# Leveraging Artificial Intelligence of Things and Big Data Analytics for Enhanced Predictive Maintenance

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**Abstract:** This research aims at establishing the role of AIoT and Big Data Analytics in improving PdM techniques by providing failure prognosis and condition-based upkeep. The proposed framework utilizes IoT sensors installed on the industrial assets to always track vital parameters which are as follows; Temperature, Vibration, Pressure and Humidity which inversely reflect the status of equipment. The information gathered from these sensors is preprocessed and analyzed in real time by the means of Edge computing that helps in minimizing the latencies of the large amount of data collected and in turn makes the decision making possible at the edge of the network. Pulse signal data of equipment are used together with the Long Short-Term Memory (LSTM) networks for prediction of degradation, identification of abnormality, and determination of Remaining Useful Life (RUL) that enable prescriptive maintenance. The inclusion of Big Data Analytics in the evaluation of this framework also improves this aspect by providing a way of storing and processing large volumes of data and the review of patterns in the data to refine the model over time. Evaluation metrics such as accuracy, precision, recall together with Mean Absolute Error (MAE) summarize the ability of the proposed AIoT based PdM system to effectively prognosticate maintenance requirements effectively.

**Keywords -** Predictive Maintenance, Artificial Intelligence of Things, Big Data Analytics, Industrial IoT, Machine Learning, Edge Computing.

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2 (1) : 84 - 102 | Received: 01/10/2024 | Reviewed: 21/11/2024 | Accepted: 28/04/2025

# 1. INTRODUCTION

PdM has therefore emerged as a new tool of industrial asset management where the general idea is to move assets' availability to the highest level possible with less costs on maintenance and with less interruptions (Baroud et al., 2024; Yazdi, 2024). While, as mentioned in its two categories of maintenance, the reactive and the preventive maintenance, PdM deals with the analysis of data in order to forecast a machine's failures before they occur (Rezae and Toulikas, 2024). Therefore, there are notable disparities in PdM to the traditional planned maintenance strategies that results in greater worth of operation by coordinating and adapting with the actual condition of assets through minimal standby and maximal life expectancy (Yazdi, 2024). Big Data Analytics is a key enabler of taking benefit of complete value chain of Predictive Maintenance as it offer tools for Machine data acquisition along with data processing and analysis and decision making on the usage of data output from the PdM system for effective maintenance implementation forecast. The nature of data that are generated in industrial settings – in terms of size, speed and sources – makes it very difficult to garner useful information for probabilistic maintenance prediction (Yan et al., 2017; Diez-Olivan et al., 2019). Big data analytics finally emerged as an effective way of data processing and analysis that provides methods of machine learning and statistical modeling used to identify possible failure of the equipment (Diez-Olivan et al., 2019; Ning et al., 2021). Internet of Things, IoT was also used in making Big Data Analytics in predictive maintenance better whereby IoT devices feed live data from the various industrial assets that form the basis of an advanced analytics and timely, precise maintenance decision-making. IoT assists the monitoring of crucial performance characteristics such as the temperature, pressure, vibrations, power usage, and so on, in real-time and assist in fine-tuning for highest performance and estimating the time and frequency for maintenance (Rezai and Ansari, 2024). This integrated web makes it possible to monitor diligently the conditions of equipment and assets and decrease the rate of unscheduled outage and enhance safety (Bhanji et al., 2021). Internet of Things structures, normally edge/fog/cloud computing, allow large-scale IoT data processing and offer centralized remote control of distributed assets (Alli and Alam, 2020).

In the improvement of the IoT in industrial applications, AI algorithms were applied to the collected data by AIoT for real-time, autonomous decision-making concerning the maintenance of IoT devices and for making operation wise decisions to predict and maintain the IoT devices. In industrial context or more specifically, AIoT implies the combined sense and control of observation and decision of industrial processes without dependence on human command(Babu et al., 2024). Accompanied by the concepts of AIoT, Machine Learning, and Deep Learning, this move of optimizing the application of predictive maintenance is then further advanced as the AIoT systems utilize complex computations as well on the real-time data obtained from IoT devices to forecast the possibilities of failure and decide the nature of anomaly to enable better or improved approach to the problem solving of maintenance. Seed analysis, decision trees and support vector machines are widely applied for past and current data and are the right solution for early signs of equipment wear and tear identification (Shahin et al., 2023). Mathematical models of these kinds are most useful for condition monitoring, identification of anomalies and prediction of failure events (Rabatel et al., 2011). Of RNNs, LSTM networks are appropriate for capturing long term dependencies in the time-series data, thus suitable for estimating the RUL of equipment(Ma and Mao, 2020; Sheikh et al., 2024). The subsequent application of Machine Learning and Deep Learning techniques for predictive maintenance was complemented with Edge Computing capabilities that allow processing data at the edges where it is collected tremendously decreasing latency and enabling real-time analysis to support maintenance decisioning at a faster rate. Traditionally, the IoT data generated using sensors was sent to a centralized cloud where analysis was done, this creates problems such as latency and additional loads to the network particularly in areas with limited internet connection (Stolpe, 2016).

These disadvantages are avoided by edge computing since data is analyzed where it is collected giving real-time results that are essential to timely maintenance in the PdM systems (Yazdi, 2024). This localised processing was particularly advantageous for PdM applications due to its real-time anomaly identification, equipment health monitoring, and failure prognosis without relying on a cloudy system (Mourtzis and Angelopoulos, 2024). While Edge Computing makes a significant contribution to improving Digital Twin technology for predictive maintenance, it is necessary to highlight the key benefits that stem from data processing at the edge level, namely, the constant update and higher accuracy of the Digital Twins of assets and, as a consequence, more accurate and timely prediction of failures and target maintenance activities. Basically, a digital twin mimics the performance and state of an asset and leverages IoT device data with high-end simulation to capture the operational state and the rate of deterioration (Rasheed et al., 2020).

## 2. RESEARCH GAP

There seem to be lack of research on how to efficiently integrate IoT data flow with AI models for real-time effective PdM systems with concerns to data issues including quality, scalabilities as well as adequacy of AI for different settings within the industries for better predictive qualities and decision making. PdM in combination with AIoT is considered a major advancement to improve the effectiveness of maintenance plans in industrial settings (Awaisi et al., 2024). AIoT systems incorporate real time data gather through IoT sensors to processes real time data with the help of AI and create model that can analyse the condition of the asset and predict the probable failure before it happens. It enables active, data-driven decision-making, going beyond the conventional maintenance practice of simple time-based methods by capturing and analysing patterns, detecting abnormal conditions, and adjusting maintenance scheduling based on realistic performance of machines.

