FUSION OF VIBRATION, ULTRASOUND, AND TEMPERATURE FOR OFFLINE SMART PREDICTIVE MAINTENANCE ON OIL AND GAS PLATFORMS ROTATING EQUIPMENT: A PRELIMINARY MATHEMATICAL FRAMEWORK

Amr Y. Menisy (1), Mohamed M. ElGohary (2) Ahmed Al-Kabbany (3) and Ahmed S. Shehata (4)

(1) *Marine and Offshore Engineering Department, College of Engineering and Technology, Arab Academy for Science, Technology and Maritime Transport, Alexandria, Egypt, Amr14920@yahoo.com*

(2) *Naval Architecture and Marine Department, faculty of Engineering, Alexandria University, Alexandria, Egypt, Prof.morsy@gmail.com*

(3) *Intelligent Systems Lab, College of Engineering and Technology, Arab Academy for Science, Technology and Maritime Transport, Alexandria, Egypt, alkabbany@ieee.org*

(4) *Marine and Offshore Engineering Department · College of Engineering and Technology, Arab Academy for Science, Technology and Maritime Transport, Alexandria, Egypt, a_samir@asst.edu*

Keywords: Predictive Maintenance (PdM), Rotating Equipment, Industry 4.0, Artificial Intelligence, Machine learning, Condition Monitoring (CM), Oil and Gas platforms.

1. **ABSTRACT:** We present a deployment-oriented, offline condition-monitoring framework for rotating equipment on oil and gas platforms that fuses vibration, ultrasound, and temperature signals into a single, interpretable health index. The workflow verifies cross-sensor consistency via Pearson correlation, applies z-score normalization, and performs feature-level fusion before classifying equipment states with transparent, ISO-referenced thresholds (Normal / Alarm / Danger). Tailored to offshore constraints where continuous telemetry is impractical, the framework emphasizes low-cost periodic acquisition and auditable rules over black-box models, while remaining ready for subsequent AI/ML integration. On real platform data, the approach improved maintenance KPIs (availability/reliability/cost) by approximately 15–20% versus conventional strategies. This contribution is, to our knowledge, the first offline, multi-sensor fusion framework purpose-built for oil & gas platforms that couples correlation-validated fusion with thresholded, interpretable decisions.

2. INTRODUCTION

Rotating equipment, such as pumps, motors, compressors, and fans, forms the operational backbone of oil and gas platforms in today's safety-, reliability-, and productivity-critical industrial environment [1]. These machines operate under extreme and unique conditions—including high pressure, corrosive atmospheres, and constant mechanical loads—which accelerate wear and degradation. This exposes them to abrupt breakdowns, particularly in critical components such as bearings and shafts, which are subjected to mechanical stress, wear and tear, misalignment, and fatigue. When not detected in a timely manner, the failure of these parts may result in disastrous incidents, causing extensive unplanned downtime, safety accidents, environmental hazards, and significant financial losses [2]. According to research studies and industry reports, anywhere between 15-60% of the overall cost of production in the oil and gas industry is consumed by maintenance and outages, making intelligent, cost-effective maintenance strategies exceedingly important [3].

Condition Monitoring (CM) concerns the management of rotating equipment by capturing data and developing new methods to analyze these data, forecast trends, and evaluate current performance. CM offers many advantages. Notably, it can reduce maintenance costs by detecting incipient flaws and preventing them from growing into significant problems that are expensive to repair. Consequently, it reduces the likelihood of catastrophic failure, thereby improving supply reliability and personnel safety. It also lowers the severity of any damage sustained and eliminates or lessens the need for subsequent repair actions. Additionally, it can identify the root causes of failure and provide an excellent fault-diagnosis system. Finally, integrated condition monitoring across critical equipment can yield valuable information on the plant's life cycle [4].

On the other hand, there are challenges to implementing CM strategies. One challenge is the additional capital and operational costs associated with installing extra monitoring sensors, circuitry, and control systems. Another hurdle is the increased complexity of the protection and overall monitoring system [5]. Most modern platforms use online condition-monitoring systems that continuously collect data from sensors installed directly on the equipment. However, not every site has the infrastructure or budget for real-time monitoring, especially in remote offshore locations. This is where offline condition monitoring becomes particularly valuable.

A recurring limitation observed in recent studies is that tests involve only single-parameter monitoring—such as vibration, ultrasound, or temperature—rather than combining multiple sensor types [9], [10]. Even when sensors are combined, issues remain regarding how to synchronize heterogeneous datasets, particularly in the offline environments common to many oil and gas platforms. Some researchers have fused vibration, ultrasound, and temperature measurements to investigate multi-sensor fusion, with results indicating that fusion can considerably increase diagnostic accuracy, especially for incipient failures [11], [12], [13]. Nevertheless, such work is usually restricted to laboratory conditions and is not based on actual industrial data. Consequently, it does not pass the test of scalability or effectiveness for real-time decision-making, [14], [15].

