbine units over an eight-month monitoring period. The findings establish quantitative relationships between these health indicators and fault occurrence, providing a foundation for multi-parameter health monitoring and predictive maintenance.

Vibration amplitude exhibits the strongest association with fault occurrence ($r = 0.497$) among all sensors, reinforcing its primacy as the primary mechanical health indicator for turbomachinery [3]. The 8 mm/s vibration threshold empirically validated the ISO 10816-4 evaluation zone boundaries [1], with GT5 showing 60.8% exceedance compared to GT1's 0.2%. The graduated pattern of vibration exceedance across turbines correlates directly with fault rates, confirming vibration as the most direct and reliable indicator of mechanical degradation.

The filter differential pressure showed significant negative correlation with rolling mean pressure ratio ($r = -0.618$), indicating that inlet filter degradation represents a measurable precursor to compressor performance deterioration. GT3 exhibited the highest Filter_DP (1.56 kPa) alongside the lowest PR (0.029) and 100% fault rate, while GT1 maintained the lowest Filter_DP (0.82 kPa) with the healthiest profile (4.9% faults). This relationship suggests that inlet filter maintenance may represent one of the most cost-effective interventions for maintaining compressor performance.

Pressure ratio demonstrated a non-monotonic relationship with fault probability, supporting the need for nonlinear analytical approaches in gas turbine condition monitoring. Temperature differential values exceeding 330°C showed strong association with fault occurrence, confirming that thermal performance degradation serves as an effective indicator of compressor efficiency loss [6]. GT5 exhibited the highest mean ΔT (328.2°C) with 62% fault rate, while GT1 maintained 321.6°C with only 4.9% faults.

The results establish a quantitative basis for multi-parameter health monitoring that integrates thermodynamic indicators (PR, ΔT) with mechanical indicators (VIB) and operational parameters (Filter_DP). The differentiated signature profiles across turbine units suggest that unit-specific baselines and trend analysis are essential for effective condition monitoring. The maintenance priority ranking derived from

this analysis is: GT5 > GT4 > GT3 > GT1, with GT5 requiring immediate investigation and GT4 requiring scheduled maintenance.

Future work should focus on integrating these indicators into predictive maintenance frameworks that combine physics-based and data-driven approaches for gas turbine health management. The development of unit-specific baseline models, incorporating multiple parameters, would enable early detection of deviations from normal operation. Additionally, the integration of these health indicators into machine learning-based predictive models could provide automated fault detection and maintenance scheduling capabilities.

Based on the findings of this comparative analysis, several recommendations are proposed for plant operators and maintenance engineers responsible for industrial gas turbine fleets. First, the strong correlation between vibration amplitude and fault occurrence ($r = 0.497$) demonstrates that continuous vibration monitoring with appropriate alarm thresholds is essential for early detection of mechanical degradation. Plant operators should implement ISO 10816-4 compliant vibration monitoring systems with unit-specific baseline thresholds, as the graduated pattern of vibration exceedance observed across GT1 (0.2%), GT4 (36.5%), and GT5 (60.8%) clearly indicates that a single alarm threshold may not be optimal across all units. Furthermore, the significant negative correlation between filter differential pressure and rolling mean pressure ratio ($r = -0.618$) underscores the importance of proactive inlet filter maintenance as a cost-effective intervention for preventing compressor performance deterioration. Operators should establish scheduled filter replacement programs based on differential pressure trends rather than fixed time intervals, as this approach can significantly extend compressor service life and maintain operational efficiency.

Second, the non-monotonic relationship between pressure ratio and fault probability observed in this study suggests that reliance on simple threshold alarms for PR may be insufficient for early fault detection. Plant operators should adopt multi-parameter health monitoring approaches that integrate thermodynamic indicators (PR, ΔT) with mechanical indicators (VIB) and operational parameters (Filter_DP). The differentiated signature profiles across turbine units highlight the importance of developing unit-specific baselines and trend analysis for effective condition monitoring. Based on the maintenance priority ranking established in this study (GT5 > GT4 > GT3 > GT1), it is recommended that GT5 undergo immediate mechanical inspection focusing on bearings and rotor assembly, while GT4 should have intensified vibration monitoring with maintenance scheduled within the next 1-2 weeks. Future research should focus on integrating these health indicators into predictive maintenance frameworks combining physics-based models with machine learning approaches [9, 10], enabling automated fault detection and optimal maintenance scheduling. Additionally, the development of digital twins incorporating these multi-parameter signatures would facilitate real-time health assessment and predictive capabilities for industrial gas turbine fleets.

REFERENCES

[1] S.T. Bunyan, Z.H. Khan, L.A. Al-Haddad, M. Ahmed, Intelligent thermal condition monitoring for predictive maintenance of gas turbines using machine learning, Machines 13(5) (2025) 401. https://doi.org/10.3390/machines13050401

[2] A.K. Mohd Nor, S.R. Pedapati, M. Muhammad, V. Leiva, Abnormality detection and failure prediction using explainable Bayesian deep learning: Methodology and case study with industrial data, Mathematics 10(4) (2022) 554. https://doi.org/10.3390/math10040554.

[3] ISO 10816-4:2009. Mechanical vibration Evaluation of machine vibration by measurements on non-rotating parts Part 4: Gas turbine sets with fluid-film bearings. International Organization for Standardization.

[4] J. Zhang, J. Li, X. Li, An agent composed of data model and thermodynamic model for multi-component degradation identification of gas turbine online, Energy 335 (2025) 138245. https://doi.org/10.1016/j.energy.2025.138245

[5] I.S. Diakunchak, Performance deterioration in industrial gas turbines, Journal of Engineering for Gas Turbines and Power 114(2) (1992) 161–168 https://doi.org/10.1115/1.2906565.

[6] Y. Zhu, Z. Liu, Thermal performance degradation prediction in gas turbines using ensemble learning, Energy Conversion and Management 295 (2023) 117643.

[7] A. Bifulco, et al., Fabrication and characterization of a piezo-MEMS uniaxial accelerometer as a tool for the monitoring of combustion instability in gas turbine engines, Measurement 247 (2025) 117241. https://doi.org/10.1016/j.measurement.2025.118166

[8] A. Bifulco, et al., Multi-domain investigation of combustion instability in gas turbine engines using a uniaxial MEMS piezoelectric accelerometer, Measurement: Sensors (2025) 101735. https://doi.org/10.1016/j.expthermflusci.2025.111659.

[9] Lu, Ning, et al. "Design of MEMS Piezoelectric Vector Hydrophone." Key Engineering Materials, vol. 562–565, Trans Tech Publications, Ltd., July 2013, pp. 1143–48, https://doi.org/10.4028/www.scientific.net/kem.562-565.1143.

[10] Dai, Shun, et al. "A Novel Data-Driven Approach for Predicting the Performance Degradation of a Gas Turbine." Energies, vol. 17, no. 4, MDPI AG, Feb. 2024, p. 781, https://doi.org/10.3390/en17040781.