Design and Development of Machine Learning Based Predictive Maintenance Strategies for DC Motor

Sumit Vishwakarma[1], Prof.(Dr) Dipesh Makwana[2]

[1]Sumit Vishwakarma, Department of Applied instrumentation, LD College of engineering, Ahmedabad
[2] Prof. (Dr) Dipesh Makwana , Department of Applied instrumentation ,LD College of engineering, Ahmedabad

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Abstract - *In the modern industrial landscape, Direct Current (DC) motors are critical components used in a wide array of applications, from manufacturing processes to automotive systems. However, frequent downtime due to unexpected failures or inadequate maintenance can lead to operational inefficiencies, financial losses, and safety risks. Predictive maintenance, driven by machine learning (ML) techniques, provides a proactive approach to mitigate these challenges by anticipating potential motor failures before they occur. This dissertation focuses on the design and development of machine learning-based predictive maintenance strategies tailored specifically for DC motors*

Key Words: **Predictive maintenance, DC Motor, Fault Detection, Machine Learning , Orange Software, Hybrid Model**

1.INTRODUCTION

Maintenance involves a involves a regular approach aimed at reducing outfit failures, enhancing machine uptime, and maintaining harmonious trustability. A well- structured conservation strategy is essential for associations to minimize time-out, control conservation charges, and boost overall productivity. By using listed examinations, preventative conduct, and prophetic analytics, companies can minimize dislocations, insure smooth operations, and promote long- term outfit health.

Maintenance refers to the combination of technical, administrative, and managerial activities carried out to ensure that equipment, machinery, or systems remain in working condition or are restored to functional status. The primary objective of maintenance is to improve equipment reliability, extend asset life, and reduce unexpected breakdowns, thereby ensuring smooth and uninterrupted operations. In industrial environments, maintenance plays a vital role in productivity, safety, and cost control.

- There are three main types of maintenance in industries. They are as follows:

- Reactive Maintenance
- Preventive Maintenance
- Predictive Maintenance

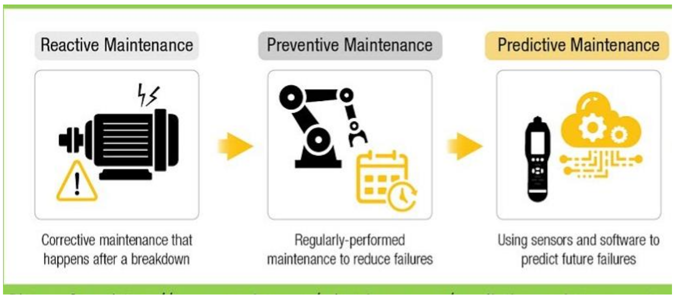


Figure 1 Types of Maintenance

1.1 Common Issues and Maintenance Challenges in DC Motors

Overheating is often caused by excessive load or inadequate ventilation, which can result in internal damage and a shortened lifespan.
Electrical Faults

Brush Sparking: Caused by worn-out brushes or contamination. Voltage Instability: Arises from a faulty power supply.
Short Circuits: Caused by overheating or damaged insulation.

Mechanical Faults
Worn Bearings: Can lead to excessive noise and vibration. Imbalanced Rotors: Cause irregular motion and reduced efficiency. Low Torque: Can occur due to brush wear or motor overload.

Brush and Commutator Issues
Brushes degrade over time and require regular replacement. Misaligned brushes can damage the commutator, reducing its effectiveness

1.2 Maintenance Challenges

Improper repairs can cause safety issues and lead to repeated failures.In industrial settings, DC motors are commonly used because of their straightforward design and ease of control. However, unexpected breakdowns in these motors can cause significant production delays, unplanned downtime, and increased maintenance expenses. Conventional maintenance methods—like reactive or preventive maintenance—often fall short, as they don't consider the real-time condition of the equipment, leading to inefficiencies or higher costs.

Although condition-based monitoring techniques have seen progress, many small and medium- sized industries still struggle to adopt machine learning-based predictive maintenance systems. The main reasons include the high cost of implementation, technical complexity, and the need for advanced coding skills.

Moreover, there is a noticeable gap in the availability of real-time fault detection systems that use low-code or no-code platforms. Such platforms would allow engineers with minimal programming experience to set up and manage these systems effectively.