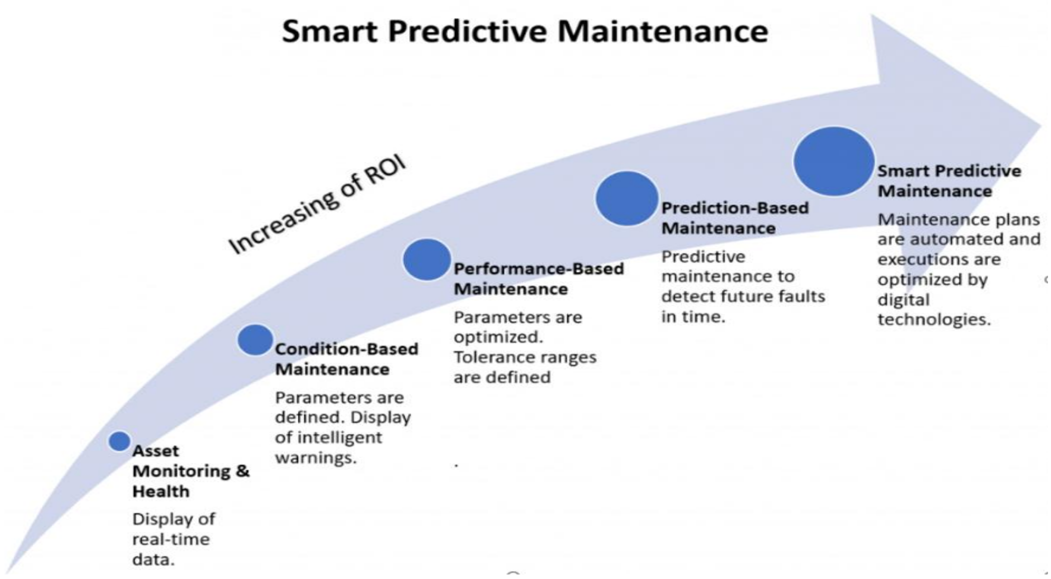

Figure 1: Smart Predictive Maintenance Steps

Offline monitoring involves manual collection of data at scheduled intervals using portable instruments. While it doesn't provide continuous insight, it offers a practical, cost-effective alternative — especially when combined with smart data analysis methods. The present paper aims to strengthen this offline approach by developing a mathematical framework model to interpret vibration, ultrasonic and temperature signals, enabling identify early signs of failure even when not monitoring the machine 24/7.

The figure 1 illustrates the gradual evolution from basic asset monitoring and condition‐based maintenance to performance and prediction‐ based strategies, capping in smart predictive maintenance with automated, data‐ driven decisions. Each stage increases the use of real‐ time data, analytics, and digital technologies, leading to higher equipment reliability and a progressive improvement in return on investment. This maintenance development path shows how maintenance practices can be systematically advanced toward fully optimized smart predictive asset management.

3. METHODOLOGY AND DATA PREPROCESSING

Predictive maintenance systems are significantly more effective when multiple condition-monitoring signals are fused into a unified analytical framework. However, fusing signals such as vibration, ultrasound, and temperature presents challenges due to their different sampling frequencies, physical units, noise characteristics, and sensor response times [12]. This section outlines the mathematical foundation for sensor fusion in the context of offline data acquisition, focusing on synchronization, feature transformation, and data-alignment techniques applicable to rotating machinery on oil and gas platforms.

The primary objective is to establish a robust framework for transforming raw sensor data into actionable intelligence. The methodology, as shown in Figure 2, is designed to be systematic and reproducible, ensuring data integrity and preparing it for advanced machine-learning analysis [12], [14]. In particular, we aim to establish the linear relationship between Vibration (Root Mean Square (RMS) mm/s), Ultrasound (dB), and Temperature (°C) [11], [13], [16].

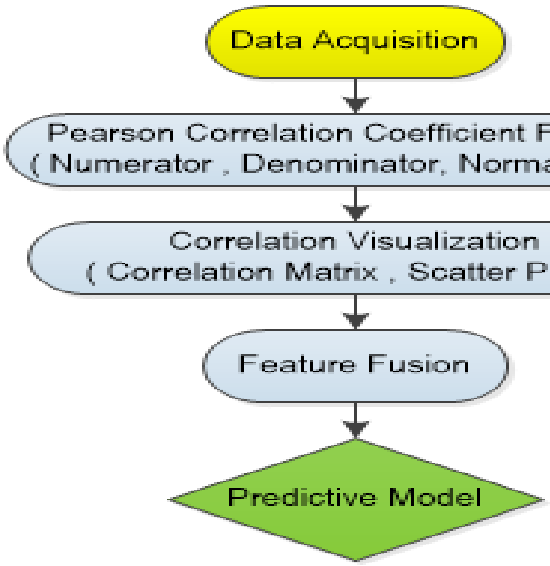

Figure 2 : Methodology and Process Flow Chart

3.1 Data Acquisition and Alignment

Initial data from multiple sensors often have different sampling rates. While providing data is already synchronized by pump Tag, in a real-world scenario, time-domain alignment is crucial. This involves either resampling or interpolating slower signals to match the timestamps of the fastest signal. For example, if temperature readings were sparse, linear interpolation would be used to estimate values at each vibration timestamp [16], [19], [6].

3.2 Mathematical Correlation Analysis

To understand the relationships between the features, the Pearson correlation coefficient (r) is calculated. This is a crucial step in exploratory data analysis as it reveals the strength and direction of linear relationships, which can inform feature selection and model design.

3.2.1 Pearson Correlation Coefficient Formula

The Pearson correlation coefficient, r, is a powerful statistical measure that quantifies the strength and direction of a linear relationship between two variables. The value of r always falls between −1 and +1.

- r = +1: A perfect positive linear relationship. As one variable increases, the other increases proportionally.
- r = -1: A perfect negative linear relationship. As one variable increases, the other decreases proportionally.
- r = 0: No linear relationship between the variables.

$$r = \frac{\sum_{i=0}^{n}\left((x_i - \bar{x})(y_i - \bar{y})\right)}{\sqrt{\sum_{i=0}^{n}(x_i - \bar{x})^2 \cdot \sum_{i=0}^{n}(y_i - \bar{y})^2}} \tag{1}$$

Where:

- n is the number of data points.
- x_i and y_i are the individual data points for variables x and y.
- $\bar{x}$ is the mean (average) of the x values.
- $\bar{y}$ is the mean of the y values.

The formula is composed of two main parts: the covariance in the numerator and the product of the standard deviations in the denominator [12], [18].

