FACULDADE DE ENGENHARIA DA UNIVERSIDADE DO PORTO

Predictive Maintenance Support System in Industry 4.0 Scenario

Rodrigo Ardachessian Costa

Mestrado Integrado em Engenharia Eletrotécnica e de Computadores

Orientador Interno: Prof. Luis Miguel Pinho de Almeida

Orientador Externo: Eng. Fábio Silva

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Resumo

A quarta revolução industrial que está a ser testemunhada atualmente, também conhecida como Indústria 4.0, está fortemente associada à digitalização dos sistemas de produção e à integração de diferentes tecnologias para otimização da produção. Ao combinar a aquisição de dados através de sensores específicos e algoritmos de *machine learning* para analisar os dados adquiridos e prever uma falha antes que esta aconteça, a Manutenção Preditiva é uma ferramenta crítica a ser implementada para reduzir o tempo de paragem devido a erros ou falhas.

Com base na realidade da fábrica de *Conti Special Tires* da Continental Mabor - Indústria de Pneus, S.A., o presente trabalho fornece uma descrição de vários problemas relacionados com a manutenção de equipamentos. Aproveitando as informações recolhidas no estudo dos processos incorporados na fábrica, concebemos um modelo de solução para aplicar um sistema de manutenção preditiva sobre esses processos.

O modelo é dividido em duas camadas principais, o *hardware* e o *software*. A camada de hardware consiste em sensores e respectivas aplicações. A camada de software compreende técnicas de análise de dados, nomeadamente algoritmos de *machine learning*, para analisar os dados adquiridos e detectar possíveis falhas.

Os algoritmos de *machine learning* para detetar, diagnosticar e prever falhas com base nos sinais de vibração de rolamentos foram desenvolvidos para serem implantados numa máquina específica que deve ser equipada com os sensores adequados. Após testar os algoritmos, estes poderão ser expandidos para lidar com outro tipo de sinais complexos.

Os algoritmos foram desenvolvidos em MATLAB e testados com dados disponibilizados pela MathWorks, com apoio da *toolbox* de MATLAB relativa a Manutenção Preditiva. Com os dados utilizados, os resultados obtidos foram positivos, sendo que foi possível detetar, diagnosticar e prever a ocorrência de falhas.

Abstract

The fourth industrial revolution that is being witnessed nowadays, also known as Industry 4.0, is heavily related to the digitization of manufacturing systems and the integration of different technologies to optimize manufacturing. By combining data acquisition using specific sensors and machine learning algorithms to analyze the data and predict a failure before it happens, Predictive Maintenance is a critical tool to implement towards reducing downtime due to unpredicted stoppages caused by malfunctions.

Based on the reality of Conti Special Tires plant at Continental Mabor - Indústria de Pneus, S.A., the present work provides a description of several problems faced regarding equipment maintenance. Taking advantage of the information gathered from studying the processes incorporated in the plant, we conceived a solution model for applying predictive maintenance in these processes.

The model is divided in two primary layers, the hardware and software. The hardware layer consists of sensors and respective applications. The software layer contains techniques of data analysis namely machine learning algorithms to study the collected data to detect possible failures.

Machine learning algorithms to detect, diagnose, and predict failures based on bearing vibration signals were developed to be deployed into a specific machine that should be equipped with the proper sensors. After testing the algorithms, these could be expanded to handle other complex signals.

The mentioned algorithms were developed using MATLAB, with the support of the Predictive Maintenance toolbox, and the datasets used for training and testing are available in the MathWorks database. We obtained positive results, as the implemented algorithms were able to detect, diagnose, and predict the occurrence of failures.

Acknowledgements

I want to thank my supervisor, Professor Luis Almeida, for all the guidance, help, and availability shown throughout the project. I would also like to thank Eng. Fábio Silva for all the support and advice provided. To the rest of the Engineering Department #7 team at Continental Mabor - Indústria de Pneus, S.A., thank you for welcoming me and making me feel like a team member, even if it was for a short period.

To my family and friends, thank you for all the support and encouragement.

Rodrigo Ardachessian Costa

*“I will not lose, for even in defeat,
there’s a valuable lesson learned, so it evens up for me.”*

Shawn "Jay-Z" Carter

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Glossary

BR	Big Radial
CGMS	Continental Global Manufacturing Systems
CPS	Cyber-Physical Systems
CST	Conti Special Tires
FFT	Fast Fourier Transform
HMI	Human-Machine Interface
MCSA	Motor Current Signature Analysis
ML	Machine Learning
PM	Predictive Maintenance
PCA	Principal Components Analysis
RUL	Remaining Useful Life

Chapter 1

Introduction

1.1 Context & Motivation

The present dissertation was carried out in an industrial environment, at Continental Mabor - Indústria de Pneus, S.A., a company whose main focus is tire manufacturing. Production is divided into two plants: Passengers & Light Tires (PLT) Tires and Conti Special Tires (CST). The work was developed in the Engineering Department #7, associated with the CST plant.

Today's industry is extremely oriented towards increasing efficiency and reducing costs and downtime at the production level. With this, efforts have been made to evolve to zero time loss due to malfunctions. However, malfunctions are usually difficult to solve since they involve the detection of the problem and correction or replacement of the equipment, being one of the main causes of delays in terms of production [60]. Therefore, the new industrial revolution, known as Industry 4.0, aims at implementing a predictive maintenance (PM) system, that is, a system capable of detecting anomalies in the production line, thus anticipating possible malfunctions and providing this information to the maintenance staff so they can perform the proper maintenance before the failure occurs.

Taking into account the current industrial state, the above-mentioned system proves to be extremely advantageous as it should predict the occurrence of malfunctions before they happen, allowing the maintenance team to intervene on the machine prior to the failure, reducing stoppage time. In addition, it also makes possible discarding the current maintenance plan based on standard periods of time for calibration or equipment replacement. The referred plan is standardized as mandatory in most industries but has been proven inefficient, as mentioned in [33]. In this way, it is possible to reduce the costs related to maintenance or replacements that are sometimes unnecessary, as these will be carried out only based on the indications obtained by the new monitoring system.

In order to develop the mentioned system, it is vital to understand and characterize the machine in which the system will be implemented. Therefore, a scheme containing the processes, inputs and outputs, failure rates, installation complexity, and criticality for the process, should be developed.

In addition, a reliability study must be carried out, which will represent the probability of the system performing the function for which it was designed continuously for an interval of time. For this, the characterizations of failures and the frequency of their occurrence must be understood [50].

The aforementioned monitoring implies the proper sensor placement in the equipment to be controlled for real-time data acquisition. Depending on the system selected, the critical parts to be monitored may fall into the categories of hydraulics, pneumatics, motors, rotors, electrical panels, among others. For this, the set of sensors must be chosen and placed carefully and appropriately. Also, as mentioned, it is intended to acquire data in real-time, which implies their integration in a communication network with this capacity. Concerning data collection, we must take into account the types of failures that may occur, how the failure process develops, and what parts of the system relate to each type of failure.

Based on the acquired data, a machine learning (ML) algorithm can be developed. The algorithm should provide automatic anomaly detection and prediction and can vary in terms of complexity, depending on the type and amount of data available and the existence of historical data for training and verification.

At last, to provide the information to system users, it is essential to create a human-machine interface that presents the acquired data and history in a simple, organized, and intuitive way.

With this motivation and context, we set out the objectives in the following section.

1.2 Dissertation Goals

This project will consider the set of preparation and construction machines at Continental Mabor's Conti Special Tires (CST) unit, as previously mentioned. Therefore, we set the following objectives:

- Contextualization with the machine set, studying processes, inputs, and outputs, and the monitoring already installed.
- Damage and breakdown reports analysis with the purpose of identifying the main components to monitor, considering their relevance on the machine and their impact on production.
- Comparative assessment of possible sensors and monitoring techniques for the different components identified, considering the complexity and cost of installing the equipment.
- Model machine identification and functional layout design, taking into account the impact of failure rates of the various components and respective failure modes.
- Solution development, presenting the main components to be monitored and the respective monitoring techniques to be carried out. Sensor listing for budgeting purposes should be taken into account, as the solution is intended to be installed in an industrial environment. Furthermore, algorithms to detect, diagnose and predict failures should be developed, trained, and tested.

- Sensor installation and PLC level data acquisition and treatment.
- Developed algorithms deployment and adjustment based on the acquired real data.
- Implementation of a HMI to provide clear information to the maintenance team.

1.3 Results of this Dissertation

With the objectives referred above, we started by doing a preliminary study of subjects related to the work to be developed, such as PM, ML algorithms, reliability models, and sensors for component monitoring. Within the premises of Continental, we performed an analysis of the processes included in the CST plant and a review on the 2019 breakdown report. Unfortunately, the COVID-19 pandemic forced a shutdown of the plant that forced us to continue the work remotely. However, this had a strong impact on the work since it was impossible to deploy an actual system in a concrete machine. Therefore, we used MATLAB as a basis for developing our work, implementing and testing our algorithms with the data set provided in the MATLAB Predictive-Maintenance Toolbox. In summary, we achieved:

- Process contextualization, reviewing operation manuals and the breakdown report available.
- Model machine layout design and maintenance protocols.
- Sensor identification for different types of components and quantities.
- ML algorithms developed with MATLAB for detecting, diagnosing and predicting failures, using MathWorks data sets.

1.4 Dissertation Outline

In addition to the Introduction, this document includes 4 chapters. Chapter 2 reviews the literature approaching the main concepts in the scope of this dissertation. Chapter 3 describes the problem in which this work is based on, analyzing failure reports and identifying the main components to monitor from these. It also describes the methodology to be followed. The proposed solution is exposed in chapter 4 which explains the methods and tools (software and hardware) to be used. Lastly, chapter 5 reviews the work that was carried out in this project and presents perspectives for future work.

Chapter 2

Literature Review

This chapter describes critical techniques and concepts for a better understanding of the solution that will be presented later on. It covers the topics of data treatment, machine learning algorithms, reliability models, sensors working principles, and development of human-machine interfaces.

2.1 Machine Learning applied to Predictive Maintenance

Failures in industrial machines have a wide range of variety regarding the failure complexity and the consequences it incurs. While simpler cases may only require components replacement, others can cause serious accidents, costing millions in terms of production, injuries, and environment pollution [2]. Thus, maintaining good maintenance programs to quickly solve or avoid faults can be very rewarding. Currently, there are 3 types of maintenance being used in the industrial context [33][46]:

- Run-to-Failure - interventions occur only after failures occur.

- Time-based - maintenance is performed according to a schedule based on the number of the process iterations. It is better than the Run-to-Failure type in terms of avoiding failures but sometimes incurs in unnecessary expenses or the failure still occur ahead of schedule.

- Condition-based - through automatic fault detection and prediction systems, this type monitors the state of the machine or component in real-time, and maintenance is performed based on the state estimate, which enables efficiency improvement and cost reduction, regarding equipment replacement and associated down-time.

The last type, also called PM, is the one with a higher economic benefit and production efficiency. Therefore, it is the principal focus in the sections that follow.

2.1.1 Predictive Maintenance Basic Concepts

PM is based on a decision support system that contains indicators representing the system state. These indicators are associated with specific problems to be solved [46] [67]. Consequently, considering all types of failures is crucial. The failures can be detected through parameter analysis such as geometric measurements, vibrations, temperature, lubrication oils, among others [48].

In this case, to deal with large amounts of data from various sensors ML algorithms are very beneficial, as they allow building different analysis and forecasting models. The type of algorithm used may vary depending on historical data availability.

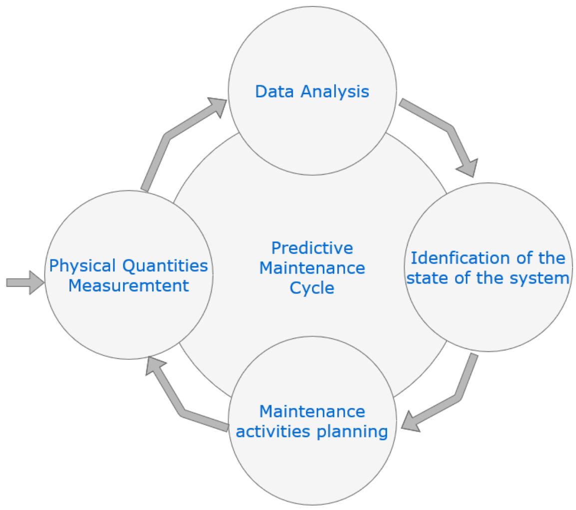

Figure 2.1: Predictive Maintenance Process

As described in figure 2.1, a PM cycle starts by measuring machine physical characteristics through the installed sensors. The acquired data is then transmitted to the module responsible for processing and analyzing using an appropriate ML algorithm, which will try to characterize the current system state, identifying if it is correct or has some type of anomaly or defect. If an anomaly is detected, it must be displayed on the HMI allowing the user to make an informed decision regarding the equipment maintenance or correction.

2.1.2 Data Pre-Processing

The collected data often contains irrelevant or redundant parts, in particular noise or incomplete data, which needs to be filtered before starting the ML detection algorithm training phase. For this, the data must go through several pre-processing phases, as stated in [48]:

- Cleaning - Filter the signal to reduce noise and irrelevant data. The corrupted data, like outliers points, should be smoothened or eliminated.

- Integration - Group data from different sources, improving the component estimated state precision. Considering that data from different sources may have different standard scales, it is crucial to adjust the scales ensuring that all measurements have the same "impact" classifying the component. Autoscaling, mentioned in [55], is a technique used for this purpose.

- Reduction - reduce the data volume, simplifying the detection algorithm complexity, while ensuring that the same classification is obtained.

- Transformation - consolidate the data in order to apply the desired algorithm.

The acquired data can be simple, where only a certain absolute value is recorded at each moment along with the respective timestamp, or it can be more complex, like acquiring component vibrations, in which it is necessary to filter the noise, extract the relevant part within the time spectrum and possibly make a conversion to the frequency domain. This last function requires a higher pre-processing treatment. Therefore, the complexity of the steps mentioned above may vary, depending on the amount and type of the data being acquired.

For the latter case, i.e., more complex signals such as vibration or current, it is not the acquired signal that is used directly as input to the monitoring system, but rather some of its characteristics in the time and frequency domain, for instance, maximum, minimum, mean, standard deviation, asymmetry, kurtosis, and RMS values [7][83]. Generally, two methods are used to extract the referred characteristics in the frequency domain: a Fourier transform or wavelet transform. The first is useful in simpler cases, especially when the signal resembles a sinusoidal wave and does not exhibit sudden variations. However, frequently the signal presents abrupt irregularities and in this case, the wavelet transform is most suitable, as it does not express the signal as a sum of sine waves, but as a sum of wavelets, granting better analysis flexibility [86].

After extracting the characteristics, as already mentioned, it is essential to reduce data quantity to be inserted in the model, since often excessive data is proved to be irrelevant or redundant, only contributing to increasing model complexity while not affecting the quality of the solution. The most common method used for this purpose is called Principal Components Analysis (PCA), which highlights the most relevant components of the dataset. The PCA algorithm transforms the data matrix into a projection of that same matrix sorted by order of variance, allowing the columns with the highest variance to be emphasized while discarding the ones with the lowest variance, considering that the latter will have a near-zero impact on the detection algorithm, performing the desired dimensional reduction [54][55]. The algorithm works as follows [6]:

1. Considering the acquired dataset stored in a matrix $[\mathrm{X}]_{\mathrm{mxn}}$, where each line (m) represents a different acquisition and each column (n) a different measure;

2. The mean is subtracted to each dimension:

$$[X]_n - [\bar{X}]_n \tag{2.1}$$

3. Compute de covariance matrix $[\mathrm{c}]_{\mathrm{mxn}}$ and the respective eigenvectors and eigenvalues:

$$([c]_{nxn} - I_{nxn}\lambda)X_{nx1} = 0 \tag{2.2}$$

4. Store the eigenvector in a matrix and the eigenvalues in a diagonal matrix:

$$[P]_{nxn} = [\{X_1\}\{X_2\}...\{X_n\}] \tag{2.3}$$

$$[Val]_{nxn} \tag{2.4}$$

5. Sort the eigenvalues matrix by decreasing order and determine the number (r) of values to keep. The same process should be applied to eigenvectors matrix:

$$[Val]_{rxr} \tag{2.5}$$

$$[P]_{nxr} = [\{X_1\}\{X_2\}...\{X_r\}] \tag{2.6}$$

6. Lastly, the principal components matrix [U] is calculated, which is projected in the data matrix:

$$[U]_{mxr} = [X]_{mxn}[P]_{mxr} \tag{2.7}$$

Ultimately, we can analyze the importance of each component and define how many components we intend to consider to obtain a certain precision. Some programs, like MATLAB, already have functions that automatically apply this algorithm based on the Singular Value Decomposition.

2.1.3 Types of Algorithms

Generally, ML algorithms use 3 different types of inputs: previous failures records, maintenance records, and real-time machine operating conditions. Depending on the availability of these types of information, the choice of an algorithm may vary. The algorithms fall into two broad categories: predictive or supervised and descriptive or unsupervised [46][48].

2.1.3.1 Supervised Algorithms

Supervised algorithms are suitable for situations where the input and result data are available, enabling the training of a classification system. By using the trained classification system with new input data (interpolated or extrapolated), it is expected that the results will remain consistent [26]. Algorithms like Decision Table, Random Forest, Support Vector Machine, Neural Networks (Perceptron) are some examples in this class.

As stated in [18] and [26], the procedure for implementing this type of algorithms must follow the steps in the figure 2.2.

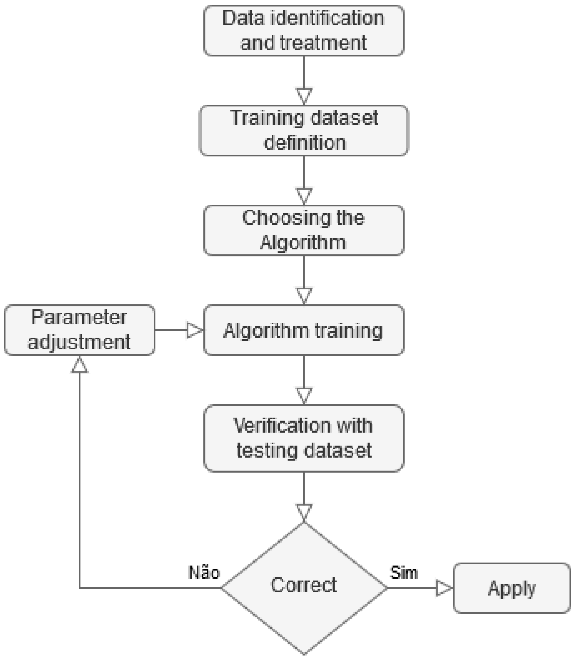

Figure 2.2: Supervised Algorithms Implementation Process - Source: [26]

The first step is to define what is to be detected, i.e., the function outputs, based on the available data. Then, determine the set of examples that will be used for training the algorithm, and the set for testing and validating. With these established, algorithm training should be started, evaluating its reliability at the end of each iteration and making the necessary parametric adjustments, until the model provides a consistent detection, reflecting what was initially observed from the data source.

2.1.3.2 Unsupervised Algorithms

The unsupervised algorithms class is utilized when there are only logistical and process data and there is no data related to failures and previous maintenance, i.e., it is not known beforehand the corresponding correct detection values for the input data. These algorithms are used to build models without historical data since these allow cluster identification. Therefore, to classify the obtained data, the recognized clusters may be classified as 'stable', 'in danger', and 'faulty', for example. Through tests using acquired data, the algorithm parameters can be adjusted, improving the accuracy of the solution until it reaches a static level. Hotelling T^2 Statistic, Hierarchical clustering, K-means, Fuzzy C-Means clustering, and Model-based clustering, are some of the algorithms included in this class [6][46]. Considering that in the present work there is no historical data available to train the algorithms, these type of models should be preferred.

Hotelling T^2 consists in a multivariate analysis used for online monitoring as it is calculated for each new observation [35]. The upper confidence limit is obtained using the F-distribution, where n is the number of samples, a is the number of principal components, α is the level of significance [6]:

$$T^2_{l,n,\alpha} = \frac{l(n-1)}{n-l} F_{l,n-l,\alpha} \tag{2.8}$$

It is used as a detection method and does not provide fault classification, as it only allows comparing the values with a defined threshold and the points above this will indicate the occurrence of a fault.

The clustering algorithms are able to identify different failure stages by assigning each cluster to a different stage. The number of clusters can be determined using various methods, such as the elbow method or Bayesian inference.

Regarding the Hierarchical Clustering algorithm, as the name implies, the clustering is performed hierarchically and follows the subsequent steps:

1. Define each data point as an individual cluster;
2. Group into one cluster the two nearest clusters;
3. Calculate new distances between clusters, having into consideration the new cluster;
4. Repeat the previous steps until the ideal number of clusters previously defined is reached.

The K-means algorithm divides data into a predetermined number of clusters based on the Euclidean distance between them. In the Fuzzy C-means algorithm, each data point belongs to all clusters in different degrees.

Model-based algorithms assume that data can be grouped according to a given model, for example, the Gaussian Mixture Model. This model is used when the data points can be modeled by a Gaussian distribution. Thus, it seeks to calculate an estimate of density as a non-parametric method, since it tries to group a set of supposedly random values according to a known distribution, providing a probability for the equipment state.