To address this gap, there is a strong need for a predictive maintenance solution that is affordable, user-friendly, and tailored for DC motor applications. Using intuitive tools like Orange, it becomes possible to carry out fault detection, classification, and early warning generation—without relying on heavy programming or complex infrastructure.

2. Predictive Maintenance System Architecture

2.1 What is PDM ?

Predictive maintenance (PdM) uses data analysis to identify operational anomalies and potential equipment defects, enabling timely repairs before failures occur. It aims to minimize maintenance frequency, avoiding unplanned outages and unnecessary preventive maintenance (opens in new tab) costs.

Predictive maintenance involves monitoring equipment conditions, analyzing data, and predicting potential failures to optimize maintenance schedules and minimize downtime.

2.1 Why is predictive maintenance so important today?

Predictive maintenance is important because it important because it saves companies time and plutocrat by heading off expensive and disruptive outfit failure. As consumer demand for product vacuity grows, associations with prophetic conservation programs can produce without dislocations. The result is ongoing client fidelity, advanced earnings, and bettered competitive advantage.

Smart predictive results prognosticate when asset conservation is demanded, help increase cost effectiveness, and streamline complex enterprise asset operation conditions. Put simply,employing prophetic conservation technology helps your business save time, plutocrat, and procedural headaches.

2.3 How Does PDM Works?

1. Data Acquisition

PdM begins with the continuous or periodic collection of real-time operational data from outfit. This is achieved through colorful detectors and monitoring bias installed on critical machine factors. Common parameters covered include

- Temperature
- Voltage and current
- Pressure
- Speed or RPM
- Acoustic emissions
- Oil quality or particulate count (in mechanical systems)

These detectors communicate with original regulators, data lumberjacks, or edge bias, which prisoner and further the data for processing..

2 Data Preprocessing and Feature Extraction

Before analysis, raw sensor data is cleaned and preprocessed to remove noise, inconsistencies, or missing values. Important features are then extracted from the data which help in identifying the machine's behavior.

Feature extraction may involve:

- Aggregating statistics (mean, variance)
- Identifying peaks or outliers
- Time-series trend analysis

3 Data Storage and Preprocessing

- Storage: Raw data is stored in databases or cloud systems to handle large volumes (Righetto et al. highlight Big Data and Cloud Computing in PdM 4.0).
- Cleaning: Data is filtered to remove noise, inconsistencies, or missing values, ensuring quality for analysis (Compare et al. note significance of data applicability).
- Integration: Combines historical data (past failures, repairs) with real-time data to provide context (Trodd's system imported contracted data into an in-house database)..

Step 4: Data Analysis

Machine Learning: Algorithms (e.g., ANN, RUSBoost, XGB) learn patterns from data to predict failure timing (e.g., Righetto et al.'s transformer failure prediction).

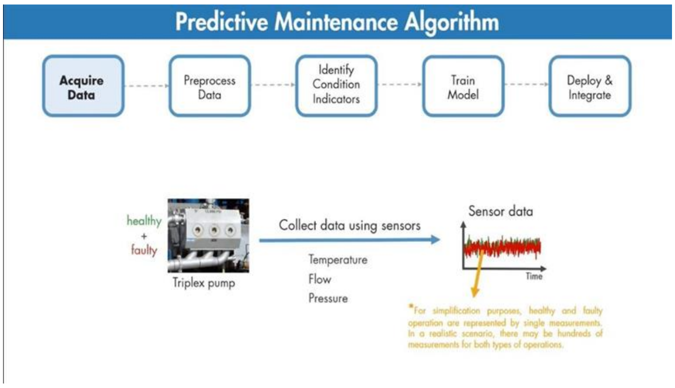


Figure 2 STEPS OF PDM

Common predictive models include:

Decision Trees / Random Forest

- Support Vector Machines (SVM)
- Neural Networks / Deep Learning
- Regression models
- Time-series forecasting models (e.g., ARIMA, LSTM)

These models can estimate:

- Remaining Useful Life (RUL)
- Probability of failure within a given timeframe
- Root causes of potential faults Prediction and

Decision-Making

- Failure Prediction: Estimates remaining useful life (RUL) or time-to-failure (e.g., Righetto et al.'s wind turbine predictions up to 2 months ahead).

Prescription: Suggests maintenance timing and scope (e.g., Trodd scheduled a pump replacement during a planned shutdown).

