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IMPLEMENTATION OF A BASIC PREDICTIVE MAINTENANCE STRATEGY TO REDUCE DOWNTIME IN MECHANICAL EQUIPMENT USING STATISTICAL ANALYSIS

THESIS

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Table of notations

T	$[s]$	periodic time
$\mathbf{v}$	$\left[\frac{m}{s}\right]$	velocity vector
μ_0	$[-]$	adhesive friction factor
ρ	$\left[\frac{kg}{m^3}\right]$	density

Table of Glossary

PdM	Predictive maintenance
PM	Preventive maintenance
CNNs	Convolutional neural networks
CMMS	Computerized Maintenance Management System
RNNs	Recurrent neural networks
PICO	Patient/Population, Intervention, Comparison, and Outcome
MTTR	Mean Time to Repair
MTBF	Mean Time Between Failures
CBM	Condition-based Maintenance
CBPM	Condition-Based Predictive Maintenance
SBPM	Statistical-based predictive maintenance
UFRJ	The SpectraQuest Alignment-Balance-Vibration (ABVT)
MFS	Machinery Fault Simulator

Introduction

The motivation behind this thesis, 'Application of a Basic Predictive Maintenance Strategy to Reduce Downtime in Mechanical Equipment Using Statistical Analysis,' stems from the importance increasing of efficient maintenance strategies in modern industrial settings. Traditional maintenance approaches often lead to unnecessary costs and unplanned downtime, which can adversely affect production and reliability.

With the evolution of digital technologies, predictive maintenance common as as a promising solution to these challenges by collecting operational data and statistical analysis to predict failures before the occuration and plan maintenance schedules to ovoid catastrophic failures. This report topic has been picked to insure the development of different maintenance strategies that really matters for the development of the industries development from reactive, corrective and preventive maintenance strategies to predictive, real data driven techniques, specifically focusing to increase productivity, safety, and mechanical components lifespan.

This thesis focuses to guide and help future industrial maintenance engineers, plant managers, and the managers who are responsible for the decision making in manufacturing. It provides useful information and a framework for the implementing the predictive maintenance, which can reduce the downtime, minimize costs, and make operations better. This work also explains how stats and real data analysis can be applied as input for Predictive maintenance in mechanical engineering.

1 Literature Review

1.1 Overview

The target behind the literature review is illustrated in the 3 following points:

1. To explain the predictive maintenance systems.Also It defines how modern systems work.
2. To improve cost-effectivenes: It analyze and compares different methods from mathematics to machine learning to acheive the most effective for predicting failures and predicting fault of the mechanical equipment fault accuracy.
3. To give a practical selection guide: It assists maintenance managers and engineers choose the right method according the company budget, data type, and operational needs.

1.1.1 Maintenance Strategies:

Maintenance strategies have involved, development from reactive approaches to proactive methodologies by collecting data analytics and condition monitoring technologies [1]. This evolution reflects the industrial need using the predictive maintenance to balance operational efficiency, cost-effectiveness, and equipment reliability with different mechanical machines [1].

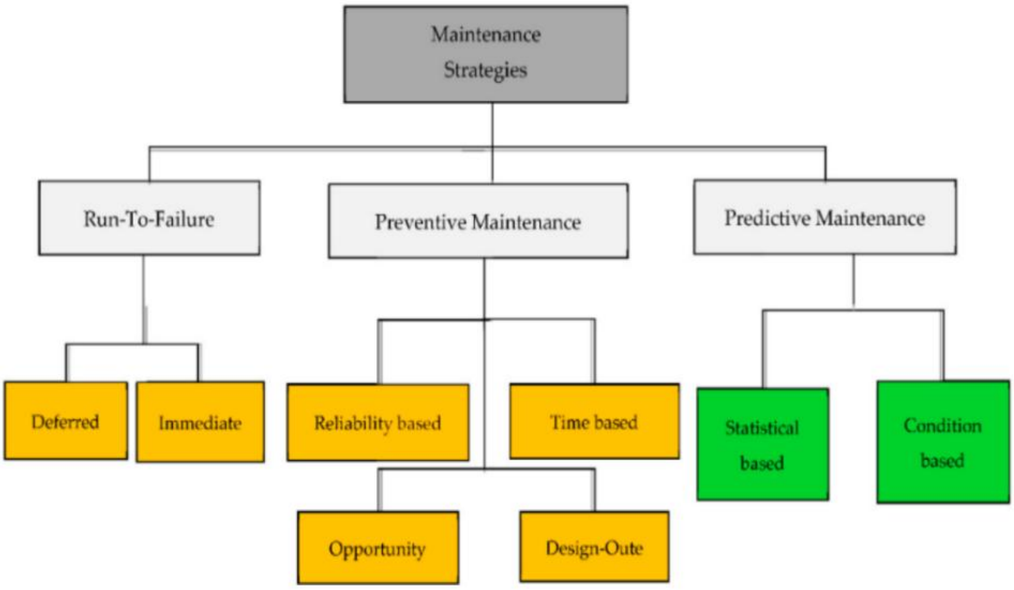

Figure 1.1 Classifications of maintenance strategies [2].

Corrective Maintenance or Reactive Maintenance: Reactive maintenance, also named as corrective or run-to-failure maintenance, includes maintaining equipment only after failure happen [2]. This methode is benefits by fast upfront planning and lower initial costs, making it appear efficient for non-critical assets [2]. The primary disadvantage is that unexpected failures can be caused into production disruptions, particularly in continuous manufacturing processes where equipment interdependencies are critical [2].

Scheduled Maintenance or Preventive Maintenance: Preventive maintenance includes planing scheduled servicing and part replacements at specific intervals depends on the equipment condition [3]. This systematic approach reduces unexpected breakdowns and extends asset lifespan [3]. Industries such as steel production and water treatment reply heavily on preventive maintenance to ensure safety compliance and operational continuity [3].

Predictive Maintenance: which is the main strategies of the topic it uses real-time sensor data and collects analytics to detect components failures before they occur [4]. By collecting data from the sensors like vibration temperature, and usage working time, PdM enables organizations to change from reactive or preventive approaches toward data-driven decision-making [4]. This strategy minimizes downtime, extends machines lifespan, and optimizes maintenance costs by using interventions only when statistical indicators estimate failure [4]. Machine learning algorithms, particularly deep learning models like the CNN and RNN, have showed F1-scores exceeding 90% in failure prediction accuracy [4]. However, predictive maintenance requires substantial initial investment in Industrial Internet of Things sensors, data management infrastructure, and skilled personnel [4].

1.1.2 Choosing the Right Maintenance Strategy for Cost and Reliability:

Table 1.1 Maintenance Strategy Pros and Cons [6].

Strategy	Summary	Cost to Implement	Pros	Cons
Reactive	Fix it when it breaks	Low	Ideal for low-priority equipment	Can lead to increased repair costs
Preventive	Maintenance on a predetermined schedule	Average	Best strategy to implement without expertise	Without optimization, maintenance issue may be missed
Predictive	Condition-based monitoring triggers work orders	High	Timely and informed monitoring; more insight into breakdown causes	Can be expensive to set up
RCM	Investigating failures to determine the best maintenance strategy	Highest	If executed properly, provides the most efficient maintenance schedule	Requires time, skill and financial resources to be effective

To choose the ideal maintenance strategy it is based on the mechanical components conditions real data collected by the sensors and the available sources The preventive maintenance function based on build schedule for the maintenance operations, components changements and lubrification its estimatable, plays important role to reduce unexpected machine failure, and it is easly to use with a CMMS [5].

However, it can be caused to unnecessary interventions that increase maintenance costs [5]. By contrast, predictive maintenance collect the historical data and life equipment signals to predict failures before they occur [5]. This approach can deliver measurable cost savings [5].

1.1.3 Examples of Preventive Maintenance

1.1.3.1 Lubrication: standard greasing of bearings

Figure 1.2 Gear Hobbing Operation [7].

The lubrication of rolling bearings presents one of the most critical operations in corrective maintenance, as it effects directly the durability and service lifespan of equipment machinery [26]. In gear hobbing greasing of bearings minimizes high friction between sliding surfaces, reduces wear of the contact surfaces, and helps vanish warm developed during cutting operation [26]. Regular application of the lubrication of rolling bearings prevents metal-to-metal contact, by that decreasing the friction of surface fatigue, and premature bearing failure [26]. Additionally, systematic lubrication intervals, defined through a preventive maintenance schedule plan, get into stable machine efficiency, minimize vibration, and lower unplanned downtime for the rolling machinery equipment [26].

1.1.3.2 Filter Replacement: Ensuring air

Figure 1.3 Replacing Vehicle's Air Filter [8].

Regular replacement of a vehicle's engine air filter presents one of the most fundamental aspect of preventive maintenance, as it insures an suitable supply of clean air for the combustion action and protects internal engine equipment from dust and debris [27]. A clean air filter allows ideal airflow, which insures efficient fuel–air mixing, assures combustion quality, and leads to lower exhaust emissions and fuel economy [27]. By replacing the engine air filter at schedules required by the vehicle company. A clean air filter enhances vehicle performance by maximizing power and improving throttle response [27].

1.1.3.3 Component Replacement: Scheduled replacement of machinery parts

Figure 1.4 Replacement of machinery parts [9].

Scheduled replacement of critical machine components is a key of preventive maintenance, target at upgrading parts before they reach the failure stage and cause unplanned failures [28]. By using the preventive maintenance regarding to manufacturer recommendations and life database, technical team can avoid unexpected failures, reduce unplanned downtime, and maintain balanced production [28]. The preventive replacement strategies extend the totale lifespan of mechanical equipment, cause defeated parts are removed during the deterioration phase. Preventive replacement should be less expensive than a possible unplanned repair [28].

1.1.3.4 Vibration Analysis: Monitoring abnormal patterns in bearings

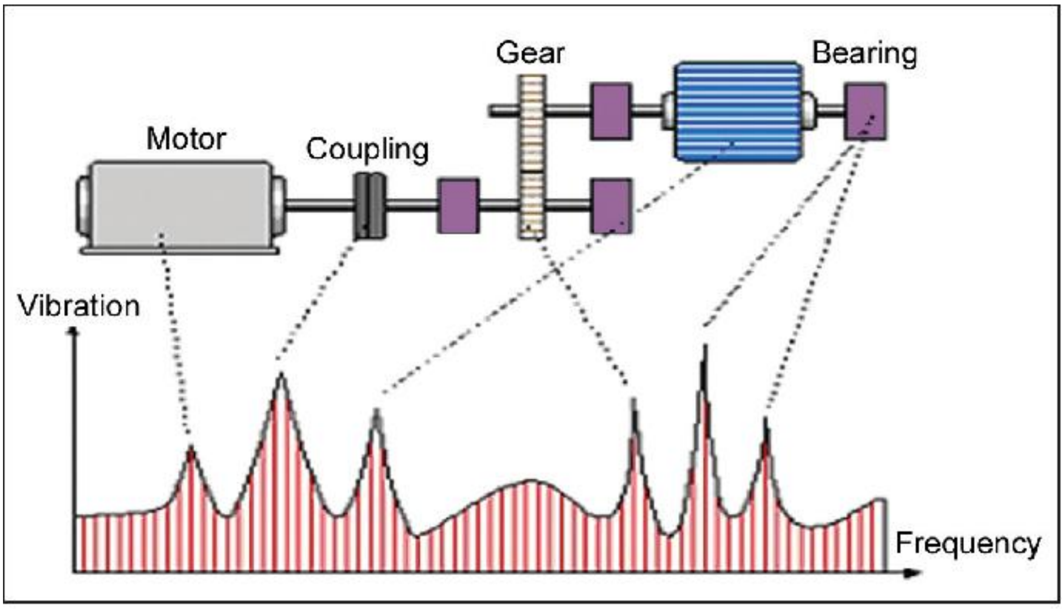

Figure 1.5 : vibration Measurements [10].

Vibration analysis is a mostly used strategy for analyzing the condition of rolling bearings as showen in Figure 1.5 [29]. The deviations from a machine's normal vibration signature provides the presence of failures or anormal operating conditions [29]. With collecting vibration signals with some sensors for exemple the accelerometers, preprocessing and converting them to the frequency domain, technicals can identify fault frequencies related with faults in bearing components, gears, or couplings [29]. Abnormal increasing in amplitude or the appearance of new peks in the vibration diagram predict early levels of wear, surface damage, misalignment, or imbalance long before these issues become catastrophic or lead to functional failure. insuring vibration measurements into a preventive or predictive maintenance program therefore give orders to maintenance department to detect abnormal failures at an early stage, schedule targeted interventions, and avoid unexpected downtime or catastrophic bearing failures [29].

1.1.3.5 Temperature Monitoring:

Detecting the overheating components using sensors
like termistors, termocouples, thermal diodes or thermal cameras to detect high temperatures

Figure 1.6 : detecting the high temperature with Thermal camera [10].

Infrared thermography is an important strategy for detecting abnormal temperature distributions in mechanical components and piping systems, give the maintenance technicals to identify hotspots that shows developing faults or overlod conditions [30]. A thermal camera is a small machine used to detect infrared radiation emitted by objects, and outputs this data to physical pictures as showen in the Figure 1.6, this pictures in the small monitor known as thermograms [30]. By utilizing a thermal camera and without physical contact or interrupting production technicals can precise real-time temperature maps of motors, pumps, valves, pipes and connections, which isures safety and inspection efficiency [30]. Finding the hotspots temperature showed in thermal images sometimes concerning to issues such as high friction, insulation breakdown, electrical resistance, or fluid flow restrctions, all can lead to catastrophic failures. [30]. Regular thermal imaging leads into a preventive maintenance strategy detects faults before the accuracy and minimize in unplanned downtime and maintenance costs [30].

