





# DEVELOPMENT OF A PREDICTIVE MAINTENANCE MODEL FOR SUGAR CANE SHREDDERS

Presented by:

**Author:** Juan Sebastián Mera Ibarra

**Directors:** Jhon F. Pazos M.Sc.
Dr.-Ing. Esteban Rosero

A Thesis to apply for a degree of Bachelor of Science in
**Mechanical Engineering**




Research Group in Industrial Control

School of Mechanical Engineering
Universidad del Valle
December 2024

# Abstract

This thesis focuses on the development of a predictive maintenance model for sugarcane shredders, with a specific emphasis on predicting the replacement of hammers. The research identifies key signals, including vibration levels, motor current, energy consumption, milling rate and their time-domain features, as critical condition indicators to predict hammer degradation and assess the machine's health. A combination of regression and classification machine learning models is explored to predict the remaining useful life (RUL) of the hammers and classify wear levels based on operational data.

The study analyzes data collected over two years from a sugar factory, integrating preprocessing techniques and feature engineering to enhance model accuracy. A classification model is trained, achieving an accuracy of 64.4% in predicting the remaining useful life of the hammers up to 5 days in advance. A comparative analysis using data from another shredder demonstrates the influence of operational load on maintenance needs, revealing that vibration and energy consumption are distinct indicators based on load conditions. Moreover, the thesis proposes future innovations, such as the development of an in-line image recognition system to estimate the cane preparation index (POC) in real time, linking hammer wear to shredding efficiency.

The findings highlight the significant cost savings and operational benefits of predictive maintenance. By reducing machine downtime, labor and material costs while increasing effective milling time and sugar extraction efficiency, the proposed model offers a substantial improvement over traditional maintenance strategies. These advancements contribute to the optimization of the sugar milling process, paving the way for more sustainable and efficient industrial practices.

**Keywords:** predictive maintenance, industry 4.0, machine learning, feature engineering, sugarcane shredder, remaining useful life (RUL), sugar mill.

# Contents

**Abstract** **2**

**List of Figures** **4**

**1 Introduction** **7**
1.1 Contextual Framework . . . 7
1.2 Problem Statement . . . 8
1.3 Project Justification . . . 9
1.4 Project Contribution . . . 9
1.5 Literature Review . . . 10
1.6 Objectives . . . 11
1.6.1 General Objective . . . 11
1.6.2 Specific Objectives . . . 11
1.7 Theoretical Framework . . . 12
1.7.1 Maintenance Management Methods . . . 12
1.7.2 Time Domain Features for Fault Detection . . . 13
1.7.3 Classification and Regression in Supervised Machine Learning . . . 15
1.8 Structure of the Thesis . . . 15
1.9 Methodology . . . 16
1.9.1 Process and Machine Description . . . 16
1.9.2 Data Acquisition and Preprocessing . . . 17
1.9.3 Predictive Model Development and Condition Indicators Assessment . . . 17
1.9.4 Cost-benefit Ratio Estimation . . . 17

**2 The Sugar Cane Shredding Process and the Wear of the Hammers** **18**
2.1 Introduction . . . 18
2.2 Overview of Sugar Production . . . 18
2.3 Cane Preparation . . . 21
2.4 Heavy Duty Cane Shredders . . . 22
2.5 Sugarcane Shredder Hammers . . . 24
2.6 Case Study: Sugar Cane Shredder at Factory 1 . . . 26
2.7 Conclusions . . . 28

**3 Data Acquisition and Preprocessing** **29**
3.1 Introduction . . . 29
3.2 Information Gathering Management . . . 29
3.3 Data Acquisition . . . 30

3.4 Data Preprocessing . . . . . 32
3.5 Conclusions . . . . . 37

**4 Condition Indicators Assessment and Model Development 38**
4.1 Introduction . . . . . 38
4.2 Milling Rate Importance . . . . . 38
4.3 Condition Indicators Assessment through Model's Performance . . . . . 40
4.4 Power Consumption and Vibration Behavior . . . . . 50
4.5 Conclusions . . . . . 53