Numerator: Covariance of x and y

The numerator calculates the covariance, which indicates how x and y change together. A positive value means they tend to move in the same direction, while a negative value means they tend to move in opposite directions. The denominator normalizes this value by the product of the standard deviations of x and y, standardizing the result to be between −1 and +1.

The numerator $\sum_{i=0}^{n}\left((x_i - \bar{x})(y_i - \bar{y})\right)$ calculates the covariance between the two variables. This part of the equation measures how much x and y vary together.

$$\sum_{i=0}^{n}\left((x_i - \bar{x})(y_i - \bar{y})\right) \tag{2}$$

- For each data point, we find the difference between the value and its mean: $(x_i - \bar{x})$ and $(y_i - \bar{y})$.
- The product of these differences, $(x_i - \bar{x})(y_i - \bar{y})$ will be positive if both data points are either above or below their respective means. This indicates a positive relationship.
- The product will be negative if one data point is above its mean and the other is below, indicating a negative relationship.
- Summing these products over all data points gives us the total covariance.

Denominator: Product of Standard Deviations

The denominator, $\sqrt{\sum_{i=0}^{n}(x_\mathrm{i} - \bar{x})^2}\,\sqrt{\sum_{i=0}^{n}(y_\mathrm{i} - \bar{y})^2}$ Normalizes the covariance. It's the product of the standard deviations of x and y.

$$\sqrt{\sum_{i=0}^{n}(x_\mathrm{i} - \bar{x})^2}\,\sqrt{\sum_{i=0}^{n}(y_\mathrm{i} - \bar{y})^2} \tag{3}$$

- $\sum_{i=0}^{n}(x_\mathrm{i} - \bar{x})^2$ is the sum of squared differences for variable x.
- $\sum_{i=0}^{n}(y_\mathrm{i} - \bar{y})^2$ is the sum of squared differences for variable y.
- Taking the square root of their product normalizes the value so that r is always between −1 and +1.

This normalization step is what makes the Pearson correlation coefficient so useful, as it provides a standardized measure of the strength and direction of the linear relationship, regardless of the scale of the variables.

Feature Normalization

To prevent features with a larger magnitude from disproportionately influencing a machine learning model, a standard score (Z-score) normalization is applied to each feature. This process transforms the data to have a mean of 0 and a standard deviation of 1, placing all features on a comparable scale [12], [17].

$$Z_{norm} = \frac{x-\bar{x}}{\sigma} \tag{4}$$

Where:

- x is the raw signal value.
- $\bar{x}$ is the mean of the feature.
- σ is the standard deviation.

3.2.2 Correlation Matrix and Visualization

The correlation matrix provides a tabular summary of the Pearson r values, while the heat map offers a powerful visual representation. Referring to Table 1, all three condition indicators exhibit very strong positive correlations (r = 0.95–0.98), indicating that vibration, ultrasound, and temperature vary together and capture closely related aspects of the machine's operating condition, consistently signaling emerging faults.

Table 1. Correlation Matrix

	Vibration (RMS mm/s)	Ultrasound (dB)	Temperature (°C)
Vibration (RMS mm/s)	1.00	0.98	0.95
Ultrasound (dB)	0.98	1.00	0.95
Temperature (°C)	0.95	0.95	1.00

The heat map in figure 3 provides a clear visual representation of the correlations. The color and numerical values indicate the strength and direction of the relationships.