Visualization: Dashboards or reports display predictions and recommendations (Righetto et al. emphasize intuitive interfaces).

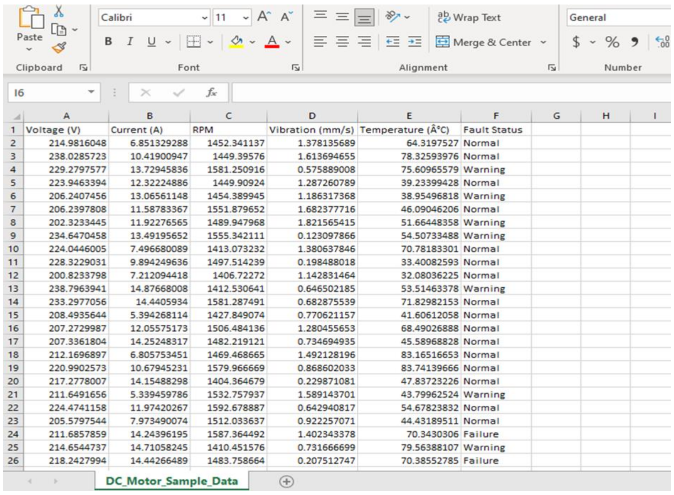
Planning Work orders are listed grounded on prognostications, optimizing resource use(Trodd's system integrated force control).

• Action Technicians form or replace factors before failure(e.g., Trodd's bearing relief averted pump time-out).

3. IMPLEMENTATION

3.1 DATA COLLECTION

Sensor data was simulated based on real-world conditions and expected sensor behavior. The simulation focused on four key parameters — current, voltage, vibration, and temperature



	Voltage (V)	Current (A)	RPM	Vibration (mm/s)	Temperature (Â°C)	Fault Status
2	214.9816048	6.851329288	1452.341137	1.378135689	64.3197527	Normal
3	238.0285723	10.41900947	1449.39576	1.613694655	78.32593976	Normal
4	229.2797577	13.72945836	1581.250916	0.575889008	75.60965579	Warning
5	223.9463394	12.32224886	1449.90924	1.287260789	39.23399428	Normal
6	206.2407456	13.06561148	1454.389945	1.186317368	38.95496818	Warning
7	206.2397808	11.58783367	1551.879652	1.682377716	46.09046206	Normal
8	202.3233445	11.92276565	1489.947968	1.821565415	51.66448358	Warning
9	234.6470458	13.49195652	1555.342111	0.123097866	54.50733488	Warning
10	224.0446005	7.496680089	1413.073232	1.380637846	70.78183301	Normal
11	228.3229031	9.894249636	1497.514239	0.198488018	33.40082593	Normal
12	200.8233798	7.212094418	1406.72272	1.142831464	32.08036225	Normal
13	238.7963941	14.87668008	1412.530641	0.646502185	53.51463378	Warning
14	233.2977056	14.4405934	1581.287491	0.682875539	71.82982153	Normal
15	208.4935644	5.394268114	1427.849074	0.770621157	41.60612058	Normal
16	207.2729987	12.05575173	1506.484136	1.280455653	68.49026888	Normal
17	207.3361804	14.25248317	1482.219121	0.734694935	45.58968828	Normal
18	212.1696897	6.805753451	1469.468665	1.492128196	83.16516653	Normal
19	220.9902573	10.67945231	1579.966669	0.868602033	83.74139666	Normal
20	217.2778007	14.15488298	1404.364679	0.229871081	47.83723226	Normal
21	211.6491656	5.339459786	1532.757937	1.589143701	43.79962524	Warning
22	224.4741158	11.97420267	1592.678887	0.642940817	54.67823832	Normal
23	205.5797544	7.973490074	1512.033637	0.922257071	44.43189511	Normal
24	211.6857859	14.24396195	1587.364492	1.402343378	70.3430306	Failure
25	214.6544737	14.71058245	1410.451576	0.731666699	79.56388107	Warning
26	218.2427994	14.44266489	1483.758664	0.207512747	70.38552785	Failure

DC_Motor_Sample_Data

Figure 3 DATA COLLECTION

to represent the motor's operational health

The dataset was manually created in CSV format, using Excel or similar spreadsheet tools. Each row represented a single reading, and columns included time, speed, sensor values, and a labelled class for fault detection.