**5 Cost-benefit Ratio Estimation 54**
5.1 Introduction . . . . . 54
5.2 The Cost Equation . . . . . 54
5.3 Impact of the Model on Effective Milling Time . . . . . 55
5.4 Cost-benefit Ratio Estimation . . . . . 55
5.5 Conclusions . . . . . 57

**6 Conclusions and Future Work 58**

**References 64**

# List of Figures


1.1 Continuous monitoring variables . . . 8
1.2 Problem tree . . . 9
1.3 Project methodology . . . 15

2.1 Sugar production process at the factory . . . 19
2.2 Cane preparation . . . 21
2.3 Shredder rotor and hammers . . . 23
2.4 Sugar cane shredder . . . 23
2.5 Clearance between the hammers and the grid plate and cane trajectory . . . 24
2.6 Grid plate and hammers from a sugar factory in the Colombian sector . . . 24
2.7 Types of wear in a shredder hammer . . . 25
2.8 Hammer before and after recovery . . . 26
2.9 Sugar cane heavy-duty shredder, motor side . . . 27
2.10 Interior of the shredder . . . 27

3.1 Flowchart of the data acquisition and preprocessing stage . . . 29
3.2 Final Excel file with the data . . . 31
3.3 Portion of the final Excel file with the weights before and after operation (confidential information blurred) . . . 31
3.4 Portion of the Excel file containing the dates of hammer replacements and some additional data . . . 32
3.5 Missing values filling (vibration turbine side on the top and speed of the 1st Mill on the bottom) . . . 33
3.6 Current (top) and vibration turbine side (bottom) signals fragment (Oct 2022 - Dec 2022) . . . 34
3.7 One of the machine runs with every signal available . . . 35
3.8 1st mill speed signal preprocessing . . . 36
3.9 Processed signals except 1st mill speed . . . 37

4.1 Linear fit between total cane processed per operational run and the total revolutions made by the 1st mill motor (applicable in stationary state) . . . 39
4.2 Linear fit between current and the 1st mill motor speed . . . 39
4.3 Linear fit between vibrations and the 1st mill speed . . . 40
4.4 Response plot for the first regression model to predict mean weight loss . . . 41
4.5 Mean weight loss histogram . . . 43
4.6 Response plot for the second regression model to predict mean weight loss . . . 43
4.7 Confusion matrix of the 1st weight loss classification model . . . 44

4.8 Data processing for the RUL classification model approach using 5 days in this example, increasing the number of data points for training . . . . . 45
4.9 Confusion matrix of the second classification model for RUL estimation using data for training of 2675 points . . . . . 47
4.10 Confusion matrix of the third classification model for RUL estimation using data for training of 3313 points from 14 operational runs . . . . . 48
4.11 Confusion matrix using a separate set of 368 labeled points from the same 14 operational runs . . . . . 49
4.12 Specific energy consumption through the three longer runs gathered at the factory 1 51
4.13 Specific energy consumption through all the runs gathered at the factory 2 . . . . . 51
4.14 Correlation between capacity and width from sugar cane shredders . . . . . 52

6.1 Power behavior of the three runs (Sugar factory 2) . . . . . 59
6.2 Health indicator exploration using the energy consumption and speed of the turbine at the first mill . . . . . 60
6.3 Exponential regression model used for RUL prediction . . . . . 61
6.4 Shredded cane images and their respective POC . . . . . 62
6.5 Shredded cane images with particles defined and classified by image processing . . . 63

# Chapter 1

# Introduction

## 1.1 Contextual Framework

During the operational period, every machine undergoes wear and tear due to the action of loads and requires preventive and corrective maintenance, which includes the replacement or restoration of short-lived components to maintain its working capacity at minimal cost. Preparation machines operate with short-lived components (such as hammers or blades) that require periodic replacement or restoration.
Typically, as machines age, their performance changes, and their maintenance becomes more costly. Eventually, when the service properties of the machine are completely depleted or its operation is no longer cost-effective, it becomes necessary to retire and decommission it.
In the Colombian sugar industry, during the extraction process, it is a well-established fact that the level of cane preparation will significantly impact the successful progress of milling. Therefore, continuous control of cane preparation through measurement methods is necessary. This necessity arises because cane is highly resistant to the application of pressure. Consequently, during milling, when subjected to high pressures, optimal juice extraction becomes challenging due to the difficulty of releasing juice from the cells where it is contained if these cells are not fractured by a machine like the sugar cane shredder [1].
To the date of writing this thesis no other study could be found involving predictive maintenance in a sugar cane factory machine like the shredder, so it is safe to say that there are few studies like this, if any. This work aims to contribute to the development of the sector by creating a predictive model for the timely replacement of hammers in cane shredders, which is one of the most critical machines in the factory. Maintenance and downtime associated with these machines incur expenses that, if reduced, would significantly enhance the overall profitability of the preparation process. The variables measured in this process are listed below and depicted in the figure 1.1:

- Vibration signal motor side in the x-axis
- Vibration signal turbine side in the x-axis
- Current signal of the motor
- Speed of the 1st mill Motor

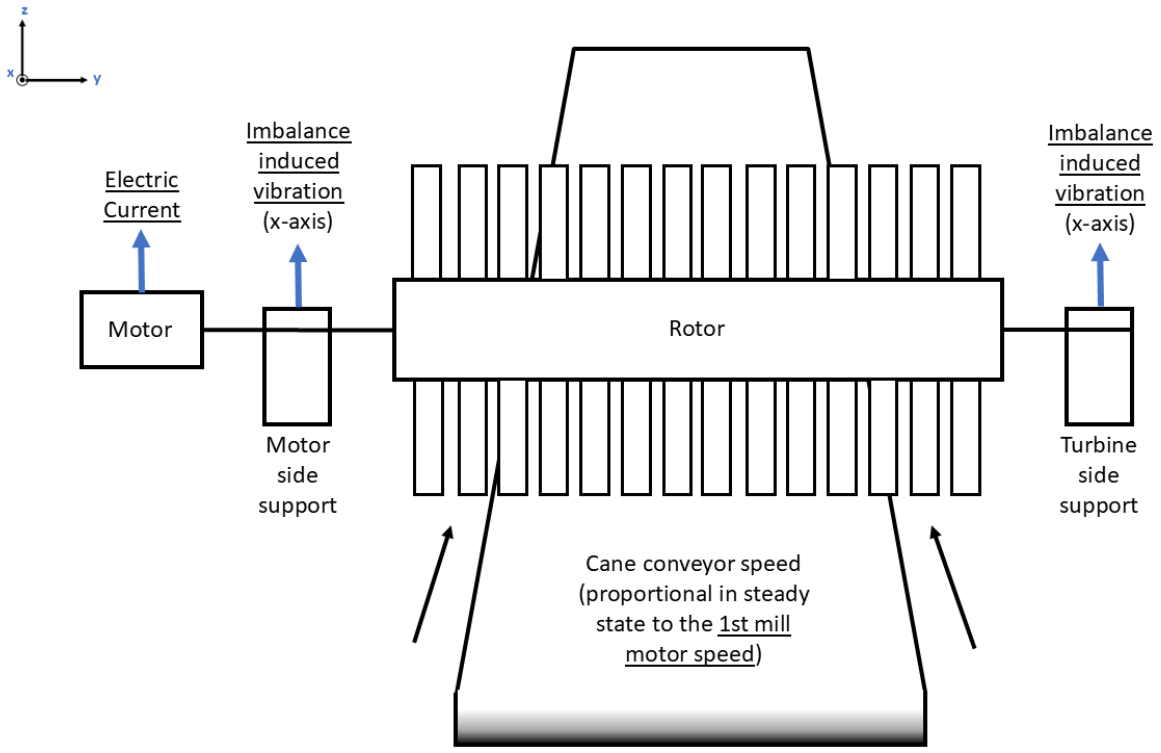


**Figure 1.1:** Continuous monitoring variables (underlined). Figure made by the author

## 1.2 Problem Statement

Within the sugar production process, one of the most crucial and power-consuming subprocesses in the factory is cane preparation. During this stage, the goal is to prepare the sugarcane in such a way that the extraction during milling is maximized. The machine responsible for preparing the harvested sugarcane is the shredder, a heavy-duty rotodynamic machine. It is essential for the shredder to operate with as few interruptions as possible. Each machine stoppage for changing the swinging hammers, also known as a "hammer stop," results in significant production losses and high maintenance costs. Currently, in the Colombian agro-industry, maintenance strategies are based on the machine's operating time, a decrease in the preparation index or a significant increase in energy consumption and/or vibrations. However, there is still no model that allows for the interrelation of these data to predict the appropriate time for a machine stoppage to replace the hammers.
The Cenicaña Research Center, as part of the Industry 4.0 Project, requires the development of a predictive model to make this forecast, aiming to reduce maintenance costs and enhance the overall profitability of production. To guide this initiative, the central research question is posed: How would a predictive model for such a machine be developed?.