2.2 Reliability Models

As stated in [50], reliability is defined as the probability of a system acting according to its design purpose, i.e., fulfilling the function it was designed for, during adequate time intervals.

Reliability models are mathematical models that associate different system components and respective failures, which can be conducted by ML data analysis, as seen previously.

2.2.1 Principles and Methodology

System characterization in terms of reliability is based on a model development that should take into account the type of data and quantity available, whether it is regarding a machine or a production cell. Furthermore, it is also vital to consider the fault coverage, i.e., the probability of the system being able to perform its function after the occurrence of a failure.

The standard methodology is based on the following steps [13]:

1. Define the elements susceptible to failure, i.e., the components or subsystems that constitute the system and the connections among them;

2. Identify failure modes and equipment performance limits;

3. Develop a simulation model based on a given platform, to test the failure's effect;

4. Perform tests by simulating faults;

5. With the results obtained, analyze all combinations of existing failures, in order to define the system failure coverage index;

6. Finally, with all the necessary data acquired, build the reliability model.

During the application of this methodology, some difficulties may be uncovered, such as quantifying all the system characteristics. Ergo, it might be necessary to assume some of the unknown values, based on the component structure, or consider generic parameters values [12]. Regarding the causes of failure, two groups of responsible mechanisms are considered: shock and degradation or natural wear [85]. In other words, typically historical data is required to perform the model estimation, however, if this data is not available, the model can be based only on the known failure rates.

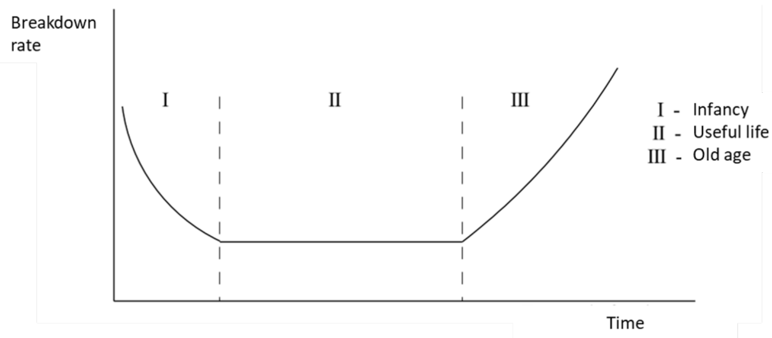

Figure 2.3: Breakdown Rate Evolution Overtime - Source: [50]

As highlighted in figure 2.3, the failure rate evolution is divided in three major periods:

- Infancy - the rate is high in this period with a tendency to decrease and stabilize. The main causes of damage are equipment deficiencies or defects caused during transportation or installation.

- Useful life - usually the reliability studies focus on this time interval, where the variation is practically zero.

- Old age - Period in which specific equipment or components reach high levels of wear becoming obsolete, causing an increase in the failure rate. This condition can be avoided by performing maintenance, by repairing or replacing components.

2.2.2 Component Reliability

Considering that the reliability studies are made for the useful life span of the equipment as mentioned in [50], i.e., after passing the infancy period, the reliability of a component at time t (R(t)) can be defined as in Eq. 2.9, in which λ(t) is the failure rate as a function of time

$$R(t) = e^{-\int_0^t \lambda(t)dt} \tag{2.9}$$

Thus, reliability can be described as the probability of obtaining 0 malfunctions at a certain time t. Assuming a constant failure rate λ in the useful life period, reliability can be obtained through Eq. 2.10.

$$R(t) = e^{-\lambda t} \tag{2.10}$$

Ergo, it is possible to define the mean time between consecutive failures (MTBF - Mean Time Between Failures) as

$$MTBF = \frac{1}{\lambda} \tag{2.11}$$

2.2.3 Availability

In addition to the reliability of a component, system, or equipment, availability is also very significant information. In some industry cases, availability is even more valued than reliability, as it provides an easier understanding of maintenance downtime issues. According to [41], availability can have several definitions, such as inherent, achieved, or operational.

Inherent availability (D_I) considers only corrective maintenance interventions, i.e., when system malfunctions occur and it is necessary to repair or replace a component. This allows to evaluate the performance of a given system between planned shutdowns and is given by:

$$D_I = \frac{MTBF}{MTBF + MTTR} \tag{2.12}$$

where MTTR - Mean Time To Repair - is the average time it takes to perform a corrective maintenance activity.

Achieved availability (D_A) aims to quantify the probability of a system being available to operate at a certain time, taking into account all the maintenance work, i.e., corrective but also preventive maintenance activities. It is calculated as:

$$D_A = \frac{MTBM}{MTBM + \bar{M}} \tag{2.13}$$

where MTBM - Mean Time Between Maintenance - represents the average time between maintenance activities on the system, regardless of its type, and $\bar{M}$ - represents the average time of these activities,where stopping the machine is mandatory.

Lastly, operational availability (D_O) is an indicator used often at administrative level or customer perspective assessments as it represents precisely availability from the customer's point of view. It considers the total monitoring time in which the calculation is performed (cycle) and the actual time the system was operating/producing during the monitoring cycle (uptime). Thus, is determined by:

$$D_O = \frac{Uptime}{Cycle} \tag{2.14}$$

2.2.4 Types of Predictive Models

As mentioned in [60] and [72], predictive modeling techniques are divided into 3 major groups:

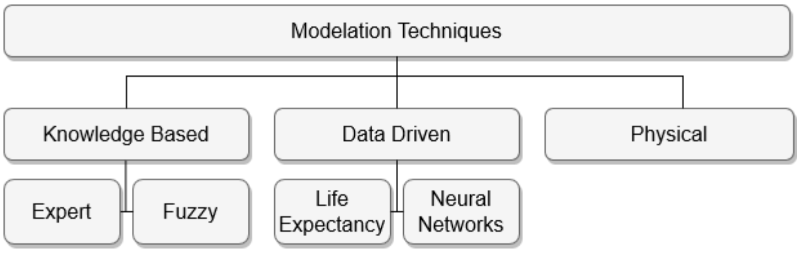

Figure 2.4: Predictive Models Taxonomy - Adapted from [72]

Regarding the Knowledge-Based category, the models are defined based on a set of previously defined rules. These are divided into Expert Systems - where the knowledge of an expert in the matter is translated into a set of rules - and Fuzzy Logic - for when there is a lack of information and it is not possible to define specific intervals for rule establishment.

The models in the Data-Driven category are built based on historical and real-time data. They are divided into Life Expectancy and Artificial Neural Networks. Life Expectancy models are characterized by individually determining the reliability for each component taking into account the expected deterioration, while Artificial Neural Networks determines an estimate of the system reliability based on a mathematical model generated from historical data, without needing to understand failure processes.

Physical models are the most complex and challenging because they consist of mathematical analytical models that simulate physical processes and are very specific to each application, making the adaptation to different situations very hard.

2.3 Systems and Components Monitoring

One of the reasons for the evolution that has been observed in the detection of anomalies and failures in equipment is the sensors' quality and precision improvement. The sensors have evolved in terms of the quantities they are capable of measuring, the response time, the reliability and precision with which measurements are carried out. In parallel with these improvements, the communication protocols responsible for integrating the sensors in modern networks and transmitting the acquired data have also evolved by using time synchronization, becoming more robust, and reducing noise and errors. Ergo, it is possible to acquire more data with better quality, allowing the user to get a more accurate picture of the system status in real-time.

2.3.1 Components Description

This section presents a description and analysis of some common systems and components present in the industry, and more specifically in the plant related to the present work. The description considers their subcomponents and main points and characteristics of failures.

2.3.1.1 Motors

Electric motors are the most used elements at an industrial level and are associated with all types of machines and systems, like extruders, treadmills, rollers, cutting tools, among others.

The main constituents to be taken into account are the rotor, stator, housing, shaft, bearings, and electrical supply. Sometimes, it may also be interesting to consider the gearbox for monitoring purposes.

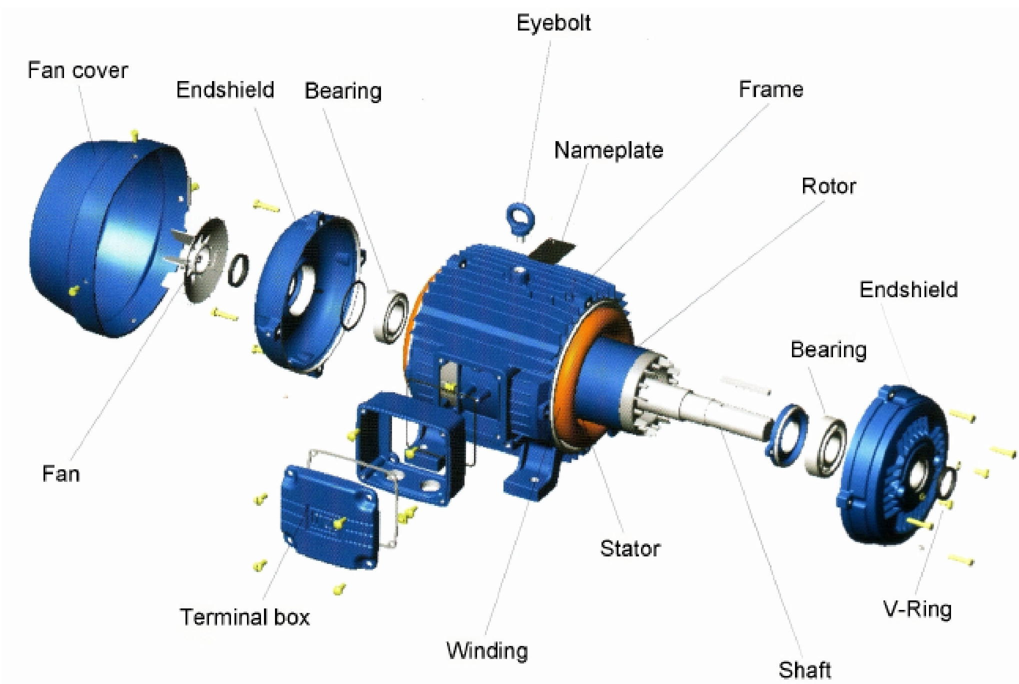

Figure 2.5: Electric Motor generic composition - Source: [81]

The possible faults observed in a motor are full breakdown (when the motor can not even start), slower start, excessive noise when starting or during operation, increasingly working temperature, and accentuated vibration levels. The faults can be caused by several problems and in most cases, these are only identifiable when inspecting the motor. Some examples of fault causes regarding electric motors are overloads, phase interruption, converter or drive errors, obstructions in the fan and heat dissipation surfaces, damage to the bearings or other mechanical components, and imbalance or misalignment of the rotor or shaft.

Consequently, monitoring motor vibrations, noise, temperature, and the current supplied is crucial in order to detect anomalies, some of which may not be directly monitored but may be acquired based on the interpolation of others [39] [77] [78].

2.3.1.2 Bearings

Bearings are often present in motors and one of the main reasons for their failure. Besides, they are also associated with other systems in the manufacturing field and for that reason are elements to be monitored. There are several types of bearings such as simple, ball, roller magnetic, among others. Although they may behave slightly differently, in essence, they all fulfill the same objective: facilitating and stabilizing the rotation of a shaft, some of which are inserted directly into motors, as mentioned above.

In the case of ball bearings, the main constituents are outer ring, spheres, cage (surrounding the spheres), and an inner ring.

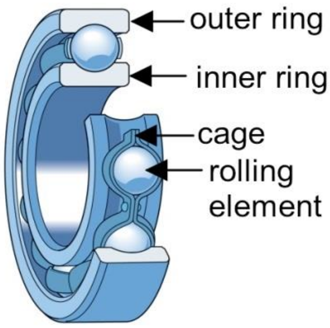

Figure 2.6: Bearing generic composition - Source: [56]

All these elements are exposed to wear and spontaneous tear, thus any component can be the reason for a malfunction. Therefore, monitoring the status of every component is essential. Generally, all have a certain vibration frequency associated and deviation in it can be a good indicator of wear and the consequent need for repairment or replacement [63].

As mentioned, bearing elements defects have specific components in the vibration frequency. Given the bearing dimensions and the standard rotation speed, the characteristic frequencies of the subcomponents can be calculated as follows [21], where n is the number of spheres, f_r the speed of rotation (rot/min), dB the diameter of the spheres, dA the inner diameter of the outer ring, and ϕ the contact angle of the spheres:

- Outer ring (f_{OR})
$$f_{\mathrm{OR}} = \frac{n}{2} \cdot f_r \cdot (1 - \frac{dB}{dA} cos\phi) \tag{2.15}$$

- Inner ring (f_{IR})
$$f_{\mathrm{IR}} = \frac{n}{2} \cdot f_r \cdot (1 + \frac{dB}{dA} cos\phi) \tag{2.16}$$

- Sphere (rolling element) (f_{SPH})

$$f_{\mathrm{SPH}} = \frac{dA}{2dB} \cdot f_r \cdot (1 - (\frac{dB}{dA} cos\phi)^2) \tag{2.17}$$

- Cage (f_C)

$$f_C = \frac{1}{2} \cdot f_r \cdot (1 + \frac{dB}{dA} cos\phi) \tag{2.18}$$

2.3.1.3 Extruder

The extruder is the element responsible for extracting and shaping the rubber used in some components that integrate the tire. It consists fundamentally on a compound feeder, a spindle or screw, a cylinder body that surrounds the spindle, a gate (where the rubber exits the extruder, passing through the die, responsible for defining the desired rubber profile) and other adjacent elements, such as the motor (responsible for the rotation of the spindle), the temperature control units (responsible for heating and cooling other extruder parts) and the hydraulic system, in charge of fixing the desired opening in the gate.

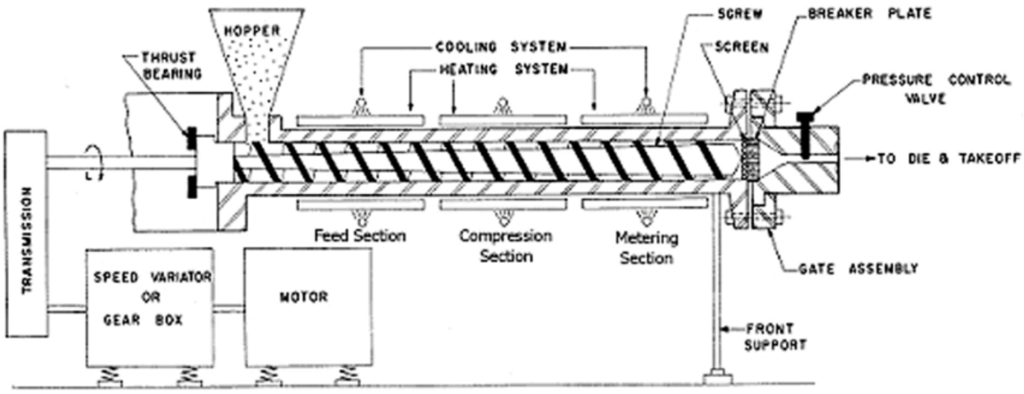

Figure 2.7: Extruder generic composition - Source: [19]

The main failure reason regarding the extruder is not removing all the rubber from the extruder at the end of the production process, which causes damage to its spindle.

2.3.1.4 Temperature Control Unit - TCU

The temperature control units (TCU), in this case, associated with the extrusion process, are responsible for controlling the temperature of the extruder components (body, spindle, and gate). In essence, they consist of a water circuit (piping and valves), a pump responsible for ensuring circulation, a tank responsible for heating the water, and a temperature controller, that includes temperature meters and the electrical circuit that allows heating and regulating the water temperature. In conclusion, TCUs are in charge of preheating the extruder components prior to the production and dissipating the heat generated by the material while operation, maintaining the desired working temperature in a stable manner.

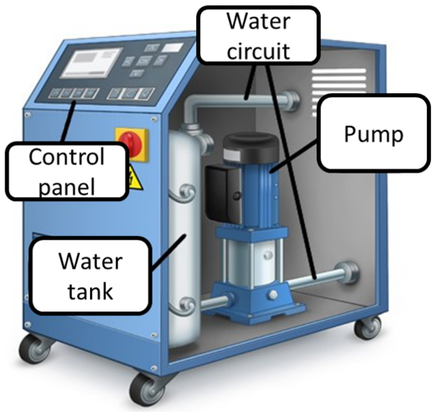

Figure 2.8: TCU generic composition - Adapted from [84]

The principal faults recorded are pump malfunctioning, the temperature falling below the requested value, and insufficient cooling power. These can be related to errors like insufficient pressures, valves in the wrong position, clogged filters, and worn heating resistors.

2.3.1.5 Hydraulic Unit

The hydraulic unit, like the TCUs, is associated with the extrusion process and is responsible for ensuring the desired pressure in the extruder gate. It is constituted by an oil reservoir, a pump responsible for oil pressure (powered by an electric motor), control valves (for pressure control and fluid direction), filters (for filtering the returning oil), and finally an actuator (engine or cylinder) that converts hydraulic pressure into a mechanical movement. The system also contains sensors and respective oil level indicators, manometers, and thermometers, providing operational control.

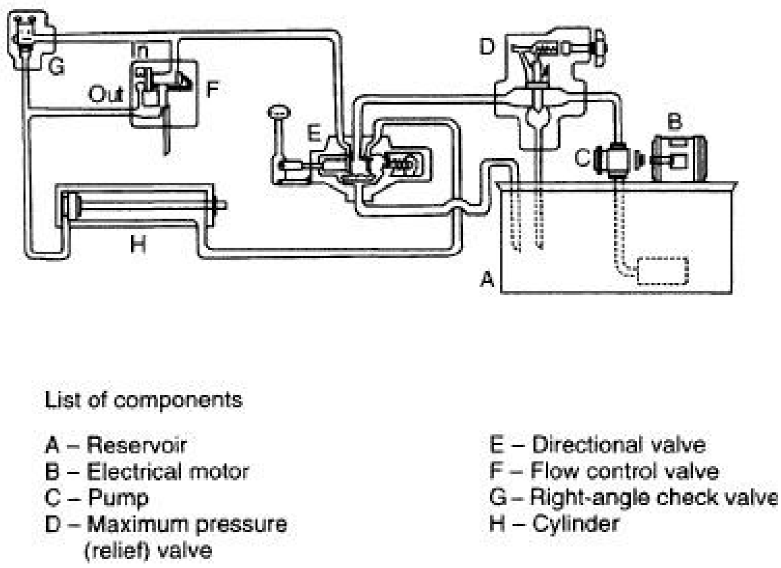

Figure 2.9: Hydraulic unit generic composition - Source: [37]

The main faults that can occur are pump not supplying the liquid with the desired pressure, excessive noise or heat when working, and leaks through cylinders or valves. The causes of these failures are mainly due to lack of liquid, wear of components, and filter clogging.

2.3.2 Monitoring Systems

This section describes the types of monitoring and data acquisition systems. Sensors used by these different techniques are also studied, in order to understand which systems can be used to monitor the different selected components, taking into account the existing constraints.

According to [49] there are 4 main technologies for monitoring equipment: temperature measurement, vibration analysis, chemical analysis (oil), and ultrasonic measurement. In addition to the above-mentioned, current signal analysis, pressure measurement, and displacement detection.

Another method that allows irregularities detection in the machines is based on the collection of utility consumption data, whether it is water, compressed air, or electricity. Through the analysis of trends, anomalies, or components malfunctioning can be identified, as these errors can imply a higher consumption rate.

Concerning sensors selection, it is essential to take into consideration some specific characteristics, such as: "range of use, sensitivity, frequency (or response time), compatibility with the environment, precision, electrical characteristics, application conditions and robustness" [70].

2.3.2.1 Temperature Measurement

Four types of sensors are considered regarding temperature measurement [79]. Mechanical temperature sensors are based on volume varying of a fluid, such as mercury or alcohol. Taking into account that the volume of the fluid varies with temperature, it is possible to calculate the latter by establishing a linear relationship between them. However, these have been abandoned due to the toxicity of mercury and not being adaptable to some situations.