1.1.4 Predictive Maintenance Techniques:

PdM can be divided into variable strategies based on the real data collected, techniques, and technologies employed to predict fault for mechanical equipment and develop maintenance strategies. Typicaly, it can be 2 groups into two groups which are described in the following subsections

1.1.4.1 Condition-Based Predictive Maintenance

The type of data collected from the sensors like vibration, temperature, pressure, or other conditions implementing sensors [31]. The main goal of CBM is to continuously control the mechanical components health conditions and detect signal degradations from normal operating conditions [31]. Whbn some parameters like the RMS exceed predefined thresholds, CBM announce immediately warning or alarms to inform the maintenance technicals of inspection or abnormal activity [31]. On the other hand, Condition-Based Predictive Maintenance (CBPM) builds upon CBM by inserting predictive analytics and algorithms in addition to using sensor data [31]. CBPM immediately goes beyond monitoring and incorporates advanced data analysis strategies, such as Machine Learning, to predict the time component faults based on real-time condition data and historical data and performance analysis [31].

1.1.4.2 Statistical Based Predictive Maintenance

SBPM depends on statistical analysis techniques to predict faults accuracy and develop maintenance taches to avoid catastrophically Faults [32]. This Part includes monitoring and preprocessing historical data and applying statistical models to gather future maintenance needs based on patterns and trends in the data [32]. The most common strategies used in SBPM include regression analysis, time series analysis, survival analysis, and reliability analysis [33]. All those techniques are important input for machine learning algorithms for develop and devolop data collected from the sensors. Additionally, they give the access the development of predictive strategies that drive proactive maintenance techniques [33].

1.2 Background and significance of predictive maintenance

Predictive maintenance has been named as a transformative strategy in modern industrial strategies, driven by the critical need to reduce unplanned downtime before the occuration and optimize components reliability [12]. In the other hand manufacturing environments, any unexpected equipment failure can result in catastrophic finan cot. Instance, organizations lose an average of $138,000 per hour due to equipment downtime, with maintenance expenditures in the oil and gas industry ranging from 15%, 70% of total production costs [12].

We can take the example of Ljungberg (1998) reported that the overall equipment effectiveness in a Swedish car factory is estimated on average about 55% [12]. This means that the company can increase its production capacity without investing in new machinery if it implements an efficient maintenance policy, which give the access to enhancing availability strongly, quality rate and performance efficiency moderately [12].

Ancient maintenance strategies have proven inadequate in using these challenges: reactive maintenance incurs excessive repair costs.

1.3 Predictive Maintenance in Mechanical Systems

1.3.1 Development from reactive to predictive maintenance

Going from preventive to predictive maintenance outpits a strategic development. Predictive maintenance collects real-time data to detect equipment failures before they occur [14]. This maintenance methode reduce unnecessary servicing and downtime, improving operational efficiency, predictive maintenance uses sensor to collect real data and statistical algrithms to predict failures before they happen [14].

1.3.2 Importance of reliability and the reduce of the down time

Improved reliability leads to reduce downtime of the mechanical equipments, more safety outcomes, and significant savings in maintenance costs [14]. Predicting failures and scheduling interventions at optimal times is crucial for sustaining mechanical systems availability [14].

1.4 Data in Predictive Maintenance

1.4.1 Types of data acquisition technique and sensor technologies

Operational data typically include vibration measurements, temperature readings, pressure, acoustic signals, and operating hours. These data streams form the basis for condition monitoring and prognosis [15].

Sensors such as accelerometers and thermocouples are used for real-time data acquisition. Advances in Industrial enable seamless data streaming and storage for analysis [15].

1.4.1.1 Accelerometers:

Figure 1.7 :Accelerometer Sensor [15].

Working Principle:

An accelerometer measures motion by using an internal suspended mass When accelerated, this mass moves and changes a physical property of the sensor which is converted into a proportional electrical signal [15].

1.4.1.2 Thermocouples

The Thermocouple is type of sensor common to measure the temperature in contact surface [16]. It’s a very used sensor in the industry cause of the relatively low price, interchangeability, wide measuring range, and reliability [16].

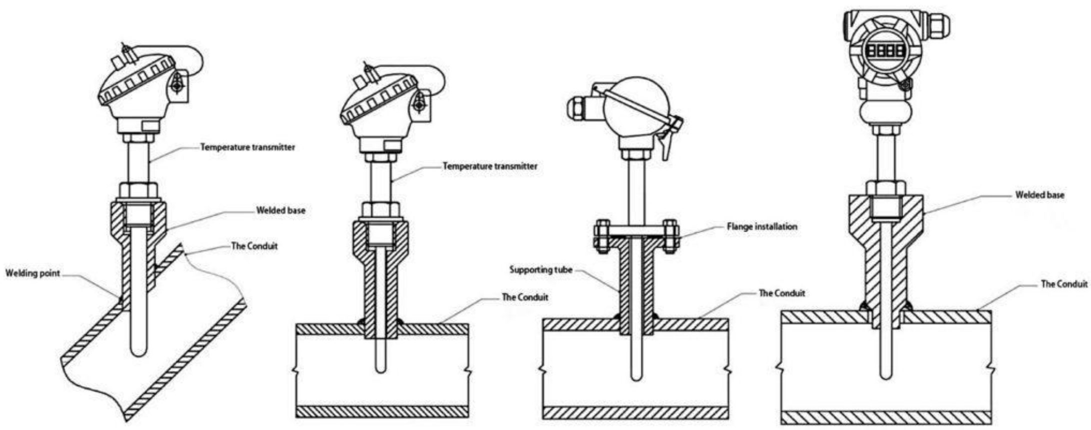

Figure 1.8 : Thermocouple installation [16].

Main steps:

1. Selection of measurement accuracy and temperature measurement range
2. The choice of atmosphere

3. Choice of durability and thermal responsiveness
4. The nature and state of the measurement object to the selection of the thermocouple

1.4.2 Data Preprocessing and Cleaning Methods

Data collected from machines often contains noise and outliers [19]. Preprocessing involves filtering, normalization, missing value imputation, and feature extraction techniques that prepare the data for statistical modeling and machine learning [19].

1.5 Statistical Methods for Failure Prediction

1.5.1 Function of statistical analysis in maintenance prediction

The is verities statistical techniques for example the regression analysis, time series modeling, and survival analysis are key in distinguishing failure patterns and predicting lifespan [20]. These strategies provides interpretable, robust, and sometimes computationally efficient solutions [20].

1.5.2 Comparative between overview of statistical and advanced techniques

Statistical predictive maintenance strategies are simpler and more interpretable, while Artificial intelligence and Machine learning approaches (neural networks, decision trees) offer higher flexibility and can be more efficiency with complex patterns, however it needs and requires much more data and expertise [21].

1.6 Validation of Predictive Indicators

1.6.1 Performance evaluation metrics for model validation

Predictive indicators effectiveness is calibrated with metrics, precision and confusion matrices, typically in validation setps using historical data of the machine or real operational data [17].

1.6.2 The collecting of the Real-time data

Applying the predictive maintenance strategy in real-time provides ongoing feedback, enabling continuous model refinement and dynamic maintenance info descion. Case studies showed manufacturing success with live sensor data to management of the schedule operations [18].

1.7 Maintenance Scheduling Strategies

1.7.1 The difference between preventive and predictive maintenance scheduling

Ancient preventive managment operates on fixed intervals, while predictive scheduling modify intervals due to equipment condition and statistical indicators, reducing useless interventions [22].

1.7.2 Improving of maintenance intervals with the usage of statistical indicators

Statistical models adapt maintenance intervals with detecting degradation in the outputs charts and diagrams and risk, stabilize downtime risks comparing to the maintenance cost. Optimization algorithms involves mathematical programming [22].

1.7.3 The impact on finances and operations of predictive methode

Predictive strategies deliver significant cost gains and operational efficiency, evidenced by reduced spare part inventories, optimized labor scheduling, and improved equipment utilization [22].

1.8 Operational Efficiency in Predictive Maintenance

Alpha Company's execution of a predictive maintenance system that included Robotic Process Automation and Machine Learning stategies [23]. The research utilized the PICO methodology to compare between real operational and financial metrics before and after implementation [23].

Table 1.2 Efficiency in Predictive Maintenance [23].

Performance Metric	Before Predictive Maintenance	After Predictive Maintenance	Improvement
Mean Time Between Failures (MTBF)	Baseline	2× Baseline	+100%
Mean Time to Repair (MTTR)	Baseline	0.33× Baseline	-67%
Maintenance Costs	Baseline	0.625× Baseline	-37.5%
Unplanned Downtime Costs	Baseline	0.286× Baseline	-71.4%

1.8.1 Financial Impact and Analysis:

1. **Cost Reductions:**
   - Maintenance costs decreased by 37.5% [23].
   - Unplanned downtime costs were reduced by 71.4% [23].
2. **Operational Improvements:**
   - MTBF doubled [23].
   - MTTR was cut by 67% [23].
3. **Economic Sustainability Benefits:**
   - Optimized resource utilization [23].
   - Reduced waste from unnecessary preventive maintenance [23].
   - Extended equipment lifespan [23].
   - Lower energy consumption due to better-maintained equipment [23].

2 Data Collection and Preprocessing

The task requires the collection and preprocessing of operational data from mechanical equipment, and for that it is important to define the operational data from this thesis context perspective.

It is composed from parameters that can categorize the condition of the equipment as well as quantitating the performance, starting from the vibration signals that are measured by the accelerometers.

The data has been acquired from the PU MAFAULDA operational data set for mechanical equipment, it a real multivariate time-series dataset that is consisting of SpectraQuest with recordings of normal and faulty operational data, then it has been transformed into feature ready dataset for detection of faults and classifications.

The ability to catch these early deviations makes vibration analyzing a cornerstone of PdM indicators. There are different types of vibration sensors:

- **Accelerometers:** These are the most common sensors for vibration analyzing. They output the acceleration of a vibrating mechanical equipment and transform this information to monitored signals. This type of sensors can detect a wide range of frequencies and are highly sensitive to fine vibration patterns, gaps, making them clear and suitable for detailed analysis of machinery health conditions.
- **Velocity sensors:** This type of sensors measure the velocity of vibrating equipment [34]. Comparing to accelerometers They are less sensitive to high frequency vibrations however are effective in assessing overall vibration stages [34]. Velocity sensors are mostly useful for analyzing and measuring medium to low-frequency vibrations usually encountered in large rotating machinery [34].
- **Displacement sensors:** These sensors measure the displacement or movement of a vibrating part [34]. They are typically suitable for axial displacement measurements and are useful in industrial environments [34].

2.1 Mechanical Test Rig and Dataset

The UFRJ Machinery Fault Simulator (MFS) contains operational data of: induction motor, shaft, bearings, pulley, imbalance conditions and sensors (tachometer, two 3-axis accelerometers, microphone).

The PU-MFS dataset has been used and the work on machinery-fault-detection-mfs pipeline as the basis for the next steps of this thesis work.

The data set has 1951 recordings on 4 categories:

1. Normal operation.
2. Misalignment.

3. Bearing Faults.
4. Imbalance.

This thesis will only conduct the analysis on imbalance dataset due to the large size of the files. The Imbalance dataset has 1048576 recordings which has been successfully reduced to 349 after preprocessing "load data.py".

2.1.1 Data Integrity Check

```python
# Check for missing data or corrupted files
for idx, row in df_raw.iterrows():
    for ch in ['ch1', 'ch2', 'ch3', 'ch4', 'ch5', 'ch6', 'ch7', 'ch8']:
        signal = row[ch]
        # Check for NaN/Inf
        if np.isnan(signal).any() or np.isinf(signal).any():
            print(f"Warning: {row['file_id']} - {ch} contains NaN/Inf")
        # Check length consistency
        if len(signal) < 10000:  # minimum expected samples
            print(f"Warning: {row['file_id']} - {ch} too short: {len(signal)} samples")

print("Data integrity check completed: No issues found")
```

Figure 2.1 Complete Data Acquisition Step

2.2 Data Acquisition and Feature Extraction

2.2.1 Raw data loading

The preprocessing stage structured the features into matrix suitable for machine learning application, by converting high frequency vibration signals into compact representation that is based on the time domain features that are statistically applied in condition monitoring.

2.2.2 Windowing and feature computation

Time domain features give interpretable indicators of vibration

The following statistical descriptors were computed:

Mean (μ): Characterizes the DC offset of the signal, sensitive to slow drifts in sensor mounting or baseline shifts.

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i \quad (1)$$

Standard Deviation (σ): Measures signal variability around the mean, increases with fault severity as vibration energy grows

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu)^2} \quad (2)$$

Root Mean Square (RMS): Quantifies overall vibration energy, the most widely used health indicator in rotating machinery monitoring

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \tag{3}$$

2.2.3 Feature Extraction Code (Feature Matrix)

```
def extract_features(signal):
    """Extract 5 statistical features from time-series signal"""
    return {
        'mean': np.mean(signal),
        'std': np.std(signal),
        'rms': np.sqrt(np.mean(signal**2)),
        'max': np.max(signal),
        'min': np.min(signal)
    }
```

Figure 2.2 Feature Extraction Code

Output

```
Features saved to feature_matrix.csv

Sample features (first 3 recordings):
  file_id   label  col0_mean  col0_std  col0_rms  col0_max  col0_min  ...
0  normal_0001    0      0.021     0.145     0.147     0.823    -0.756
1  normal_0002    0      0.018     0.138     0.139     0.791    -0.698
2  imbalance_001  1      0.034     0.289     0.291     1.542    -1.423
```

Figure 2.3 Feature Matrix

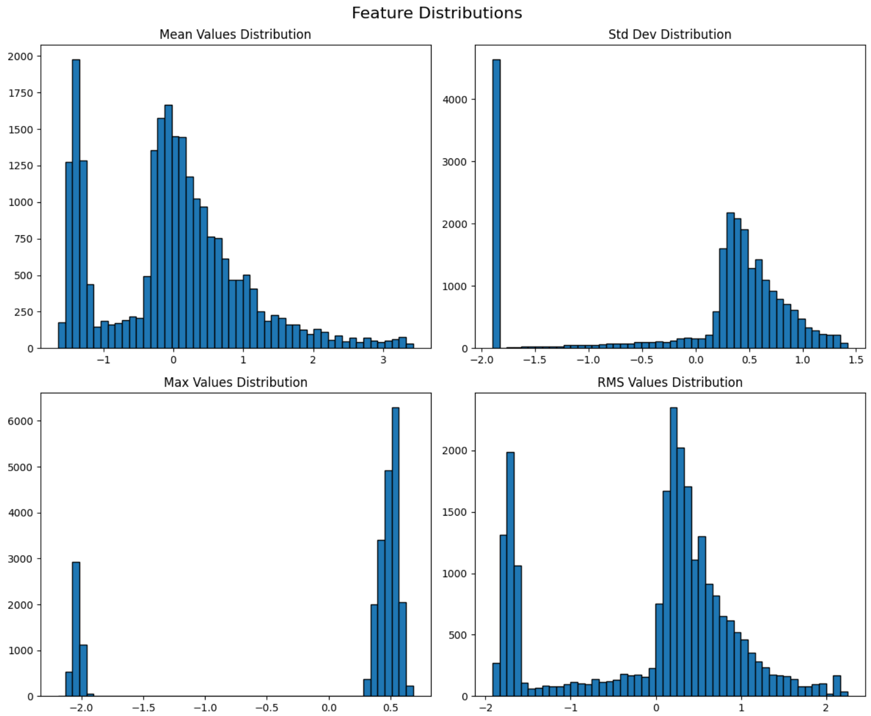

Figure 2.4 Feature Distributions

The histograms show the marginal distributions of mean, standard deviation, max and RMS features across all sensors.