### Problem Tree

The problem tree diagram is depicted in Figure 1.2, illustrating the issues to be addressed in this project, it highlights the root causes of the central issue and how they ultimately impact the sugar production process.

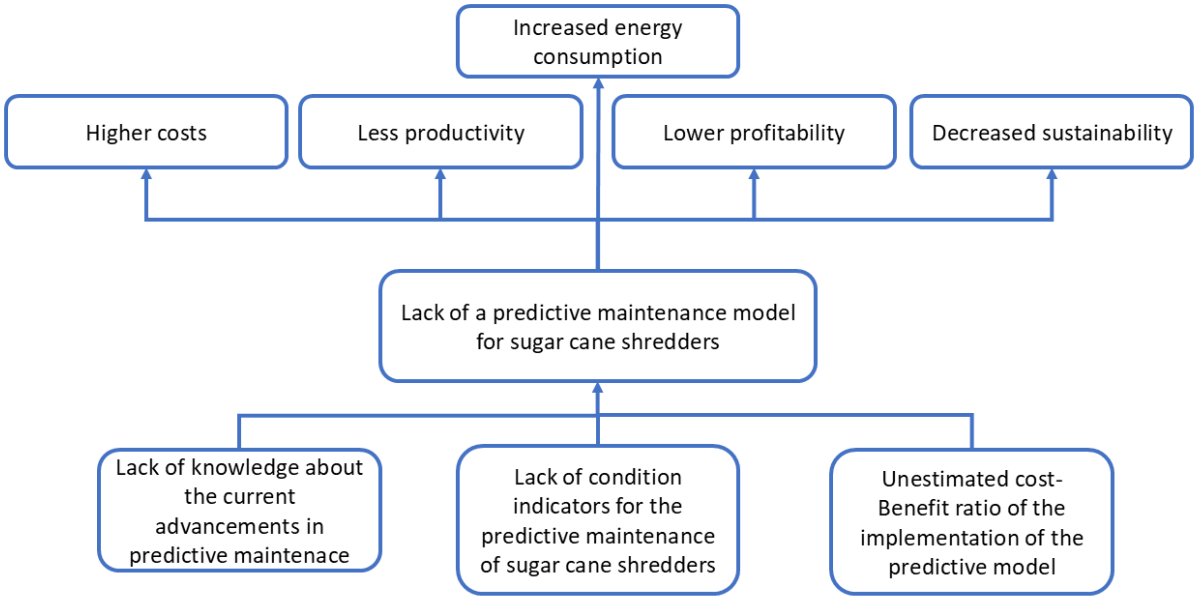


**Figure 1.2:** Problem tree

## 1.3 Project Justification

This project is not only relevant but also highly feasible given the tangible need and practical aspects of the sugar industry's operational challenges. The reasons that originated the urge for this study start from the inherent wear and tear experienced by machines during their operational lifespan, particularly in the context of sugar cane preparation machines. The identified need for timely maintenance, specifically the replacement of short-lived components like hammers, is a real-world concern with direct implications for cost-effectiveness. The project makes a lot of sense because how well the sugarcane is prepared directly affects how successful the milling process is in the sugar industry. The continuous control of cane preparation is imperative due to the unique resistance of cane to pressure during milling, affecting optimal juice extraction. Importantly, the absence of predictive maintenance studies for sugar cane factory machines like shredders presents a clear opportunity for this project to make a pioneering contribution. The feasibility of the project is also supported by the Industry 4.0 initiative's alignment and the specific requirement of the Cenicaña Research Center for a predictive model. By addressing this gap in the literature and providing a practical solution to enhance maintenance practices and overall profitability, this project is not only justified but poised for successful implementation.