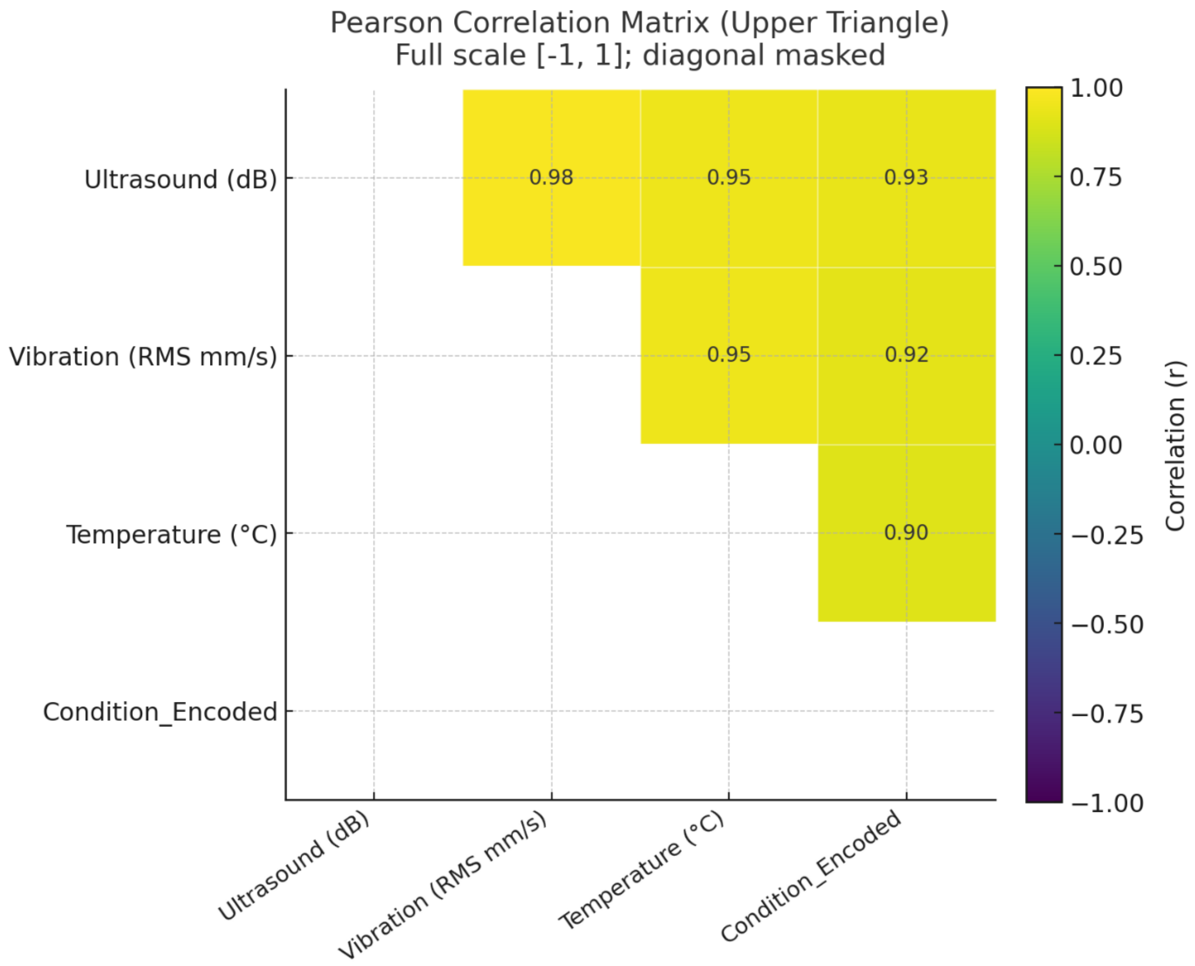

Figure 3 : Heat Map represents Pearson Correlation between Vibration, ultrasound and temperature.

Scatter plots are the most direct way to visualize a linear relationship. Each point on the graph represents a single data point from the acquired equipment data. The plots in Figures 4 and 5 show the strong positive linear correlations. As the value on the x-axis increases, the value on the y-axis also increases in a consistent, straight-line pattern. This visual evidence supports the high r values found in the correlation matrix. The first plot shows the relationship between Vibration and Ultrasound (r = 0.98). The second plot shows the relationship between Vibration and Temperature (r = 0.95). This visualization confirms the findings from the correlation matrix: Vibration, Ultrasound, and Temperature are all very strongly and positively correlated with each other. This is visually evident from the tight, upward-sloping patterns in all the scatter plots.

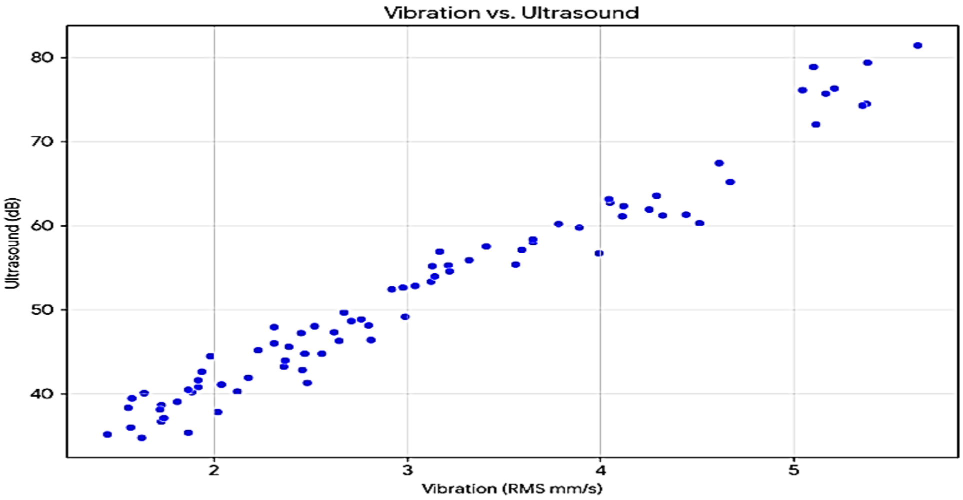

Figure 4 : The first scatter plot shows the relation between Vibration and Ultrasound

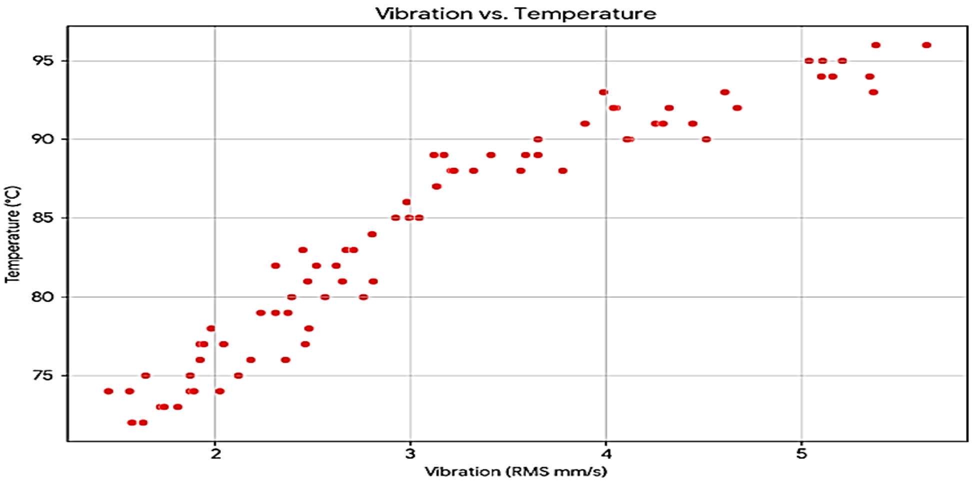

Figure 5 : The second scatter Plot relation between vibration and Temperature.

3.3 The process of Feature Fusion

This process is to create a single row in a spreadsheet for each Equipment or Pump. Before doing this, all the data for that row is standardized and ready to be used together [10], [12], [21].