Electric temperature sensors are the most commonly used and can be separated into four different types:

- Thermocouples

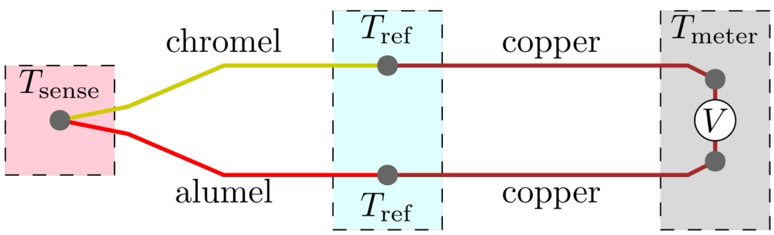

Figure 2.10: Thermocouple circuit diagram - Source:[57]

Thermocouples are the most common for industrial applications and operate based on the Seebeck Effect, joining two metals at two different points (measurement point and reference point). Assuming the reference is always kept at the same temperature, with the temperature variation at the measurement point, an electromotive force is generated due to the temperature difference between the two points. By calculating the electromotive force it is possible to obtain the respective temperature (T_{sense}) using the established relationship between both, where E_{0j} is the calculated electromotive force and G () is the relation between this and the temperature. This relation is usually given by an equation or can be tabulated [65].

$$T_{\text{sense}} = G(E_{0\text{j}}) \tag{2.19}$$

- Resistance Temperature Detector (RTD)

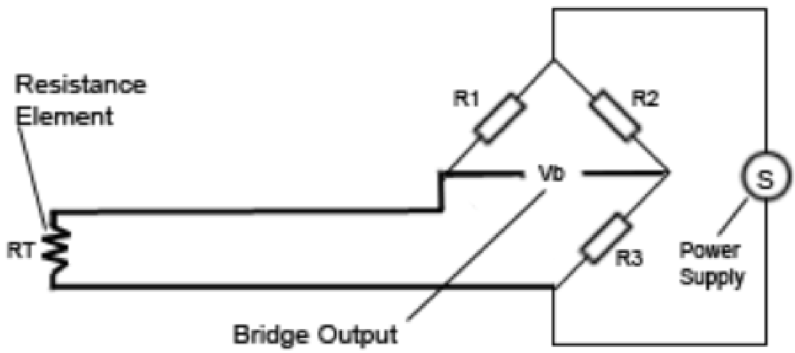

Figure 2.11: RTD circuit diagram - Source:[64]

RTD operation is based on the use of a resistive material (usually platinum) as a temperature gauge, as its electrical resistance varies almost linearly with the temperature. Ergo, the resistance value is easily obtained by measuring the voltage in the bridge hence the temperature is easily obtained by the relation given by the Callendar-Van Dusen equation, where R_T is the resistance value at a certain temperature and R_0 is the resistance at 0 °C.

$$R_T = R_0\left[1 + AT + BT^2 + CT^3(T-100)\right] \; (-200\,^{\circ}\mathrm{C} < T < 0\,^{\circ}\mathrm{C}), \tag{2.20}$$

$$R_T = R_0\left[1 + AT + BT^2\right] (0\,^{\circ}\mathrm{C} \leq T < 850\,^{\circ}\mathrm{C}) \tag{2.21}$$

For positive temperatures, we have:

$$T = \frac{-A + \sqrt{A^2 - 4B\left(1 - \frac{R_T}{R_0}\right)}}{2B}. \tag{2.22}$$

- Thermistors - similar function to RTD, i.e., the temperature is measured through a resistance that varies with temperature. They are usually cheaper than the previous ones, but they are also less accurate. The most commonly used are the NTC (Negative Temperature Coefficient), that despite having a non-linear relation, with the increase in temperature there is a decrease in resistance and vice versa.

- Integrated circuits semiconductors - these sensors measure the temperature considering the physical properties of a transistor and its behavior with temperature variation. Since they are used to control the temperature of all types of circuits, like computers, they are among the most used today. The output can be analog or digital, depending on the application.

Ultrasonic sensors measure temperature based on the variation in the propagation speed of the emitted ultrasonic wave. These are the lesser used for temperature measurement purposes.

At last, the main objective of thermography or thermal imaging is to detect temperature peaks and hot spots (overheating). By detecting an unexpected temperature rise, this technique enables the identification of anomalies or wear and tear. This solution turns out to be quite expensive compared to others, due to the measuring equipment used. The technology is based on the fact that all bodies with temperatures above absolute zero (0K) emit infrared radiation and that emitted radiation can be given as a function of the object's temperature, i.e., the higher the temperature, the greater the intensity of the radiation emitted [11].

The incident radiation on an object can be dissipated through absorption, reflection, and transmission and each body can be characterized with specific parameters that indicate the fraction of energy dissipated in each form. Nevertheless, the three parameters sum must always equal 1, regardless of the wavelength [80][62]:

$$\alpha_\lambda + \rho_\lambda + \tau_\lambda = 1 \tag{2.23}$$

In the case of black bodies, all incident radiation is absorbed ($\alpha_\lambda = 1$). In this case, the relation between radiation intensity and wavelength is dictated by Planck's Law, where C_1 and C_2 are radiation constants, λ is the wavelength, and T the temperature. [53]:

$$W_n = \frac{C_1}{\lambda^5 (e^{\frac{C_2}{\lambda T}} - 1)} \tag{2.24}$$

As shown in figure 2.12, the radiation curve for higher temperatures has a higher peak, and the higher the temperature, the shorter the wavelength at which the peak occurs. The wavelength of this peak can then be calculated by Wien's law:

$$\lambda_{\text{peak}} = \frac{2898}{T}\ (\mu m) \tag{2.25}$$

Integrating equation 2.24 from 0 to ∞, we obtain the Stefan-Boltzmann formula, allowing the intensity of radiation from a black body to be calculated using the Stefan-Boltzmann constant

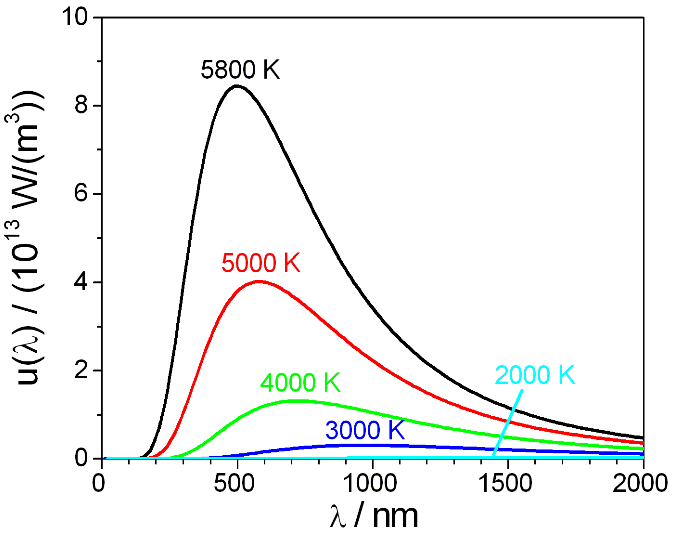

Figure 2.12: Planck Law example - Relationship between radiation, temperature and wavelength - Source:[76]

($\sigma = 5,67 \cdot 10^{-8} W/m^2K^4$):

$$W_n = \sigma \cdot T^4 \tag{2.26}$$

Regarding real objects, only a fraction of the radiation emitted by a blackbody at the same temperature is emitted and this relationship is given by the emissivity of the object:

$$\varepsilon_\lambda = \frac{W_\lambda}{W_n} \tag{2.27}$$

The emissivity usually varies with the wavelength, but considering the thermography works only in a small range of the spectrum (between 0.8μm and 14μm approximately), we can consider real objects as bodies gray, i.e., the energy emitted by these is the same as the energy emitted by a blackbody reduced in a proportion of value ε. Thus, the Stefan-Boltzmann law for real bodies is defined as:

$$W_{\text{obj}} = \varepsilon\sigma \cdot T_{\text{obj}}{}^4 \tag{2.28}$$

It is now possible to move on to the temperature measurement. It is important to consider that not all radiation is emitted by the object, so it is necessary to filter radiation from other sources like the atmosphere. The total radiation received by the measuring equipment will be a sum of the radiation coming from the object, the surfaces around the object and reflected by it, and also from the atmosphere.

$$W_{\text{tot}} = E_{\text{obj}} + E_{\text{refl}} + E_{\text{atm}} \tag{2.29}$$

$$E_{\text{obj}} = \varepsilon_{\text{obj}} \cdot \tau_{\text{atm}} \cdot W_{\text{obj}} \tag{2.30}$$

$$E_{\text{refl}} = \rho_{\text{obj}} \cdot \tau_{\text{atm}} \cdot W_{\text{refl}} = (1 - \varepsilon_{\text{obj}}) \cdot \tau_{\text{atm}} \cdot W_{\text{refl}} \tag{2.31}$$

$$E_{atm} = \varepsilon_{atm} \cdot W_{atm} = (1 - \tau_{atm}) \cdot W_{atm} \tag{2.32}$$

It is noteworthy that for the radiations emitted and reflected by the object, the transmittance of the atmosphere is considered since to reach the measuring equipment camera, the radiation has to go through the atmosphere.

By replacing the equations 2.30 to 2.32 in the equation 2.29 the object temperature is obtained as follows:

$$W_{tot} = \varepsilon_{obj} \cdot \tau_{atm} \cdot W_{obj} + (1 - \varepsilon_{obj}) \cdot \tau_{atm} \cdot W_{obj} + (1 - \tau_{atm}) \cdot W_{obj} \tag{2.33}$$

$$T_{obj} = \sqrt[4]{\frac{W_{tot} - (1 - \varepsilon_{obj}) \cdot \tau_{atm} \cdot W_{refl} - (1 - \tau_{atm}) \cdot W_{atm}}{\varepsilon_{obj} \cdot \tau_{atm} \cdot \sigma}} \tag{2.34}$$

2.3.2.2 Vibration Analysis

Vibration analysis is one of the most used techniques in condition monitoring as it allows extracting information of several components in a mechanical system, with a low implementation cost. It intends to create a graphical representation of the various components working frequencies, enabling the detection of problems related to misalignment or imbalance and deterioration or wear of components. This technique is widely used in motors and bearings and generally uses multiple sensors, each one placed on a different axis (vertical, horizontal, and axial), to acquire the vibration frequencies [40] [89]. To fulfill this purpose, 3 types of sensors are usually employed - accelerometers, strain gauges, and proximity probes. In some special cases, speed sensors (when operating at very high temperatures) or laser sensors for detecting displacement can be used.

Different types of accelerometers can be utilized for PM, for example, piezoresistive, capacitive, electromagnetic, optical, et cetera [8]. The most commonly used in vibrations measurement at an industrial level is the piezoelectric sensor. Preference is given to these due to the low cost, durability, robustness, variety, and ease of assembly (various types of mounting like screw, glue, magnetic base, ferrule) [70].

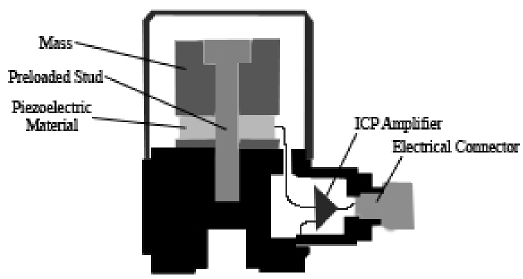

Figure 2.13: Piezoelectric accelerometer schematic - Source:[9]

Piezoelectric sensors are capable of converting a force into an electrical signal and, for that reason, they require direct contact with the device to be monitored. The above-mentioned conversion is based on the piezoelectric effect, which states that piezoelectric materials/crystals, when exposed to a certain force (in this case caused by vibration), generate an electric charge proportional to the mechanical deformation they suffer due to the force. The generated charge is then amplified to be suitable for the data acquisition software [28]. The applied force can be considered as a product of mass and acceleration, according to Newton's Second Law. Thus, the generated charge is proportional to this product, and, taking into account that the mass is constant, the generated charge will be proportional to the acceleration [82], where Q is the electric charge, V the voltage, C_1 and C_2 piezoelectric constants, e the material thickness, and Ar its area:

$$F = m \cdot a \tag{2.35}$$

$$Q = C_1 \cdot F = C_1 \cdot m \cdot a \tag{2.36}$$

$$V = \frac{C_1 \cdot e}{C_2 \cdot Ar} \cdot F = \frac{C_1 \cdot e}{C_2 \cdot Ar} \cdot m \cdot a \tag{2.37}$$

Strain gauges are widely used in construction applications, such as critical buildings, cables, rails, et cetera. However, they can be applied in industrial scenarios as well. These consist of a small wire organized in a zigzag placed on a thin material applied directly on the equipment to be monitored. The sensor orientation has to be parallel to the direction of deformation/vibration to be monitored [4].

Assuming tension as the amount of deformation suffered, we can characterize it mathematically as a fractional length variation [27]:

$$\varepsilon = \frac{\Delta L}{L} \tag{2.38}$$

Thus, the fundamental parameter to consider regarding strain gauges is known as Gauge factor (G_f) and reflects the device voltage sensitivity:

$$G_f = \frac{\Delta R/R}{\Delta L/L} = \frac{\Delta R/R}{\varepsilon} \tag{2.39}$$

To guarantee an accurate measurement, the devices are usually inserted in a Wheatstone bridge with a power source (as illustrated in the figure 2.14), allowing the detection of even small changes in the resistance of the strain gauge.

The generic electrical output voltage (V) of a Wheatstone bridge is given by the equation:

$$V = \left(\frac{R_4}{R_4 + R_2} - \frac{R_3}{R_3 + R_1} \right) \cdot V_i \tag{2.40}$$

If $R_1 = R_3$, R_4 is replaced by the strain gauge (modeled as standard resistance R_g with a variation $\Delta R_g = R_g \cdot G_f \cdot \varepsilon$), and assuming that $R_2 = R_g$, the following equation is obtained:

$$V = \left(\frac{R_g + \Delta R_g}{R_g + \Delta R_g + R_g} - \frac{1}{2} \right) \cdot V_i \tag{2.41}$$

$$V = \left(\frac{\Delta R_g}{4} \cdot \frac{1}{R_g + \frac{\Delta R_g}{2}} \right) \cdot V_i \tag{2.42}$$

$$V = \left(\frac{G_f \cdot \varepsilon}{4} \cdot \frac{1}{R_g + \frac{G_f \cdot \varepsilon}{2}} \right) \cdot V_i \tag{2.43}$$

To deal with some uncertainties or noise caused by temperature variations or vibrations in different directions other, more complex configurations that use more strain gauges can be employed.

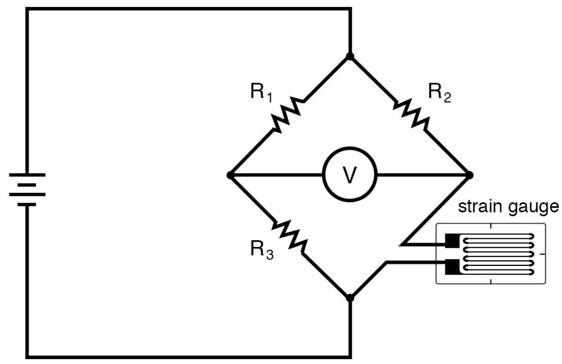

Figure 2.14: Wheatstone bridge diagram with a strain gauge - Source:[22]

Finally, the proximity probes distinguish from the above-mentioned as they do not need direct contact with the equipment to be monitored. In some cases where it is not possible to directly install sensors on the equipment, this characteristic can be of great value. These work according to the eddy currents principle.

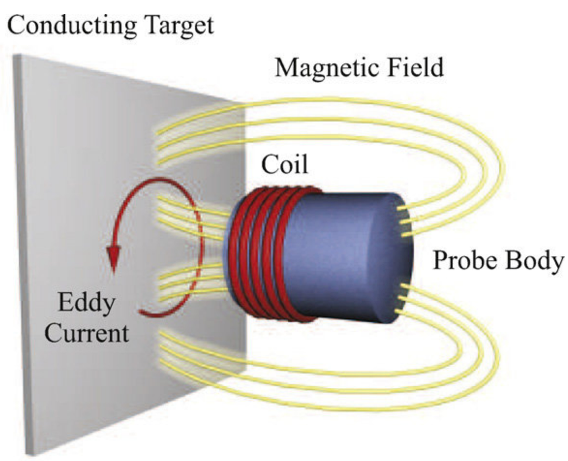

Figure 2.15: Proximity probe functioning principle - Source:[24]

The probe consists of a coil exposed to an alternating current, generating a magnetic field that will induce a current on the equipment surface, which is then responsible for creating a magnetic field opposite to the first one, as shown figure 2.15. By monitoring the interaction of these two magnetic fields, the sensor is able to detect equipment movement (vibration), as the sensor output voltage will be proportional to this interaction, varying with the equipment movement.

When implementing a vibration analysis, regardless of the sensor used, it is crucial to understand that vibrations, specifically in motors, have two main origins: mechanical (typical of all rotating machines) and electromagnetic (specific for electric machines). Mechanical vibrations are usually associated with shaft imbalance, misalignment, wear, discrepancies in bearings or couplings, or belt errors. Vibrations of electromagnetic origin, on the other hand, result from electromagnetic functions imposed on the motor rotor and stator and can be grouped into two types: radial and tangential. The imposed functions are usually due to power supply poor quality (causing current and voltage asymmetries) or variations in the load [77] [78].

In addition, it is also crucial to consider the component dimensions and working conditions, such as load and power supply, so that the sensors can be properly placed and the acquisition noise can be reduced. Concerning the specific case of motors, vibrations are usually transmitted from the shaft to the bearings, so it may be necessary to measure both bearings, through the bearings housing, if the motor has big dimensions.

The principal difficulty using this method relies on the acquired signal complexity and the necessary treatment it requires in order to properly extract the signal characteristics that reflect the equipment's health status. Assuming the component to be monitored by the system is a bearing (as it is one of the most common ones submitted to this kind of analysis), some precautions must be taken in order to ensure that the system is capable of performing correct analysis. As seen in [56], there may be some variations in the methods used, yet they all use filtering and signal segmentation and convert the signal to the frequency domain using a Fast Fourier Transform, in order to evaluate the frequencies amplitudes associated with certain faults in the component. Techniques like envelope spectrum analyses are highly valued for this in this matter. As mentioned in section 2.1.2, this analysis may require some feature extraction from the raw signal, as it is hard to extract valuable information directly from the raw signal.

Bearing in mind that irregular vibrations cause noise, another way of detecting anomalies can be performed by the acquisition of sound using a specific microphone and relating that same noise to certain anomalies. This method implies isolating specific frequencies from the rest of the spectrum, which makes this solution barely feasible in a manufacturing environment, taking into account the high noise level.

2.3.2.3 Chemical Analysis

Lubricating oil chemical analysis allows checking the consistency of the oil additives, water levels, and viscosity, these being factors that in case of deviation from the standard values may indicate the need for an oil change. Using the same analysis, the quantity of metal present in the oil can serve as a good indicator of metallic components wear. However, this technique is not used widely as it has a very high-cost and difficult implementation associated, and is only applicable to machines with continuous oil supply.

2.3.2.4 Ultrasonic Measurement

Ultrasonic measurement is mainly used to detect leaks in air or steam systems, however, sometimes it is also used to measure temperatures, as mentioned previously. The instruments utilized seek to detect and present high frequencies sounds, inaudible by humans, produced by the referred leaks. Therefore, it is a solution appropriated only for specific cases and generally does not justify a permanent detection system setup.

2.3.2.5 Current Signal Analysis

The method of analyzing the current signal, in specific, Motor Current Signature Analysis (MCSA), has been highly valued recently since it generates a lot of information about the system to be obtained and does not require the installation of any sensors, as most machine drives already provide this data. However, in some cases where the drives do not have this function incorporated, it may be necessary to use current meters. These do not present great adversities as they are usually easy to install and low cost.

The mentioned technique implies a good application of data mining concepts since it is required signal processing in order to gather valuable information. Similar to what is performed in vibration analysis, the current signal must be initially filtered to eliminate, as much as possible, noise, and unnecessary information. Thereafter, we can analyze the frequencies amplitudes that correspond to certain faults and extract the significant harmonics, guaranteeing a correct fault detection and estimation of the Remaining Useful Life (RUL).

Furthermore, it is also essential to define a normal working condition for the equipment, develop an evolution historic, recording the failures associated with certain occurrences, thus establishing a solid basis to compare with the occurring trends [16].

Regarding the methods to treat and analyze the obtained signal, several are mentioned in [21] and [68]. All methods are based on the assumption that the anomalies, whether they are of mechanical or electromagnetic origin, are reflected in changes in the current signal, which must then be "separated" from the base signal so that the anomalies can be correctly identified. For example, as mentioned in [21], the motor mechanical vibration caused by defects in bearings results in an eccentricity of the air gap, these variations in the air gap cause variations in the flow density which in turn affect the inductances of the machine, producing harmonics in the stator current. Using the wavelet decomposition technique and defined formulas for the bearing components working frequencies, it is possible to extract these frequencies from the acquired signal, allowing the detection of an anomaly in the motor bearing.

In the case presented in [68], a model based on a Decision Tree to classify certain anomalies is defined. This model has as inputs power spectrum harmonics, to which the Fast Fourier Transform

(FFT) algorithm is applied before being applied to the model. In this case, 3 current meters are used to acquire the signal.

2.3.2.6 Pressure Measurement

Pressure measurement is used in liquids and gas circuits and has many industrial applications such as leak detection in a compressed air system or water circuit. The pressure (P) is normally defined as the force (F) exerted per unit area (A):

$$P = \frac{F}{A}(N/m^2) \tag{2.44}$$

Pressure units used are Pascal (1 Pa = 1 N/m^2), Bar (1 bar = 10^5 Pa) or PSI (1 psi = 6 894.757 Pa).

There exist several types of pressure sensor technologies, such as piezoelectric, electromagnetic, and capacitive. Its behavior is very similar to vibrations sensors, as they seek to convert a force applied to a diaphragm or membrane into an electrical signal, using a transducer. The signal amplitude will be proportional to the force applied by the fluid [5].

The technology is applied through 3 different types of sensors, each one with a different objective:

- Absolute sensors - measure fluid absolute pressure of the fluid, i.e., comparing to vacuum pressure (0 Pa).
- Gauge sensors - measure fluid pressure compared to atmospheric pressure (101325 Pa standard)
- Differential sensors - measure the pressure difference between two different spots in a circuit.

Besides pressure measurement, sensors can be used to measure the liquid level inside of a tank, according to the formula, where P_t is the fluid abolute pressure, P_e the external pressure (atmospheric), ρ fluid density, and g the gravity acceleration:

$$P_t = P_e + (\rho \cdot g \cdot h) \tag{2.45}$$

$$h = \frac{P_t - P_e}{\rho \cdot g} \tag{2.46}$$

In the case of a closed tank (in vacuum) P_e = 0.