## 3. RESEARCH METHODOLOGY

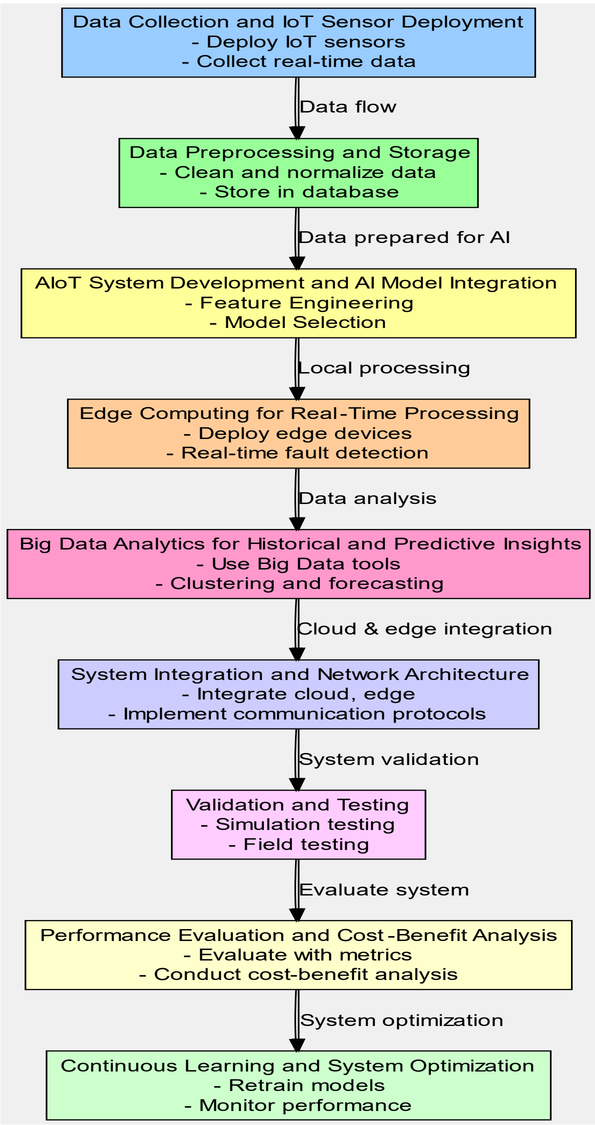


Figure 1. Leveraging AIOT and Big Data Analytics for Enhanced PdM

### 3.1 Data Collection and IoT Sensor Deployment

Speaking of the research into applying AIoT and Big Data Analytics for advancing PdM, the first stage involved the development of a strong data acquisition system with IoT sensors (Su et al., 2024). IoT sensors had been chosen in accordance with the working parameters and importance of the industrial assets explored (Kwon et al., 2016). These sensors where installed on equipment to read the basic parameters such as vibration, temperature, pressure, humidity, current, voltage and Acoustic signals which are very critical indicators of machine's health and its performance . These parameters were necessary to monitor the health state and output of the machinery, variations in which could signify existing problems (Wang et al., 2017). Sensors' choice and location were crucial because proper operation required capturing the survey of operation environments. Such approach ensured that the system could only gather pertinent data indicating the different conditions of the equipment and use it in predictive models. Every sensor was to be tuned in order to collect real-time data properly, allowing to diagnose equipment conditions and predict possible wear or malfunctioning.

#### 3.1.1 Temperature Sensors

Function: Temperature sensors monitor overheating or undercooling, critical for equipment health.
Steinhart-Hart Equation (for thermistors):

$$\frac{1}{T} = A + B\ ln(R) + C(ln(R))^3 \quad (1)$$

Where:

- $T$ was the temperature in Kelvin.
- $R$ was the resistance of the thermistor.
- $A$, $B$, and $C$ are constants specific to the thermistor.

Linear Approximation for RTDs:

$$R(T) = R_0\big(1 + \alpha \cdot (T - T_0)\big) \quad (2)$$

Where:

- $R(T)$ was the resistance at temperature $T$.
- $R_0$ was the resistance at reference temperature $T_0$.
- $\alpha$ was the temperature coefficient of resistance.

Applications: Variations in $R$ help detect abnormal temperature rises due to friction, misalignment, or load strain.

#### 3.1.2 Vibration Sensors

Function: Vibration sensors track oscillations in rotating or reciprocating machinery, indicating issues like misalignment, imbalance, or bearing wear.
Root Mean Square (RMS) Vibration Velocity:

$$V_{rms} = \sqrt{\frac{1}{T}\int_0^T v(t)^2 dt} \quad (3)$$

Where:

- $V_{rms}$ was the RMS velocity.
- v(t) was the instantaneous velocity.
- $T$ was the total period of measurement.

Fast Fourier Transform (FFT) (for frequency domain analysis): FFT helps isolate specific frequencies indicating certain mechanical issues (e.g., imbalance, misalignment).
Peak Vibration Velocity:

$$V_{peak} = max(|\ v(t)\ |) \quad (4)$$

Where:

- $V_{peak}$ helps in detecting sudden impacts or impulses that are signs of faults.

Applications: RMS and peak values are compared against normal operational limits; FFT helps identify the source of vibration issues.

### 3.1.3 Pressure Sensors

Function: Pressure sensors monitor fluid dynamics in systems like hydraulics or pneumatics, with deviations often indicating leaks, blockages, or valve failures.
Bernoulli's Equation (for fluid flow):

$$P + \frac{1}{2}\rho v^2 + \rho g h = constant \qquad (5)$$

Where:

- $P$ was the pressure.
- $\rho$ was the fluid density.
- $v$ was the fluid velocity.
- $g$ was the gravitational acceleration.
- $h$ was the height.

Ideal Gas Law (for pneumatic systems):

$$PV = nRT \qquad (6)$$

Where:

- $P$ was pressure, $V$ was volume.
- $n$ was the amount of gas in moles.
- $R$ was the ideal gas constant.
- $T$ was temperature in Kelvin.

Applications: Changes in pressure based on Bernoulli's principle or the Ideal Gas Law provide insights into equipment wear, leakage, or energy efficiency.

### 3.1.4 Humidity Sensors

Function: Humidity sensors detect moisture levels that can lead to corrosion or electrical faults.
Relative Humidity (RH):

$$RH = \frac{P_{water\ vapor}}{P_{saturation}} \times 100\% \qquad (7)$$

Where:

- $P_{water\ vapor}$ was the partial pressure of water vapor.
- $P_{saturation}$ was the saturation vapor pressure at a specific temperature.

Dew Point Calculation (approximate):

$$T_{dew} = T - \frac{(100 - RH)}{5} \qquad (8)$$

Where:

- $T_{dew}$ was the dew point temperature.
- $T$ was the ambient temperature.
- RH was relative humidity.

Applications: High relative humidity or dew points indicate moisture risks, guiding the use of dehumidifiers or seal inspections.

### 3.1.5 Acoustic Sensors

Function: Acoustic sensors analyze sound levels and patterns, often revealing early signs of mechanical deterioration.
Sound Pressure Level (SPL):

$$SPL\ (dB) = 20\ log_{10}\left(\frac{P}{P_0}\right) \quad (9)$$

Where:

- $P$ was the measured sound pressure.
- $P_0$ was the reference sound pressure (usually 20 $\mu$Pa in air).

Applications: SPL increases or changes in frequency indicate potential issues like part loosening or lack of lubrication.

### 3.1.6 Current Sensors

Function: Current sensors measure power usage in electric machinery, revealing efficiency levels and possible electrical faults.
Ohm's Law:

$$V = IR \quad (10)$$

Where:

- $V$ was voltage.
- $I$ was current.
- $R$ was resistance.

Power Calculation:

$$P = IV \quad (11)$$

Where:

- $P$ was power.
- Variations in $P$ and $I$ help in diagnosing motor overloads or wiring issues.

Applications: Monitoring current can identify electrical faults like short circuits or inefficiencies in motor operation, prompting maintenance.