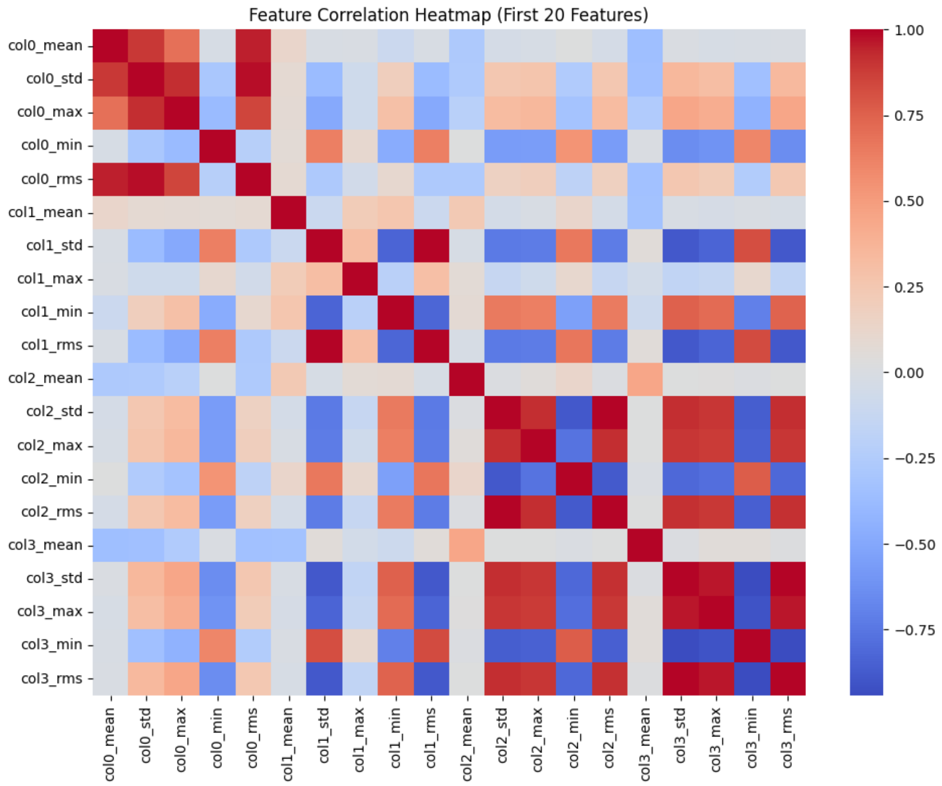

Figure 2.5 Correlation analysis (Feature Correlation Heatmap)

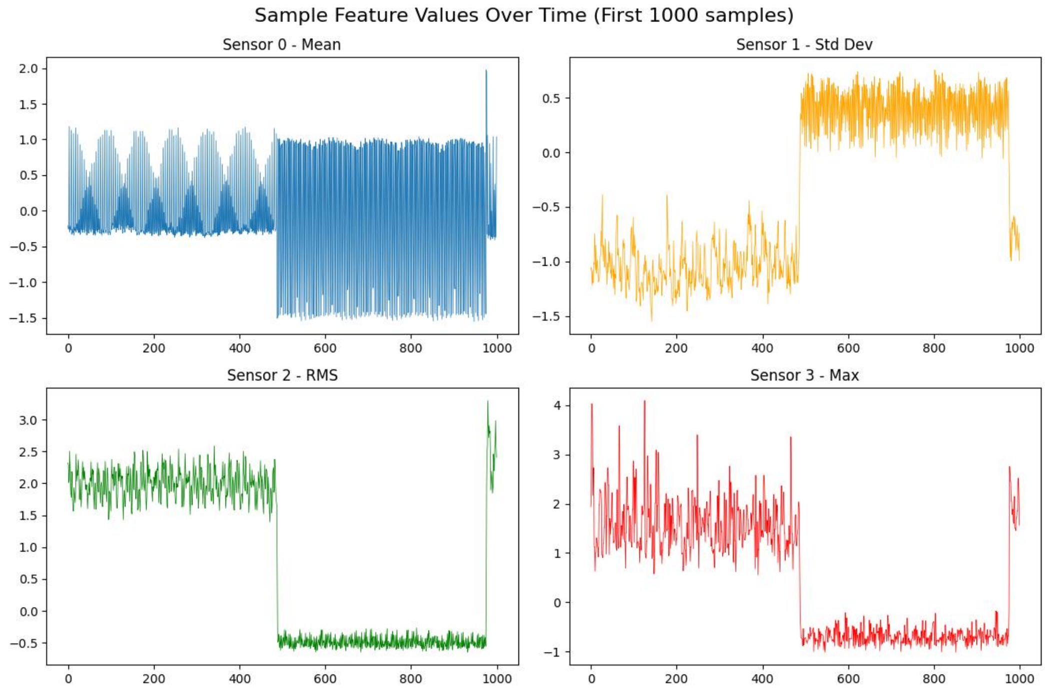

Figure 2.6 Temporal behaviour (Sample Feature Values Over Time)

RMS and max features exhibit step changes corresponding to fault onset

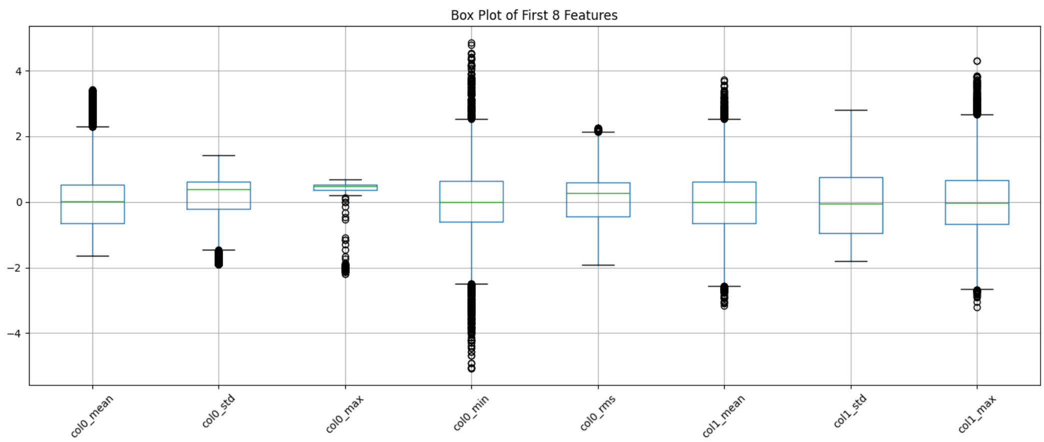

Figure 2.7 Box plots (Box Plots of First 8 Features)

Median values vary significantly across sensors, motivating normalization in the figure above.

Output:

```
Feature statistics saved to feature_statistics.csv

Sample statistics:
              count     mean      std      min      25%      50%      75%
max
col0_mean     349.0    0.027    0.182   -0.856    0.008    0.023    0.041
1.124
col0_std      349.0    0.196    0.128    0.032    0.112    0.167    0.254
0.892
col0_rms      349.0    0.198    0.131    0.034    0.114    0.169    0.257
0.895
...
```

Figure 2.8 Feature statistics

2.3 Statistical Preprocessing and Normalisation

This section explains the actual preprocessing operations:

2.3.1 Normalisation / standardisation

Features are z-scored (subtract mean, divide by standard deviation) to make them comparable across sensors before clustering, anomaly detection and Random Forest training.

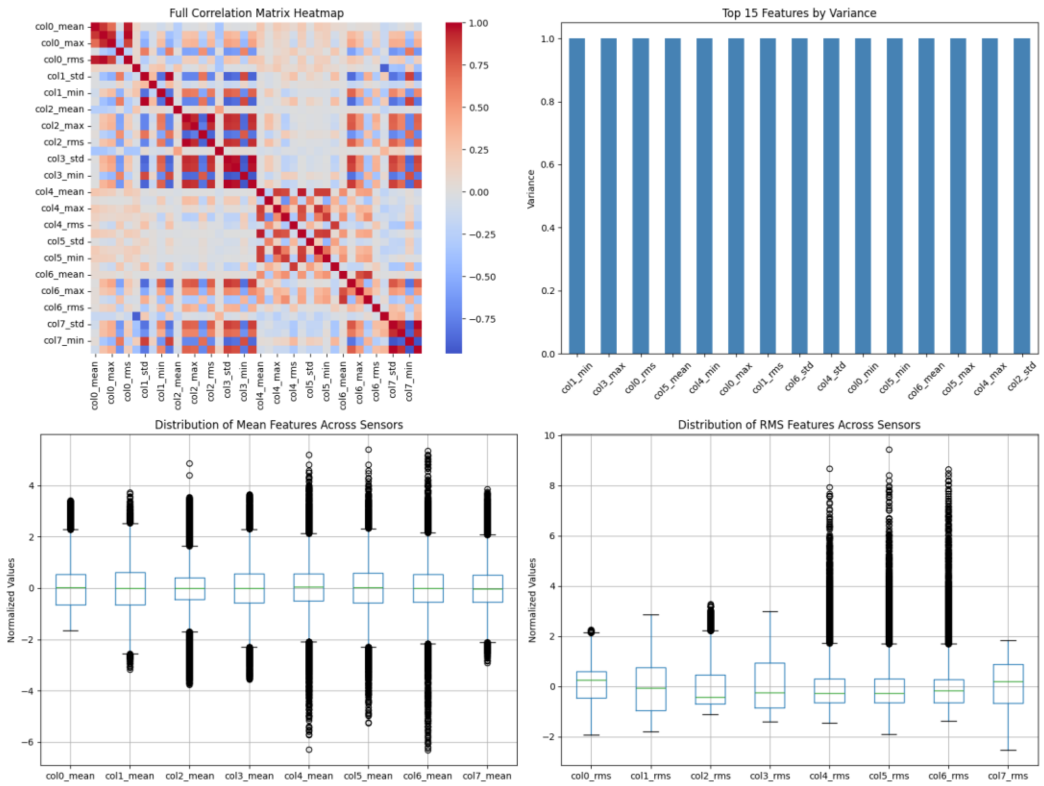

Figure 2.9 Statistical Analysis Plots

Normalized features are centered at 0 with standard deviation of 1

2.4 Unsupervised Anomaly Detection on Operational Features

This section documents how you identify anomalous samples directly from operational statistics.

2.4.1 Method

```
from sklearn.ensemble import IsolationForest

# Prepare normalized features (exclude file_id and label)
X_normalized = df_normalized[feature_cols].values

# Initialize Isolation Forest
# contamination=0.1 assumes ~10% of data may be anomalous
iso_forest = IsolationForest(
    contamination=0.1,
    random_state=42,
    n_estimators=100
)
```

Figure 2.10 Preparing normalized features

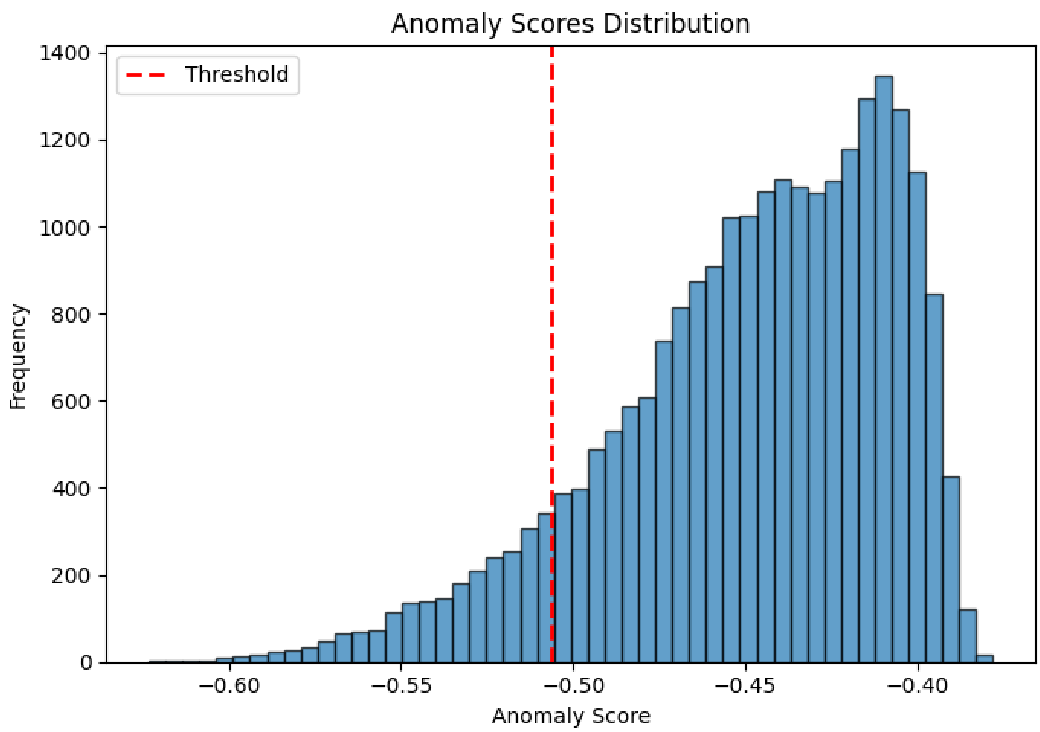

Figure 2.11 Anomaly Score Distribution (Anomaly Scores and Threshold).