It is also possible to measure the fluid flow according to the venturi effect, A_1 and A_2 being the areas of the surface where pressure is measured, D_1 and D_2 the respective diameters, and P_1 and P_2 the actual pressures:

$$Q = \frac{A_2}{A_1} \cdot \frac{\pi}{4} \cdot D_2^2 \cdot \sqrt{\frac{2}{\rho} \cdot \frac{P_1 - P_2}{1 - (\frac{D_2}{D_1})^4}} \tag{2.47}$$

2.3.2.7 Displacement Detection

Detecting displacement or misalignment of components is highly valued for rotating machines, as this type of failure can cause severe damages to the entire machine and low-quality output products. Apart from rotating machines, this method can be viable in other types of machines, when a certain alignment precision is required to correctly operate.

Regarding rotating machines, e.g., motors, the principal components to monitor concerning misalignment are the shaft and the connection between the motor and the gearbox. Vibration monitoring is an indirect method to detect displacement as this type of error usually causes increasing vibrations. In specific cases, laser or eddy current sensors can be used too, as they can detect a variation in the distance between the sensor and the monitored object, indicating a misalignment.

The direct method most commonly used is via inclinometers [25]. This type of sensor measures the tilt angle considering the gravity direction, regarding one or two-axis (usually orthogonal and parallel to the floor). Basic inclinometers operate using an accelerometer, which measures the change in acceleration caused by gravity when the object tilts.

The output value can be affected by certain factors, such as temperature, vibrations, and shock. Therefore, the most recent inclinometers use a specific algorithm to deal with non-linearities caused by temperature variation and combine the accelerometer with a gyroscope, as this is less sensitive to external vibrations, reducing their impact on the output signal.

2.3.3 Sensors Placement

Regarding sensor installation and placement, it is crucial taking into account the system structure and performance restrictions, as well as maintaining a balance between the relevance of the information acquired and the economic viability installing the necessary sensor. In theory, the more sensors are installed, the more and better data is collected. However, in practice, increased acquired data causes a rise of complexity related to data analysis, which may not be supported by the system. Also, some data can be obtained through linear interpolation through neighbor sensors, reducing the number of sensors required [17].

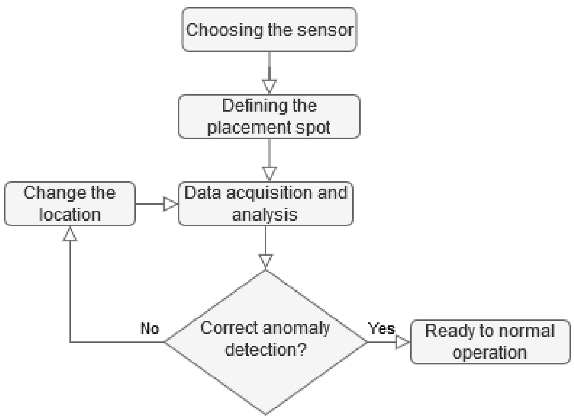

Figure 2.16: Sensors choosing and placement process - Adapted from [17]

As demonstrated in figure 2.16, the sensor choice and placement process must begin with the selection of appropriate sensor types, taking into account the parameters to be measured. Given the machine's structure, a location for installing the chosen sensor should be defined considering operation conditions. After this process is complete, it is possible to start data acquisition and analysis. If the obtained data does not correspond to what is expected, the sensor must be replaced until the expected information is obtained, i.e., until it is possible to correctly detect the occurrence of an anomaly or failure.

By installing the necessary sensors, it is possible to carry out adequate data acquisition, and after the correct data treatment, it is possible to implement reliable PM models.

2.4 Human-Machine Interface

With the evolution and automation of components and machines, the manufacturing scenarios have become more complex, which requires an improvement of the human-machine interfaces (HMI), since these are the bridge between the operator and the system [30]. This integration must be carried out without disturbing the distributed control system functioning, while faithfully representing its state and presenting the operation control options. The distributed control system represents the concept of Cyber-Physical Systems (CPS) in which the control of a given physical process is carried out using a complex computational infrastructure that takes into account appropriate physical and computational models [47]. According to [59], the implementation of an HMI for a CPS can take advantage of the concept of service-oriented architecture, allowing the organization of the system to be a set of entities that invoke services among themselves.

HMI's main objective is to provide information about the system to the user and receive feedback [29], for example through operation logs and configuration files. Functionalities at the industrial level may vary depending on the type of industry, its flexibility, or even the type of maintenance used. However, some features are considered standard when it comes to operator-process interaction [10]:

- Real-time process visualization and control;
- Process values storage and display;
- Management of parameters related to machines;
- Warnings and listing of alarms and other occurrences.

Taking into account the increasing complexity of industrial systems, HMI development should focus on guaranteeing process comprehension and helping the operator decision making. Therefore, some criteria and characteristics must be taken into account when developing the HMI [29]:

- System accessibility and usability, considering the interface several pages;
- Information display organized in graphs and tables;

- Page coordination and organized element distribution, distinguishing between main and secondary elements;
- Different color utilization, taking into account the meaning of each one.

2.5 Conclusion

A PM system implementation implies the correct understanding and functioning of several parts related to it. Initially, it is usual to choose the proper ML algorithm to be applied considering the available data. Then, it is necessary to train the system with this algorithm so faults and anomalies are correctly detected. The definition of a machine reliability model starts from an analysis of the machine critical components and respective failures. In certain cases, information on the availability is valued more than the reliability of the machine, as it gives concrete information to the engineering and production teams.

For data acquisition, defining the relevant quantities to be measured is crucial, ensuring correct sensor and communication protocol selection and installation. This involves a detailed study on types of sensors and their characteristics, taking into account the situations they will be undergoing.

To successfully present the information acquired to the operator, building a simple and effective HMI is essential, since it allows the necessary maintenance operations to be carried out effectively.

Table 2.1 summarizes the technologies studied and the respective quantities that are monitored.

Table 2.1: Studied technologies summary

Quantity	Technologies
Temperatue	Mechanical, Electric, Ultrasonic, Thermography
Vibration	Accelerometer, Strain Gauge, Proximity probe (eddy current)
Chemics	Oil analysis
Ultrasonics	Ultrasonic sensors for leak detection
Current	Current/Voltage sensors, via Motor drive
Pressure	Absolute, Gauge, Differential
Displacement	Inclinometers, Vibration sensors (indirect method)

Chapter 3

Maintenance Analysis

This chapter provides an analysis of the maintenance operations of specific parts of interest in the plant in which this work is based on. We start by describing the system, analyzing the type of faults and failures that occur, their impact in downtime, the most relevant ones for maintenance purposes and selecting the components that are object of our proposed PM approach. We end this chapter with an overview of the methodology to be used.

3.1 Maintenance analysis and component selection

Currently, the CST plant produces two major types of tires: AGRO and Big Radial (BR) and is organized in three large groups of machines: preparation, construction, and vulcanization. The work to be carried out will be focused on the first two. The preparation group includes machines responsible for the extrusion, cutting, and assembly of tire components. The second group, construction, includes machines in charge of assembling and fixing the various parts produced, resulting in a final sketch that is then followed by vulcanization. Recipes for components and tire production are taken directly from the Continental Global Manufacturing System (CGMS). This system is also in charge of receiving and presenting the alerts generated by the occurrence of failures or stops.

3.1.1 Production Process Contextualization

As mentioned, the project focus is on the preparation and construction machine groups. In the first, the machines are divided into two groups: hot preparation (machines that include extrusion in their process) and cold preparation (machines used for material cutting and splicing, with no extrusion).

The following machines are included in the hot preparation group:

- Combi Extruder - wall extrusion for AGRO tires and BR profiles;
- Innerliner - profiled and non-profiled layer extrusion;

- 2 Bead Winder (AGRO and BR) - construction of beads by winding wire impregnated with rubber;
- 2 APEX (AGRO and BR) - application of rubber wedge on the beads;

Regarding cold preparation, the following machines are considered:

- Combi Cutter - textile ply and break cutting;
- Ply Steel Cutter - wire mesh cut;
- Breaker Steel Cutter - metal breaker cutting;

Construction machines are defined in Construction Modules (1st and 2nd Stage) or Carcass Machine and Green Tire Machine - responsible for assembling the various ARO tires components. Three modules of each type are installed. Also, two TBM OTR or OTR Construction Machine are installed - in charge of assembling the BR tires components.

By studying the process inherent to each machine and developing a representative block diagram, it was possible to define blocks common to several machines and their criticality in the production process, as well as to identify standard components, described in the section 3.1.3.

3.1.2 Data Classification

The data to be acquired can be organized into three groups, depending on the type of information you want to retrieve and the purpose it may serve.

The first group is related to utility consumption by each machine, with the objective of identifying and studying trends over time. Compressed air, water, and electricity are the three utilities considered. By analyzing the acquired data, it is expected to relate consumption patterns with certain modes of operations or interventions performed.

The second group deals with issues of energy efficiency improvement, i.e., data that allows identifying unnecessary use of utilities. It can be taken directly from components consumption, which will allow determining whether these components are consuming more than supposed when the machine is not producing, or by monitoring the utility inputs on the machines, which may even serve as a means to identify possible leaks in the system.

Finally, the third group relates to components behavior and operation and the data to be acquired will be the basis for detecting anomalies or wear, which may lead to equipment failures. This type of data can also be based on components consumption or it can be obtained through specific sensors that allow acquiring certain specific quantities such as vibration frequencies, temperatures, or composition of substances such as water or oil.

3.1.3 Identification and Selection of Components to Monitor

The information related to components existing in each machine was collected via visual observation and analysis of their manuals.

One of the main components identified was the electric motor and associated components (gearbox, shaft, bearing, and belt). Taking into account the different levels of existing power supplies and the different tasks each one is associated with, electric motors were grouped into classes to facilitate identification and selection:

- Elevated power (111kW to 403kW):
  - Larger extruders: Combi Extruder, Innerliner, Module - 2nd Stage
  - Mills: Combi Extruder
- High power (17kW to 60kW):
  - Smaller extruders: Apex and Bead Winder
  - Calender: Innerliner
- Average power (2kW to 16kW):
  - Building rings: Bead Winder
  - Conveyors
  - Rollers
  - Component translation movements
  - Calenders: Module - 2nd Stage
  - Tensioners and cooling drum: Bead Winder
  - Cutting systems
- Low power (0.042kW to 1.9kW):
  - Component translation movements
  - Conveyors
  - Rollers

The extruders were also divided into components: cylinder, head, spindle, die, motor, and gearbox. Some complementary systems to their operation were also identified, such as the hydraulic unit, temperature control unit (TCU), and water circuit.

Regarding pneumatic systems, the main components identified correspond to the portion directly connected to the actuation, i.e., the air preparation unit, valves, piping and actuators or cylinders. In the conveyor system belts and rollers were considered, in addition to the components associated with its movement, i.e., the motor, gearbox, shaft, and bearings.

Cutting systems with a rotating blade, knife and scissors were also identified, as well as systems for measuring and controlling weight, temperature, centering, and rubber thickness. PLCs, I/O cards, fuses, and circuit breakers for control and protection of all the elements mentioned above were also found.

Based on the systems identified, in order to select the most relevant components we defined a classification system using the following criteria:

- Systems/components common to several machines;
- Process criticality;
- Downtime/replacement time;
- Maintenance costs.

The above-mentioned classification considers as the main objective of the project the development of a standard solution that is applicable in the largest number of machines possible and therefore the first parameter (system/components common to several machines) reflects the number of machines/systems in which each component is found, considering the total of the 15 installed machines for counting purposes. Another important characteristic is the component criticality for the process, i.e., the impact on the creation of scrap material. In addition, the average downtime for component replacement or repair, which indirectly reflects availability, and the maintenance costs associated with its repair and replacement are also taken into account.

By assigning a score from 0 to 5 to each criterion, each identified component receives a final classification, with the highest one being then prioritized in the PM system development.

The evaluation related to the parameter of common systems was performed by counting in how many machines a component can be found, assuming 15 machines in total, as referred. The obtained number was then converted into a 0 to 5 scale.

To assign values regarding downtime, an analysis of the 2019 breakdown reports was carried out. To reduce the volume of data, only the stops with downtime over an hour were taken into consideration.

The classification obtained taking into account the defined criteria is exemplified in table 3.1. In annex A the table A.1 with all components identified is presented.

Table 3.1: Components classification example concerning relevance for the maintenance process

Sistema	Componente	Blocos comuns	Criticidade	Tempo de paragem	Custos de manutenção
Extrusoras	Corpo	3,00	5,00	4,00	4,00
Extrusoras	Fuso	3,00	5,00	4,00	4,00
Acionamento	Motores PM (2kW a 15,7kW)	5,00	3,00	3,00	3,50
Complementos	TCU	3,00	4,00	2,00	4,00
Complementos	Unidade hidraulica	3,00	4,00	2,00	4,00
Acionamento	Motores PME (111kW a 403kW)	1,33	5,00	3,00	5,00
Acionamento	Rolamento	5,00	2,00	3,00	2,00
Extrusoras	Cabeça	3,00	4,00	1,00	4,00
Acionamento	Motores PE (17,5kW a 60kW)	1,67	5,00	1,00	4,00
Componentes elétricos	Fusíveis	5,00	1,00	5,00	1,00
Componentes elétricos	Disjuntores	5,00	1,00	5,00	1,00
Componentes elétricos	PLC	5,00	1,00	5,00	1,00
Componentes elétricos	Cartas I/O	5,00	1,00	5,00	1,00
Componentes elétricos	Módulos de controlo	5,00	1,00	5,00	1,00

As some components are strongly associated and their classification is the same, in order to simplify the table these were grouped into systems resulting in table 3.2 (full table in A.2). For example, the extruder body and spindle were merged into one and all control components (PLC, I/O section, and control modules) were also grouped.

Table 3.2: Example of reduced components list - grouped by system

Sistema	Componente	Blocos comuns (25%)	Criticidade (25%)	Tempo de paragem (25%)	Custos de manutenção (25%)	Avaliação Final
Extrusoras	Corpo e Fuso	3,00	5,00	4,00	4,00	4,00
Acionamento	Motores PM (2kW a 15,7kW)	5,00	3,00	3,00	3,50	3,63
Acionamento	Motores PME (111kW a 403kW)	1,33	5,00	3,00	5,00	3,58
Complementos	TCU	3,00	4,00	2,00	4,00	3,25
Complementos	Unidade hidraulica	3,00	4,00	2,00	4,00	3,25
Acionamento	Rolamento	5,00	2,00	3,00	2,00	3,00
Extrusoras	Cabeça	3,00	4,00	1,00	4,00	3,00
Componentes elétricos	Proteção Elétrica (Fusíveis e Disjuntores)	5,00	1,00	5,00	1,00	3,00
Componentes elétricos	Controlo (PLC, I/O, Mód. de controlo)	5,00	1,00	5,00	1,00	3,00

Initially, we considered a common arithmetic mean to obtain a final value for the component, i.e., equal weights for all criteria are considered, which resulted in the list presented in 3.3 (full table in A.3).

Table 3.3: Example of final classification considering the same weight for every criteria

Sistema	Componente	Blocos comuns (25%)	Criticidade (25%)	Tempo de paragem (25%)	Custos de manutenção (25%)	Avaliação Final
Extrusoras	Corpo e Fuso	3,00	5,00	4,00	4,00	4,00
Acionamento	Motores PM (2kW a 15,7kW)	5,00	3,00	3,00	3,50	3,63
Acionamento	Motores PME (111kW a 403kW)	1,33	5,00	3,00	5,00	3,58
Complementos	TCU	3,00	4,00	2,00	4,00	3,25
Complementos	Unidade hidraulica	3,00	4,00	2,00	4,00	3,25
Acionamento	Rolamento	5,00	2,00	3,00	2,00	3,00
Extrusoras	Cabeça	3,00	4,00	1,00	4,00	3,00
Componentes elétricos	Proteção Elétrica (Fusíveis e Disjuntores)	5,00	1,00	5,00	1,00	3,00
Componentes elétricos	Controlo (PLC, I/O, Mód. de controlo)	5,00	1,00	5,00	1,00	3,00

Thereafter, we considered that the first 2 parameters should have a greater influence on the final assessment, so the weights were changed to:

- Systems/components common to several machines - 30%;
- Process criticality - 30%;
- Downtime/replacement time - 20%;
- Maintenance costs - 20%.

The classification obtained through the weighted average with the above-mentioned weights is found in table 3.4 (full table in A.4).

Table 3.4: Example of final classification with a weighted average

Sistema	Componente	Blocos comuns (25%)	Criticidade (25%)	Tempo de paragem (25%)	Custos de manutenção (25%)	Avaliação Final
Extrusoras	Corpo e Fuso	3,00	5,00	4,00	4,00	4,00
Acionamento	Motores PM (2kW a 15,7kW)	5,00	3,00	3,00	3,50	3,70
Acionamento	Motores PME (111kW a 403kW)	1,33	5,00	3,00	5,00	3,50
Complementos	TCU	3,00	4,00	2,00	4,00	3,30
Complementos	Unidade hidraulica	3,00	4,00	2,00	4,00	3,30
Acionamento	Rolamento	5,00	2,00	3,00	2,00	3,10
Extrusoras	Cabeça	3,00	4,00	1,00	4,00	3,10
Componentes elétricos	Proteção Elétrica (Fusíveis e Disjuntores)	5,00	1,00	5,00	1,00	3,00
Componentes elétricos	Controlo (PLC, I/O, Mód. de controlo)	5,00	1,00	5,00	1,00	3,00

After an analysis of component classification, the ones prioritized (chosen for our PM approach) are listed below with the main quantities to be measured in each one taken into account.

- Extruder (body and spindle) - temperature, pressure, and vibrations;
- Motors with supply power between 2kW and 403kW (the two motor classes were grouped even though they do not belong to the same types of system, because they obtained a very similar classification and the monitoring method is the same) - current, temperature and vibrations;
- TCU - temperature and water pressure;
- Hydraulic Unit - temperature, pressure, level, and fluid composition;
- Bearings - vibrations.

Regarding the bearings, in addition to those included in the motors, others associated with shafts are also critical and therefore must be monitored.

In addition to components directly included in machines, utility consumption (water, compressed air, and electricity) per machine and the position (open or closed) of some critical valves were also considered as a possibility for monitoring.

3.1.3.1 Previously Installed Maintenance Support Systems

At this moment, there are already some monitoring systems in place based on the sensor installation to monitor specific quantities such as pressure, flow, or temperature. Other systems implemented are based on monitoring data directly obtained from the control system. Relying on this data, alarms are sent to the CGMS system when certain events occur. While some systems are oriented towards helping to equipment maintenance, others are oriented towards reducing consumption and improving energy efficiency. The 5 monitoring systems implemented, installed in the APEX - AGRO machine, are:

- Malfunction Prevention
  - Water pressure measurement before and after the filter placed in the supply system - when the pressure difference between the two points reaches a certain value, an indication that the filter needs to be cleaned is given.
  - Temperature measurement of the main electrical cabinet for overheating control - alarm signal is triggered when the detected temperature exceeds a certain value.
  - Pressure measurement in the extruder to detect the presence of rubber - if the extruder is stopped for a certain time and rubber is detected in it, a signal is sent to indicate the need to act, to prevent damaging the extruder screw.

- Energy Efficiency

  - TCU's eco mode control - when the extruder has not been producing for a certain time and the TCU's are not in eco mode, an alarm signal is triggered.

  - Measurement of compressed air flow before the air preparation unit (FRL) to detect possible leaks in the pneumatic system - when this flow remains high with the machine stopped, an alarm signal is sent, indicating the possibility of leakage in the actuation circuit.

  - Detection of opening electrical panel doors to automatically turn off air conditioning, saving energy.

3.1.4 Failure Report Analysis

For a better understanding of the breakdowns that occur and have a high impact in production, in order to focus and adapt the solutions to be implemented in the most critical systems and components, we analyzed the 2019 failure report. The report includes stops on all machines and has an indication of the zone/system that caused the shutdown, the repairing time, and a brief description regarding the cause and how it was solved. In that year, 2929 malfunctions were recorded, resulting in 890 hours and 16 minutes of total downtime, with an average of approximately 18 minutes per stop.

Initially we carried out a study regarding the number of stops and total stop time per month, taking into account the average, variance, and standard deviation of these values. It is relevant to consider that in 1023 cases (34,93% of the total number of cases) the downtime was not recorded which affects the representativity of these data. Since the production system architecture is not aligned in series, the breakdown of a machine might not affect the rest of the production and other components may continue to be built on machines that are on parallel branches.

An average of 244 stops per month was calculated, with a standard deviation of 93.7, which leads us to conclude that there is a wide variation in values over the months relative to the average. In addition to some discrepancies in the records, these variations may also be associated with the variation of production volume in different months. It is noteworthy that generally the number of monthly stops is between 150 and 250 but there are some significant outliers, these being, July, September, October, and November, as observed in the graph in Figure 3.1.

Moreover, as the graph in Figure 3.1 shows, the stoppage time variation is relatively consistent with the number of stops, i.e., when the number of stops is higher, the stoppage time is too.