## 3.2 Data Preprocessing and Storage

While promoting predictive maintenance under the umbrella of AIoT and Big Data Analytics, the preprocessing and storage of harvested data played a significant role in addressing data issues before feeding them for model development (Su et al., 2024). The preprocessing phase started with checking for; missing data, wrong data and noisy data. It was necessary in order to eliminate the causes which contribute to the increased inaccurate values interfering with the accuracy of the predictive maintenance models. Techniques including imputation, error correction and, outlier rejection were used to generate a more refined data set meaning only usable information went to the analytic phase. After data cleaning, normalization process were used in order to transform values to that are common between the different units and scales in which data was captured in. This step was instrumental in getting sensor data into a format directly understandable to AI models(Zhang and Zhang, 2022)

## 3.3 AIoT System Development and AI Model Integration

In the field of application of predictive maintenance that uses AIoT and Big Data Analytics, it was critical to create an AI system that analyzes the data from sensors to identify equipment failures and decide when it is appropriate to perform maintenance work. This phase followed feature engineering where the researchers identified prominent features and characteristics of the program through the sensor data that would help in improving the model(Preece et al., 2008). The next step in the creation of a powerful and efficient predictive maintenance system was to choose correct AI algorithms. Random Forest classification, Decision Tree and Support Vector Machines were used for classifying the operational patterns and for detecting potential fault conditions for which Random Forest was exceptionally effective in detecting anomalies as well as in recognizing patterns (Omol et al., 2024). To analyze time series data from the sensors LSTM networks and Convolutional Neural Networks (CNN) were utilized to identify trends and predict the equipment deterioration over efficient time span.

### 3.4 Edge Computing for Real-Time Processing

In the perspective of AIoT-driven predictive maintenance, the use of edge computing was planned to solve the problem associated with latency and real-time decision making (Matin et al., 2023). In this case, instead of transferring the data from the IoT sensors measuring the state of industrial equipment to an external cloud, the edge computing devices could be placed closer to the source and analyze the data there and then.

### 3.5 Big Data Analytics for Historical and Predictive Insights

In the case of AIoT based predictive maintenance, the usage of big data analytics allowed for examination of large historical data gathered with help of IoT sensors. With Big Data processing architectures such as Apache Hadoop and Spark, the enormous operational data including data regarding the status of the equipment, their usage cycle, and conditions under which they are used were synthesized effectively (Su et al., 2024). This data management approach enabled supporting a large number of assets and their information handling and analysis, effectively providing a framework for further analysis.

### 3.6 System Integration and Network Architecture

For enhancing PdM in industrial environments, an integrated network system architecture was developed to facilitate its data interfacing at the edge, fog as well as cloud computation systems. This worked was helpful in transporting obtained data from the IoT sensors to another place where it could be processed in real-time or later. With cloud, fog and edge computing the developed system built a tiered, scalable structure that could be optimised to meet the high data rate needed for real-time surveillance across all layers at an efficient cost. This architecture was very useful to provide a continuous connectivity, optimized routing of the data which was necessary for PdM to work at a large scale.

### 3.7 Validation and Testing

During the validation and testing phase, more focus was placed on the robustness and effectiveness of the AIoT-enabled PdM system in accomplishes its tasks based on the results from both the simulation analysis and real environment. Actual validation is seen to have been performed in a paper or simulated like manner meaning that the algorithms were exposed to a setting that was very close to the real world environment.

### 3.8 Performance Evaluation and Cost-Benefit Analysis

When testing the PdM system and its impact on the system performance, the success of the AIoT in predicting the failure of equipment was evaluated . The following evaluation parameters were chosen as the set of parameters that is sufficient to evaluate the predictive accuracy, accuracy, precision, recall, F1-score, and MAE. The metrics above provided a qualitative glance at how the system was fairing when it comes to recognizing maintaining requirements, suspicious patterns, and filter out invalid alerts. In this assessment, effectiveness of the system in presenting accurate estimate of the equipment failure was critically evaluated to ensure that the estimation was compared with the actual status on the ground in order to enable proper preventive measures to be implemented.

### 3.9 Continuous Learning and System Optimization

The goal of integrated learning and system improvement in the proposed AIoT-enabled PdM system was to maintain the ability of the system in terms of accuracy and adaptability throughout its development. When new data is collected in the operational environment, the accuracy of the system may be increased by having a feedback set. Such a loop helped the system to give updated data for its AI models in order to provide more accurate predictions derived from the new conditions and patterns. In this way, the PdM system remained sensitive to the known and unknown changes in equipment dynamics and conditions and remained relevant.

## 4. Result and Discussion

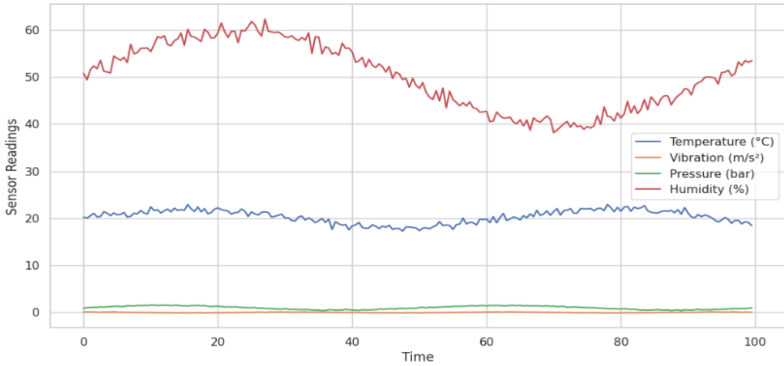


Figure 2. Sensor Data over Time

This time-series graph provides a continuous visualization of the sensor readings across critical operational parameters: vibration, pressure, humidity as well as temperature. All of these parameters act as health metrics of the equipment and whenever certain values deviate in these parameters they may point to an equipment failure.

For example, temperature, as marked by the red line, reveals multiple variations associated with operation heat creation during the use of machines. Such fluctuations and, especially, sustained increases are indicative of overheating, which, if unresolved, may degrade components thermally. Likewise with vibration data shown in the green line, while not indication as erratic as temperature, they provide information of structural health. Vibration characteristics are always in some way an indication of the balance, alignment and mechanical condition of the machinery. Larger fluctuations or nonperiodic oscillations are associated with bearings misaligned, under mechanical load or even production of destructive damages in essential components.

In predictive maintenance, he said that vibration analysis was vital as it helps the maintenance teams to observe any mechanical degradation, which if not addressed promptly, means that some equipment will stop working for a while. Other important parameters for failure prediction, significant in applications where the dynamics of the fluid or atmospheric conditions are essential for the functioning of the tested equipment, include pressure (blue line) and humidity (orange line). Many control and indication applications are associated with pressure in hydraulic or pneumatic systems, and changes in pressure readings indicate blockages, leakage or a malfunctioning compressor that results in huge system failures if not corrected soon. On the other hand, humidity was checked on areas that could experience corrosion or electrical fail all over time if they are wet, if they exceed designs level of wetting. These time-series data patterns are analyzed by the PdM system by the help of machine learning algorithms that are integrated in the models developed to the PdM system for identifying those patterns as anomalies to be responsible from indicates an emerging problem in the system. Big Data processing systems also help in creating trends of large data volumes over a period of time which will enable maintenance decision rather than being arbitrary thus reducing the ability of machinery and other industrial products to go for unscheduled periods of time off line causing them to be more efficient.