## 1.4 Project Contribution

The study aims to fill the identified gap by contributing a predictive model for the timely replacement of hammers in cane shredders, a critical component of sugar production. The absence of such models in existing studies underscores the novelty and importance of this work. The predictive model seeks to enhance the sector's development by reducing maintenance costs and improving

overall profitability. The machine condition indicators identified through data acquisition and analysis serve as a foundation for predicting the residual useful life of hammers. The comparison of cost-benefit ratios between the developed predictive model and traditional strategies provides valuable insights into potential economic gains. The project aligns with the Industry 4.0 initiative, specifically addressing the needs of the Cenicaña Research Center. Ultimately, the project aims to contribute not only to the academic knowledge base but also to practical advancements in the sugar industry, optimizing maintenance practices and production efficiency.

## 1.5 Literature Review

Remaining useful life estimation and machine condition prognosis have been explored and studied using a large number of methods. Some of these studies aim to predict as precise as possible future machinery condition.

In 2010, Hong Thom Pham introduced an innovative approach to enhance machinery maintenance by accurately predicting health conditions based on vibration analysis. Vibration is a critical parameter for assessing machine dynamics, but its precision is often affected by noise. The study utilizes autoregressive moving average (ARMA) and generalized autoregressive conditional heteroscedasticity (GARCH) models to estimate the actual severity of vibrations, considering both steady wear development and fluctuating fault progression. The combination of ARMA and GARCH, known as the ARMA-GARCH model, aids in making informed decisions about maintenance and repair, preventing unplanned breakdowns. The model's efficacy is empirically validated using a methane compressor in a petrochemical plant, showcasing its potential for improving industrial machinery reliability [2].

In 2015, Minghang Zhao et al. employed novel tools based on time-frequency representation and supervised dimensionality reduction to estimate the residual life of bearings. They utilized a multiple linear regression model for prediction. The results demonstrated that the methodology employed outperformed traditional approaches using conventional statistical methods [3].

In 2017, Lei Xiao et al. used historical data that did not extend up to the failure to predict the residual life of bearings. They developed an inference method by employing condition monitoring data up to the current date. Extracted features were divided into different time windows, with window sizes increasing progressively. Features from two adjacent time windows were used as inputs and outputs for training a neural network. The results demonstrated that this method has significant potential for forecasting [4].

In 2023, Miguel Ángel Bermeo-Ayerbe et al. estimated the residual life of ball bearings in machinery by characterizing the variation in torque transmitted through the three-phase stator current. After modeling a failure-free machine state, they created a condition indicator that compares the current state to the state considered as failure-free. Based on a defined failure threshold, they employed exponential regressions to estimate the time to failure [5].

## 1.6 Objectives

### 1.6.1 General Objective

Develop a predictive model that allows for the timely prediction of hammer replacement in sugarcane shredders

### 1.6.2 Specific Objectives

- Acquire, process, and analyze field data from the sugarcane shredder to identify condition indicators of the hammers.
- Assess the trend of condition indicators to estimate the residual useful life of the hammers.
- Compare the cost-benefit ratio of implementing the predictive model versus the strategies traditionally employed.

## 1.7 Theoretical Framework

### 1.7.1 Maintenance Management Methods

#### 1.7.1.1 Reactive Maintenance (Run-to-failure Management)

Run-to-failure maintenance, also known as reactive maintenance, operates under the principle of only fixing equipment once it has broken down. While it avoids the immediate costs associated with scheduled maintenance, this method tends to be the most expensive form of maintenance in the long term. The logic of "if it isn't broken, don't fix it" may seem cost-effective on the surface, but this approach leads to high costs associated with machine downtime, overtime labor, and the need for large inventories of spare parts. Facilities that adopt run-to-failure maintenance typically avoid major repairs or overhauls until the equipment is no longer operational. As a result, they must maintain a stock of critical spare parts or rely on suppliers who can deliver parts quickly at a premium cost, which adds to the overall expense [6].
The unpredictability of equipment failures in this reactive model forces the maintenance team to respond immediately to breakdowns, leading to higher labor costs and longer downtimes. Furthermore, studies show that repairs done in a reactive mode can be up to three times more expensive than repairs performed under scheduled or preventive maintenance. Planned repairs allow for better labor management, reduced repair times, and lower shipping costs for parts. In contrast, reactive maintenance not only increases direct repair costs but also reduces equipment availability, negatively impacting production efficiency. In the end, while run-to-failure may seem like a way to save on maintenance, it ultimately leads to higher operational costs and lower productivity [6].