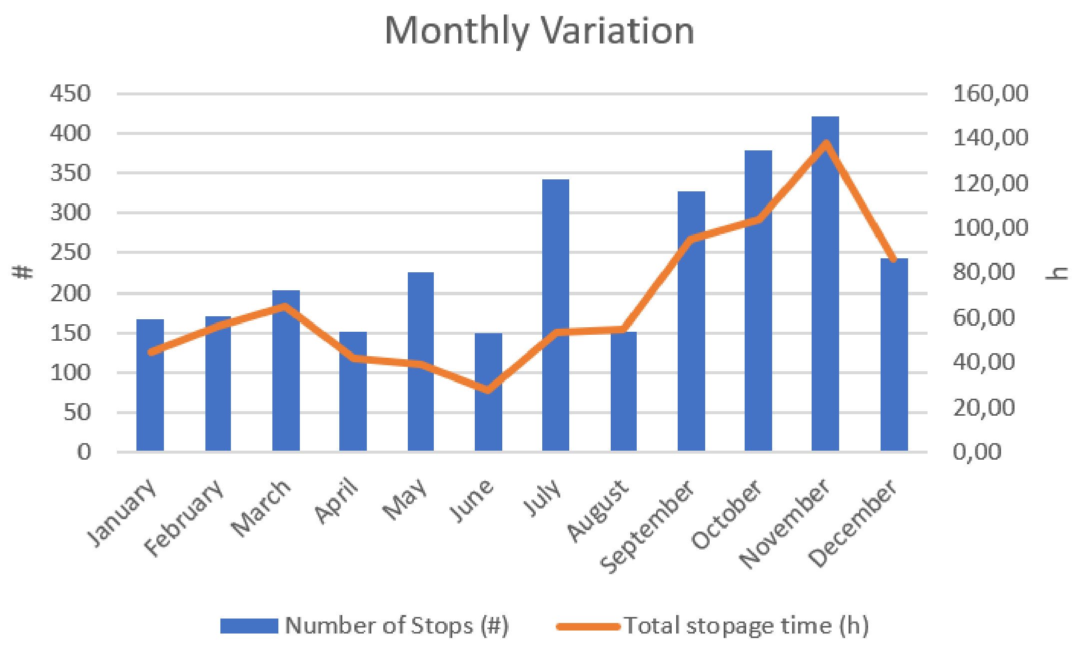

Figure 3.1: Monthly breakdown of number of stops and their duration (in min)

3.1.4.1 Machine Failure Analysis

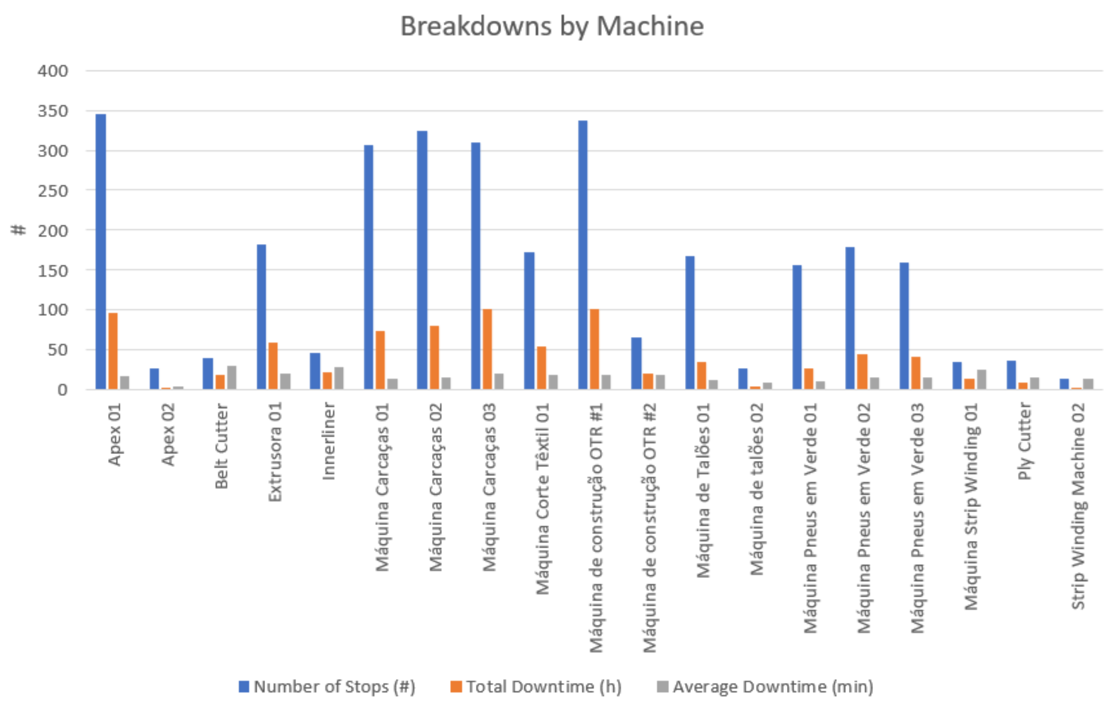

Figure 3.2: Breakdwons recorded by machine

The graph in Figure 3.2 shows that the machine with the highest number of stops was the APEX1, however, the machine with the longest total downtime was the TBM OTR 1. As one would expect, the machines with the highest number of stops are also the ones with the longest downtime. The table with the exact values used for the building the graph can be found in the annex B.

From this machine analysis, it is possible to estimate the inherent availability per machine (section 2.2.3).

Table 3.5: Inherent Availability by machine

Machine	MTBF (h)	MTTR (h)	Inherent Availability
APEX 01	26,792	0,278	0,9897
APEX 02	243,049	0,052	0,9998
Belt Cutter	205,283	0,491	0,9976
Extrusora 01	46,409	0,327	0,9930
Innerliner	91,014	0,477	0,9948
Máquina Carcaças 01	30,223	0,237	0,9922
Máquina Carcaças 02	28,636	0,246	0,9915
Máquina Carcaças 03	24,395	0,325	0,9869
Máquina Corte Têxtil 01	50,934	0,316	0,9938
Máquina de construção OTR 01	27,809	0,300	0,9893
Máquina de construção OTR 02	37,891	0,300	0,9922
Máquina de Talões 01	53,095	0,206	0,9961
Máquina de Talões 02	163,823	0,136	0,9992
Máquina Pneus em Verde 01	53,848	0,174	0,9968
Máquina Pneus em Verde 02	49,139	0,254	0,9949
Máquina Pneus em Verde 03	46,325	0,259	0,9944
Máquina Strip Winding 01	252,732	0,405	0,9984
Ply Cutter	223,622	0,255	0,9989
Máquina Strip Winding 02	371,289	0,222	0,9994

Although the plant is in continuous operation, many machines are not and are only used with specific timings to meet the needs of other machines with slower production processes. Therefore, the inherent availability can provide wrongful estimates about the effective use of the machines.

3.1.4.2 Systems Breakdown Analysis

Bearing in mind that one of the project objectives is to develop and implement solutions that can be integrated in different machines, it is essential to identify which systems and components common to several machines have higher malfunctions tendencies and consequently cause longer downtime. Therefore, we performed a study focused on systems.

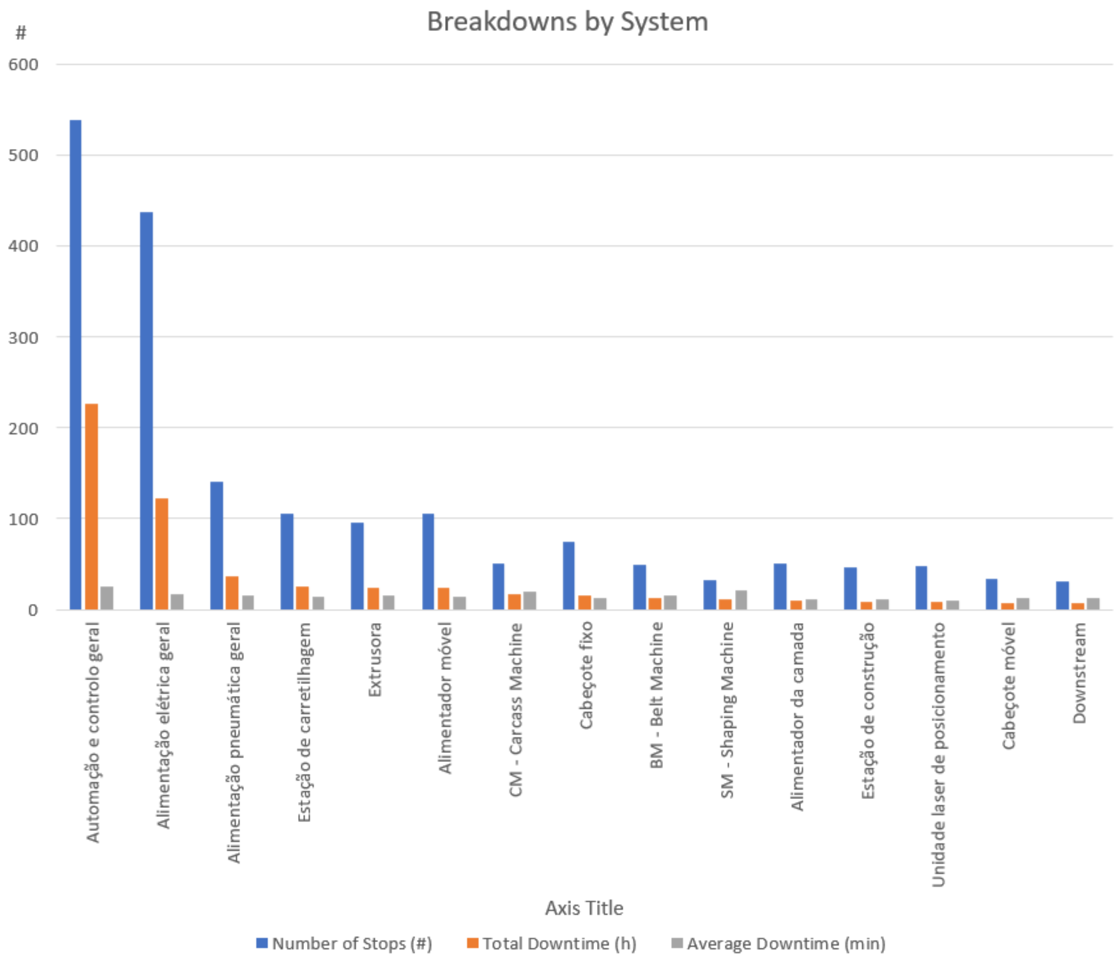

Figure 3.3: Breakdowns recorded per system/component

For reasons of data simplification, only systems with a higher number of stops (greater than 30) were considered to build the graph in Figure 3.3. As highlighted, most errors are associated with electrical and control systems, concerning the number of stops and the average time per stop. This is an indication that most malfunctions are associated with control errors, such as software failures in drives.

3.1.4.3 Breakdown Categorization

For a better understanding of the faults per analyzed system in Figure 3.3, we decided to classify these faults and study their impact.

In order to simplify the data processing and focus the work on the most relevant failures, only over 1-hour stops were considered. This classification was then carried out based on the failure cause, reported in its description, and the categories defined are as follows:

- System Errors - mainly associated with software problems, such as PLC errors, drive configurations, errors in production recipe parameters. These are usually solved by correcting the error detected in the software or by resetting the system.
- Mechanical failures - related to misplacement or deviation of machine equipment or to component failure due to wear or incorrect use.
- Electrical failures - related to electrical components breakdowns, such as power sources and drives.
- Sensor errors - associated with poor sensor positioning or displacement, giving wrong indications to the system.
- Valve failure - related to filters that fail to fulfill their purpose and need to be replaced and wrong valve positioning, which prevents machine correct functioning.
- Undefined (?) - in addition to the cases above, it was not possible to determine the cause of the problem by reading the associated description in these cases. Thus, in these cases, the cause was considered as undefined, for data processing purposes.

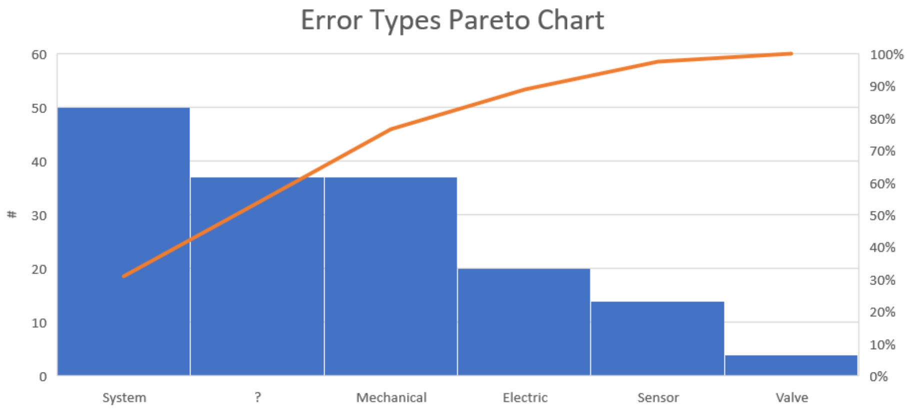

Figure 3.4: Error categorization Pareto chart

The graph in Figure 3.4 shows that the system errors and mechanical failures are the most relevant, as they show a higher number of occurrences, having a large impact on total downtime. Thus, concerning the downtime parameter, the components associated with these failures should be the most valued.

3.2 Methodology

Beyond the analysis of the manufacturing process, which we presented in the previous section, the methodology must ensure the highest standardization in the development of the various monitoring subsystems so that all information is available to the operator and easily accessible, helping in the maintenance interventions decision making process.

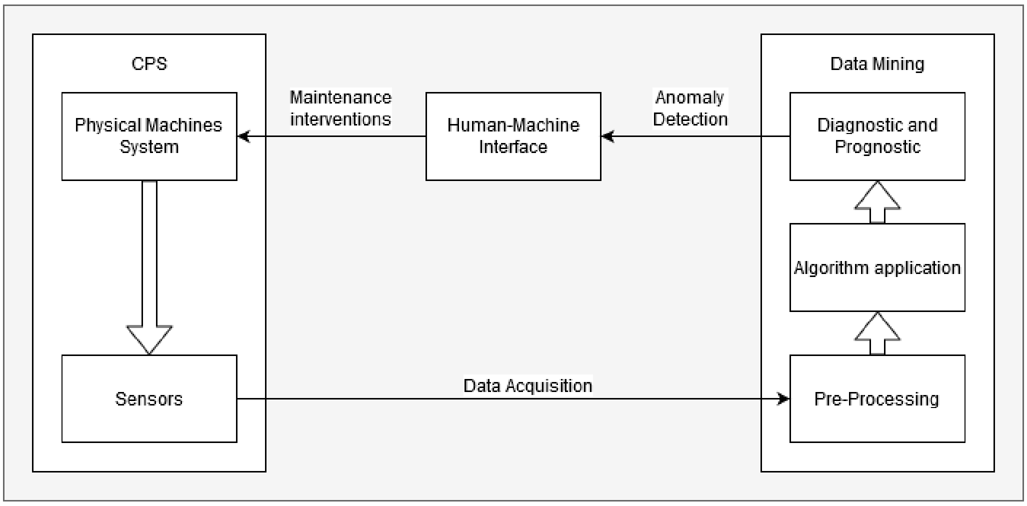

Figure 3.5: System framework to be implemented

For this purpose, we aim at developing a PM system like the one represented in figure 3.5. This type of system is usually divided into three main blocks [48]:

- CPS - where production machines are integrated with sensors for data acquisition;
- Data Mining - where all the acquired data is processed and anomalies or faults are detected
- Human-Machine Interface - responsible for presenting to the user the analyzed information and the anomalies detected to the user, as support for decision-making.

Regarding the anomaly detection method, this may vary for each situation, taking into account the degree of precision required and the information available in each one. In some cases, this detection can be made by setting thresholds for certain quantities, triggering alarms when these are exceeded. In other cases, a trend analysis of the data may be carried out and with the support of an ML algorithm to identify different types of faults.

After testing and implementing this solution on the selected machine, we target its extension to other machines.

3.3 Conclusion

This chapter showed a study based on historical data, namely, breakdowns reports and feedback from the engineering team, to develop a better understanding of the process and identification of critical components and the respective quantities to be monitored. The breakdown reports are also relevant to establish an availability model of the machines, which is beneficial for the engineering and production team. At the end of this analysis, we selected the APEX - AGRO machine for the application of our PM approach.

After having selected the components to be monitored, this chapter ended with a generic maintenance methodology that we will follow in our PM approach.

Chapter 4

Solution Proposal

In this chapter a predictive maintenance system is projected and presented, based on the technologies and algorithms studied in chapter 2 and the maintenance analysis and methodology described in chapter 3. The following sections will describe in detail the system structure and behavior, considering its applicability to a specific machine.

To design a solution it is crucial to have into consideration which technologies have already been installed and how they can work in parallel with the new ones, to optimize the solution. This solution has to be properly structured, in order to simplify the implementation and usability.

4.1 Solution Overview

The machine selected to illustrate the designed system is APEX - AGRO. This machine was chosen because it was identified as critical andit already contained some monitoring systems installed on it.

4.1.1 Machine Architecture and its Maintenance

As mentioned in section 3.1.3 the principal components to be monitored (extruders, engines, TCUs, hydraulic units and bearings) are all included in the part of the machine shown in Figure 4.1.

To monitor and predict faults in bearings the best method is via vibrations. Usually, one or two accelerometers (one in each axis) are used for this purpose. It is possible to use oil inspection in some cases too, but this technique implies stopping machine operation and can only be performed periodically while vibration monitoring can be done continuously while operating. In this case, bearings are associated with conveyor's pulley, as an example, but can be inserted in many other systems.

Supervising motors is crucial as they are difficult to repair or replace and are constituted by various components that can be damaged and cause damages on the rest of the motor. The main failures observed are mechanical wear or cracks in components, such as bearings or the shaft, but misalignment with the gear box or electrical unbalance can also be found. The best way to identify all these failures is by monitoring vibrations in certain points or by monitoring electric current. By

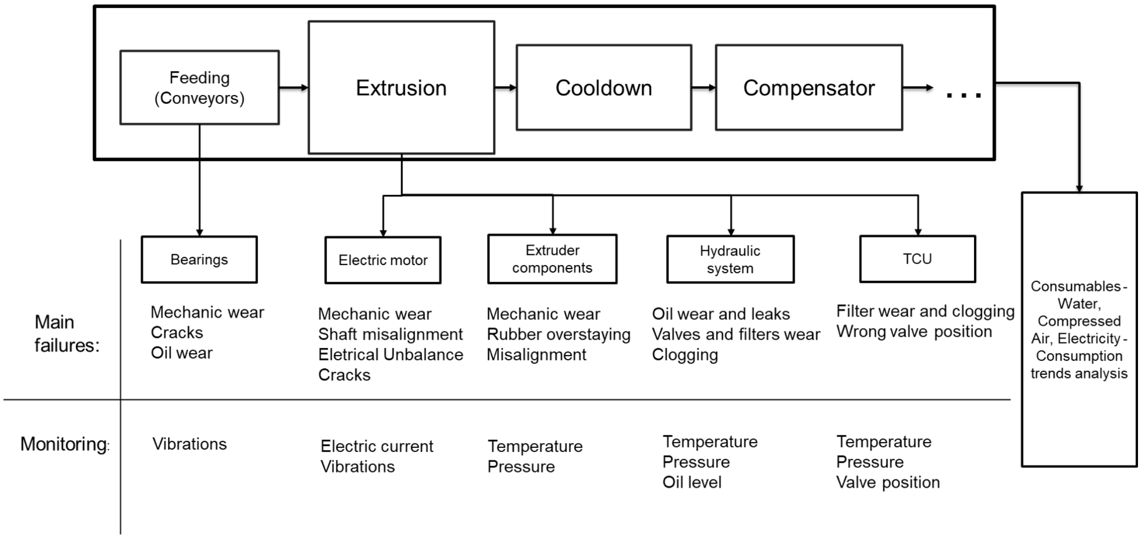

Figure 4.1: APEX components, respective types of failures and relevant signals to monitor

extracting some features of the acquired signals it is possible to detect patterns or tendencies and associate these with potential failures, using ML algorithms.

The focal piece to monitor in the extruder is the screw as it is the moving component and therefore the most susceptible to damage due to the overstaying of rubber, misalignment, or mechanical wear. The presence of rubber inside the extruder can be controlled by continuously monitoring pressure inside. Assuring the correct temperature at the various stages of the extruder is also significant since this has direct impact on the quality of the extruded rubber.

In this case, the hydraulic system is used to assure that the die installed on the head of the extruder is kept in the right place while extracting rubber. On other machines, it may be associated with actions that compressed air actuators are unable to perform. The main flaws correlated with this system are problems in the oil circulation, like oil leaks or clogging, due to valves and filters damage. Therefore, pressure and oil level are the key measurements to be carried out. Temperature variations and peaks can also be a good indicator of some form of error.

Regarding the TCUs, responsible for heating the different sections of the extruder through a water circuit, the primary faults or malfunctioning are associated with filter clogging and valves in the wrong positions thus, pressure and valve position are the fundamental conditions to keep track of. Although it is also important to guarantee that the system reaches the correct temperature levels, the department of metrology is responsible for that matter and therefore should not be considered when developing the system.