Table 1. Sensor Types and Monitored Parameters

| Sensor Type | Parameter Monitored | Role in PdM | Normal Range | Failure Indicators | Potential Corrective Actions |
|---|---|---|---|---|---|
| Temperature | Temperature | Overheating detection | 50-80°C | Sudden spikes | Increase cooling, check lubrication |
| Vibration | Vibration | Mechanical integrity | 0.1-5 mm/s | Irregular patterns | Realign components, inspect bearings |
| Pressure | Pressure | System stability | 100-300 psi | Drops or spikes | Check for leaks, adjust pressure valves |
| Humidity | Humidity | Environmental influence | 40-60% | High moisture levels | Inspect seals, use dehumidifiers |
| Acoustic | Sound frequency | Detects abnormal noise | 30-60 dB | Sharp sounds | Inspect moving parts, check lubrication |
| Current | Electrical current | Power load assessment | 5-10 A | High currents | Assess motor efficiency, inspect wiring |

Table 1 below gives a detailed description of some of the most basic yet crucial sensors used in PdM systems. I made my choice of each sensor type depending on their capability of giving out key operational parameters that reflect the conditions of industrial tools. For example, temperature sensors have a crucial function in overheating detection – they estimate thermal levels within the normal limits of 50-80°C. Such prescriptions as change of temperature or sudden rise in temperature can be due to some components wearing out, or due to some friction that may generate heat and this calls for some rectification measures such as cooling interferences or Lubrication checks respectively. Vibration sensors on the other hand only check the mechanical integrity. Since variation in vibration levels are above 0anian1 to 5 mm/s, irregularity show's some problem such as misalignment, bearing worn out or mechanical stress, such sensors help to identify structural problem in rotating or reciprocating equipment with ease. Pressure sensors are also used to control system reliability mainly in hydraulic or pneumatic systems, where they tend to indicate presence of leakages, obstructions or over pressure conditions.

Normal pressure should range from 100 to 300 pounds per square inch and anything outside this should be checked for leaks, or pressure valve settings need to be adjusted. Environmental and operational conditions comprise the additional sensors in the PdM framework. Relative and dew point moisture sensors are paramount in controlling environmental conditions, particularly where aggressive humidity levels detrimental to structures, electrical components, and materials are likely to be encountered. The normal humidity level fell between forty and sixty percent while high humidity required dehumidification or examination of seals. Abnormal noise frequencies and loudness settings of 30dB to 60dB suggest component wear, loose parts or inadequate lubrication are picked by acoustic sensors. These sensors are particularly effective in identifying problems in areas that would have otherwise required inspection including in enclosed or complicated mechanical systems. Last of all, current sensors measure electrical power loads with a typical level set to 5-10 A in order to identify different electrical problems, including motor overloads or ineffective power usage. High current readings are indications of abnormal wiring or motor efficiency that call for rewiring or load sharing. In total, these sensors create an all-encompassing system for predictive and prescriptive maintenance, which helps to detect faults before they occur, and perform maintenance only where required.

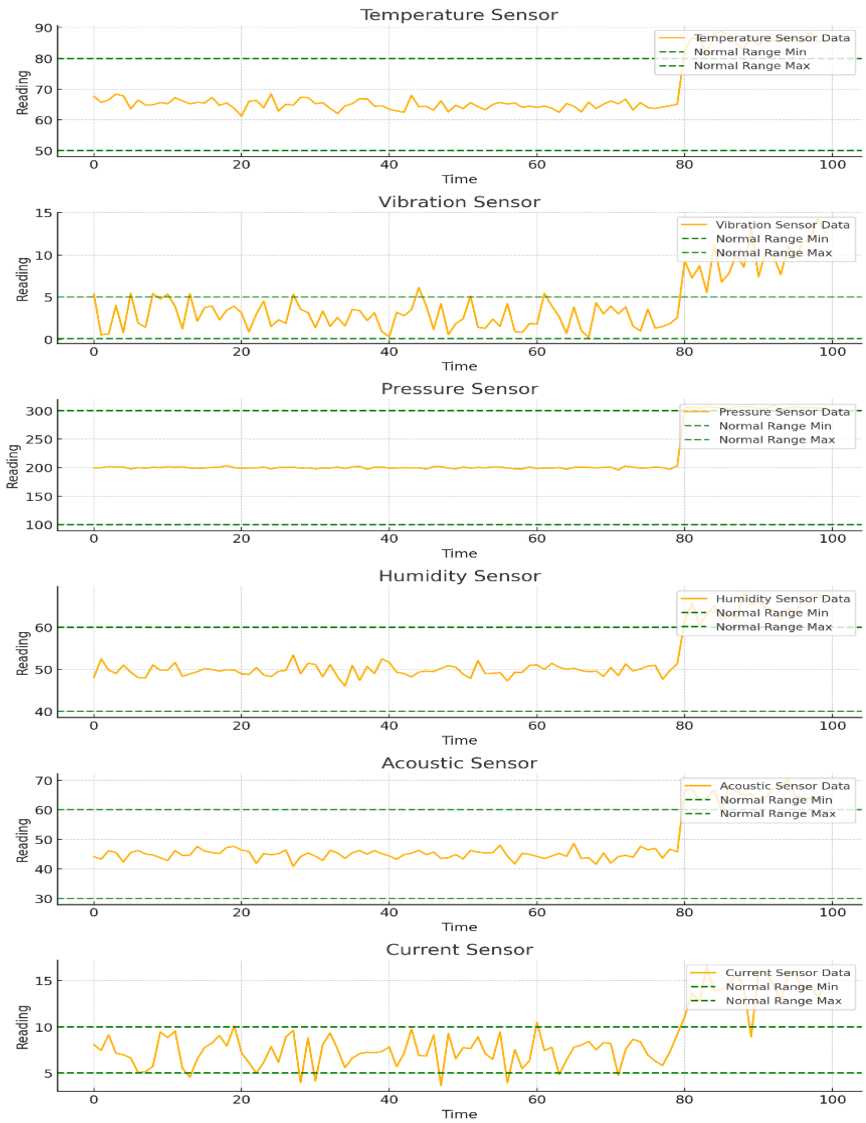


Figure 3. Sensors

## 4.1 Temperature Sensor:

Temperature sensors are basic in predictive maintenance systems because they highlight evidences of overheating, a common sign of possible equipment failure. These normally working at a temperature of between 50-80°C, continually measure thermal status in machines and equipment. Abnormal temperature changes particularly rise in temperature may be associated with excessive friction between mating parts, lack of lubrication or with electrical failure such as short circuits, overload etc. With reference to the temperature data, the maintenance teams can also be able to predict failures that can cause irreparable damages.

## 4.2 Vibration Sensor:

Vibration and shock meters are also essential for evaluating the state of the mechanical structures of equipment and specific components that rotate or reciprocating motion, such as motors, pumps, and turbines. Vibration data are often collected by these sensors; the normal range remains between 0.1 mm/s and 5mm/s. Indeed, frictional characteristics contain lots of diagnostic information relating to the status, position, orientation and health of the oscillating components; such features as periodicity, repetition or random signals are often a sign of underlying mechanical faults. It should be noted that any deviation from the normal vibration level may be an indication of one or the other of the following; misalignment of the component, imbalance in some or all of the critical section including bearings.

## 4.3 Pressure Sensor:

Both hydraulic and pneumatic applications which are subcategories of fluid mechanical applications may be kept at relatively consistent pressures by virtue of the pressure sensors that are preferably in the range of 100 – 300psi. In theory, these systems are unable to bear pressure changes since small fluctuations indicate significant disease conditions. Reduced pressure is a sign of leakage, blockage or failure in valves while high pressure suggests blocked filters or a bad compressor. For instance, in hydraulic systems, constant low pressure could indicate a steady and gradual seepage; if not attended to means a shutdown of hydraulic power and useful equipment that relies on the system.