3.2 DATA PREPROCESSING

- Handling Missing Values

Checked for missing or null values in voltage, current, RPM, etc.

- Data Normalization & Scaling

Min-Max Scaling or Standardization to ensure consistent ranges.

- Feature Selection & Engineering

Identified the most important parameters (High V-T any Failures)

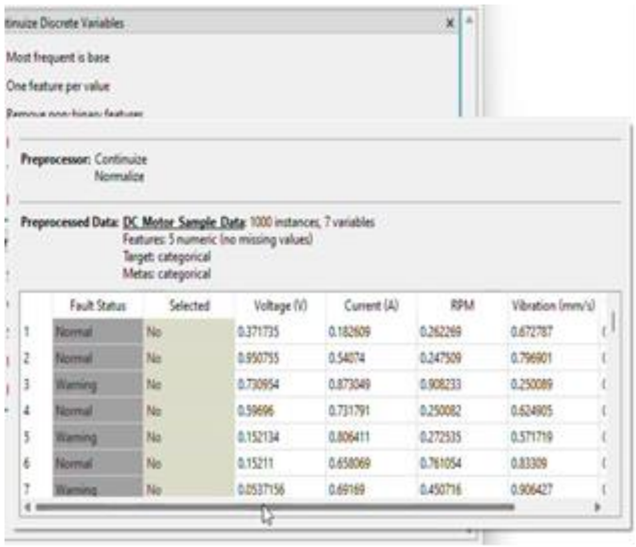


Figure 4 DATA PREPROCESSING

3.3 APPLYING MACHINE LEARNING ALGORITHM

This Dissertation implements a hybrid machine learning approach to improve the fault classification accuracy of a DC motor. Rather than relying on a single algorithm, multiple models—Random Forest, Support Vector Machine (SVM), and k-Nearest Neighbors (k- NN)—were used together to form a robust prediction system. The hybrid model leverages the strengths of each algorithm to deliver more reliable and accurate predictions, especially when handling diverse operational data.

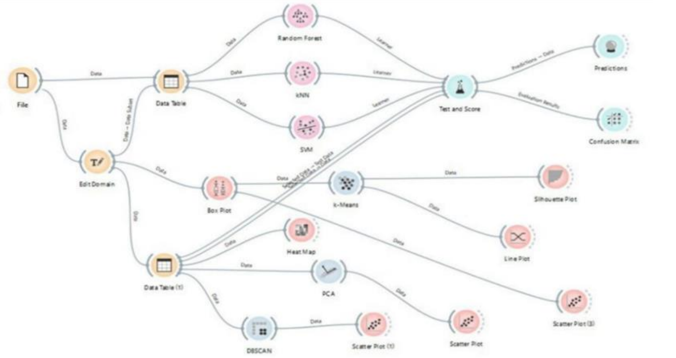


Figure 5 WORK FLOW OF ORANGE

3.4 MODEL EVAULATION

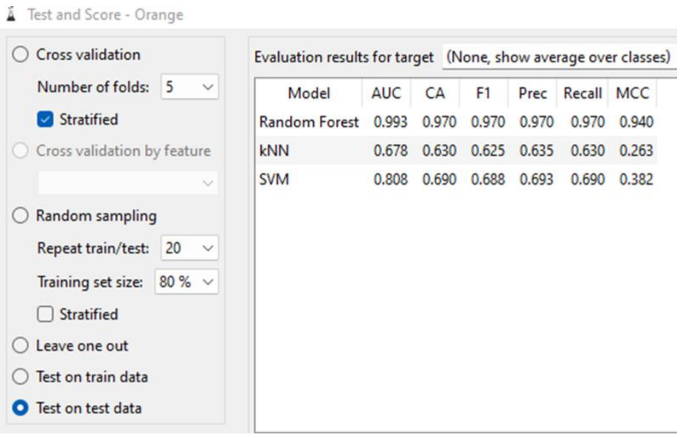


Figure 6 MODEL PERFORMANCE

- This picture shows the model evalution perfomed in orange using test and score widget
- Here This Result indicates How your model Preapare verywell in my case test data classification accuracy is around 0.97% it means 97% accuracy Which means correctly predicted Test data .
- Also training data accuracy is 98% Which means Well trained model.
- Other svm is provide moderate range of accuracy around 69% and knn is the lowest range of accuracy it means algorithm need to train.