This process is critical for several reasons:

- Creating a Unified View: Instead of each sensor reading as a separate piece of information, fusion creates a single, multi-dimensional data point that the model can process.
- Enabling Multivariate Analysis: Fusion allows moving beyond analyzing a single variable at a time. It enables a model to understand the complex interactions and patterns between all three sensor readings simultaneously. For example, a model might learn that a high vibration reading is only a concern when it's combined with a high temperature reading, but not on its own.
- Improving Model Performance: By providing a comprehensive and standardized view of the data, feature fusion often leads to more accurate and robust machine learning models for tasks like fault detection or condition monitoring.

3.3.1 Feature-Level Fusion

Once aligned and normalized, features are extracted from each signal domain and concatenated into a unified feature vector:

$$\vec{f} = [f_{vib}, f_{ultra}, f_{temp}] \tag{5}$$

This vector captures the multivariate representation of the machine's state.

Typical features include:

- Vibration Features RMS: Represents signal energy.
- Ultrasound Features dB: Burst Count: Number of high-energy acoustic emissions.
- Temperature Features C Moving Average: Tracks overheating.

These features serve as inputs for Model algorithms and are essential for robust fault classification. For a single pump, in the spread data sheet row, the normalized values are:

- Vibration: 0.5
- Ultrasound: 1.2
- Temperature: 0.8

Then the fused feature vector for that pump would be: ***f*** = [0.5, 1.2, 0.8]

3.4 The Predictive Model

The culmination of this process is the development of a predictive model that takes the fused feature vector and outputs a classification [14], [16], [17].

$$y\ predection = f(x) \tag{6}$$

Where:

- $y\ predection$ is the predicted class (example, Normal, Alarm, Danger)?
- $f(x)$ is the logical condition that defined as Decision Boundaries?
- x is the fused feature vector from Equation 2.

3.4.1 Decision Boundaries

Based on data and the correlation analysis, establish the mathematical rules or "boundary conditions." Will be establish reference to ISO and best industrial practice.

- *Vnormthresh: Threshold for normalized Vibration.*
- *Unormthresh: Threshold for normalized Ultrasound.*
- *Tnormthresh: Threshold for normalized Temperature.*

These thresholds, or "boundary values," are the heart of the predictive model.

$$y\ predection = f(x) \tag{7}$$

$$= \begin{cases} Danger, if\ (V_{normal} > V_{Normal}^{Danger}) \wedge (U_{normal} > U_{Normal}^{Danger}) \wedge (T_{normal} > T_{Normal}^{Danger}) \\ Alarm, if\ (V_{normal} > V_{Normal}^{Alarm}) \wedge (U_{normal} > U_{Normal}^{Alarm}) \wedge (T_{normal} > T_{Normal}^{Alarm}) \\ Normal, Otherwise \end{cases}$$

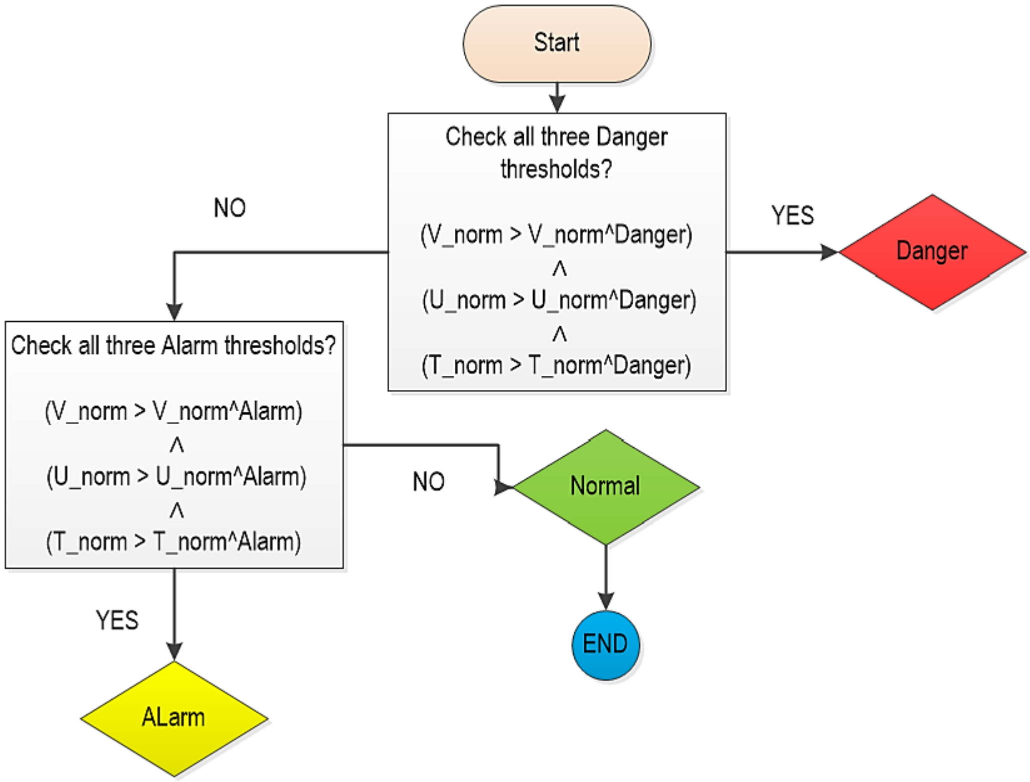

Figure 6 : The Smart Predictive Model process flow

4. RESULTS

The results of this research highlight a key advantage of smart predictive maintenance framework systems over traditional rule-based or upper-/lower-limit alarm approaches. Threshold-based alarms—which trigger when a pre-specified vibration or temperature limit is reached—are often inadequate on oil and gas platforms for detecting early-stage degradation [18]. This is especially problematic for incipient faults, which begin subtly and may go unnoticed until they progress to severe damage. Conversely, traditional preventive maintenance and online condition monitoring that rely on independent sensors—without fusion across condition-monitoring algorithms—remain areas in need of improvement [19], [21].