## 4.4 Humidity Sensor:

Relative humidity sensors are particularly important in regions with high humidity levels that can be destructive to most devices. In some areas and within a certain tolerance of 40-60% these moisture sensors are used to ensure that the moisture content level does not exceed a certain safe level. Moisture whether in gas or in kerosene form is observed to harm the fabric of Stone as is, damages metal parts, affects the ability of an electrical part to insulate from other parts and makes more likely the occurrence of short circuit or other electrical faults. Applications could involve operating environments such as a chemical plant, electric power generation plant or electronic manufacturing plants for instance; such operating environments are sensitive to humidity and this leads to problems in with the machines and the materials used in the mentioned fields. Since relative humidity varies over time, mil –environments that may be are hazardous to the life of the equipment can be detected by the predictive maintenance systems.

## 4.5 Acoustic Sensor:

Abnormal sound in several types of machinery are detected by acoustic sensors which is a very useful diagnostics tool, as you cannot always see problem. With sound frequency and volume ranging from the commonly used 30-60 dB, these sensors detect possible changes in sound frequency and volume manifested by other problems such as loose components, low lubrication, or wear on the rotors. Sudden loud noises may indicate wear and tear of some components for instance a cracked gear or a bent shaft. Specifically, thermal acoustic sensors are extremely beneficial in large and intricate machinery systems where the physical check was not feasible in the first place, and adds an extra diagnostic layer alongside the conventional PdM strategies.

## 4.5 Current Sensor:

The present sensors calculate the electrical load on the machinery and the load is maintained within the range of 5-10A, excessive electrical current indicates the problems like motor overloading, combination of power consumptions and wiring defects which cause electrical faults if not corrected earlier. Current monitoring in electrically powered systems, was important because fluctuation prevents and caused equipment to malfunction or slows down the working rate. For instance, if a motor is drawing excessive current, it is definitely going to overheat or break down because some of the parts are worn out. High current usage also may give signals about the inefficiency which may result in higher operational cost.

As integrated, these sensors provide comprehensive monitoring of equipment condition and provide backup for predictive maintenance scheduling and attempts at preventing or postponing failure, minimizing equipment availability losses and extending the useful lives. Every sensor provided valuable information which made it possible to maintain what was needed to avoid interrupting the flow of the industrial business at a cheap and effective approach.

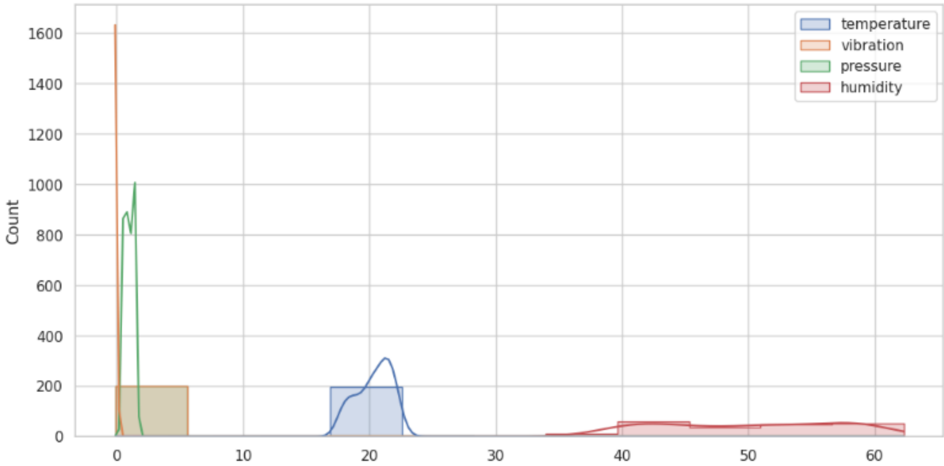


Figure 4. Distribution of Sensor Readings

This graph depicted how each of those sensors sampled data over the period, which formed the basis of initial benchmarking of operational ranges as well as identifying anomalies. Temp, Vib, Pressure and humidity all have different probability distributions that provide an understanding of what is typical behavior. Some variables, such as temperature, are rarely distributed at a distance from a certain interval, probably, the norm for the operation of the monitored equipment. Under and over this band can immediately signal to the system the risks of overheating which if not detected can lead to severe mechanical breakdowns. With periodicity maximal for units between 40 and 60, humidity implies an anticipated environmental condition for which exceeding rendered elevated risk of part corrosion or electrical troubles. PdM systems are also always able to establish dynamic threshold alerts for every sensor based on these operational baselines if operated in this way continually.

They also help to cascade information about the underlying system into those machine learning models which underpin predictive maintenance techniques. The strength of statistics and 'a priori' knowledge of what range each such parameter should be within, lets these models refine their predictions when any such sensor values fall outside of normal range. If an AIoT based PdM system has found data which is outside the statistical distribution especially multiple data situations that are outside a system it can then give preemptive maintenance advice. These insights also dictate relations between those parameters, like temperature and pressure – while the former increases, the later suggests overheating, and certain leaks. From Big Data Analytics, big data with distribution information improve evaluation and adjustment of the model so that the predictive maintenance system can reply more accurately to various stresses of equipment and operations.

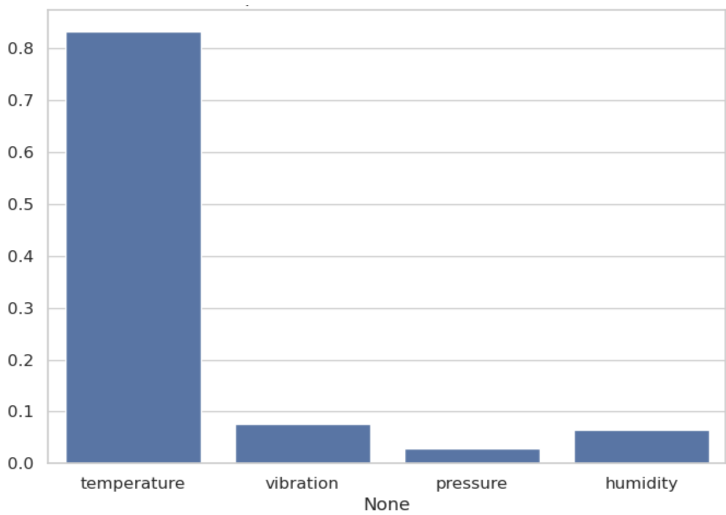


Figure 5. Feature Importance in Predictive Maintenance Model

This is what is known as feature importance graph: solution for showing how valuable each of the sensor parameters is to the PdM model; temperature being the most valuable with a feature weight of more than 80% of the total. This high value for temperature probably results from its direct association of the various essential operational parameters such as friction and component wear, which are usually indicative of initial degradation of industrial machines. High or low temperatures always point towards a mechanical problem, such as a lot of rubbing of contact points, or an electrical problem like fouled circuits. Vibration, pressure, and humidity are ranked as the next three factors that indicate their importance in the perform Galeu pricing regression analysis but their individually relatively low impact, yet can be significant in terms of context.

Table 2. Data Preprocessing Techniques in PdM

| Preprocessing Step | Technique | Purpose | Common Methods | Benefits | Challenges |
|---|---|---|---|---|---|
| Data Cleaning | Imputation | Address missing/incomplete data | Mean, median imputation | Improves data reliability | Potential loss of data accuracy |
| Error correction | Corrects sensor anomalies | Rule-based filtering | Enhances data quality | Labor-intensive for large data | |
| Normalization | Min-max scaling | Standardizes data to uniform scale | Min-max, z-score scaling | Facilitates model training | Distort extreme values |
| Data Transformation | Feature extraction | Derives valuable features from raw data | PCA, Fourier transform | Increases model effectiveness | Complex and time-consuming |
| Storage | Data lakes | Centralizes data for analysis | HDFS, AWS S3 | Scalability, real-time access | Security and privacy concerns |

The following table explains critical data preprocessing techniques used in PdM, as well as the steps and methods required in preparing raw sensor data for analysis.