- Also one key highlighted feature is training time is only 2 to 3 seconds its high efficiency model give real time data.
- Here I used random sampling method in this method it auto detect data into 80% training data and 20% test data

3.5 PREDICTION

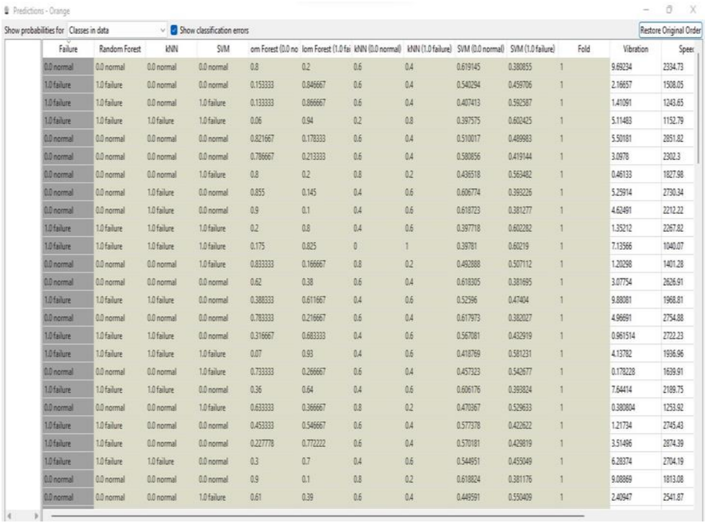


Figure 7 PREDICTION

In This Picture Shows Prediction made by different machine learning algorithm used in orange software

- On the left-hand side, the actual class label condition of motor “0”-Normal, “1”-Failure
- And right-hand side the sensor parameter value speed, voltage, current, vibration
- And middle Grey colour part is our predicted part different algorithm have different value
- For instance, the first row shows a true class of 0.0 (Normal) with Random Forest predicting

0.0 (Normal) with a probability of 0.8, KNN predicting 0.0 (Normal) with 0.6, and SVM predicting 0.0 (Normal) with 0.4. This indicates varying confidence levels among the models, with Random Forest exhibiting higher certainty.

3.6 CONFUSION MATRIX

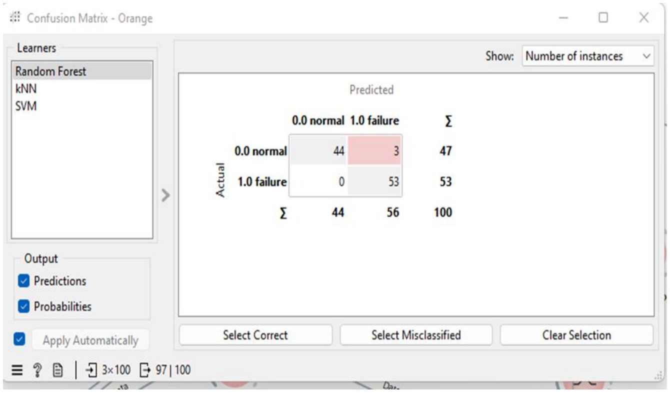


Figure 8 CONFUSION MATRIX

- The matrix indicates high accuracy for the Random Forest model, with 44 + 53 = 97 instances correctly classified out of 100 (97% accuracy).
- Only 3 instances of normal (0.0) were incorrectly predicted as failure (1.0), and no failure (1.0) instances were misclassified as normal (0.0).

After applying Classification model and prediction on data we classified fault now we want to find pattern of those faults or hidden faults so we are moving on unsupervised learning because our model is hybrid model

3.7 K-MEANS CLUSTERING

First of all when we applying clustering you need to select k value for suited in your data set which value is provide good cluster in my case 8th different types of clusters given it means 8 no of unsual patterns identified.