By fusing vibration, ultrasound, and temperature algorithms, the proposed mathematical smart predictive model aligns with the Industry 4.0 paradigm. AI models and machine learning, particularly when trained on aggregated features from multiple sensor modalities, can recognize multivariate and multidimensional patterns that indicate early signs of failure.

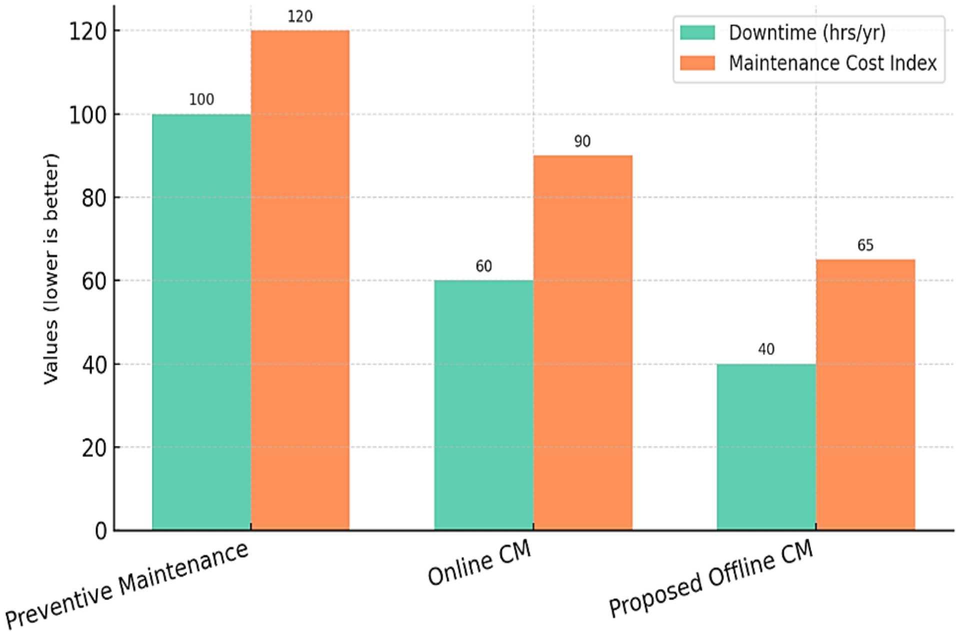

Figure 7 : KPI Comparison : Maintenance Approaches

As shown in Figure 7, 15 to 20 % cost savings had been achieved in a real oil platform by implementing the smart predictive maintenance strategy. The mathematical proposed framework was applied to a dataset of vibration (RMS, mm/s), ultrasound (dB), and temperature (°C) signals collected from rotating equipment under different operating conditions. KPI indicate improvement in cost saving, operation availability and reliability by 15 to 20 % compared to traditional preventative maintenance and online monitoring [5], [7], [22].

5. DISCUSSION

The scatter plots (The Off-Diagonal Plots) in figure 8 illustrate the relationship between each unique pair of variables. The strong positive linear correlation is such that as one variable increases, the other increases along a straight-line trend [10], [14].

The plots on the diagonal show the distribution of each variable. They are kernel density estimates (KDEs) that show the frequency of different values for each sensor.

The high correlation coefficients and clear linear trends in the scatter plots confirm a strong interdependence among the three monitored variables. This is a common finding in machine diagnostics, where an underlying mechanical issue can manifest as simultaneous increases in vibration, temperature, and specific high-frequency sounds. The consistency of these relationships can be a valuable asset in a predictive maintenance strategy [12], [18], [20].

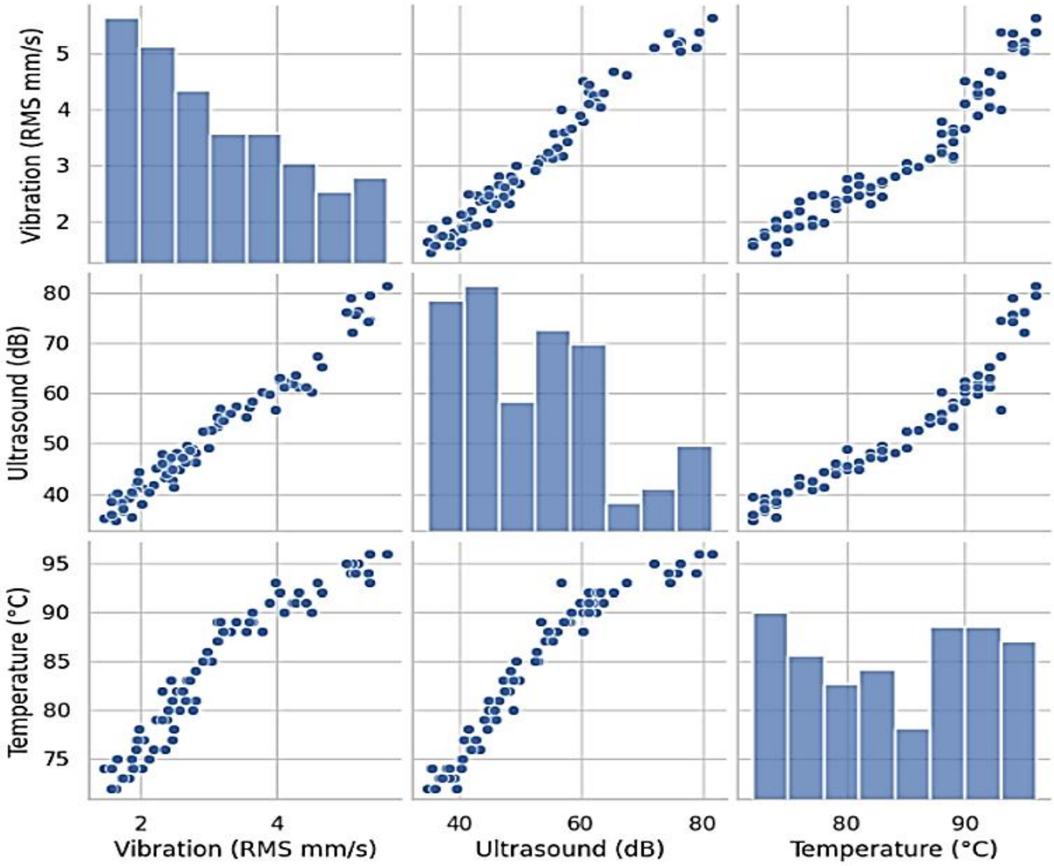

Figure 8 : The relation between a pair of variables and Kernel Density estimates (KDEs).