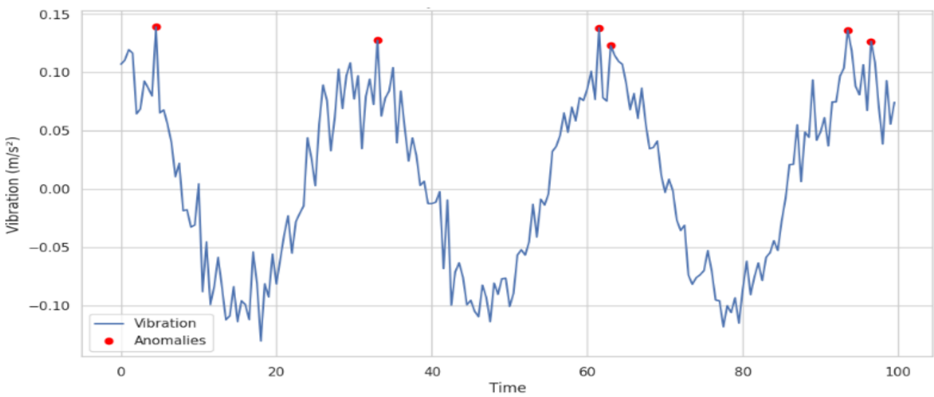


Figure 6. Anomaly Detection in Vibration Data

This graph illustrates an anomaly detection analysis of the vibration data which is significant in predictive maintenance since comparative vibration data acts as basic check of mechanical condition of the equipment. The red dots are used to pointed out that at this specific moment, vibration levels have gone outside the interval defined as normal by the predictive model. Periodicity in the data sets could be due to regular standard operational cycles or variation in the load patterns and hence is identifiable by the AI model as compared to the spikes. The highlighted anomalies, depicted by these spikes, could pointing at problems such as misalignment; an unbalance;

or bearing problems – these are all mechanical ailments that must be fixed to avoid mechanical breakdowns. Since vibration analysis can help identify potential problems before they become critical, such anomalies mean a chance to attend to equipment health problems before they become severe. Combining AIoT with Big Data Analysis means the real time analysis of vibration data and depiction of the irregular pattern to identify signs of equipment stress in real time. However, utilizing data-driven expertise, the PdM system safely filter between acceptable fluctuation and alarm-worthy anomalies and reduce false alarms and delays. The use of statistical, time-based, or machine learning approaches to identify anomalous signals for failure prediction enhances the approach by learning from cycles of past vibration data to enhance failure prediction and minimize false negatives. By passively collecting and processing data on the current vibration in real-time through edge computation, this approach not only provides a direction for identifying anomalies but also helps to request timely maintenance, that means providing evidence of mechanical stress for specific equipment.

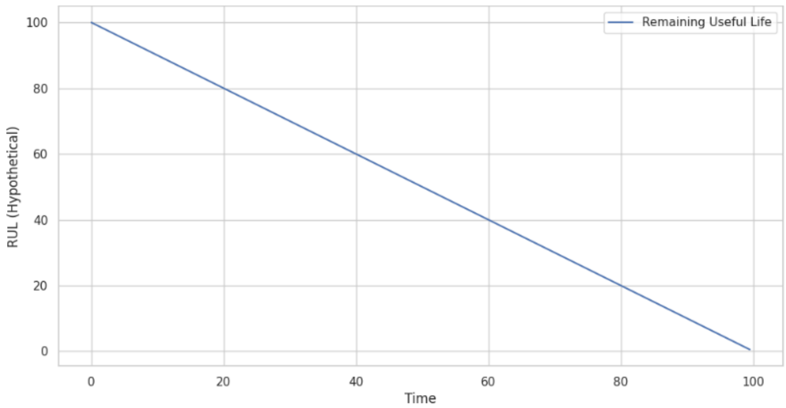


Figure 7. Predicted RUL over Time

On this graph, equipment's predicted RUL is shown, which, if decreases continually, implies that the equipment is degrading linearly. The RUL was valuable for planning future maintenance to prevent failures in PdM, since it will give a prognosis about how much time a certain component would be able to last before it needs repair or replacement. And in the case of AIoT integration, IoT sensor data is updated in real-time to constantly update the RUL model to reflect the most current trends based on operational data feed. In this way, the PdM system transforms from reactive to proactive maintenance model where the actions are scheduled in advance on the basis of proactively analyzed data. This approach improves the life span of assets, because maintenance was planned at the right time that eliminated extra expenses and breakdowns due to wear out. Based on historical and real time data, RUL model uses the machine learning algorithms that help in detecting temperature, vibration, stress indicating features etc to improve the predictive analysis. Data is generated in the AIoT system and Big Data platforms store and analyze data for the steady improvement of the RUL computations. This gave a feedback loop subsequently, as the RUL model was fed with more operational conditions and degradation characteristics, ensuring enhanced precision in the RUL prediction. This capability was very useful especially in industries where equipment is prone to stop in operation and am beneficiary expense when it does. With help of the interval estimation of RUL it is possible to solve the problem of optimal frequency of equipment maintenance minimizing the general amount of expenses and maximizing the time of continued, uninterrupted service.

Table 3. Performance Evaluation Metrics

| Metric | Description | Formula | Importance in PdM | Implications |
| --- | --- | --- | --- | --- |
| Accuracy | Correct predictions over all cases | (TP + TN) / (TP + TN + FP + FN) | Overall model effectiveness | High values indicate reliability |
| Precision | True positives over predicted positives | TP / (TP + FP) | Reduces false maintenance alerts | High precision avoids over-maintenance |

| | | | | |
|---|---|---|---|---|
| Recall | True positives over actual positives | TP / (TP + FN) | Reduces missed failure detections | High recall avoids undetected faults |
| F1-Score | Balance between precision and recall | 2 * (Precision * Recall) / (Precision + Recall) | Consistency of model predictions | Balanced metric for reliability |
| MAE | Average of absolute errors | Σ | actual - predicted | / n |

In PdM, quantitative index was employed to assess and analyze the reliability associated with the models that predict preliminary failure of equipment. The Accuracy, which is derived as the number of true positive plus true negative divided by the total positive and negative gives an overall measure of the performance of the model. Based on the evaluations, high accuracy entails that there are few misclassifications between failure and non-failure cases and, therefore, a significant metric that must be considered in PdM systems. However, accuracy alone may be inadequate in a scenario where there are data classes that are skewed for example where failures are few but crucial. Thus, Precision was also important, as it determines the percentage of the actual failures among all predicted failures, demonstrating the model's performances in avoiding unnecessary alarms. PdM work required high precision to reduce the chances of creating extra work that would only lead to higher costs and plant downtime. On the other hand, recall targets at determining the number of actual failures that the model correctly pins down and it was crucial in making sure that at least one serious failure was not overlooked.