Cluster 0 – Normal operation with low vibration and stable speed
Cluster 1 – Slight fluctuation in voltage, still operational
Cluster 2 – Early signs of imbalance or wear
Cluster 3 – High vibration, possible misalignment
Cluster 4 – Sudden drop in speed, indicating load issue
Cluster 5 – Sharp current spikes, electrical fault
Cluster 6 – Random noise or sensor errors
Cluster 7 – Clearly abnormal readings — potential failure (e.g., vibration too high)

3.8 VISUALIZATION

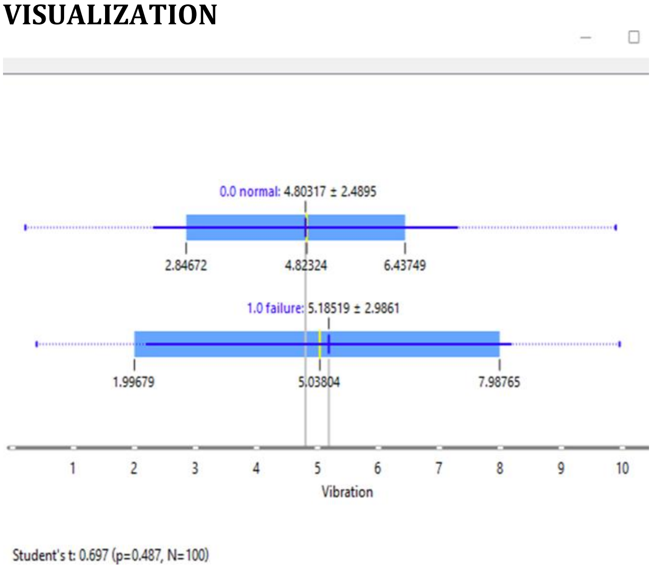


Figure 9 BOX CHART

A box plot was used to identify abnormal sensor values and highlight outliers between normal and fault conditions

The p-value for vibration is 0.05, which is on the borderline of statistical significance.

- Vibration instability (p = 0.05) indicates that mechanical faults such as bearing wear or rotor misalignment .

- The p-value for speed is 0.906, which is significantly above the normal threshold.

- Abnormal speed variation (p = 0.906) suggests that the motor is operating under faulty conditions, possibly due to excessive load, power supply fluctuations, or control system failure

- The p-values for voltage and current are within the normal range, indicating that these parameters are not exhibiting significant variations at this stage.

3.9 PRINCIPAL COMPONENT ANALYSIS

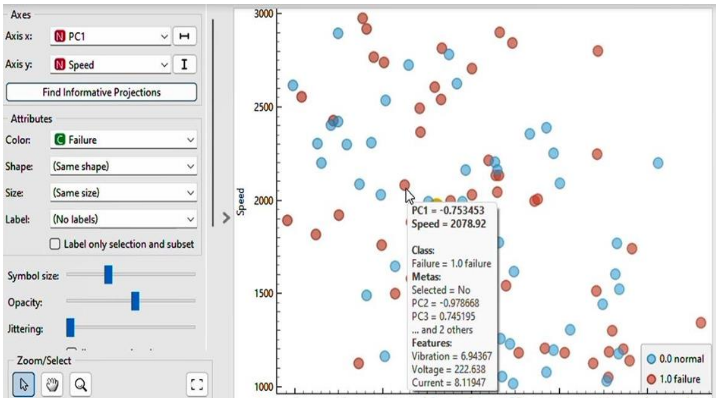


Figure 10 PCA

PCA helps in identifying key patterns and relationships among variables, allowing for efficient failure prediction.

- Your dataset has multiple features like Vibration, Speed, Voltage, and Current. So PCA helps to combines these features into Principal Components (PC1, PC2, etc.), which capture the most variance (patterns) in the data.

- This helps reduce complexity while retaining the most important information.

- As observed in the PCA scatter plot, the separation between failure and normal instances is clearly visible, demonstrating PCA's effectiveness in identifying critical features contributing to fault detection.

4 CONCLUSIONS

- The implementation of machine learning-based predictive maintenance strategies for DC motors represents a significant step toward enhancing operational efficiency and reducing unplanned downtime. By utilizing sensor data related to vibration, speed, voltage, and current, algorithms like Support Vector Machine (SVM), Random Forest, and K-

Nearest Neighbors (KNN) were applied to effectively classify failure conditions.

• This proactive approach helps identify potential faults early, enabling timely maintenance and extending the overall lifespan of the motor. Furthermore, the integration of these models with real-time data visualization tools and dimensionality reduction techniques like Principal Component Analysis (PCA) improves interpretability and decision-making, supporting more intelligent and responsive maintenance systems.

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