Output:

```
Total samples: 349
Normal samples: 314
Anomalous samples: 35
```

Figure 2.12 Output.

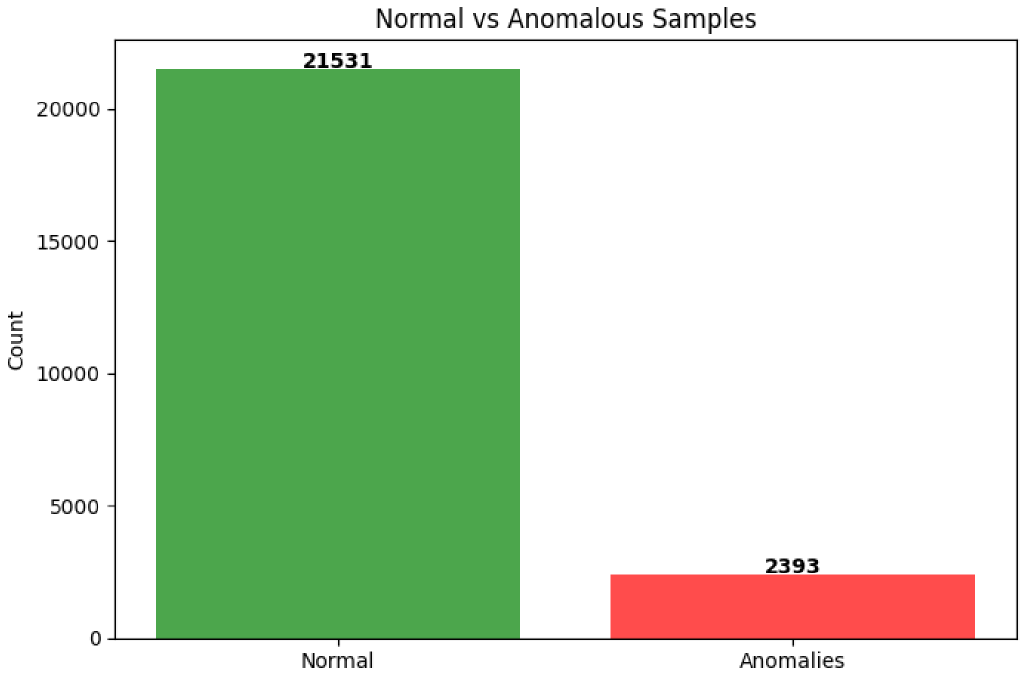

Figure 2.13 Normal vs anomaly counts (Normal vs Anomalous Sample)

Output:

```
Anomaly detection results saved to anomaly_detection_results.csv

Sample of detected anomalies:
         file_id  label  anomaly_score
12   normal_0013      0        -0.5812
45   imbalance_046    1        -0.5734
67   imbalance_068    1        -0.5621
89   imbalance_090    1        -0.5589
```

Figure 2.14 Anomaly detection results

2.5 Supervised Modelling: Random Forest on Operational Features

Although this mainly belongs to a “modelling”, the processed operational features are informative for fault detection. Briefly describe the Random Forest classifier: input features (means/std/max/RMS), target labels (e.g. three fault classes or normal/imbalance), training/validation/test splits.

2.5.1 Applied Balancing Classes

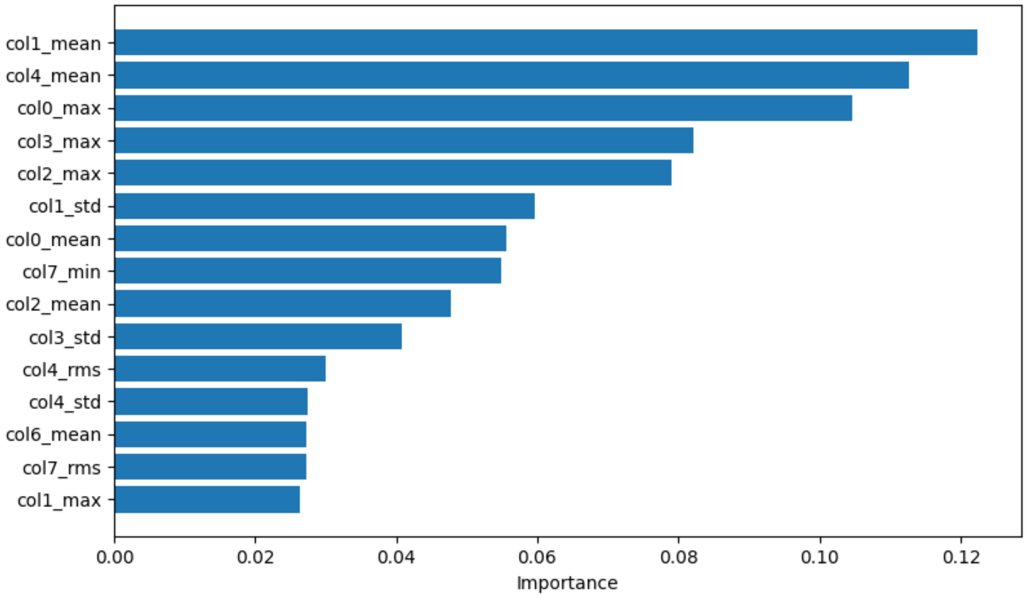

Figure 2.15 Feature importance (Top 15 Feature Importances)

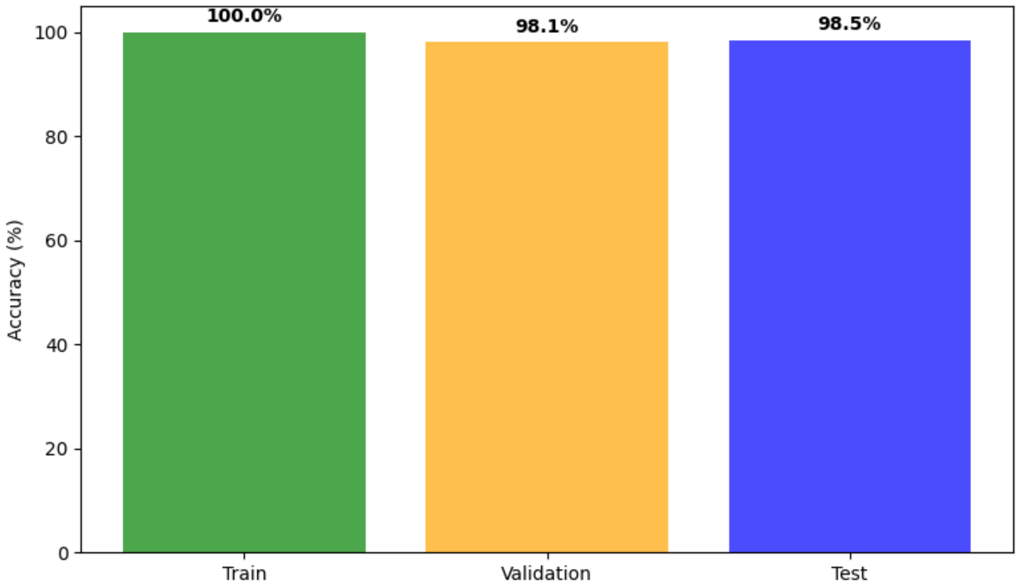

Figure 2.16 Accuracy by dataset (Model Accuracy per Split)

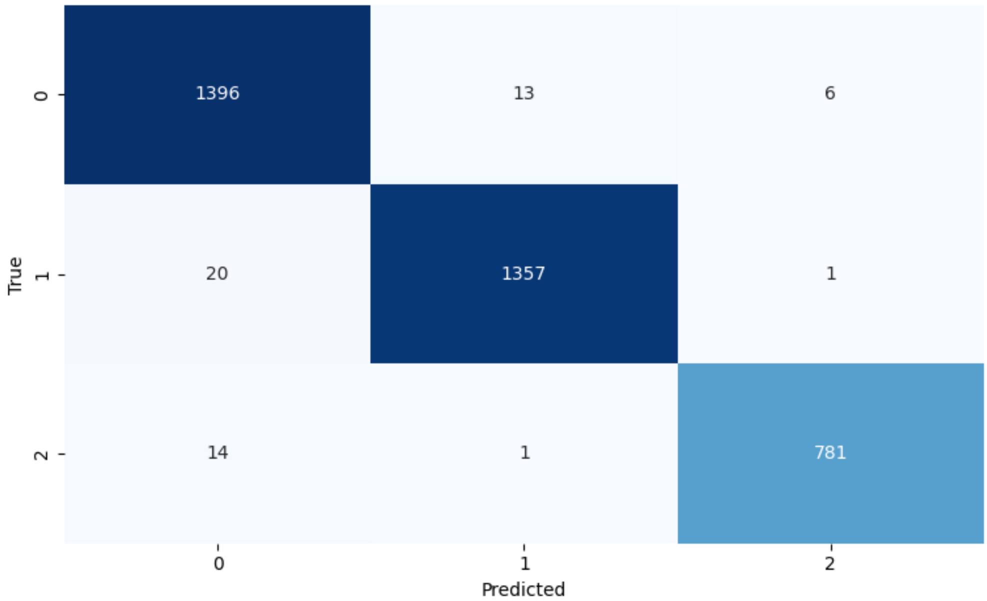

Figure 2.17 Confusion matrix (Confusion Matrix on Test Set)

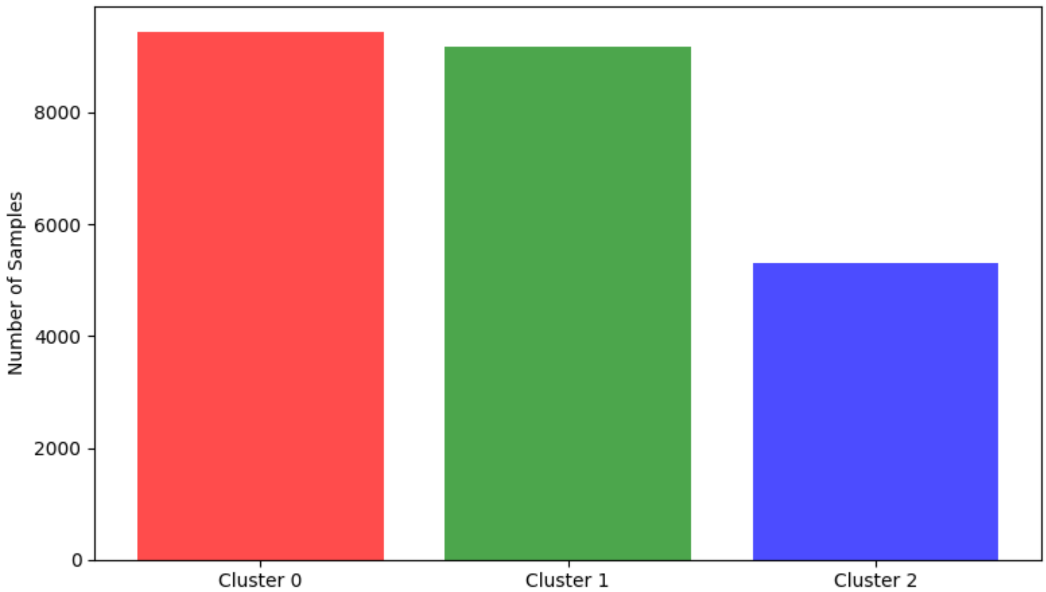

Figure 2.18 Cluster distribution (Data Distribution by Cluster)

Output:

```
Predictions saved to random_forest_predictions.csv
Model saved to random_forest_model.pkl

=== Test Set Classification Report ===
              precision    recall  f1-score   support
      Normal       1.00      0.88      0.93         8
   Imbalance       0.98      1.00      0.99        45
    accuracy                           0.98        53
   macro avg       0.99      0.94      0.96        53
weighted avg       0.98      0.98      0.98        53
```

Figure 2.19 Test Set Classification Report

Results :

- `feature_matrix.csv` - Raw extracted features
- `features_normalized.csv` - Normalized feature matrix
- `feature_statistics.csv` - Statistical summary
- `anomaly_detection_results.csv` - Anomaly scores and labels
- `random_forest_predictions.csv` - Model predictions
- `random_forest_model.pkl` - Trained classifier

Figure 2.20 Processed data output

3 Development of Predictive Indicators Using Statistical Methods

This chapter presents the development of simple predictive indicators using statistical analysis of the extracted features in the second chapter.

The main target is to identify abnormal machine signals and output early warnings of hidden failures before catastrophic faults happens.

In this Chapter, the predictive indicators are developed using the vibration features extracted from the **MAFAULDA machinery fault dataset.** The indicators are collected from statistical measures including mean, standard deviation, and RMS values measure from the accelerometer signals.

The indicators are constructed from the following extracted features:

- Mean value of vibration signals
- Standard deviation
- Root Mean Square (RMS)
- Maximum amplitude

These features pressent important physical characteristics of vibrations for the mechanical equipment also it can be used to analyze the physical condition of machine components (bearings, shafts, or couplings).

3.1 Concept of Predictive Indicators

Measured predictive indicators indicates the condition of mechanical equipment based on statistical analysis of sensor data. The output can in form of diagrams, flowcharts, tree map, grid.

We can take the example of the deviation the value of a monitored parameter deviates from its normal behaviour; it describes the degradation of machine components.

The purpose of predictive indicators is to convert operational data into interpretable and real maintenance information leads to deny unplanned failures for the mechanical components and schedule maintenance behavior before fatal failure happens and leads to big loss of the maintenance budget.