Lastly, tracking the utilization of consumables is relevant to establish operation trends and hopefully optimize the respective consumption. Furthermore, it can be used indirectly to detect leaks in the distribution system or in the front-end system.

4.1.2 Pre-installed Monitoring System

Some systems are already equipped with sensors purposefully placed to monitor specific features within these systems, as it is highlighted in figure 4.2. The same type of sensors can be found on different systems and have different applications in each one.

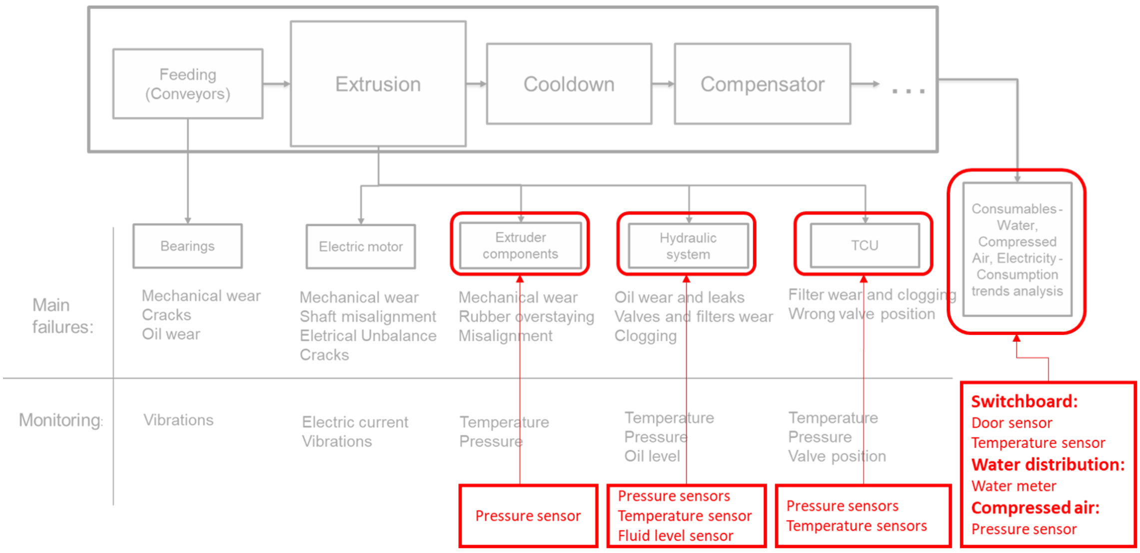

Figure 4.2: Pre-installed monitoring on the APEX machine

As previously mentioned in section 3.1.3.1, the pressure sensor in the extruder is used to detect the presence of rubber inside of it and when this detection happens while the machine is not operating the system should trigger an alarm. The hydraulic system also has the necessary sensors installed. However, no data analysis is being done with the information gathered from them. The TCUs have two pressure sensors at the water entry point to detect filter ware and at the time the difference between the two increases above a certain point, the system triggers an alarm. Temperature sensors are used only as a provider of information to the operator and not as a PM tool. Concerning the consumables mentioned above, some quantities are already being measured regarding electricity and compressed air. These quantities are highly related to improving energy consumption efficiency but can be adapted to implement PM. The water meter is installed in some machines but the collected data is not being analysed.

4.1.3 Monitoring Systems to be Installed

Figure 4.3 shows the sensors that should be installed to accomplish the target PM system, specifically one or more accelerometers on bearings and motor to monitor vibration, and an inclinometer to detect misalignment in the motor. Motor misalignment can be detected indirectly from vibration monitoring turning inclinometers dispensable. However, since the current system has no historical data to develop a precise detection algorithm for misalignment, using inclinometers is a safer option. Regarding the motor, the acquisition of electric current is also important because this method can be used to replace other methods referred previously and does not require any type of

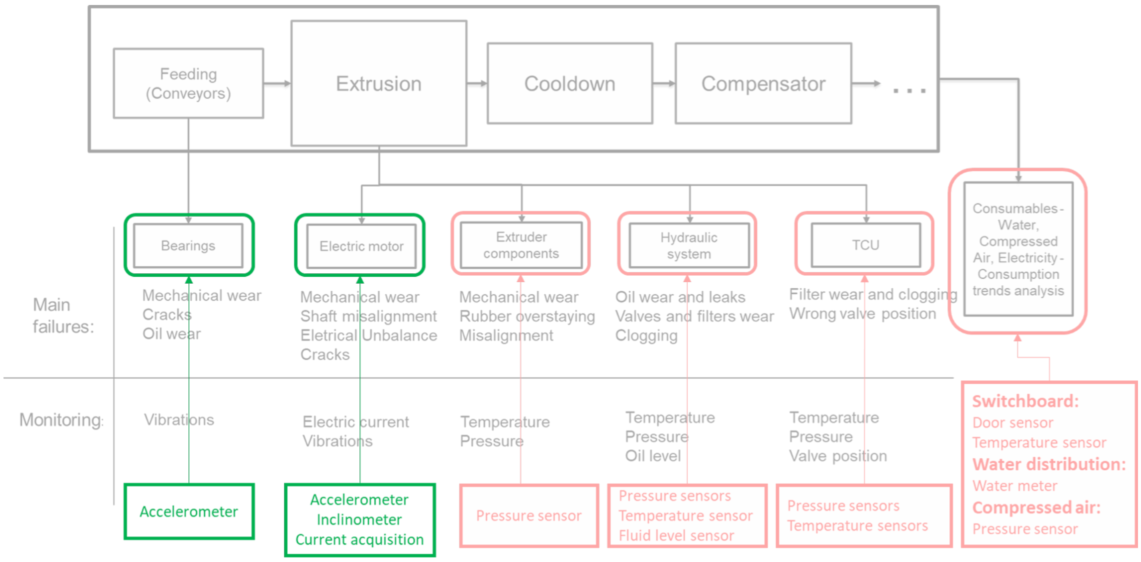

Figure 4.3: Additional monitoring hardware to be installed on the APEX - AGRO machine

sensor installation, as it can be acquired via motor drive. The above-mentioned techniques can be alternatives to each other or can be combined. This combination should grant a better solution.

In addition to the installation of the previously mentioned sensors, it is crucial to develop the software (i.e., data cleaning and analysis using ML algorithms) related to the various subsystems. There are mainly two types of software monitoring rules that can be applied: defining thresholds based on manufacturers' information and triggering alarms when these are exceeded or, analyzing the behavior of a certain characteristic over time, establishing tendencies and clusters, and associating these with specific failures. The latter gives more accurate results, however, it is harder to implement as it requires a vast collection of data over time and more complex algorithms. The implementation and applicability in every case will be thoroughly described in the following sections.

4.2 Sensors Listing

To analyze the proposed PM approach before actual industrial deployment, it is relevant to present a list of the necessary equipment. Concerning software, the necessary programs to acquire data are already integrated into the manufacturing process, and only MATLAB is used to deal with data treatment and ML algorithm implementation.

Regarding the monitoring systems already implemented, there are three main types of sensors to be considered:

- Air flow meter - compressed air monitoring - [66]
- Pressure meter - filter status in water distribution - [3]
- Temperature meter - temperature control in switchboard - [69]

The sensors related to the hydraulic system and TCUs are not mentioned as they are primarily used for control purposes and therefore are directly integrated into the system. As already stated, the information from these sensors only needs to be treated and adapted to condition monitoring purposes and no change to the hardware is needed.

Thus, the only hardware that needs to be installed is accelerometers and inclinometers, to monitor vibration and inclination, respectively. Concerning the accelerometers, there may be some differences between the ones used on motors and the ones used on separate bearings, but in most cases, standard accelerometers serve both purposes. As mentioned, to provide a more accurate prediction it might be needed one accelerometer for each axis. There are many variations, specialized in specific working conditions, but, in this case, accelerometers for general purposes such as those presented below are adequate.

- Quartz based single axis accelerometer - [31]
- Quartz bases triaxial accelerometer - [32]

When choosing an inclinometer it is crucial to consider resistance to vibration. Since it is supposed to be mounted on a motor, it must be prepared to handle the vibration produced by the motor, so that it does not have an impact on the inclination measurement. A good example of an inclinometer for our purposes is the one show in [1].

4.3 Detection Methods

As referred in section 4.1 there are mainly three types of detection methods, in terms of software, to be implemented: detection via threshold setting (basic monitoring), applying ML algorithms to collected data (advanced monitoring) and tracking the consumables and their respective evolution over time (consumables monitoring).

4.3.1 Basic monitoring

Basic monitoring corresponds to defining threshold points related to a certain component behavior characteristic. It is an elementary type of solution regarding industrial systems monitoring with several limitations since it is not able to provide detailed information about the state of the respective component, particularly when the state is continuous. However, it can be a very useful solution when only the manufacturer information is available and no data was yet collected. Therefore, in most cases, this would only be a transitory PM implementation while an ML algorithm is developed and trained. Merely in simpler cases, basic monitoring would be a permanent solution, such as when the component state is limited to a few discrete values

Concerning threshold setting, as above-mentioned, it should be conducted based on manufacturer information, i.e., using values referred to in component's datasheet and a possible tolerance. By way of illustration, when monitoring the oil level in a hydraulic system, the manufacturer should provide the standard values for the lowest and highest accepted levels and from there we can set the threshold values for oil level control.

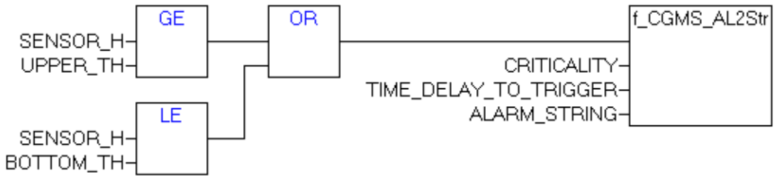

Figure 4.4: Projected implementation for oil level monitoring in PLC programming environment (TwinCat2) using function blocks

The implementation shown in figure 4.4 is an example of a basic monitoring approach already used in the systems mentioned in section 3.1.3.1. This case considers as input the height value of a sensor acquiring the oil level in the hydraulic system tank (SENSOR_H). Moreover, two thresholds, bottom and upper, are defined. As exemplified, if the height value is greater than or equal to the established upper threshold (UPPER_TH) or is lower than or equal to the bottom threshold (BOTTOM_TH) the system triggers a signal used as input in the function block responsible for communicating with the CGMS (f_CGMS_AL2Str). This function has as input the referred signal, criticality (integer number representing the alarm importance), delay sending the alarm, and a string (containing the information to be displayed on the CGMS).

This solution can be adaptable to different cases, containing a greater number of sensors and more complex operations. It is also noteworthy to take into account that values acquired from sensors may need some previous adjustment, depending on the manufacturer's indications.

An elementary case where this approach is adequate as a permanent solution, is valve position control, because it is a discrete information with two or few more values. By using a valve position sensor, e.g., an on-off switch or a rotary switch with various positions, applying a program similar to the preceding example already provides a reliable monitoring solution.

4.3.2 Advanced monitoring

We designate as advanced monitoring the combination of data acquisition and analysis based on ML algorithms, which is particularly relevant when components have a continuous state. Considering vibration acquisition through an accelerometer as an example, it is essential to understand that the acquired signal is very complex and needs to be simplified and reduced to the significant information to condition monitoring. This process is known as feature extraction and selection. In some cases, before executing the mentioned procedure it is critical to clear the noise generated from outside sources or the sensor itself.

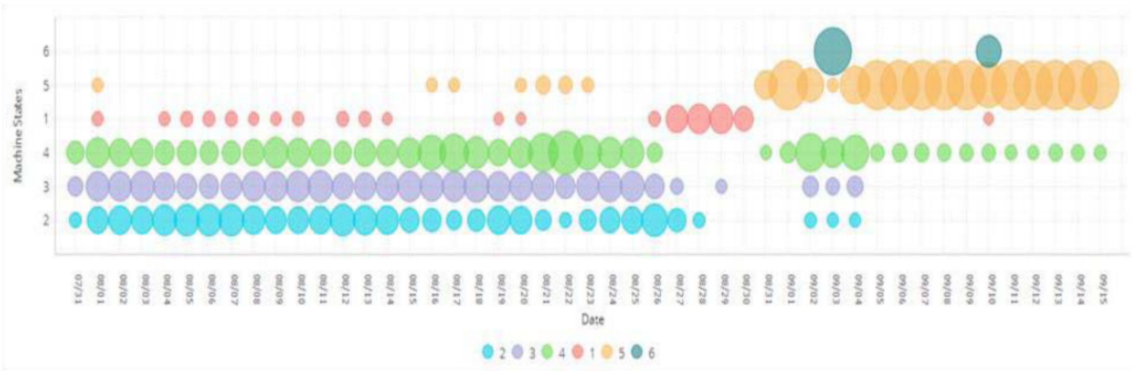

Figure 4.5: Fault type detection using density estimation via GMM - Source: [7]

Figure 4.5 reflects vibration data clustering based on a Gaussian Mixture Model, after feature extraction performed by PCA [7]. As there is no historical data, at first we can only hypothesize about the different computed states. Clusters 2, 3, and 4 as normal operation patterns since they are regular overtime. Conversely, cluster 1 should be considered as a faulty state. In fact, after observing the machine in this state, it was confirmed that there was a faulty component indeed, which was replaced. Cluster 5 reflects the new regular operation condition after switching the defective component.

This system should improve over time as new data is acquired and new faults are found, allowing the system to reduce the time to predict and detect failures by observing patterns and trends that were witnessed previously.

In addition to vibration monitoring, this advanced monitoring approach is also well suited to monitor the electric current because it is also a highly complex signal.

4.3.3 Consumables monitoring

Consumables monitoring identifies utility consumption and relates it with operation schedules and patterns to optimize plant consumption. The system should be designed to allow easy and intuitive access to consumables current and historical information, allowing the user to adapt the history time window and compare different periods. Artificial intelligence can be applied to identify and highlight certain patterns to the user, supporting the decision-making process. Moreover, this monitoring approach should observe all the machines separately, allowing the plant management to make decisions about the best schedule for every machine.

Additionally, consumption monitoring may be applied to components condition monitoring, too, as an indirect method. It is possible to recognize a possible failure, by pinpointing unexpected changes to certain utility consumption.

4.4 Software Development

A part from the basic control method to be implemented at PLC level concerning simpler signals referred in section 4.3.1, other methods for detection, diagnosis and prediction must be implemented regarding complexer signals, for instance, vibration or current. This section focus on software development and algorithm implementation to deal with these signals, identifying and predicting specific failures. The platform used for this purpose is MATLAB, as it provides built-in tools and functions to predictive maintenance problems. The following implementation is based on the tutorials associated with the used datasets [74, 75].

4.4.1 Fault Detection

Considering a vibration signal acquired from a bearing provided by a MATLAB® support dataset [74], it is possible to detect a failure without historical data based on the manufacturer's datasheet. This dataset reflects the evolution of a fault in a bearing overtime.

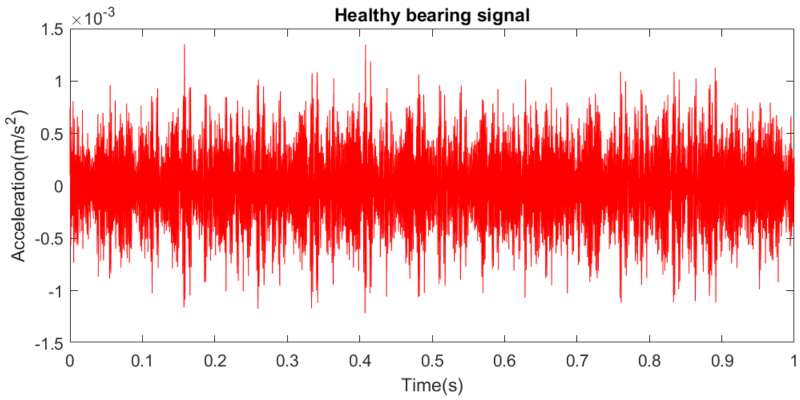

Figure 4.6: Healthy Bearing signal

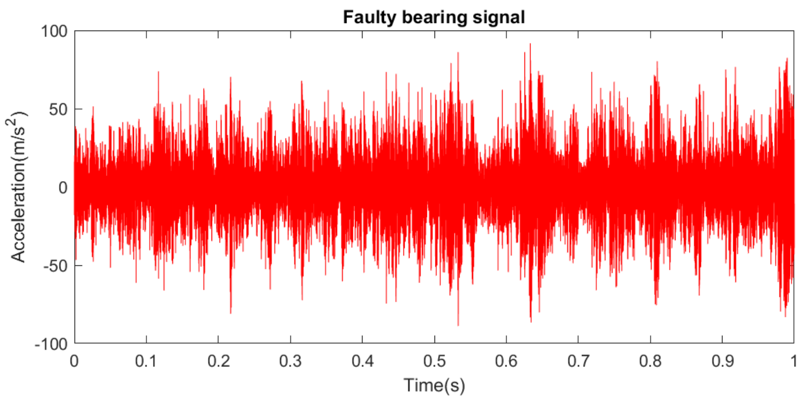

Figure 4.7: Faulty Bearing signal

Figure 4.6 and 4.7 reflect the signal for two different bearing conditions, healthy and faulty, respectively. As shown, the raw signal does not present a noticeable difference, and for that reason it is important to extract specific features in order to detect a failure.

As mentioned before, the proposed project does not include historical data, so only simple detection will be possible in the beginning. For this purpose, straightforward time and frequency-domain features such as mean peak values are enough, as they provide an overview on the signal evolution. It is important to mention that the relevant features to fault detection may vary with different signal behaviours, and therefore it is important to analyze specific characteristics to determine which features to consider.

Analyzing signal characteristics is also essential to understand what kind of filtering is needed before applying any kind of feature extraction and detection. By looking at the signal spectrogram shown in Figure 4.8 it is possible to recognize a lot of high frequency noise that can affect the process and therefore some filtering must be applied.

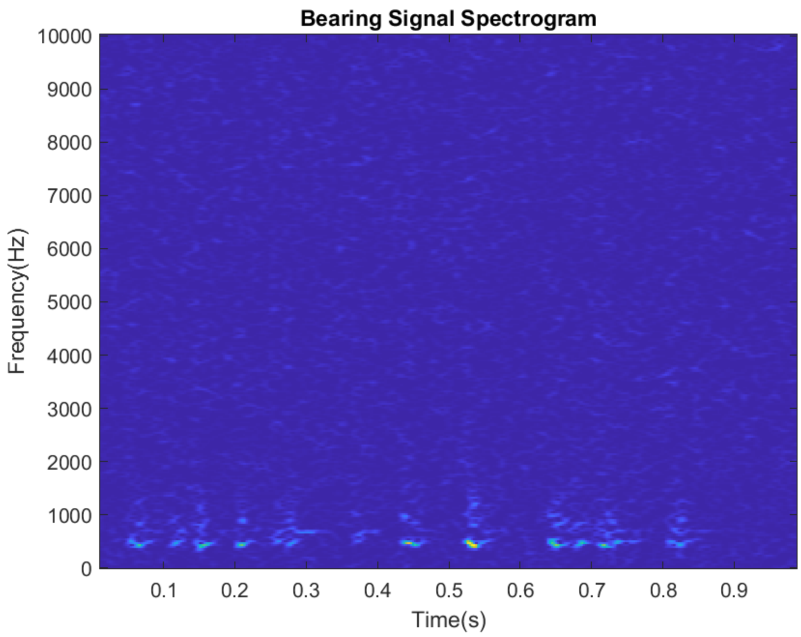

Figure 4.8: Unfiltered Bearing Signal Spectrogram

The areas with a lighter color indicate higher signal energy in the respective frequencies. After applying a median filter, the high frequency noise is suppressed, as shown in Figure 4.9, and feature extraction is now possible, without the risk of compromising the detection result.

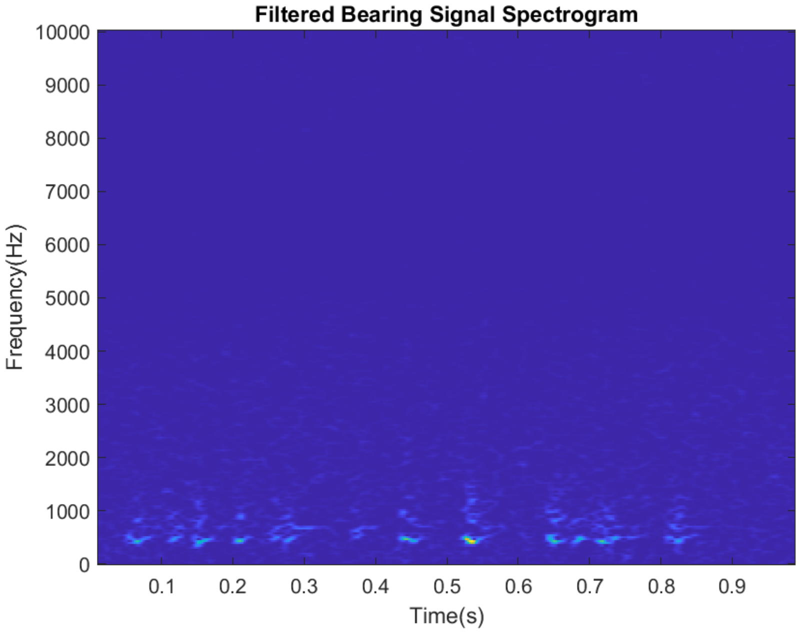

Figure 4.9: Filtered Bearing Signal Spectrogram

As mentioned above, average peak frequency is a good indicator of bearing condition and this is confirmed looking into the spectrogram and observing that the energy is mostly concentrated in a specific frequency. Therefore, after filtering the signal, we extract the average peak frequency for every time instance and the result is demonstrated in Figure 4.10.