A high recall value ensure that all potential failure was detected hence avoiding expensive and sudden downtimes, which was important in industrial applications to avoid complications in the event a failure is unnoticed. The F1-Score is an intermediary of precision and recall, and has all characteristics of both in detail, and, additionally, to facilitate in assessing the model's performance it reduces the false positive and false negative values. Lastly, the individual probabilities are summed up, and to come up with a single measure of performance the Mean Absolute Error of Failure (MAE) formula which is the average of the absolute difference between the estimated and actual failure times is used. Another metric that can be calculated directly is mean absolute error (MAE), which was most helpful when comparing the model's accuracy in determining the RUL of equipment is, with lower values of MAE reported a higher precision of the predictions. Combined, these metrics provide a clear picture of a model's ability to predict and prescribe improvements in PdM practices for optimal system functionality.

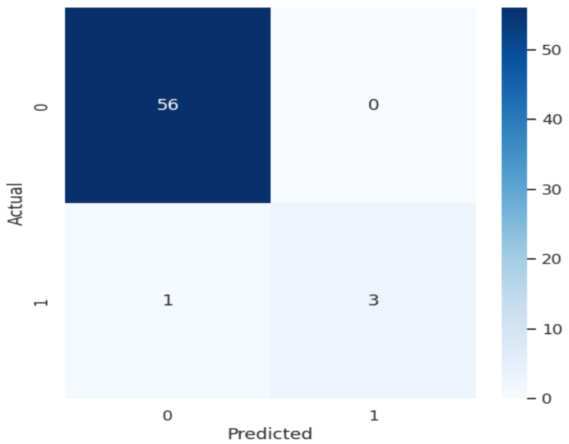


Figure 8. Confusion Matrix for Predictive Maintenance Model

The confusion matrix graph assesses the effectiveness of the PdM model in making accurate predictions of maintenance requirements in comparison with the actual results; the graph also shows information about the prediction and types of errors made. In this matrix, class 0 has no meaning of maintenance and class 1 has a meaning of maintenance is required. The actuality revealed that a model has the high accuracy 56 times correctly identified the instances where maintenance not required, and three times identified that maintenance is necessary. Still, it illustrates one false-negative case where the model erroneously did not indicate any maintenance is needed, and it is dangerous in terms of equipment health because unnoticed problems can result from it. Lack of false negatives also means that the model was not causing unnecessary maintenance interjections, which in the long run amounted to cost and resource saving. For AIoT powered PdM, the objective for optimization was to increase the true positive (correct predictive maintenance) while ensuring that false negatives (failure to predict failure) were kept to a minimum. The Big Data Analytics to support the PdM model enhance the model with such data, and help the model better perceive early signs of deterioration or wear, and therefore, improve the reliability of the model in various future predictions. As for the current issue of high error rates, the simplicity of the algorithm used in the PdM system can be optimized more to reduce such rates to the barest level; the PdM system can employ ensemble learning techniques or even more advanced algorithms such as deep learning. Actual maintenance data generated in the course of operations provides the system with a basis for tweaking its sensitivity and settings to the circumstances. This feedback loop aids the establishment of a strong framework for an efficient predictive maintenance plan that corresponds with technical and financial goals on refining PdM.

Table 4. AI Algorithms for Predictive Maintenance

| **Algorithm** | **Function** | **Typical Applications** | **Strengths** | **Limitations** | **Recommended Usage Scenarios** |
|---|---|---|---|---|---|
| Decision Trees | Classification | Fault detection | Easy to interpret | Prone to overfitting | Simple tasks, small datasets |
| Random Forest | Anomaly detection | Multi-class classification | Handles high dimensionality | Computationally intensive | High-dimensional data analysis |
| LSTM | Time-series prediction | Remaining useful life | Captures long-term dependencies | Requires large datasets | Complex, long-term predictive models |
| CNN | Image data analysis | Visual inspection | Excellent for spatial data | High processing needs | Image-based fault detection |
| SVM | Classification | Fault vs. non-fault data | Works well on small data | Not suitable for large datasets | Limited fault classification tasks |

Table 4 above highlights various AI algorithms used in PdM together with their applicability, advantage, disadvantage, and recommended areas of utilization. Decision Trees are one of the widely used classifiers when it comes to classification issues in PdM systems where fault detection is an objective. Easy to interpret and highly useful where there is a need to explain the thought process behind someone's decisions. Nevertheless, it is sensitive to the data overfitting especially when used when handling small data sets or complex models.

This is why Decision Trees worked best in simple tasks with small datasets where high interpretability was a concern. Random forest, an extension of multiple individual decision trees to reduce the problem of overfitting of individual decision trees, was better suitable for this task of anomaly detection and multiclass classification. It is outstanding in tackling high-dimensional data and can enhance the stability of the model; however, it is computationally large; it takes a lot of computing time when working on big data. This makes it efficient for use in high dimension PdM but is not very effective for real time use in environments where there is limited processing power. Specifically, LSTM networks are visualized as a form of RNN that is suitable to solve time series prediction problems like the estimation of the RUL of equipment.

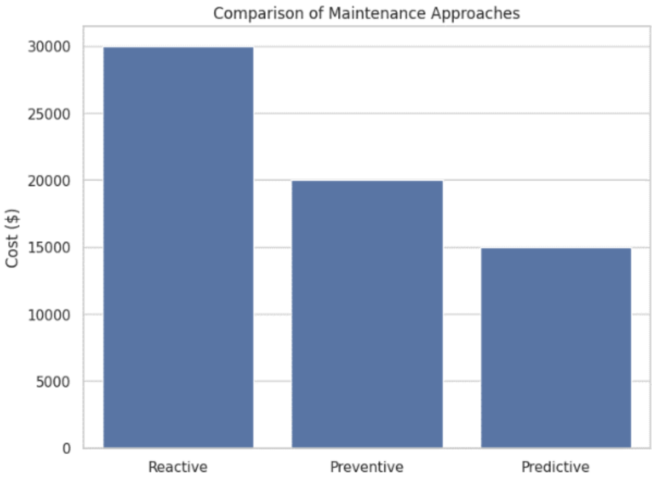


Figure 9: Cost Comparison for Various Maintenance Strategies

Figure 9, compares the costs associated with three different maintenance strategies: There are three types of maintenance: Reactive, Preventive and Predictive. This cost was expressed on the cost-effective bar chart as nearly $30000 and was the highest because equipment was only maintained once it had developed a fault. This high cost was sign post to the fact that the cost of the machine breakdown or the likelihood of breakdowns, and the likely hood of losses in production was high. Re-active maintenance is usually the costliest one since it becomes costly once specific failures have happened and so much more could have been avoided. In addition, the reactive strategy is installed for enhancing the machine useful years as it does not repair the faults before they manifest hence affecting other part of the equipment severely. This was usually used by organizations that lacked adequate maintenance capacity or situations where breakdown of equipment as not a big deal. Nevertheless, as is shown below the graph, it was the most costly strategy in the long run anyway. The preventive maintenance is another upkeep measure that is relatively less costly to the former and is performed in a time-based, or the usage-based schedule. It was still a kind of high amount as compared to the amount that was being incurred at the time of predictive maintenance which was slightly above $ 20000. Planned maintenance contributed a little to the prevention of failure and breakdown because machines used in production were taken for service often.

However, it still led to a lot of unnecessary maintenance activities main as equipment were serviced before it was time for service to be conducted. This inefficiency was broken in predictive maintenance where rather than waiting to receive a signal to do maintenance, data and AI were used to do the math and figure out when maintenance is needed based on the condition. The most cost effective of all the strategies used in this analysis was the predictive maintenance with overall cost of being less than $ 20000. Predictive maintenance occurs where potential problems which cannot self-correct themselves are identified, while employing this caught problem can occur at the wrong time making it possible to set the right time and schedule the maintenance to be done without having to perform maintenance on a machine that does not need it. This strategy incorporates the use of new tech such as artificial intelligence and IoT to replace the current traditional approach to maintenance for equipment-centered organizations with a data-based approach that enhances the reliability of equipment as well as drastically reducing the expense of maintenance.