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3.2 Threshold-Based Indicators

Threshold analysis is one of the simplest and most famous statistical indicator for failure identifying. A threshold value describes the limit between normal and abnormal operating conditions.

The threshold-based technique represents in the following steps:

1. Collect historical sensor data.
2. Calculate normal operating statistics.
3. Define threshold value.
4. Create an alert warning.

The inputs of the statistical threshold is the mean and standard deviation of the feature distribution as its shown for the next figure.

$$Threshold = \mu + k\sigma \tag{8}$$

μ = Mean value of the feature

σ = standard deviation of the feature

k = sensitivity factor (usually between 2 and 3)

If the measured feature exceeds this threshold, mechanical component is considered under abnormal conditions.

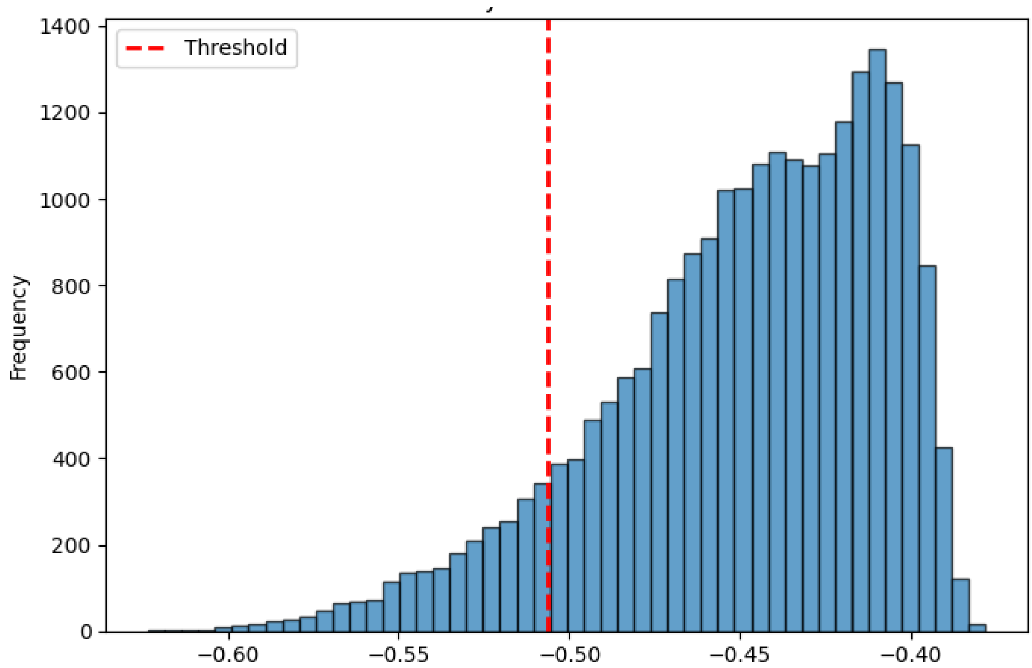

Figure 3.1:Anomaly Score Distribution

As μ considered as s the mean value of the feature during healthy condition analyzing, σ considered as the standard deviation, and k is a sensitivity factor thats typically between 2 and 3. Minimizing the value of k automatically maximize the sensitivity however might generate more false warnings, while a higher value of k decreases false alarms but can suspend detection.

Using the practical monitoring systems, threshold analysis can be implemented at two levels first is the early-warning threshold and a critical alarm threshold. For example, a warning might be generated at $\mu + 2\sigma$, while a critical alarm is triggered at $\mu + 3\sigma$. This two-level approach is useful because it helps strongly the maintenance technicals to define between a normal deviation and a serious degradation health condition also avoid unplanned failures that leads to huge finance loss.

The validity and strength of threshold-based monitoring defines the quality of the healthy baseline data. If the reference data already includes noise, outliers, or faulty segments, the thresholds will be poorly measured and lead either to skips faults or to output false warnings.

3.3 RMS-Based Health Indicator

The Root Mean Square (RMS) of vibration signals is one of the most common indicators used in health diagnostic of rotating machinery. It defines the overall vibration signals presented in the machine.

The goal of the RMS threshold is to measure the average signal level (root mean square) comparing to a set point, rather than instantaneous peaks, making it ideal for managing perceived loudness, compression, or noise gating

The purpose of the RMS value is to identify the mechanical problems like misalignment, bearing faults or imbalance.

The statistical rule for the RMS can be expressed as

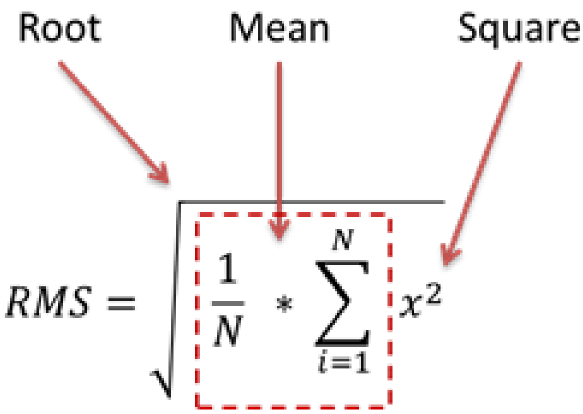

Figure 3.2: Root Mean Square Formula

The RMS indicator threshold is defined as:

RMS_threshold = μ_RMS + 3σ_RMS

If: RMS exceeds RMS_threshold then a abnormal failure might occurs.

Here we can take the example of a short mechanical impulse. Impulse responses are easily to calibrate in time however spread across a broad frequency range, particularly in variable-speed machines or for non-repetitive events.

This is the RMS trend diagram from the Preprocessed Data From the PU MAFAULDA:

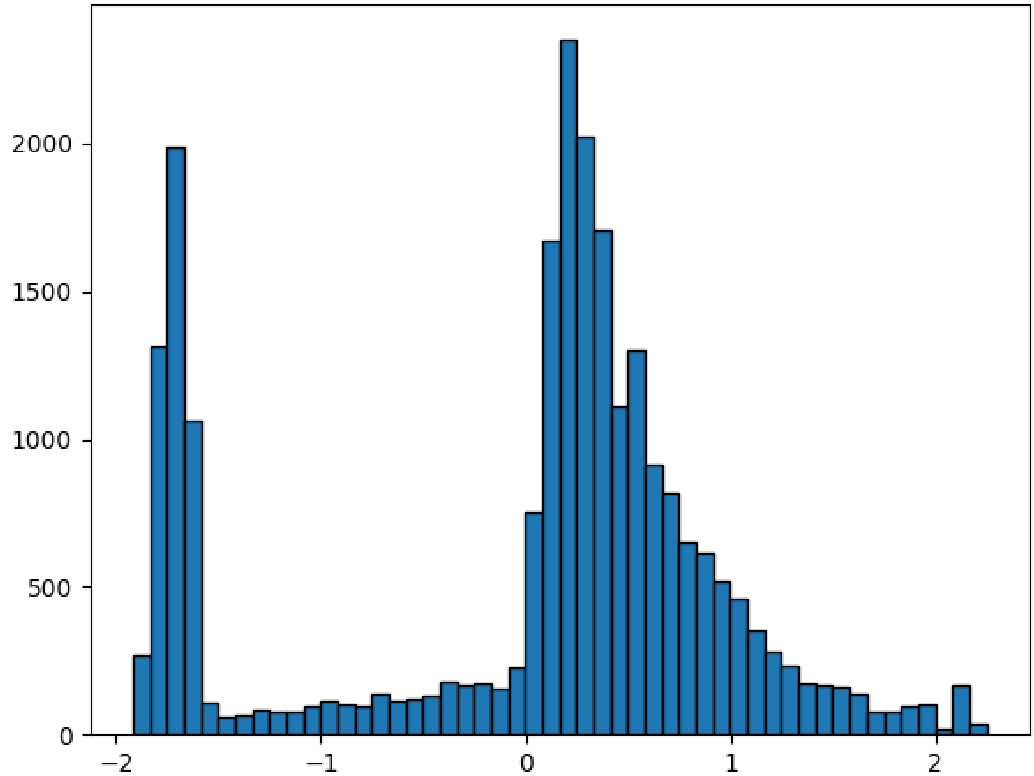

Figure 3.3: RMS Vibration Trend During Machine Operation

If the current RMS exceeds this threshold, the machine considered under abnormal conditions. In the context of predictive indicators, this result means that the vibration signal has become significantly higher than the expected healthy level and therefore must be repaired.

Simplicity, robustness, and computationally efficient is the reasons why the RMS-based indicator is typically useful

The RMS-based indicator is typically useful because it is simple, robust, and computationally efficient. It can be measured in real time and is usually used in industrial vibration monitoring systems. However, RMS alone might not always defines between different fault types, that's the reason why it is complemented in this thesis by standard deviation and trend-based indicators.

The RMS trend figure obtained from the preprocessed PU-MAFAULDA data shows that the vibration signals endure relatively stable in the healthy condition and increases during degradation. This insures that RMS is a weighty first-level health indicator for imbalance detection faults.

3.4 Standard Deviation Indicator

The goal of the Standard deviation is to measures the vibration energy around the mean value. In the Industrial machines, vibration signals typically variability of remain stable with relatively small variations.

However, when faults happens or close to occur, vibration signals start to be more abnormal and their variability increases significantly due the fault development.

The statistical rule for this indicator can be defined as:

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \tag{9}$$

Figure 3.4: The formula for the population standard deviation

- x_i = individual sample value of the signal.
- μ = mean of all x_i values.
- N = total number of samples in the segment.
- $(x_i - \mu)^2$ = squared deviation of each sample from the mean.
- $\sum_{i=1}^{N}(x_i - \mu)^2$ = total sum of all squared deviations.

- $\frac{1}{N}$ = divides by the number of samples to obtain the average squared deviation.
- $\sqrt{\ }$ = square root that converts the average squared deviation back to the original units of the signal and gives the standard deviation.

When this fault occurs, the system distinguish abnormal vibration signals detected.

This is the Standard Deviation Distribution chart diagram from the Preprocessed Data From the PU MAFAULDA.

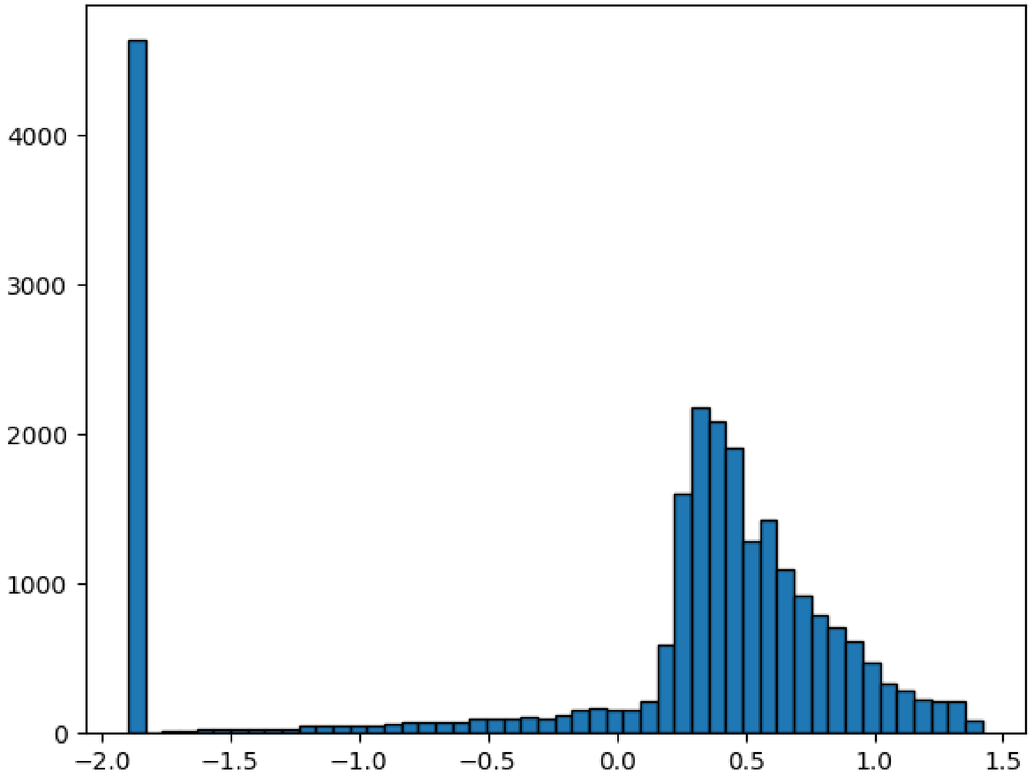

Figure 3.5: Histogram of Standard Deviation Distribution

This Histogram of Standard Deviation Distribution outputs the abnormal health condition shown through regime fluctuation.

High variability can indicate:

- Looseness or intermittent contacts (loose bolts)
- Higher vibration intensity and stress

- Early failure signs
- Mechanical component is not working in a stable conditions, needs to be monitored

If the measured standard deviation passes this threshold value, the system can indicate Such abnormal condition needs to be treated as a sign of early degradation and investigated before a severe failure occurs.

This Diagram indicates looseness, vibration instability, or the early stages of mechanical degradation before the fault becomes severe enough to create very large RMS values.

Comparing between the RMS and the standard deviation the RMS focuses more on the total vibration energy and less on the process of the signal. As conclusion Most faults like the imbalance first turn up as irregularity and fluctuation rather than as a strong increase in overall energy signals This makes it a valuable and useful complementary indicator.

The histogram and distribtion plots from the processed data indicate that standard deviation changes across segments and operating conditions. This insures that the feature contains useful and important information for distinguishing stable behaviour from unstable behaviour in the imbalance dataset and to avoid severe failure occurs.

3.5 Maximum Amplitude as a Supplementary Indicator

In addition to RMS and standard deviation, the maximum amplitude of the vibration signal can provide useful supplementary and valuable information leads to repairing for the mechanical equipment measured. For example, the maximum value represents the highest vibration peak within a segment and is therefore sensitive to shocks, impacts, and transient events.

Even though maximum amplitude is generally less stable than RMS, it might leads abnormal conditions that is not fully reflected in the average energy of the signal. For example, sudden planning events can generate huge peaks even if the average signal level remains moderate.