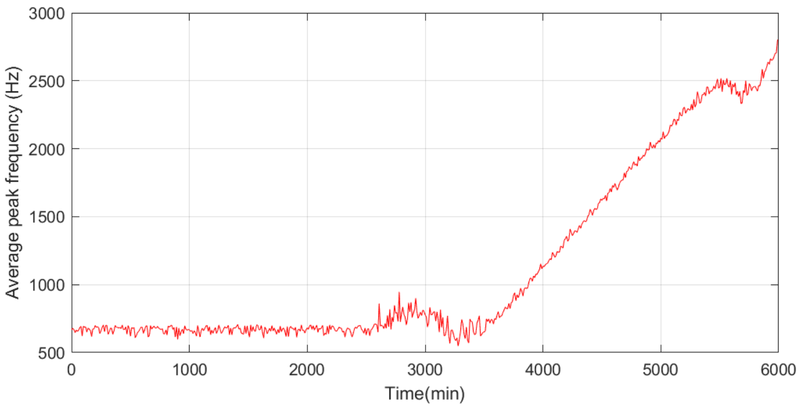

Figure 4.10: Average Peak Frequency Overtime

Figure 4.10 clearly shows a trend in average peak frequency, which can be an indication of a fault increase. Consulting the manufacturer's datasheet it is possible to define a threshold regarding the normal operation frequency limit which the bearing can sustain, triggering an alarm when this limit is reached.

4.4.2 Fault Diagnosis

After gathering data overtime and observing different types of failures related to a component it is possible to associate specific trends and signal behaviour to these types of failures, allowing a focused maintenance intervention.

The MFPT Fault dataset [14] provides a vibration signal concerning a bearing under 3 different conditions: healthy, with outer race fault, and with inner race fault. This data set provides 3 normal conditions signals, 7 inner race fault conditions signals, and 10 outer race conditions signals, that will be separated into training and testing data. Moreover, each signal has certain classes associated with it, such as the sampling rate, the test load, the 4 different fault frequencies and the respective fault condition label. The tested bearing is used at 25 Hz and has the following dimensions:

- Number of rolling elements (spheres) (n): 8;
- Roller (sphere) diameter (dB): 0.235;
- Pitch diameter (inner diameter of the outer ring) (dA): 1.245;
- Contact angle of the spheres ϕ: 0.

With this information, we can calculate the main frequencies to monitor in order to detect the referred failures, using the formulas mentioned in section 2.3.1.2.

- $f_{\text{OR}} = \frac{8}{2} \cdot 25 \cdot (1 - \frac{0.235}{1.245} \cdot cos(0)) = 81,1245 Hz$
- $f_{\text{IR}} = \frac{8}{2} \cdot 25 \cdot (1 + \frac{0.235}{1.245} \cdot cos(0)) = 118,8755 Hz$
- $f_{\text{SPH}} = \frac{1.245}{2 \cdot 0.235} \cdot 25 \cdot (1 - (\frac{0.235}{1.245} \cdot cos(0))^2) = 63,864 Hz$
- $f_{\text{C}} = \frac{1}{2} \cdot 25 \cdot (1 + \frac{0.235}{1.245} \cdot cos(0)) = 10,1406 Hz$

Concerning algorithm development, this will be focused on the first two frequencies, as the used dataset only has data regarding these types of failures. As mentioned in the previous section, not much information is obtained from studying the raw vibration signal. In some cases, not even a envelope spectrum analysis of the raw signal is enough to guarantee that every failure is correctly identified.

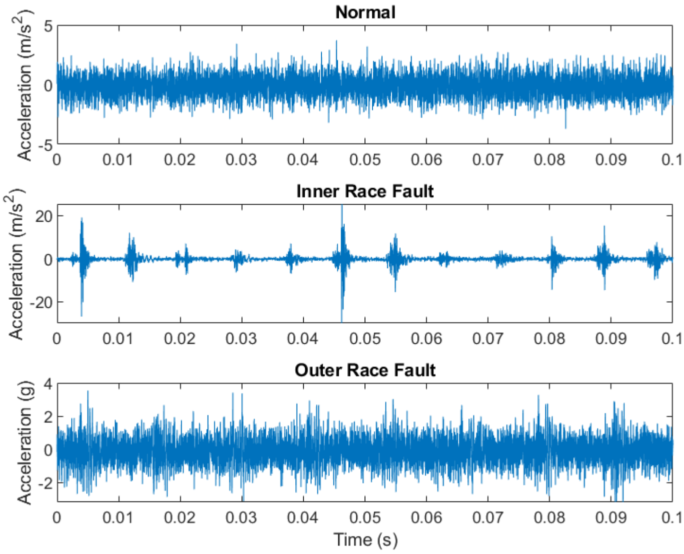

Figure 4.11: Vibration Signal for a normal bearing, a bearing with inner race fault, and a bearing with outer race fault

Observing the three signals shown in Figure 4.11 we can identify different impulsiveness for each signal. Therefore, studying the impulsiveness of the vibration signal can be a reliable way to diagnose which kind of failure is present. To characterize impulsiveness we use kurtosis. After identifying the frequency band with highest kurtosis we can apply a bandpass filter to the raw signal to provide a clearer signal to use in envelope analysis [75].

As referred, we splitted the data into training data and testing data. Training data contains 2 normal sets, 5 inner race fault sets and 7 outer race fault sets. Test data contains 1 normal set, 2 inner race fault sets and 3 outer race fault set.

Table 4.1: Training data amplitudes related to calculated fault frequencies

f_{IR} Amplitude	f_{OR} Amplitude	Fault Type
0.0036798	0.0050208	Normal
0.00359	0.0069449	Normal
0.33918	0.082296	Inner Race Fault
0.31488	0.026599	Inner Race Fault
0.52356	0.036609	Inner Race Fault
0.52899	0.028381	Inner Race Fault
0.13515	0.012337	Inner Race Fault
0.004024	0.03574	Outer Race Fault
0.0044918	0.1835	Outer Race Fault
0.0074993	0.30166	Outer Race Fault
0.013662	0.12468	Outer Race Fault
0.0070963	0.28215	Outer Race Fault
0.0060772	0.35241	Outer Race Fault
0.011244	0.17975	Outer Race Fault

The amplitudes presented in table 4.1 are calculated as part of the fault diagnosis algorithm. By performing a kurtogram, which computes local kurtosis within certain frequency bands, we can highlight the modulated amplitude regarding specific frequencies, enhancing the envelope spectrum analysis. An example of this application is given below.

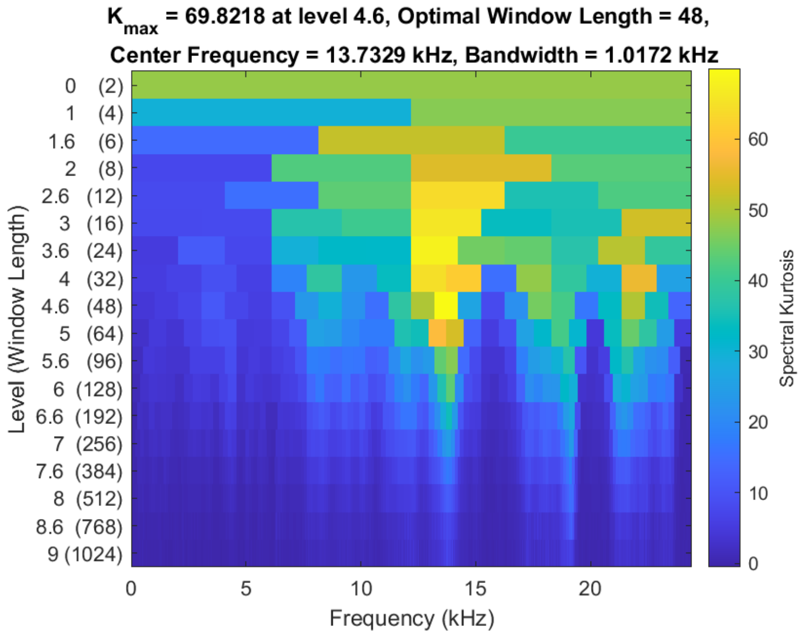

Figure 4.12: Kurtogram of a inner race fault vibration signal

Figure 4.12 shows a kurtogram regarding a vibration signal of a bearing with a inner race fault. It indicates that the highest kurtosis of 69.82 is at the frequency band (Center frequency - Cf) of 13.73 kHz with a bandwith (BW) of 1.02 kHz. With this information we can design and apply a suitable bandpass filter for every signal, using a bandwith between [Cf-BW/2] and [Cf+BW/2].

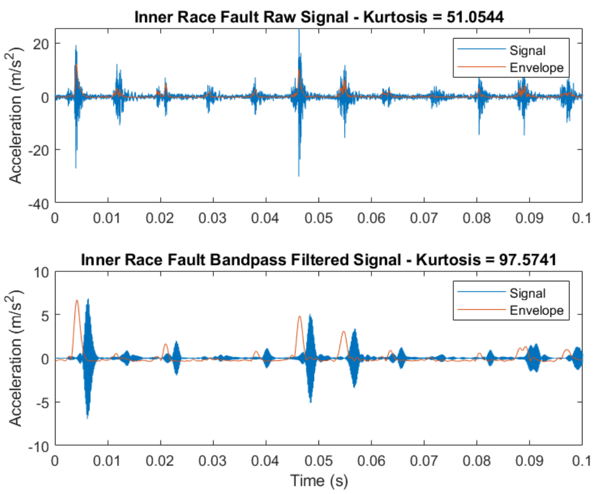

Figure 4.13: Vibration signal comparison (unfiltered and filtered)

Figure 4.13 demonstrates that a filtered signal regarding the computed central frequency and bandwith has clearer envelope and higher kurtosis, highlighting the impulsiveness of the intended frequency. Then, after filtering the signal, we can perform an envelope spectrum analyses with the confidence of a reduced noise signal and better diagnosis capability.

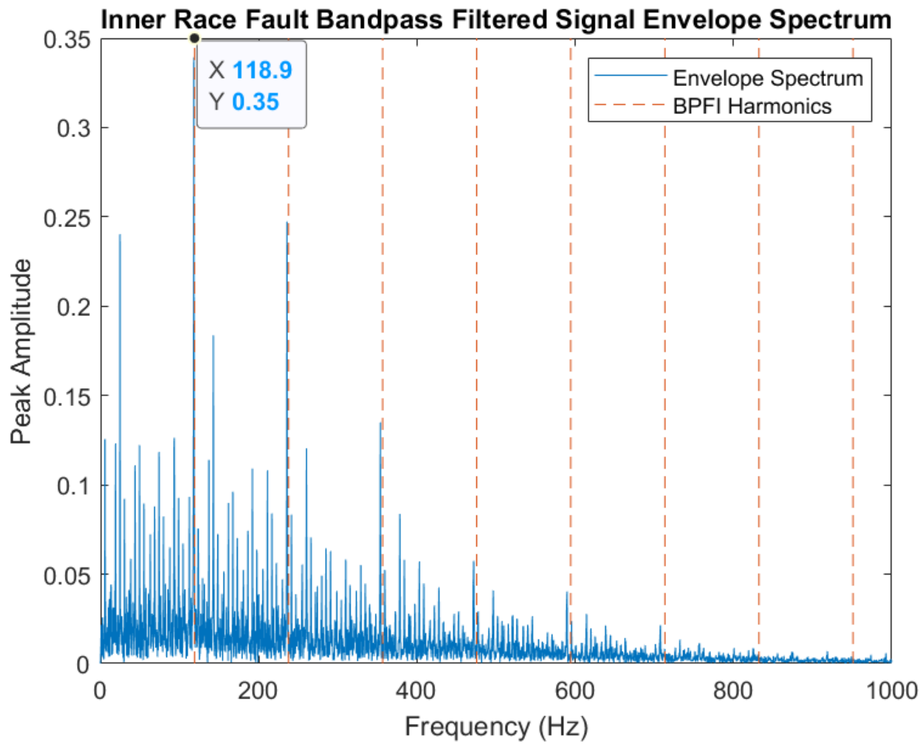

Figure 4.14: Inner race fault bandpass filtered signal envelope spectrum analyses

As expected for a inner race fault bearing vibration signal with the above-mentioned dimensions, the peak amplitude is found around 118.9 Hz, with a value of 0.35 (similar to the values registered concerning the training data).

Regarding table 4.1 it is important to notice the relationship between both amplitudes concerning the three different conditions, as they can be a good indicator to use in order to identify and separate incoming new data. By plotting the training dataset (Figure 4.15) we can clearly identify three clusters, each one related to a specific fault.

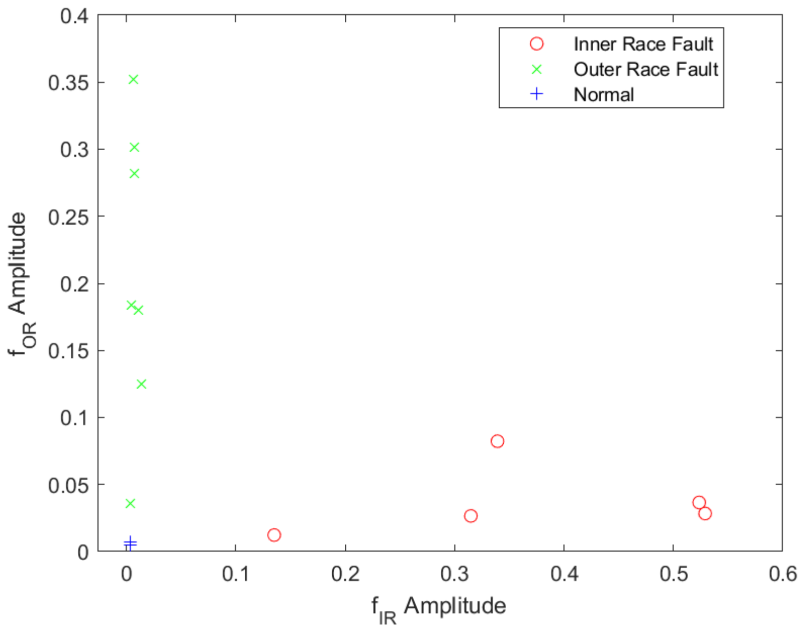

Figure 4.15: Scatter plot regarding f_{IR} and f_{OR} amplitudes of the training data

Predictably, outer race fault bearings have high amplitude regarding f_{OR} frequency and low amplitude in f_{IR} frequency. The opposite happens in inner race fault bearings, i.e., low amplitude in f_{OR} and high amplitude in f_{IR}. Normal bearings have low amplitude concerning both frequency bands, as expected.

With this, we can establish a ratio between the two amplitudes for each dataset and use it as a classification method. Based on [75] a logarithmic ratio is defined as:

- Outer race fault bearing: $log(\frac{f_{IR}}{f_{OR}}) \leq -1.5$
- Normal bearing: $-1.5 < log(\frac{f_{IR}}{f_{OR}}) \leq 0.5$
- Inner race fault bearing: $log(\frac{f_{IR}}{f_{OR}}) > 0.5$

The classification presented above is applied having into consideration that the used data set only includes bearings with one fault type. To utilize this classification in bearings that present both fault types, we would need to verify the specific fault amplitudes for bearings classified as normal and if both amplitudes were elevated we should change the classification from "normal bearing" to "inner and outer race fault bearing". Moreover, to consider the four types of faults regarding bearings, the best way to identify these faults would be by defining thresholds for each amplitude. These thresholds can be static or can variate, in order to adapt to incoming data and optimize the classification.

We can now test the developed algorithm using the remaining vibration data chosen to testing. The test data f_{IR} and f_{OR} computed amplitudes as well as the log ratio between these amplitudes are presented in table 4.2.

Table 4.2: Test data amplitudes and log ratio

f_{IR} Amplitude	f_{OR} Amplitude	Log Ratio	Fault Type
0.0043813	0.0070156	-0.47079	Normal
0.65627	0.04334	2.7175	Inner Race Fault
1.1497	0.059562	2.9602	Inner Race Fault
0.0035644	0.10248	-3.3586	Outer Race Fault
0.0087894	0.13508	-2.7323	Outer Race Fault
0.074398	0.54605	-1.9933	Outer Race Fault

The test results validate the filter and classification algorithm implemented, as all datasets fall into the expected log ratio interval, i.e., the normal bearing is between -1.5 and 0.5, inner race fault bearings are over 0.5, and outer race fault bearings are under -1.5. To provide a visual description of the results we computed a histogram with train and data results for comparison purposes.

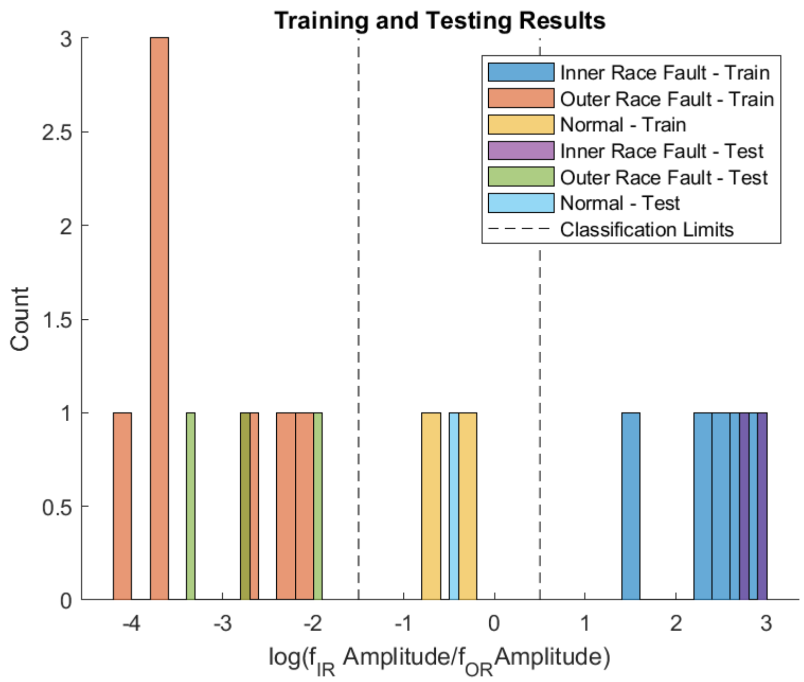

Figure 4.16: Train and test results histogram

The histogram shown in Figure 4.16 confirms the results demonstrated in tables 4.1 and 4.2, as the various datasets fall into the expected categories.

The next step would be deploying this algorithm into a real world situation and monitor its behaviour, looking for new fault types in order to adjust and optimize the algorithm and its boundaries, improving its ability to deal with a more complex environment.

4.4.3 Fault Prediction

Fault prognostics are usually performed based on a developed component behaviour model. Accomplishing a reliable fault prediction model is a very complex task as it requires high quantities of historical data.

Utilizing the dataset used in section 4.4.1 to build a detection algorithm, we try to develop a prediction model that uses historical data and incoming new data to perform an estimate of the component behaviour evolution, in order forecast a failure before it happens. Since we already verified that signal mean peak frequency is a viable feature to condition monitor, we use this same feature to build the prognostics model. However, as mentioned, in other cases it may be required combining several features to guarantee a proper solution.

We use the first 200 data points of the extracted feature to establish a initial model, as it is guaranteed that the bearing has not any type of fault during this time window. We defined a threshold on 2000 Hz to trigger an alarm when the prediction data surpasses it, according to [74]. In addition, we set the dynamic model to be updated every 30 new data points calculated, using the last 200 points stored. Moreover, we set the forecasting time limit to 100, i.e., the model is limited to estimating 100 data points ahead. These parameters can be adjusted to fulfill client preferences, bearing in mind that increasing the prediction time window will reduce precision and vice-versa, while reducing the number of new data points received to update the model will increase the computational effort.

We can compute a discrete-time series state space model, based on the following equations:

$$x(t+T_s) = Ax(t) + Be(t) \tag{4.1}$$

$$y(t) = Cx(t) + e(t) \tag{4.2}$$

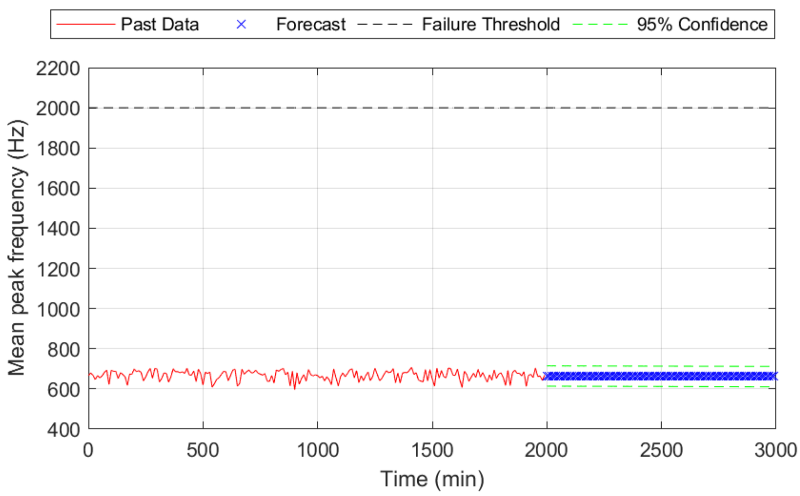

Figure 4.17: Initial dynamic model graph representation

Figure 4.17 shows a representation of the initial computed model, based on the first 200 values. As expect, a very linear and stable behaviour is represented and the prediction indicates that this behaviour should continue. We are now able to run the algorithm responsible for receiving new data and updating the above-mentioned dynamic model.