#### 1.7.1.2 Preventive Maintenance

Preventive maintenance is a time-driven approach where maintenance tasks are scheduled based on elapsed time or hours of operation. The strategy revolves around the mean time-to-failure, which follows a pattern known as the bathtub curve. Initially, new equipment has a higher likelihood of failure due to installation issues, but after this period, the failure probability remains low until the machinery approaches the end of its operational life. At that point, the probability of failure increases, and preventive maintenance is scheduled to occur just before this rise in failure risk. This approach involves scheduling repairs, adjustments, and machine rebuilds based on the expected lifespan of the machinery, with the goal of avoiding unexpected breakdowns during production [6].
However, the implementation of preventive maintenance can vary significantly. Some programs focus only on simple tasks like lubrication, while more comprehensive plans involve scheduling major repairs and machine rebuilds. A challenge with this approach is that the mean time between failures can differ based on how equipment is used and environmental factors. For example, a pump that handles abrasive materials may have a shorter lifespan than one handling water. As a result, preventive maintenance can sometimes lead to unnecessary repairs if equipment is serviced too early, or even catastrophic failures if repairs are delayed too long. In such cases, reactive maintenance may be required, which can be three times more costly than planned maintenance [6].

#### 1.7.1.3 Predictive Maintenance

Predictive maintenance involves regularly monitoring the actual condition and efficiency of machinery to predict potential failures and optimize repair schedules. It differs from preventive maintenance by relying on real-time data, such as vibration analysis, thermography, and tribology, rather than

time-based averages or fixed intervals. The goal is to use the actual operating condition of equipment to minimize unscheduled breakdowns, extend the time between repairs, and reduce maintenance costs. This approach not only enhances machinery availability but also improves productivity and product quality by ensuring that machines operate at optimal efficiency. Predictive maintenance programs use tools like vibration monitoring to detect early signs of failure, allowing for repairs before a breakdown occurs. Unlike traditional methods that rely on the mean time to failure, predictive maintenance provides more accurate data on when maintenance is genuinely needed, reducing unnecessary repairs or unexpected failures [6].

At its core, predictive maintenance is a condition-based strategy that monitors the mechanical health and operating efficiency of equipment. Techniques such as vibration analysis help identify distinct vibration patterns related to specific failure modes, while process monitoring, heat loss analysis, and other non-destructive methods provide data on the performance of non-mechanical systems. These tools allow maintenance teams to diagnose issues early, preventing major repairs and ensuring that machinery remains in good working condition. Comprehensive predictive maintenance programs often prioritize vibration monitoring for mechanical equipment but combine it with other methods for non-mechanical components, like electrical systems or lubrication analysis. By integrating multiple techniques, predictive maintenance offers a detailed, real-time picture of plant operations, giving maintenance managers the data they need to optimize machinery reliability and reduce downtime [6].

### 1.7.2 Time Domain Features for Fault Detection

When a fault occurs in mechanical systems, the stiffness of nearby structures changes, which can cause impulses or shocks. These shocks affect vibration signals, altering their amplitudes and distributions. By analyzing time-domain waveforms, statistical features can be extracted to detect mechanical faults. These features provide valuable insights into the signal's behavior and the health of the system [7]. The most commonly used features include the ones listed below, for all the equations $x(n)$ is a signal series for $n$ =1,2,....,$N$ and $N$ is the number of data points:

- **Mean Value ($X_m$)**: Represents the average value of the signal, offering a baseline to understand the overall vibration level. It is defined as:

$$X_m = \frac{1}{N}\sum_{n=1}^{N} x(n).$$

- **Standard Deviation ($X_{\mathbf{sd}}$)**: Measures the variation or dispersion of the signal from its mean, highlighting inconsistencies caused by developing faults. It is defined as:

$$X_{\mathrm{sd}} = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N}(x(n) - X_m)^2}.$$