6. CONCLUSION

This paper presents a mathematical offline, condition-based monitoring model for rotating equipment used on oil and gas platforms. By combining vibration, ultrasound, and temperature measurements, the framework demonstrates a strong positive interdependence among these parameters, confirming the value of sensor fusion for detecting early symptoms of mechanical degradation. The rule-oriented mathematical model classifies equipment states into Normal, Alarm, and Danger, providing transparent and interpretable decision support [10], [12], [18].

The framework can improve predictive maintenance by minimizing reliance on costly real-time online condition-monitoring infrastructure, enabling deployment in offline settings. Moreover, its formal mathematical basis enables integration with artificial intelligence and machine-learning algorithms that can dynamically learn decision boundaries from historical data. Overall, the solution offers an affordable, scalable, and safety-focused predictive-maintenance approach aligned with Industry 4.0 objectives in the oil and gas sector [5], [7], [23].

This mathematical model should be extracted in future by Artificial Intelligence to develop a Machine learning model using different offline condition monitoring algorithms, such as vibration and ultrasound and temperature to improve the reliability of equipment, operation productivity and reduce the cost of maintenance with improvement in Key performance indicators KPI records.

7. FUTURE RECOMMENDATIONS

This paper proposes a Mathematical smart data-driven predictive maintenance (PdM) framework of rotating equipment in an oil and gas platform through the integration of vibration, ultrasound, and temperature offline sensors measurements. This framework should be able to withstand the complexity of the real world and thus be capable of identifying early faults before the data available is too scarce. The framework can offer a platform on which AI and machine learning applications can be applied in the future by modelling the relationships between signals mathematically, so that predictive models will be employed.

In this progression, the mathematical offline CM framework serves as the foundational layer. Its role is to pre-process and structure raw offline data, preparing it for advanced AI/ML pipelines [12], [16], [24].

This work Contributes to the science of predictive maintenance by translating the theory of signal processing into real-life industrial applications, which are characterized by severe operating conditions. The suggested smart PdM framework represents the next level of asset integrity improvement with reduced costs and enabling safe, continuous operation on oil and gas platforms through sensor fusion, machine learning, and decision intelligence.

The fusion of vibration, ultrasound, and temperature signals—when integrated with AI models—enables more accurate, timely, and interpretable diagnostics. It also lays the foundation for smart predictive systems capable of operating under the environmental, logistical, and operational constraints typical of oil and gas platforms.

In order to test the effectiveness and the strength of a proposed predictive maintenance system in a real-life application, a simulation environment will be developed to simulate the performance of rotating equipment under operational conditions [7], [25].

8. ACKNOWLEDGMENTS

The authors acknowledge the technical support and insights provided by the management and team at ADNOC – Fertil – Fertiglobe. The first author would also like to express his deep gratitude to his late father, whose inspiration continues to guide me.

9. DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES:

The author(s) declare that no generative AI or AI-assisted tools were used during the preparation of this work.

10. REFERENCES

[1] Doshi, S., A. Katoch, A. Suresh, F. A. Razak, S. Datta, S. Madhavan, C. M. Zanhar, and E. Gundabattini. *"A Review on Vibrations in Various Turbomachines Such as Fans, Compressors, Turbines and Pumps." Journal of Vibration Engineering & Technologies 9,* no. 7 (2021): 1557–1575. https://doi.org/10.1007/s42417-021-00358-2

[2] Cvetković, V. M., R. Renner, and V. Jakovljević. *"Industrial Disasters and Hazards: From Causes to Consequences—A Holistic Approach to Resilience." International Journal of Disaster Risk Management 6,* no. 2 (2024*):* 149–168. https://doi.org/10.18485/ijdrm.2024.6.2.2

[3] Ghazali, M. H. M., and W. Rahiman. *"Vibration Analysis for Machine Monitoring and Diagnosis: A Systematic Review." Shock and Vibration 2021 (2021):* Article ID 9469318. https://doi.org/10.1155/2021/9469318

[4] Thoppil, N. M., V. Vasu, and C. S. P. Rao. *"Health Indicator Construction and Remaining Useful Life Estimation for Mechanical Systems Using Vibration Signal Prognostics." International Journal of System Assurance Engineering and Management 12*, no. 5 (2021): 1001–1010. https://doi.org/10.1007/s13198-021-01102-3

[5] Romanssini, M., P. C. C. de Aguirre, L. Compassi-Severo, and A. G. Girardi. *"A Review on Vibration Monitoring Techniques for Predictive Maintenance of Rotating Machinery." Engineering Proceedings 4,* no. 3 (2023): 102. https://doi.org/10.3390/eng4030102

[6] Huang, F., H. Xiong, S. Chen, Z. Lv, J. Huang, Z. Chang, and F. Catani. *"Slope Stability Prediction Based on a Long Short-Term Memory Neural Network: Comparisons with Convolutional Neural Networks, Support Vector Machines and Random Forest Models." International Journal of Coal Science & Technology 10*, no. 1 (2023): 18. https://doi.org/10.1007/s40789-023-00523-9