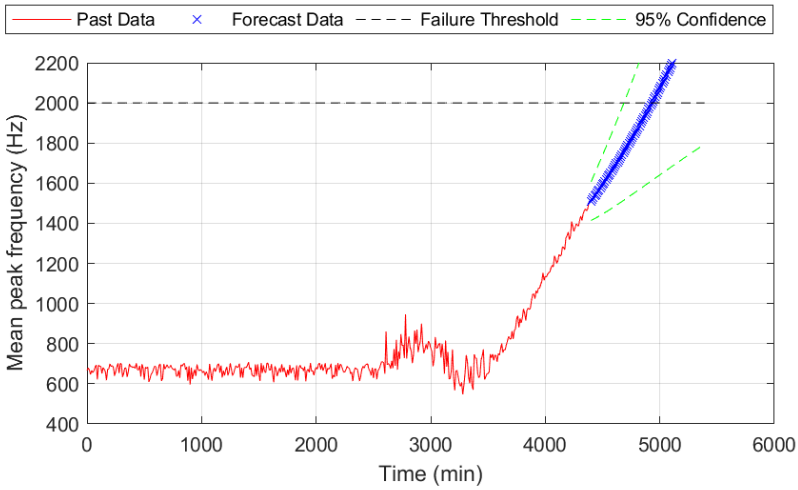

Figure 4.18: Final dynamic model graph representation (after predicting a failure)

After running the algorithm, a fault is predicted approximately 550 minutes before it happens, with a 80.85% fit. As observable, the 95% confidence interval has widened in comparison to the initial computed model, due to the increase of data variation.

4.5 Conclusion

In this chapter, we identified the essential sensors to be installed in order to acquire the necessary data to be used as inputs in the ML algorithms. We then identified three types of monitoring, regarding software, that can be implemented: basic, advanced, and consumables. Finally, we developed three algorithms using MATLAB to detect, diagnose, and predict failures. To train and test these algorithms we used datasets provided by MathWorks. We obtained positive results, as we were able to detect and identify different types of faults, as well as predicting future faults.

Chapter 5

Conclusions and Future Work

The work developed regarding the situation at the CST plant at Continental Mabor - Indústria de Pneus, S.A., was aligned with the Industry 4.0 context. This new industry philosophy is directed to increase production efficiency by reducing failures and downtime, through maintenance plan improvement and PM systems implementation.

PM systems are usually divided into two major parts: hardware and software. Hardware includes all the sensors used to acquire data from the monitored components. It is essential to select the proper sensors for each component, considering what quantities are relevant to monitor, the ranges in which these quantities vary, and the working conditions the sensor will be exposed to. Software comprehends acquired data processing and analysis as well as information display via a HMI. Before applying any type of analysis on the acquired data it is crucial to treat and filter the data to ensure that the analysis results are not compromised by errors regarding unfiltered data. To properly implement a ML algorithm is crucial to define specifically the inputs and outputs of the system and the expected behavior regarding certain situations. In this case, components reliability models should be considered when building the algorithm, to obtain precise results.

To understand the plant production process and identify the critical components of this process, an analysis of the 2019 breakdown report was conducted. With this investigation, we were able to determine the critical components in which the PM system implementation should focus, using a specific classification. We then defined the methodology to structure, develop, and deploy the mentioned system.

Regarding the proposed system, three types of monitoring were thought out: basic monitoring, advanced monitoring, and consumables monitoring. The first one consists of defining thresholds related to the acquired data and triggering alarms when these thresholds are reached, on a PLC level. Consumables monitoring is designed to pinpoint specific patterns and trends regarding utility consumption to optimize general plant consumption. Advanced monitoring is adequate for complex data analysis using ML algorithms and is the preferred method to perform component thorough monitoring. For this reason, we focused the software development in this type of system.

We started software development by implementing an algorithm capable of distinguishing a healthy bearing vibration signal from a faulty bearing vibration signal, i.e., an algorithm for fault detection. This method requires feature extraction regarding time and frequency domains, as it is not possible to identify clear differences by investigating the raw signals. Furthermore, to guarantee a proper feature extraction, we noticed a necessity to use a filtering method before applying the algorithm. A more complex algorithm was implemented to perform fault diagnosis, i.e., identifying specific faults in the component. We used a more complete dataset to train and test this algorithm as it requires more data to identify different fault scenarios. Based on the dimensions of the bearing used to generate the dataset we established the main frequencies to monitor in order to identify different failures and applied a filter around them, based on the indications given from the kurtogram function. Finally, we developed an algorithm with the intent of predicting a fault before it happens, by analyzing the historical and incoming data. The reliability of this prognostic model may vary with parameters defined regarding the prediction time window.

At this stage, we were able to study the processes inherent to the machines and breakdown reports, identifying the critical components to focus our PM system development. We also identified some sensors to be installed to acquire the desired data for monitoring the selected components. Finally, we developed ML algorithms to detect, diagnose, and predict faults. Due to the constraints imposed by the COVID-19 pandemic, we were not able to implement a real system. Therefore, as future work, we would like to install adequate sensors in the selected machine to start acquiring real data. With this, we would be able to deploy the developed algorithms into a real situation and perform the necessary adjustments. We would then be able to extend these algorithms to other signals such as current. Furthermore, implementing a HMI to provide clear information concerning the status of the components would be essential to ensure proper machine maintenance by the maintenance team.

Appendix A

Components Classification

Table A.1: Components classification concerning relevance for the maintenance process

Sistema	Componente	Blocos comuns	Criticidade	Tempo de paragem	Custos de manutenção
Extrusoras	Corpo	3,00	5,00	4,00	4,00
Extrusoras	Fuso	3,00	5,00	4,00	4,00
Acionamento	Motores PM (2kW a 15,7kW)	5,00	3,00	3,00	3,50
Complementos	TCU	3,00	4,00	2,00	4,00
Complementos	Unidade hidraulica	3,00	4,00	2,00	4,00
Acionamento	Motores PME (111kW a 403kW)	1,33	5,00	3,00	5,00
Acionamento	Rolamento	5,00	2,00	3,00	2,00
Extrusoras	Cabeça	3,00	4,00	1,00	4,00
Acionamento	Motores PE (17,5kW a 60kW)	1,67	5,00	1,00	4,00
Componentes elétricos	Fusíveis	5,00	1,00	5,00	1,00
Componentes elétricos	Disjuntores	5,00	1,00	5,00	1,00
Componentes elétricos	PLC	5,00	1,00	5,00	1,00
Componentes elétricos	Cartas I/O	5,00	1,00	5,00	1,00
Componentes elétricos	Módulos de controlo	5,00	1,00	5,00	1,00
Acionamento	Caixa redutora	5,00	1,50	2,00	3,00
Outros	Tambor de construção	1,00	4,00	3,00	4,00
Outros	Tambor de expansão	1,00	4,00	3,00	4,00
Alimentação (Utilidades)	Circuito de ar comprimido	5,00	1,00	1,00	4,00
Acionamento	Motores PB (0,042kW a 2,9kW)	5,00	1,50	1,00	3,00
Acionamento	Veio	5,00	1,50	1,00	3,00
Ferramentas de corte	Lâmina rotativa	1,67	4,00	3,00	2,00
Outros	Prensa	1,00	3,00	3,00	4,00
Extrusoras	Fieira	3,00	4,00	1,00	1,50
Passadeiras	Cintas	4,33	1,00	3,00	1,50
Outros	Anel de construção	1,00	3,00	4,00	2,50
Alimentação (Utilidades)	Circuito de água	3,00	1,00	2,00	4,00
Passadeiras	Rolos	4,00	1,00	3,00	1,50
Pneumático	Unidade de preparação de ar - FRL	5,00	1,00	1,00	2,00
Pneumático	Válvula	5,00	1,00	1,50	1,00
Pneumático	Tubagem	5,00	1,00	1,50	1,00
Pneumático	Atuadores/Cilindros	5,00	1,00	1,00	1,50
Ferramentas de corte	Lâmina quente	1,67	4,00	1,00	1,50
Medição e Controlo	Sistema de visão (centragem e deteção)	1,67	3,50	1,00	2,00
Outros	Tambores de arrefecimento	1,33	2,00	3,00	2,00
Medição e Controlo	Controlo de espessura	0,33	3,50	1,00	2,00
Medição e Controlo	Balança	1,00	2,50	1,00	2,00
Medição e Controlo	Termómetro	1,00	2,50	1,00	1,00
Acionamento	Correias	1,00	1,50	2,00	1,00
Ferramentas de corte	Tesoura	0,67	1,00	1,00	1,50
Outros	Tensores	0,67	1,00	1,00	1,00

Table A.2: Reduced components list - grouped by system

Sistema	Componente	Blocos comuns (25%)	Criticidade (25%)	Tempo de paragem (25%)	Custos de manutenção (25%)	Avaliação Final
Extrusoras	Corpo e Fuso	3,00	5,00	4,00	4,00	4,00
Acionamento	Motores PM (2kW a 15,7kW)	5,00	3,00	3,00	3,50	3,63
Acionamento	Motores PME (111kW a 403kW)	1,33	5,00	3,00	5,00	3,58
Complementos	TCU	3,00	4,00	2,00	4,00	3,25
Complementos	Unidade hidraulica	3,00	4,00	2,00	4,00	3,25
Acionamento	Rolamento	5,00	2,00	3,00	2,00	3,00
Extrusoras	Cabeça	3,00	4,00	1,00	4,00	3,00
Componentes elétricos	Proteção Elétrica (Fusíveis e Disjuntores)	5,00	1,00	5,00	1,00	3,00
Componentes elétricos	Controlo (PLC, I/O, Mód. de controlo)	5,00	1,00	5,00	1,00	3,00
Outros	Tambor de construção	1,00	4,00	3,00	4,00	3,00
Outros	Tambor de expansão	1,00	4,00	3,00	4,00	3,00
Acionamento	Motores PE (17,5kW a 60kW)	1,67	5,00	1,00	4,00	2,92
Acionamento	Caixa redutora	5,00	1,50	2,00	3,00	2,88
Alimentação (Utilidades)	Circuito de ar comprimido	5,00	1,00	1,00	4,00	2,75
Outros	Prensa	1,00	3,00	3,00	4,00	2,75
Ferramentas de corte	Lâmina rotativa	1,67	4,00	3,00	2,00	2,67
Acionamento	Motores PB (0,042kW a 2,9kW)	5,00	1,50	1,00	3,00	2,63
Acionamento	Veio	5,00	1,50	1,00	3,00	2,63
Outros	Anel de construção	1,00	3,00	4,00	2,50	2,63
Alimentação (Utilidades)	Circuito de água	3,00	1,00	2,00	4,00	2,50
Passadeiras	Cintas	4,33	1,00	3,00	1,50	2,46
Extrusoras	Fieira	3,00	4,00	1,00	1,50	2,38
Pneumático	Unidade de preparação de ar - FRL	5,00	1,00	1,50	2,00	2,38
Passadeiras	Rolos	4,00	1,00	3,00	1,50	2,38
Pneumático	At. Pneumática(Válvula, Tubagem, Cilindros)	5,00	1,00	1,50	1,00	2,13
Outros	Tambores de arrefecimento	1,33	2,00	3,00	2,00	2,08
Ferramentas de corte	Lâmina quente	1,67	4,00	1,00	1,50	2,04
Medição e Controlo	Sistema de visão (centragem e deteção)	1,67	3,50	1,00	2,00	2,04
Medição e Controlo	Controlo de espessura	0,33	3,50	1,00	2,00	1,71
Medição e Controlo	Balança	1,00	2,50	1,00	2,00	1,63
Medição e Controlo	Termómetro	1,00	2,50	1,00	1,00	1,38
Acionamento	Correias	1,00	1,50	2,00	1,00	1,38
Ferramentas de corte	Tesoura	0,67	1,00	1,00	1,50	1,04
Outros	Tensores	0,67	1,00	1,00	1,00	0,92

Table A.3: Final classification considering the same weight for every criteria

Sistema	Componente	Blocos comuns (25%)	Criticidade (25%)	Tempo de paragem (25%)	Custos de manutenção (25%)	Avaliação Final
Extrusoras	Corpo e Fuso	3,00	5,00	4,00	4,00	4,00
Acionamento	Motores PM (2kW a 15,7kW)	5,00	3,00	3,00	3,50	3,63
Acionamento	Motores PME (111kW a 403kW)	1,33	5,00	3,00	5,00	3,58
Complementos	TCU	3,00	4,00	2,00	4,00	3,25
Complementos	Unidade hidraulica	3,00	4,00	2,00	4,00	3,25
Acionamento	Rolamento	5,00	2,00	3,00	2,00	3,00
Extrusoras	Cabeça	3,00	4,00	1,00	4,00	3,00
Componentes elétricos	Proteção Elétrica (Fusíveis e Disjuntores)	5,00	1,00	5,00	1,00	3,00
Componentes elétricos	Controlo (PLC, I/O, Mód. de controlo)	5,00	1,00	5,00	1,00	3,00
Outros	Tambor de construção	1,00	4,00	3,00	4,00	3,00
Outros	Tambor de expansão	1,00	4,00	3,00	4,00	3,00
Acionamento	Motores PE (17,5kW a 60kW)	1,67	5,00	1,00	4,00	2,92
Acionamento	Caixa redutora	5,00	1,50	2,00	3,00	2,88
Alimentação (Utilidades)	Circuito de ar comprimido	5,00	1,00	1,00	4,00	2,75
Outros	Prensa	1,00	3,00	3,00	4,00	2,75
Ferramentas de corte	Lâmina rotativa	1,67	4,00	3,00	2,00	2,67
Acionamento	Motores PB (0,042kW a 2,9kW)	5,00	1,50	1,00	3,00	2,63
Acionamento	Veio	5,00	1,50	1,00	3,00	2,63
Outros	Anel de construção	1,00	3,00	4,00	2,50	2,63
Alimentação (Utilidades)	Circuito de água	3,00	1,00	2,00	4,00	2,50
Passadeiras	Cintas	4,33	1,00	3,00	1,50	2,46
Extrusoras	Fieira	3,00	4,00	1,00	1,50	2,38
Passadeiras	Rolos	4,00	1,00	3,00	1,50	2,38
Pneumático	Unidade de preparação de ar - FRL	5,00	1,00	1,50	2,00	2,38
Pneumático	At. Pneumática(Válvula, Tubagem, Cilindros)	5,00	1,00	1,50	1,00	2,13
Outros	Tambores de arrefecimento	1,33	2,00	3,00	2,00	2,08
Ferramentas de corte	Lâmina quente	1,67	4,00	1,00	1,50	2,04
Medição e Controlo	Sistema de visão (centragem e deteção)	1,67	3,50	1,00	2,00	2,04
Medição e Controlo	Controlo de espessura	0,33	3,50	1,00	2,00	1,71
Medição e Controlo	Balança	1,00	2,50	1,00	2,00	1,63
Medição e Controlo	Termómetro	1,00	2,50	1,00	1,00	1,38
Acionamento	Correias	1,00	1,50	2,00	1,00	1,38
Ferramentas de corte	Tesoura	0,67	1,00	1,00	1,50	1,04
Outros	Tensores	0,67	1,00	1,00	1,00	0,92

Table A.4: Final classification with a weighted average

Sistema	Componente	Blocos comuns (25%)	Criticidade (25%)	Tempo de paragem (25%)	Custos de manutenção (25%)	Avaliação Final
Extrusoras	Corpo e Fuso	3,00	5,00	4,00	4,00	4,00
Acionamento	Motores PM (2kW a 15,7kW)	5,00	3,00	3,00	3,50	3,70
Acionamento	Motores PME (111kW a 403kW)	1,33	5,00	3,00	5,00	3,50
Complementos	TCU	3,00	4,00	2,00	4,00	3,30
Complementos	Unidade hidraulica	3,00	4,00	2,00	4,00	3,30
Acionamento	Rolamento	5,00	2,00	3,00	2,00	3,10
Extrusoras	Cabeça	3,00	4,00	1,00	4,00	3,10
Componentes elétricos	Proteção Elétrica (Fusíveis e Disjuntores)	5,00	1,00	5,00	1,00	3,00
Componentes elétricos	Controlo (PLC, I/O, Mód. de controlo)	5,00	1,00	5,00	1,00	3,00
Acionamento	Motores PE (17,5kW a 60kW)	1,67	5,00	1,00	4,00	3,00
Acionamento	Caixa redutora	5,00	1,50	2,00	3,00	2,95
Outros	Tambor de construção	1,00	4,00	3,00	4,00	2,90
Outros	Tambor de expansão	1,00	4,00	3,00	4,00	2,90
Alimentação (Utilidades)	Circuito de ar comprimido	5,00	1,00	1,00	4,00	2,80
Acionamento	Motores PB (0,042kW a 2,9kW)	5,00	1,50	1,00	3,00	2,75
Acionamento	Veio	5,00	1,50	1,00	3,00	2,75
Ferramentas de corte	Lâmina rotativa	1,67	4,00	3,00	2,00	2,70
Outros	Prensa	1,00	3,00	3,00	4,00	2,60
Extrusoras	Fieira	3,00	4,00	1,00	1,50	2,60
Outros	Anel de construção	1,00	3,00	4,00	2,50	2,50
Passadeiras	Cintas	4,33	1,00	3,00	1,50	2,50
Pneumático	Unidade de preparação de ar - FRL	5,00	1,00	1,50	2,00	2,50
Alimentação (Utilidades)	Circuito de água	3,00	1,00	2,00	4,00	2,40
Passadeiras	Rolos	4,00	1,00	3,00	1,50	2,40
Pneumático	At. Pneumática(Válvula, Tubagem, Cilindros)	5,00	1,00	1,50	1,00	2,30
Ferramentas de corte	Lâmina quente	1,67	4,00	1,00	1,50	2,20
Medição e Controlo	Sistema de visão (centragem e deteção)	1,67	3,50	1,00	2,00	2,15
Outros	Tambores de arrefecimento	1,33	2,00	3,00	2,00	2,00
Medição e Controlo	Controlo de espessura	0,33	3,50	1,00	2,00	1,75
Medição e Controlo	Balança	1,00	2,50	1,00	2,00	1,65
Medição e Controlo	Termómetro	1,00	2,50	1,00	1,00	1,45
Acionamento	Correias	1,00	1,50	2,00	1,00	1,35
Ferramentas de corte	Tesoura	0,67	1,00	1,00	1,50	1,00
Outros	Tensores	0,67	1,00	1,00	1,00	0,90

Appendix B

2019 Breakdown Report

Table B.1: Number of errors and total and average downtime sorted by error type

Tipos de Erros	Contagem	Tempo Total de Paragem	Tempo Médio de Paragem
?	37	59,65	96,73
Electric	20	42,46	127,38
Mechanical	38	81,13	131,56
Sensor	14	25,79	110,53
system	50	95,44	114,53
Valve	4	8,81	132,15

Table B.2: Number of errors and total and average downtime sorted by machine

Máquina	Número de Paragens	Tempo total de Paragem	Tempo Médio de Paragem
Apex 01	346	96,07	16,66
Apex 02	27	1,41	3,13
Belt Cutter	39	19,14	29,45
Extrusora 01	182	59,47	19,61
Innerliner	46	21,92	28,59
Máquina Carcaças 01	307	72,82	14,23
Máquina Carcaças 02	324	79,82	14,78
Máquina Carcaças 03	310	100,73	19,50
Máquina Corte Têxtil 01	173	54,59	18,93
Máquina de construção OTR #1	338	101,54	18,02
Máquina de construção OTR #2	65	19,48	17,98
Máquina de Talões 01	167	34,47	12,38
Máquina de talões 02	26	3,54	8,17
Máquina Pneus em Verde 01	157	27,25	10,48
Máquina Pneus em Verde 02	178	45,14	15,22
Máquina Pneus em Verde 03	159	41,23	15,56
Máquina Strip Winding 01	34	13,77	24,30
Ply Cutter	37	9,45	15,32
Strip Winding Machine 02	13	2,88	13,29

Table B.3: Number of errors and total and average downtime sorted by system

Sistema	Número de Paragens	Tempo Total de Paragem	Tempo médio de Paragem
Automação e controlo geral	539	226,66	25,23
SM - Shaping Machine	32	11,33	21,24
CM - Carcass Machine	51	16,42	19,32
Alimentação elétrica geral	437	122,76	16,85
BM - Belt Machine	49	13,03	15,96
Alimentação pneumática geral	140	36,82	15,78
Extrusora	95	24,49	15,47
Estação de carretilhagem	105	25,65	14,66
Alimentador móvel	105	23,89	13,65
Downstream	31	6,64	12,85
Cabeçote móvel	34	7,18	12,67
Cabeçote fixo	75	15,14	12,11
Estação de construção	46	8,36	10,90
Alimentador da camada	51	9,11	10,72
Unidade laser de posicionamento	48	7,71	9,64

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