## 5. CONCLUSION

From this research, industries gain a clear understanding of how AIoT and Big Data Analytics that can support PdM have the potential to improve industries. Thanks to IoT sensors the information can be obtained using devices built-in to the equipment and edge computing to process the data in real time; the time decision-making process takes is very short and the maintenance teams can act using actual state of the equipment rather than putting in action at specified intervals. Specifically, LSTM networks can be used for recognition of patterns and abnormality from the sensor data; precise prognosis of equipment failure and identification of the optimal time for maintenance. The findings of this study reveal that the improved PdM offered with the help of AIoT does not only prevent not only the unknown and random stoppages but also prolongs the life expectancy of industrial assets and reduce maintenance cost. Further, the cost benefit presents the economic advantage of using a predictive, maintenance analytical approach to show that the costs are significantly lower than the reactive and preventive approaches to maintenance. Therefore, based on this study, the continuation of evolving the AIoT and Big Data has been emphasized towards improved development of the PdM. It therefore requires future work to be directed towards solving several problems of AI including the quality, growth and applicability of AI models in various industries. This is more so the case since as industries proceed to execute their digitisation strategies, AIoT-driven PdM help in a result of achieving sustainable, sustainable industrial operations.

## Reference


Alli, A. A., & Alam, M. M. (2020) The fog cloud of things: A survey on concepts, architecture, standards, tools, and applications. *Internet of Things*, *9*, 100177.

Awaisi, K. S., Ye, Q., & Sampalli, S. (2024) A Survey of Industrial AIoT: Opportunities, Challenges, and Directions. *IEEE Access*.

Babu, C. S., Saltonya, M. S., Ganapathi, S., & Gunasekar, A. (2024) AIoT Revolution: Transforming Networking Productivity for the Digital Age. In *Artificial Intelligence of Things (AIoT) for Productivity and Organizational Transition* (pp. 108-143). IGI Global.

Baroud, S. Y., Yahaya, N. A., & Elzamly, A. M. (2024) Cutting-Edge AI Approaches with MAS for PdM in Industry 4.0: Challenges and Future Directions. *Journal of Applied Data Sciences*, *5*(2), 455-473.

Bhanji, S., Shotz, H., Tadanki, S., Miloudi, Y., & Warren, P. (2021). Advanced enterprise asset management systems: Improve predictive maintenance and asset performance by leveraging Industry 4.0 and the Internet of Things (IoT). In *ASME/IEEE Joint Rail Conference* (Vol. 84775, p. V001T12A002). American Society of Mechanical Engineers.

Diez-Olivan, A., Del Ser, J., Galar, D., & Sierra, B. (2019) Data fusion and machine learning for industrial prognosis: Trends and perspectives towards Industry 4.0. *Information Fusion*, *50*, 92-111.

Kwon, D., Hodkiewicz, M. R., Fan, J., Shibutani, T., & Pecht, M. G. (2016) IoT-based prognostics and systems health management for industrial applications. *IEEE access*, *4*, 3659-3670.

Ma, M., & Mao, Z. (2020) Deep-convolution-based LSTM network for remaining useful life prediction. *IEEE Transactions on Industrial Informatics*, *17*(3), 1658-1667.

Matin, A., Islam, M. R., Wang, X., Huo, H., & Xu, G. (2023) AIoT for sustainable manufacturing: Overview, challenges, and opportunities. *Internet of Things*, 100901.

Mourtzis, D., & Angelopoulos, J. (2024) Artificial intelligence for human–cyber-physical production systems. In *Manufacturing from Industry 4.0 to Industry 5.0* (pp. 343-378). Elsevier.

Ning, S., Sun, J., Liu, C., & Yi, Y. (2021) Applications of deep learning in big data analytics for aircraft complex system anomaly detection. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, *235*(5), 923-940.

Omol, E., Mburu, L., & Onyango, D. (2024) Anomaly detection in IoT sensor data using machine learning techniques for predictive maintenance in smart grids. *International Journal of Science, Technology & Management*, *5*(1), 201-210.

Preece, S. J., Goulermas, J. Y., Kenney, L. P., & Howard, D. (2008) A comparison of feature extraction methods for the classification of dynamic activities from accelerometer data. *IEEE Transactions on Biomedical Engineering*, *56*(3), 871-879.

Rabatel, J., Bringay, S., & Poncelet, P. (2011) Anomaly detection in monitoring sensor data for preventive maintenance. *Expert Systems with Applications*, *38*(6), 7003-7015.

Rasheed, A., San, O., & Kvamsdal, T. (2020) Digital twin: Values, challenges and enablers from a modeling perspective. *IEEE access*, *8*, 21980-22012.

Rezae, R., & Toulikas, K. (2024) Predictive maintenance through data-driven decision making. Master's thesis in Production Engineering, Chalmers University of Technology.

Rezaei, S., & Ansary, A. (Eds.). (2024) *Artificial Intelligence of Things (AIoT) for Productivity and Organizational Transition*. IGI Global.

Shahin, M., Chen, F. F., Hosseinzadeh, A., & Zand, N. (2023) Using machine learning and deep learning algorithms for downtime minimization in manufacturing systems: An early failure detection diagnostic service. *The International Journal of Advanced Manufacturing Technology*, *128*(9-10), 3857-3883.

Sheikh, R., Gupta, V. K., Yadav, T., Gautham Kiran, M., & Noor, T. (2024) Temporal Dependency Analysis in Predicting RUL of Aircraft Structures Using Recurrent Neural Networks. In *Fracture Behavior of Nanocomposites and Reinforced Laminate Structures* (pp. 329-361). Cham: Springer Nature Switzerland.

Stolpe, M. (2016) The internet of things: Opportunities and challenges for distributed data analysis. *Acm Sigkdd Explorations Newsletter*, *18*(1), 15-34.

Su, N., Huang, S., & Su, C. (2024) Elevating Smart Manufacturing with a Unified Predictive Maintenance Platform: The Synergy between Data Warehousing, Apache Spark, and Machine Learning. *Sensors*, *24*(13), 4237.

Wang, D., Tsui, K. L., & Miao, Q. (2017) Prognostics and health management: A review of vibration based bearing and gear health indicators. *Ieee Access*, *6*, 665-676.

Yan, J., Meng, Y., Lu, L., & Li, L. (2017) Industrial big data in an industry 4.0 environment: Challenges, schemes, and applications for predictive maintenance. *Ieee Access*, *5*, 23484-23491.

Yazdi, M. (2024) Integration of IoT and Edge Computing in Industrial Systems. In *Advances in Computational Mathematics for Industrial System Reliability and Maintainability* (pp. 121-137). Cham: Springer Nature Switzerland.

Yazdi, M. (2024) Maintenance strategies and optimization techniques. In *Advances in Computational Mathematics for Industrial System Reliability and Maintainability* (pp. 43-58). Cham: Springer Nature Switzerland.

Zhang, L., & Zhang, L. (2022) Artificial intelligence for remote sensing data analysis: A review of challenges and opportunities. *IEEE Geoscience and Remote Sensing Magazine*, *10*(2), 270-294.