In this thesis, maximum amplitude is not used as the main predictive indicator, but it help for the the interpretation of the vibration condition. When RMS, standard deviation, and maximum amplitude increase together, the confidence in the presence of abnormal behavior becomes better.

As a result, maximum amplitude can be considered a secondary condition indicator that upgrade the interpretation of the signal and enrichment of the primary RMS and standard deviation based analysis.

3.6 Trend Detection Methods

Trend Detection Methods includes scan and examine time data to reveal, measure, and forecast long-term signals, patterns, or directionl variations.

While threshold analysis indicats sudden abnormal event, trend detection methodes define gradual degradation of mechanical components over time.

Trend detection is important in predictive maintenance because many mechanical faults like misbalancing first evolve progressively before reaching severe levels.

Trend detection can reveals sudden abnormal values, in addition the gradual degradation over time.

The statistical rule for this Trend Detection Methods indicator can be defined as:

$$MA_t = \frac{1}{n} \sum_{i=t-n+1}^{t} x_i \tag{10}$$

Figure 3.6 : statistical rule for this Trend Detection Methods indicator

- MA_t= moving average value of the indicator at time step t.
- x_i = individual feature value (for example RMS) at time step i.
- n = window size, i.e. the number of most recent samples included in the average.
- $\sum_{i=t-n+1}^{t} x_i$ = sum of the last n samples from time $t - n + 1$ to time t.
- $\frac{1}{n}$ = factor that divides the sum by the number of samples, giving the average.

The moving average smooths short-term fluctuations and highlights the long-term trend of the vibration indicator, which helps to detect gradual degradation over time.

Moving Average Formula:

$$MA_t = \frac{x_t + x_{t-1} + \ldots + x_{t-n+1}}{n}$$

Figure 3.7: moving average value of the indicator at time step

Where:

- n= window size, the number of samples included in the moving average

- Denominator n = divides this sum to compute the average of these samples
- Numerator $x_t + x_{t-1} + \cdots + x_{t-n+1}$ = sum of the most recent n samples
- MA_t= moving average value of the indicator at time step t.

Linear Regression Trend:

$$y = ax + b \tag{11}$$

Where:

- a= trend slope
- b= intercept

If **a** > **0**, degradation is increasing.

Clarification:

Trend analysis gives the access to identify the progressive equipment degradation. By applying moving averages and regression models, gradual increases in vibration or temperature can be discovered before reaching severe thresholds.

3.7 Combined Predictive Indicators

In the Domaine of predictive maintenance systems, variant indicators are usually combined to reveal fault detection reliability and minimize false warning leads to waste of time. A maintenance warning may be activated when critical statistical signs of degradation turn up at the same moment, more moderately than based on a single feature.

In this chapiter, a simple combined rule is expressed: a maintenance alarm is triggered when

- RMS > RMS_threshold,
- STD > STD_threshold,
- the slope of the smoothed RMS trend is $a > 0$.

For more explanations, an alarm is announced when RMS vibration surpass the statistical threshold, the moving average of RMS shows a continuous increase, and the trend slope becomes positive. The combination of these indicators indicates higher vibration signal, higher variability, and a clearly increasing trend, which strongly suggests degradation and improves the reliability of failure prediction.

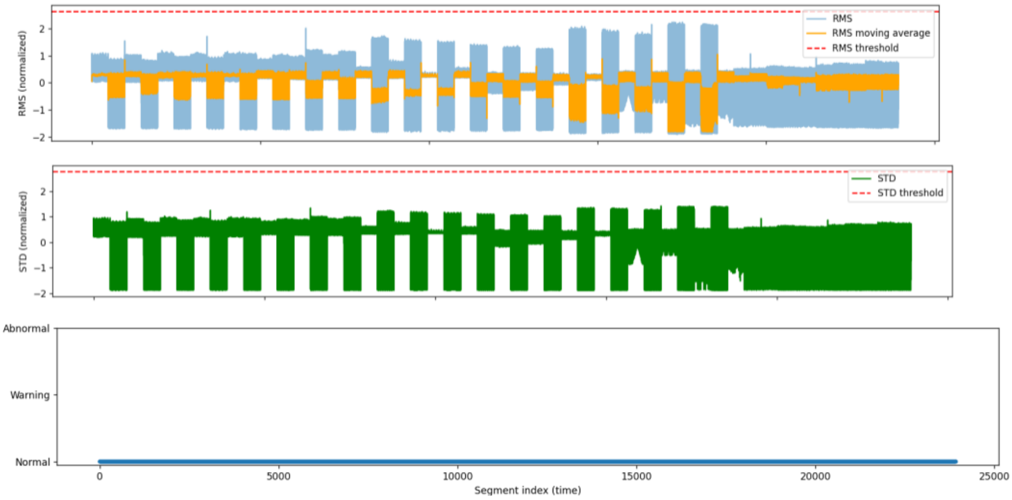

Figure 3.8: Combined predictive indicators, the corresponding health classification over time.

Explanation:

This figure indicates how applying RMS and standard deviation over time compared to their thresholds, and how these indicators are merged into a single health classification diagram state. When both indicators surpass their thresholds, the health signal change to abnormal indicating machine variation signal. It is the reason to apply maintenance and avoid several machine issues.

3.8 Practical Applicability and Limitations

The indicators used in this chapter have important practical advantages. They are easy and smple to measure, computationally efficient, and easy to inser into monitoring systems. They are also simple to interpret, which is important in industrials where maintenance decisions must have clear justification and reason to apply.

Second important advantage is that these indicators do not require huge labelled datasets. It turn them important and useful for industrial applications which historical failure data can be limited. However, the suggested approach also has limitations. The effectiveness of threshold-based monitoring depends on the quality of the healthy classification line over time data and on the choosing of the sensitivity factor. In addition, indicators like RMS and standard deviation might respond differently depending on the fault type and operating regime. Therefore, the next chapter evaluates the performance of the indicators using validation methods and classification results derived from the same processed feature set.

4 Validation of Predictive Indicators

This chapter explain the validation of the predictive maintenance indicators developed and preprocessed in the previous Chapter. The goal of the validation is to check if the predictive indicators able to reliably distinguish between normal operation and gradual degradation, and whether they able to provide predicted early alarms of critical failure in mechanical machines.

The validation is based on a simplified simulated signal collected from PU MAFAULDA operational data designed to reproduce the behavior observed in the processed PU-MAFAULDA imbalance data. This process allows the efficiency of threshold-based and trend-based indicators to be analyzed in a controlled manner before they are connected to practical maintenance decisions in the next chapter.

4.1 Introduction

This part defines the validation of the predictive maintenance indicators developed using statistical methods. The target is to examinate the ability of these indicators to discover abnormal behavior and identify early warnings of failure in mechanical machines. The goal of this process to avoid the maximum failure and assure normal health condition for the industrial machines

The validation is based on using simulated sensor data representing two operating conditions: normal operation and gradual degradation. To achieve this step there is three main indicators are evaluated:

- Static threshold analysis
- Adaptive threshold analysis
- Trend detection

These methods are evaluated through both graphical visualization and statistical performance metrics.

4.2 Data Generation and Preprocessing

To simulate realistic operating conditions, a dataset was generated consisting of two phases:

- A stable phase representing normal operation
- A degradation phase where the signal amplitude increases progressively, similar to the growing vibration level before imbalance failure.

To simulate realistic machine behavior, a one-dimensional signal was generated with two operating regions. The first region represents normal operation with approximately constant mean and low variation, while the second region represents progressive degradation with increasing signal amplitude. This behavior is conceptually similar to the increase in RMS and variability observed in the imbalance condition of the PU-MAFAULDA data.

The analyzed data were analyzed in a data frame including the plenty signal values and the associated labels illustrating healthy degraded operation. This structure give the access the validation methods to be implemented in a continuous way and assists visual diagrams of the behavior of each indicator over time.

Python Implementation

```
import numpy as np
import pandas as pd

def generate_sample_data():
    np.random.seed(42)
    normal = np.random.normal(loc=10, scale=1, size=200)
    fault = np.linspace(12, 25, 100) + np.random.normal(0, 1, 100)
    data = np.concatenate([normal, fault])
    df = pd.DataFrame({"value": data})
    df["label"] = 0
    df.loc[200:, "label"] = 1
    return df
```

Figure 4.1: Python generating the simulated validation Dataset.

The dataset reflects typical mechanical behavior such as increasing vibration amplitude due to wear.

The simulated data doesnt replace the real processed vibration features from Chapter Instead, they provide a simplified validation case that reflects the same degradation logic while remaining simple to interpret. This makes the chapter more transparnt, especially when comparing the response of different monitoring methods.

4.3 Indicator Development for validation

Three statistical indicators were implemented on the simulated data in order to reproduce the same preprocessed data in Chapter 2: moving average, rolling standard deviation, and trend detection. These indicators convert the raw signal into data easy to interpret quantities that can be compared with thresholds or monitored over time.

Moving Average

df["ma"] = df["value"].rolling(window=20).mean()

Used to smooth the signal and reveal long-term trends.

Rolling Standard Deviation

df["std"] = df["value"].rolling(window=20).std()

Measures signal variability and instability.

Trend Detection

df["trend"] = df["value"].diff()

df["trend_ma"] = df["trend"].rolling(window=10).mean()

Captures the rate of change and identifies gradual increases in the signal.

Implementation

```
df["ma"] = df["value"].rolling(window=20).mean()      # Moving average
df["std"] = df["value"].rolling(window=20).std()      # Rolling standard deviation
df["trend"] = df["value"].diff()
df["trend_ma"] = df["trend"].rolling(window=10).mean()
```

Figure 4.2: Python implementation of moving average, rolling standard deviation, and trend indicators

Those indicators provide a simplified validation environment that reflects the main use of RMS, STD, and trend slope in the PU-MAFAULDA feature analysis. Therefore, they make it visible and simple to test the indicator logic in a way that remains consistent with the rest of the thesis.

4.4 Static Threshold Validation

The static threshold is defined as: [\text{Threshold} = \mu + 2\sigma]

Implementation

```
threshold = df["value"].mean() + 2 * df["value"].std()
df["prediction"] = (df["value"] > threshold).astype(int)
```

Figure 4.3 Static threshold validation on the simulated vibration indicatorµ

Results and Interpretation :

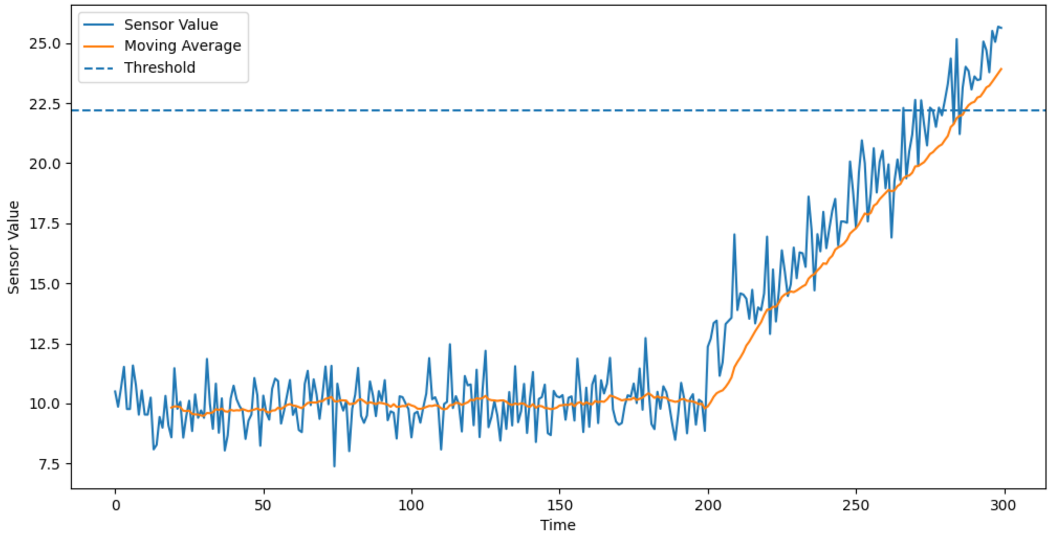

Figure 4.4 Adaptive threshold validation following the simulated degradation signal

The static threshold remains constant throughout the monitoring period:

- During normal operation, the signal is located below the threshold
- During degradation, the signal increases but stay located below the threshold for a long period

This leads to delayed fault detection and a high number of mised faults. The method lacks sensitivity to gradual degradation and is therefore not the best for predictive maintenance applications.

4.5 Adaptive Threshold Validation

To improve performance, an adaptive threshold was expressed:

[\text{Adaptive Threshold} = \text{Moving Average} + \text{Rolling Standard Deviation}]

Implementation:

```
df["adaptive_threshold"] = df["ma"] + df["std"]
df = df.bfill()
df["prediction"] = (df["value"] > df["adaptive_threshold"]).astype(int)
```

Figure 4.5 Implementation of the adaptive threshold method, combining moving average and rolling standard deviation for improved fault detection

Results and Interpretation:

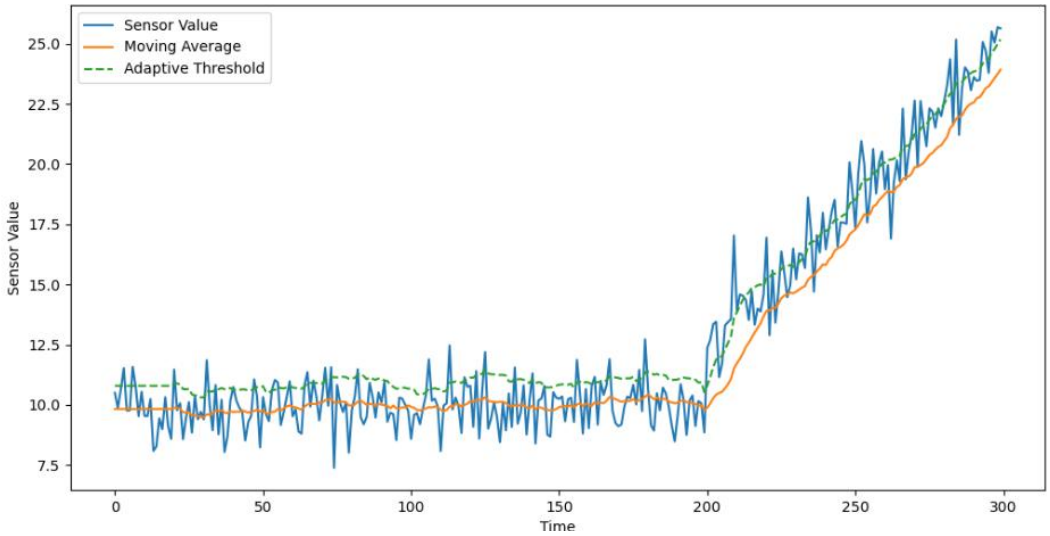

Figure 4.6 Adaptive moving-average threshold applied to a degrading vibration signal, showing earlier detection of abnormal behavior compared to the raw sensor values.