[7] Ruggiero, A., A. Bracciale, G. Falcitelli, G. Nazzaro, and A. Valenti. "*Real Time Assessment of Novel Predictive Maintenance System Based on Artificial Intelligence for Rotating Machines." International Journal of Heat and Technology 40*, no. 6 (2022): 1269–1278. https://doi.org/10.18280/ijht.400604

[8]. Agyeman, S., M. S. Nweke, R. Adnan, and A. Mehmood. "*Predictive Maintenance of Rotational Machinery Using Deep Learning." International Journal of Electrical and Computer Engineering 14*, no. 1 (2024): 635–646. https://doi.org/10.11591/ijece.v14i1.pp635-646

[9] Szczepanik, R., D. Szydło, and P. Pietrusiak. "*Beamforming Applied to Ultrasound Analysis in Detection of Bearing Defects." Sensors 21*, no. 20 (2021): 6803. https://doi.org/10.3390/s21206803

[10] Sun, R., Z. Zhang, and Y. Qin. "*Multi-Sensor Data Fusion for Bearing Fault Diagnosis Using Vibration and Acoustic Emission Signals." Sensors 18,* no. 11 (2018): 3883. https://doi.org/10.3390/s18113883

[11] Khakifirooz, M., and A. Ghasemi. "Decision Support for Predictive Maintenance in the Process Industry: A Review." Processes 11, no. 3 (2023): 860. https://doi.org/10.3390/pr11030860

[12] Peng, H., H. Li, Y. Zhang, S. Wang, K. Gu, and M. Ren. *"Multi-Sensor Vibration Signal-Based Three-Stage Fault Prediction for Rotating Mechanical Equipment." Entropy 24*, no. 2 (2022): 164. https://doi.org/10.3390/e24020164

[13] Han, T., Q. Wang, B. Zhang, and Y. Li. "*A Novel Deep Learning Method for Intelligent Fault Diagnosis of Rotating Machinery Based on Improved CNN‑SVM and Multichannel Data Fusion." Sensors 19*, no. 7 (2019): 1693. https://doi.org/10.3390/s19071693

[14] Alvarado-Iniesta, A., F. P. García-López, and E. J. Palacios-García. "*Robust Vibration-Based Faults Diagnosis Machine Learning Model for Rotating Machines to Enhance Plant Reliability." Journal of Vibroengineering 23, no. 4* (2021): 828–842. https://doi.org/10.21595/jve.2021.22110

[15] Qin, Y., C. Li, and X. Wang. "*Multi-Sensor Data Fusion and Bidirectional-Temporal Attention Convolutional Network for Remaining Useful Life Prediction of Rolling Bearing." Measurement Science and Technology 34, no. 11* (2023): 115018. https://doi.org/10.1088/1361-6501/ace733

[16] Hu, M., and R. Chen. *"Time Alignment and Fusion of Heterogeneous Sensor Data for Fault Detection." IEEE Transactions on Industrial Informatics 17*, no. 5 (2021): 3014–3022. https://doi.org/10.1109/TII.2020.3038537

[17] Li, C., M. Grellet, F. Maréchal, and P. Ravier. "*An In-Depth Study of Vibration Sensors for Condition Monitoring." Sensors 24, no. 3* (2024): 740. https://doi.org/10.3390/s24030740

[18] Bagri, I., K. Tahiry, A. Hraiba, A. Touil, and A. Mousrij. *"Vibration Signal Analysis for Intelligent Rotating Machinery Diagnosis and Prognosis: A Comprehensive Systematic Literature Review." Vibration 7, no. 4* (2024): 1013–1062. https://doi.org/10.3390/vibration7040050

[19] Zhao, X., Y. Yang, Q. Huang, Q. Fu, R. Wang, and L. Wang. "*Rolling Bearing Remaining Useful Life Prediction Method Based on Vibration Signal and Mechanism Model." Applied Acoustics 228* (2025): 110334. https://doi.org/10.1016/j.apacoust.2023.110334

[20] Carvalho, T. P., F. A. A. Rocha, J. P. Oliveira, G. M. Lima, and J. P. Ribau. *"A Systematic Literature Review of Machine Learning Methods Applied to Predictive Maintenance." Computers & Industrial Engineering 137* (2019): 106024. https://doi.org/10.1016/j.cie.2019.106024

[21] Cambow, R., and M. Singh. *"Comparative Analysis of Grain Size for Bearing Coating Using Variational Mode Decomposition of Vibration Signal." Engineering Research Express 6*, no. 4 (2024): 045577. https://doi.org/10.1088/2631-8695/acf577

[22] Fan, C., P. Wang, H. Ma, Y. Zhang, Z. Ma, X. Yin, X. Zhang, and S. Zhao. *"Performance Degradation Assessment of Rolling Bearing Cage Failure Based on Enhanced CycleGAN." Expert Systems with Applications 255* (2024): 124697. https://doi.org/10.1016/j.eswa.2023.124697

[23] Wang, H., W. Zhang, D. Yang, and Y. Xiang. *"Deep-Learning-Enabled Predictive Maintenance in Industrial Internet of Things: Methods, Applications, and Challenges." IEEE Systems Journal 17*, no. 2 (2022): 2602–2615. https://doi.org/10.1109/JSYST.2022.3145678

[24] Zhang, Y., M. G. Pecht, and Z. Deng. "*A Novel Model-Based Unbalance Monitoring and Prognostics for Rotor-Bearing Systems." Advanced in Mechcniacl Engineering 14, no.1 Manufacturing Technology 126* (2022): 1-15–. https://doi.org/10.1177/16878132221148019

[25] Bousdekis, A., K. Lepenioti, D. Apostolou, and G. Mentzas. *"A Review of Data-Driven Decision-Making Methods for Industry 4.0 Maintenance Applications." Electronics 10,* no. 7 (2021): 828. https://doi.org/10.3390/electronics10070828