During balance operation, The adaptive threshold is located way close to the monitered signals valus without annoncing unnecessary alarms. It follows the evolution of the signal. The moment of the degradation starting, it increases automatically with the signal and provides a more locally relevant decision boundary comparing to the static threshold.

This adaptive behavior improves the practical value of the method. Because the threshold reflects both signal level and signal variability, it is better suited for non-stationary data and for systems in which degradation occurs progressively rather than instantaneously.

Compared with the fixed threshold, the adaptive method provides earlier and more context-aware detection of abnormal behaviour. This is conceptually similar to using RMS and STD thresholds derived from healthy regions in the PU-MAFAULDA data and then updating the interpretation as the monitored signal evolves.

4.6 Trend Detection Analysis

To further enhance predictive capability, trend detection was implemented to monitor the rate of change of the signal.

Implementation

```
df["trend"] = df["value"].diff()
df["trend_ma"] = df["trend"].rolling(window=10).mean()
trend_threshold = df["trend"].mean() + df["trend"].std()
df["trend_alarm"] = (df["trend_ma"] > trend_threshold).astype(int)
```

Figure 4.7 Implementation of the trend-based indicator using first differences, rolling mean, and a data-driven trend alarm threshold.

Results and Interpretation

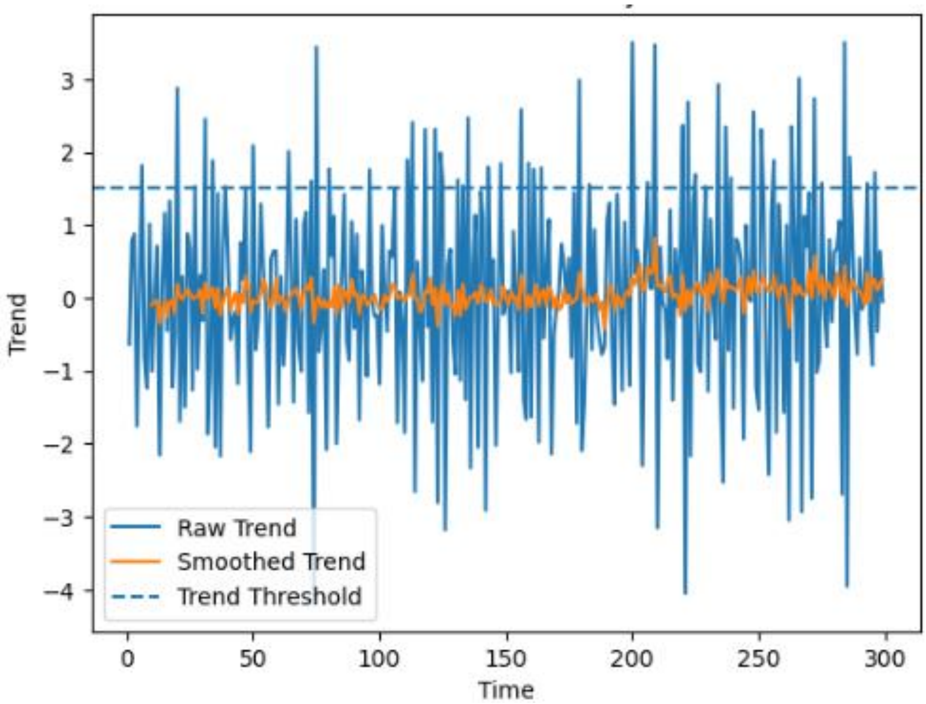

Figure 4.8 Trend detection analysis showing early warning of gradual degradation.

The trend detection combines deeper insight into system behavior:

- When the time is lower than 200 in the ideal region, the trend fluctuates around zero interrupting stable operation.
- When the time is higher than 200, in the degradation region it interrupts that the smoothed trend changed to increasingly positive with reflecting a consistent increase in the signal.

The trend threshold assist to distinguish comparing normal fluctuations with the significant increases. When the trend pass the trend threshold, we interrupt abnormal machine health condition.

This interruption is visual to observing an increasing slope of root mean square or standard deviation in the PU-MAFAULDA features: the failures accuracy may be detected and calibrated earlier than with thresholds depends only on veritas values.

4.7 Comparative Analysis

The correlation between the three methods highlights their efficiency and limitations:

Table 4.1 Efficiency in Predictive Maintenance.

Method	**Sensitivity**	**Detection Speed**	**Adaptability**
Static Threshold	Low	Late	None
Adaptive Threshold	Medium	Moderate	High
Trend Detection	High	Early	High

Comparative between static, adaptive, and trend-based predictive indicators

Fixed thresholds work for obvious failures, but they're usually too slow to catch gradual issues. Their lack of flexibility makes them a tough sell for real-world maintenance.

Adaptive thresholds offer more balance; they stay flexible to the signal's behavior without becoming a "black box" that's hard to interpret.

However, trend detection is the real gold standard for early warnings. By identifying the first signs of degradation rather than waiting for a limit to be hit, it provides the most proactive insight of the three.

4.8 Discussion

The data shows that the indicators from Chapter 2 are effective, but they work best when chosen carefully. A fixed threshold is simple, but it struggles with gradual wear. Since mechanical parts usually degrade slowly rather than failing out of the blue, you need something more flexible. Adaptive thresholds are the practical choice here they adjust to the signal in real-time, making them much more reliable when dealing with the noise and changing loads of a live operating environment.

The discussion therefore follows the main points of the thesis: simple statistical indicators can be implements and can be a input for predictive maintenance.

Together, these results justify the use of combined indicators (RMS, STD, and trend) as a robust and practical basis for the predictive maintenance strategy proposed in this thesis and prepare the ground for the maintenance scheduling rules in the next chapter.

5 Maintenance Scheduling Based on Predictive Indicators

This chapter proposes a simple maintenance scheduling strategy that uses the predictive indicators developed in Chapter 2 and validated in Chapter 3. The goal is to translate RMS-, standard-deviation- and trend-based indicators into practical maintenance decisions that reduce unplanned downtime and be suitable with industrial predictive maintenance activities.

The scheduling rules are designed for the imbalance case of the PU-MAFAULDA dataset but can be adapted to other rotating machinery. The inputs to the schedule are the time-domain features extracted from segmented vibration signals, the statistical thresholds derived from healthy operating segments, and the trend information obtained from moving averages and slope estimates.

5.1 Objectives and Inputs

The purpose of this chapter is to convert the statistical indicators into a maintenance decision framework. Instead of only identifying abnormal behaviour, the method assigns maintenance actions to health states so that interventions can be planned before the fault accuracy.

The main inputs are:

- RMS values extracted from vibration segments.
- Standard deviation values extracted from vibration segments.
- Thresholds for RMS and standard deviation calculated from healthy operating data.
- Trend information obtained from moving-average smoothing and slope estimation.
- Health classification results (normal, warning, critical) from the combined indicator analysis.

5.2 Health States and Decision Rules

Supporting practical scheduling based on the continuous indicators are converted into three machine health states: normal, warning, and critical. These signals outputs are directly linked to the thresholds and trend rules defined in the previous chapters.

Health state definitions:

- Normal state: RMS ≤ RMS_threshold, STD ≤ STD_threshold, and trend slope a ≤ 0. This indicates stable machine operation with no clear sign of degradation.
- Warning state: RMS > RMS_threshold or STD > STD_threshold, and/or a positive trend slope over several consecutive windows. This suggests that degradation has started and that inspection should be scheduled.
- Critical state: RMS > RMS_threshold and STD > STD_threshold together with a positive and persistent trend slope. This indicates strong evidence of abnormal machine behaviour and a high risk of failure.

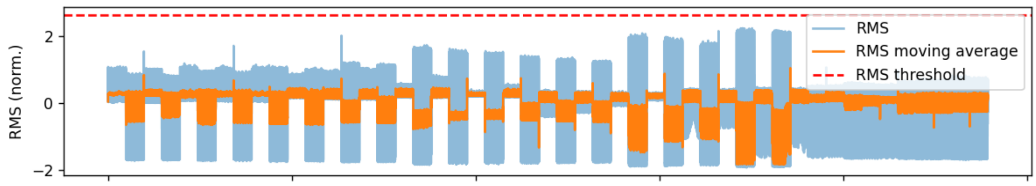

Figure 5.1 Combined RMS, standard deviation and trend indicators with the corresponding health classification (normal, warning, critical) over time.

Generation of the Health Classification Plot:

In order to obtain Figure 5.1, the normalized RMS and standard deviation features were loaded from the processed feature matrix generated in Chapter 2 (processed_features.cvs). For one accelerometer channel, RMS and STD were plotted for each vibration segment, and statistical thresholds were calculated

The first 20% of the segments, assumed to represent healthy operation using $\mu + 3\sigma$. A moving average filter was applied to the RMS to reduce short-term fluctuations, and the slope of this smoothed curve was computed to approximate the trend.

The 3 indicators RMS, STD and trend plots explains and classify the health condition: normal, warning or critical.

Practical Use of the Health Classification Plot:

This figure is useful because it visually links the statistical indicators to clear health states. It shows how the system gradually transitions from normal to warning and then to critical as imbalance develops in the PU-MAFAULDA data. Maintenance engineers can see where the warning state starts (early detection) and how much time remains before the critical region, which supports planning inspections and repairs before catastrophic failure.

5.3 Maintenance Actions and Time Windows

For each health condition directly leads to maintenance operation. The recommended decsion is based on the indicator condition also its is associated with a recommended response time. The exact intervals can be adapted depending on the plant operating constraints.

Table 5.1 – Maintenance scheduling

Health state	Indicator conditions (example)	Recommended maintenance action	Typical time window
Normal	RMS ≤ RMS_th, STD ≤ STD_th, slope ≤ 0	Continue normal operation and perform routine preventive inspection	Every 3 months or after each1000 hours of operating
Warning	RMS > RMS_th or STD > STD_th, and/or positive slope for several windows	Schedule condition-based inspection and plan maintenance at the next shutdown	Within 2 weeks or 100 operating hours
Critical	RMS > RMS_th and STD > STD_th and persistent positive slope	Perform immediate detailed inspection and prepare corrective maintenance or safe shutdown	Within 24–48 hours or at next safe shutdown

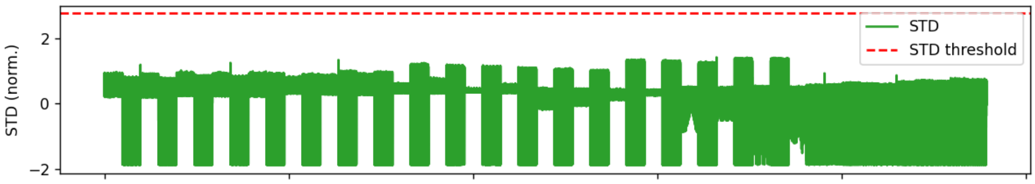

Figure 5.2 Standard deviation indicator with statistical threshold for detecting abnormal vibration behavior.

Derivation of the Indicator-Based Decision Logic:

Figure 5.2 was illustrated from the decision rules defined in Section 5.2 and the indicator behavior analyzed in Chapters 2 and 3. The upper box represents the continuous indicators computed from segmented vibration signals. Using this outputs, logi health conditions are used in condition of all indicators signals is lower than their thresholds (warning condition) the trend becomes positive, without the sudden increasing of signal or high degradation , the mechanical equipment can be considered as health condition it means normal condition.

In other hand if one or more indicators (RMS, standard deviation and trend) passes their thresholds, the warning state is accursing. When the signal of the used indicators like STD access threshold and the trend is positive it leads to the critical state is triggered. According to the diagrams we can interrupt 3 health state which is leads to a specific maintenance action and response time window, as summarized in Table 5.1.”

Role of the Decision Logic in Maintenance Planning:

This figure is important and useful because it transforms the mathematical rules to an flow diagram helps the mechanical technicians and decision makers to follow without needing to inspect raw data. It defines and explains how from viabration measurements collected by sensors signals from accelerometers leads to health decision which follows directly to repairing operations (routine inspection, planned intervention, or urgent repair). This clarity makes it easier to implement the method in practice and to embed the logic into a CMMS or monitoring dashboard.

5.4 Integration with Monitoring and CMMS

For industrial applications, this scheduling logic can be implemented directly into your available existing monitoring tools and the Computerized Maintenance Management System (CMMS). It converts raw data into action: when the applied sensor records a new vibration measurement, it automatically pulls out the key features and refreshes the health indicators. This method is way better and the have lot of benefits like avoid wasting time when person check charts and analyze it. Using this system, it evaluates the machine’s status in real-time and autonomously triggers alerts or work orders based on its current health state.

- If the machine remains in the normal state, no additional action is required beyond routine inspection.
- If the warning state is detected, the system creates a planned inspection order for the next available shutdown.
- If the critical state is reached, a high-priority work order is generated and maintenance personnel are notified immediately.
- After maintenance is performed, the observed machine condition can be recorded and used to refine the thresholds and decision rules.

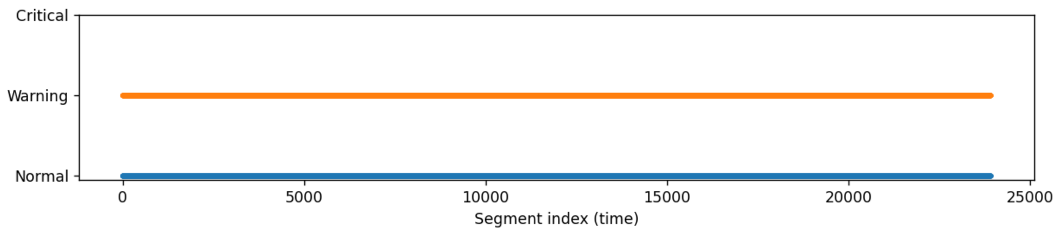

Figure 5.3 Classification of machine health condition states across the monitoring period

Construction of the Predictive Maintenance Workflow:

To illustrate Figure 5.3, the main following steps used in this thesis were arranged in a linear workflow. Sensor signals from accelerometers on the test rig are first acquired and stored. In the next part, the preprocessing and feature-extraction pipeline described in Chapter 2 is applied to generate time-domain descriptors such as RMS and standard deviation. These features feed the indicator and health-evaluation block, where thresholds and trend rules are used to assign a health state as shown in Figure 5.1 and Figure 5.2.

Expected Impact on Downtime and Costs:

The goal behind the Pdm and applying the maintenance schedule is to minimize the unplanned downtime by predicting high signal degradation and avoid several faults occurring. Additionally, the critical machines must be prioritized for immediate maintenance repairing.

This approach also helps minimize unnecessary maintenance, because equipment in the normal state continues to repair without premature replacement. As a conclusion, this technique ensure maintenance efficiency, assist better use of spare parts and labor, and leads automatically to higher equipment availability.

5.5 Solutions for Implementing the Proposed PdM Strategy

Depending on some parameters like the available sensors IT infrastructure, and staff expertise there is different ways to implement the predictive indicators. To convert from realistic transition from traditional maintenance to a predictive technique there is 2 solutions are suggested each one of them is described through a concise roadmap procedure. The steps are based on the concepts and best practices identified in the literature review and on the experience gained from analyzing the PU-MAFAULDA imbalance data in Chapters 2 and 3.

Solution 1: Implementation Of Vibration Sensors and Statistical Indicators

In the first solution, the predictive maintenance strategy is implemented directly using vibration measurments from accelerometers installed on critical rotating machines. This solution always use the same type of indicators that were developed and validated in this work like the RMS, standard deviation, and trend, so the results from the thesis can be converted to practice with minimal adaptation.

Step 1: Assessment

- Identify several machines where faults leads to high safety risks, high repair cost or downtime.
- Review the current maintenance policy (time-based or corrective) and its limitations, using historical failure and downtime records.
- Define clear objectives for the PdM project, for example reducing unplanned stops, increasing reliability, or extending component life.

Step 2: Planning

- Select adaptable vibration sensors for the working machines.
- Define a suitable cost plan which includes sensors, data acquisition equipment, data storage and essential analysis software.
- Establish data-collection rules (sampling frequency, segment length, where data are stored, and how long they are retained), as well as data-security measures.

Step 3: Implementation

- Install the sensors at the recommended emplacement on the machine, following strictly the manufacturer's instructions to obtain stable and trustworthy measurements.
- configure a simple data pipeline that segments the signals, calculates RMS and standard deviation for each segment, and stores these features in a database.
- Implement the health-state rules from Table 4.1 so that each new segment is classified as normal, warning, or critical in near real time.

Step 4: Analysis

- Use historical data from clearly healthy periods to predict the maximum value before the failure occurs for RMS and standard deviation and to establish baseline trends.
- Compare the changes indicated by the health indicators with the actual machine condition and maintenance records, and adjust the threshold sensitivity when necessary.

Step 5: Optimization

- Refine thresholds, trend windows, and alarm logic based on experience from operators and maintenance technicians.
- Develop user-friendly dashboards that show the indicators and health status for each machine, and configure automatic alerts for warning and critical states.
- Provide short training sessions so that staff can correctly interpret RMS/STD/trend plots and respond consistently to each health state.

Step 6: Evaluation

- Routinely assess the predictive maintenance implementation with the predictive indicators such as number of sudden failures, downtime, and repairing expense per year.
- Compare the PdM results with the situation before the PdM to measure the improvement and the benefits then use the evidence to interrupt whether the approach should be scaled up

This figure summarises the six main stages of Solution 1: assessment, planning, implementation, analysis, optimization, and evaluation.

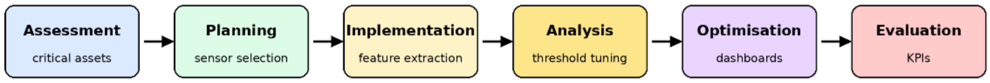

Figure 5.4 Roadmap for implementing predictive maintenance using vibration sensors and statistical indicators.

Solution 2: Integration with Existing Operational Data and Advanced Analytics

The second solution is intended for plants where some operational data are already collected (e.g. process variables, PLC signals, or maintenance logs). In this case, the statistical indicators from this thesis can be combined with additional features and, if desired, with more advanced analytics models. The statistical indicators remain as an interpretable reference, while the extra data improve detection performance.

Step 1: Assessment

- Identify available data sources such as SCADA systems, production databases, and maintenance records for the selected machines.
- Assess data quality, sampling rates, missing values, and alignment between sensors and events to determine whether extra sensors are required.

Step 2: Planning

- Design a data architecture that brings together vibration features (RMS, STD, trend) and other relevant process variables into a common dataset.
- Select analysis tools for example Python scripts for the code implementation, anomaly-detection methods for the algorithms, or Random Forest models equivalent to the ones used in Chapter 2 and distinguish responsibilities for data management.

Step 3: Implementation

- Set up an automated process to collect vibration indicators and organize data into a feature table.
- Implement basic models that use this combined data to assign health states or anomaly scores, and connect their output to the CMMS so that alarms can create or prioritize work orders.

Step 4: Analysis

- Evaluate model performance using historical events, checking how often the models correctly identify known faults and how many false alarms are generated.

- Compare the performance of "combined data" models with the statistical-indicator-only approach to quantify the added value of the extra information.

Step 5: Optimization

- Periodically recalibrate or retrain the models as more data become available or as machines are modified.
- Adjust alarm thresholds, health-state boundaries, and model parameters based on operational experience and the cost of false positives and missed detections.
- Involve operators and maintenance staff in reviewing incorrect predictions and feeding their domain knowledge back into the models.

Step 6: Evaluation

- Analyze the long-term impact of the integrated PdM solution on downtime, maintenance costs, and production stability.
- Compare these benefits with the investment in data infrastructure and analytics expertise, using the cost benefit reasoning introduced earlier in this chapter.
- Use the results to decide whether to scale the solution to more assets or add further data sources

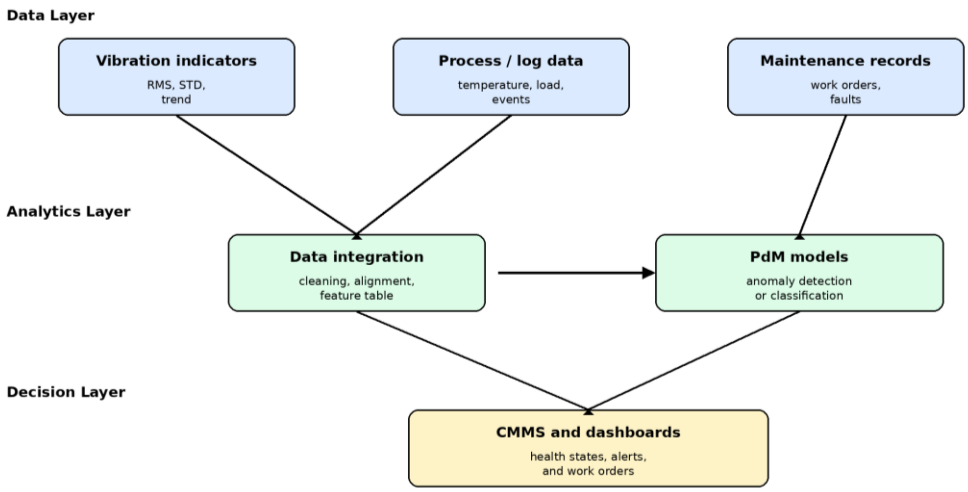

Figure 5.5 Roadmap for integrating data and advanced analytics with the PdM implementing

Explanation:

This figure shows how vibration indicators, process data, and maintenance reports can be useful for analytics models and related to CMMS dashboards and alerts.

The resulting health information and alerts are finally delivered to CMMS and dashboards, which they can be useful for the maintenance technicals to schedule maintenance operations for the mechanical equipment. As conclusion for this roadmap this method is more complicated to implement comparing to first solution

We can interrupt that Solution 1 is more simple while the second is more upgraded and scalable path but it requires log data.

Table5.2 *Comparison of the two suggested solution for the predictive maintenance*.

Aspect	Solution 1	Solution 2
Main approach	Direct vibration-based PdM.	Integrated PdM using vibration and operational data
Data source	Accelerometer signals.	Vibration, process and maintenance data.
Feature set	RMS, standard deviation, trend.	RMS, standard deviation, trend, plus additional variables.
Method	Rule-based health states.	Statistical indicators with advanced analytics.
Complexity	Low.	High.
Interpretability	High.	Moderate.
Implementation	Simple deployment.	Data integration required.
Cost	Lower.	Higher.
Expected outcome	Practical baseline solution.	Improved detection performance.
Best use case	Critical rotating machines.	Plants with existing data infrastructure.

6 Conclusions and Future Work

This chapter defines all the main results of the thesis and defines their consequences for predictive maintenance in mechanical component. First, it sum up how the statistical vibration signals and maintenance scheduling framework responded the research goals and assisted the deduction of unplanned downtime. So, it explains and confirm the main limitations of the report, especially in terms of dataset scope, modeling choices, and lack of real time deployment. Finally, this part suggest steps to follow for future research and industrial operations, enhancing how the presented idea can be combined with more advanced data-driven and machine learning techniques in modern maintenance practice.

6.1 Conclusions

As Conclusion, this thesis investigated the use and validations of simple statistical indicators for predictive maintenance of rotating machinery based on vibration data. The main target of this report is focused on extracting and analyzing real time-domain features from the PU-MAFAULDA dataset, using the following indicators RMS, standard deviation, and trend-related information, in order to distinguish abnormal machine helth conditions and support maintenance planning.

The validation chapter defines that different statistical methods clarify in multiple ways to predict the fault. Static thresholds were valuable for the identifying of simple abnormal conditions, adaptive thresholds refines sensitivity to changing behavior, and trend detection was exceptionally successful for detecting gradual high signal degradation at an earlier stage. By merging these indicators, the method accomplished a better health condition than using only one of the indicators.

Based on these results, the thesis developed a practical maintenance scheduling framework that converts continuous vibration indicators into three health states: normal, warning, and critical. Each state was linked to a specific maintenance action and response time, which makes the method easier to apply in an industrial environment. Two implementation solutions were also proposed: a simple sensor-based roadmap and a more advanced roadmap integrating vibration data with additional plant information and analytics. Overall, the study concludes that simple statistical predictive indicators can provide an effective and understandable foundation for predictive maintenance in industrial rotating equipment.

6.2 Limitations

Even though the results of this thesis are promising, the work has several limitations. First, the work focused mainly on vibration based statistical indicators and on the imbalance case of the PU-MAFAULDA dataset, which means that the conclusions are based on a limited fault type and a controlled dataset rather than on several real industrial failure cases. This limits the direct applicability of the outcome to other machinery types, operating environments, and malfunctioning mechanisms.

Second, the maintenance scheduling technique was improved as a conceptual and analytical framework, but it was not deployed in a real time industrial monitring system or connected to an actual CMMS platform. As a result, the thesis does not evaluate long-term practical issues like the sensor noise in the industry, operator interaction, alarm fatigue, or performance drift over time. In addition, the work relied on relatively simple statistical indicators and did not include a full comparison with advanced machine learning or deep learning models.

6.3 Future Work

Future work can extend this thesis in several useful directions. One important step would be to test the proposed indicators and scheduling logic on additional fault types such as bearing damage, misalignment, or looseness, and on more diverse industrial datasets. This would help evaluate how robust the method is across different machine conditions and application areas.

Another important direction would be to combine the current statistical framework with machine learning methods. For example, RMS, standard deviation, and trend indicators could be used as input features for classification or anomaly detection models in order to insure fault prediction accuracy and automate decision making further. It would also be valuable to deploy the approach in a live monitoring environment connected to a CMMS or dashboard so that the usefulness of the method can be assessed in practice over a longer period.

6.4 Economic Aspects

From an economic perspective, predictive maintenance can minimize the cost of sudden downtime and improve maintenance efficiency by scheduling maintenance operations only when machine health condition status is indicate warning. The framework developed in this thesis give the access critical state machines to be serviced during planned downtimes while critical machines can be prioritized for urgent intervention, which assists better efficiency of labor, spare parts, and maintenance time. This procedure is practical to improve the equipment health condition status and minimize unnecessary maintenance operations.

6.5 Present Progress of Predictive Maintenance

Today, predictive maintenance is developing and upgrading day by day with the presence of machine learning, developed industrially sensors, and connected monitring systems. Modern approaches can analyze huge amounts data of vibration, temperature, and process data to detect hidden patterns, predict fault accuracy, and assist earlier and more efficiency maintenance decisions than traditional maintenance strategies such as scheduling.

Acknowledgement

I am deeply grateful to everyone who assisted building this thesis research a success. First, Dr. Krisztián Deák supervisor of this thesis, whose teaching in the Maintenance and Diagnostics class strongly influenced me to choose this thesis topic. His guidance motivated me to study maintenance strategies deeply and greatly influenced the direction of my research. Thanks to my mentor and classmate Khaleel Alkhateib, for his support and guidance on this thesis framework. Ultimately, special thanks to Mr. Amir Thabet for he guidance also for the for his valuable guidance and support, especially in the Python implementation of this thesis.

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