- **Root Amplitude ($X_{\mathbf{root}}$)**: Provides a measure of the square root of the signal energy, reflecting the vibration's amplitude. It is defined as:

$$X_{\mathrm{root}} = \left(\frac{1}{N}\sum_{n=1}^{N}\sqrt{|x(n)|}\right)^2.$$

- **Root Mean Square ($X_{\mathbf{rms}}$)**: Quantifies the overall energy of the vibration signal and indicates changes as a result of the development of the fault. It is defined as:

$$X_{\text{rms}} = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x(n)^2}.$$

- **Peak Value ($X_{\mathbf{peak}}$)**: Captures the maximum amplitude of the signal, which increases with severe faults. It is defined as:

$$X_{\text{peak}} = \max|x(n)|.$$

- **Skewness ($X_{\mathbf{skewness}}$)**: Measures the asymmetry of the signal's distribution around its mean, helping to identify directional bias in the vibration signal. It is defined as:

$$X_{\text{skewness}} = \frac{\sum_{n=1}^{N}(x(n) - X_m)^3}{(N-1)X_{\text{sd}}^3}.$$

- **Kurtosis ($X_{\mathbf{kurtosis}}$)**: Quantifies the sharpness or flatness of the signal distribution, making it effective for detecting sharp impulses caused by initial faults. It is defined as:

$$X_{\text{kurtosis}} = \frac{\sum_{n=1}^{N}(x(n) - X_m)^4}{(N-1)X_{\text{sd}}^4}.$$

- **Crest Factor ($X_{\mathbf{crest}}$)**: The ratio of the peak value to the root mean square, highlighting the presence of large peaks relative to the overall signal energy. It is defined as:

$$X_{\text{crest}} = \frac{X_{\text{peak}}}{X_{\text{rms}}}.$$

- **Clearance Factor ($X_{\mathbf{clearance}}$)**: The ratio of the peak value to the root amplitude, useful for detecting wear or cracks in machinery components. It is defined as:

$$X_{\text{clearance}} = \frac{X_{\text{peak}}}{X_{\text{root}}}.$$

- **Shape Factor ($X_{\mathbf{shape}}$)**: The ratio of the root mean square to the mean value, providing insights into the overall shape of the signal and its energy distribution. It is defined as:

$$X_{\text{shape}} = \frac{X_{\text{rms}}}{\frac{1}{N}\sum_{n=1}^{N}|x(n)|}.$$

- **Impulse Factor ($X_{\mathbf{impulse}}$)**: The ratio of the peak value to the mean value, which captures the presence of sharp, short-duration spikes in the signal. It is defined as:

$$X_{\text{impulse}} = \frac{X_{\text{peak}}}{\frac{1}{N}\sum_{n=1}^{N}|x(n)|}.$$

Among these, the kurtosis value and crest factor are reliable indicators for early faults and are relatively unaffected by changes in operating conditions. While kurtosis is highly sensitive to initial faults, it may decrease unexpectedly as the fault worsens, making it less suitable for diagnosing advanced issues. Different time-domain features provide complementary insights into the health of machinery, and each feature's relevance varies at different stages of fault development. To effectively diagnose faults in rotating machinery, it is important to extract multiple features and prioritize the most sensitive indicators for early detection [7].

### 1.7.3 Classification and Regression in Supervised Machine Learning

In supervised machine learning, models learn from labeled datasets to identify patterns that allow them to make predictions or classify new data points. Two primary types of supervised learning tasks are classification and regression, both of which are valuable in predictive maintenance for monitoring machinery health and estimating remaining useful life (RUL) [8].

- Classification involves assigning data points to predefined categories. For example, in predictive maintenance, a classification model might categorize equipment states as "operational," "requires maintenance," or "faulty." This allows maintenance teams to quickly interpret machine health and take proactive steps to prevent unexpected breakdowns.
- Regression predicts continuous values, making it suitable for estimating things like the weight loss of the hammers at a certain point by using the current state of the signals as input.

#### 1.7.3.1 Fine Gaussian Support Vector Machine (SVM) for Classification

The Fine Gaussian Support Vector Machine (SVM) is a classification algorithm commonly used in predictive maintenance because of its ability to handle complex, non-linear data. SVMs work by finding an optimal boundary, or hyperplane, that best separates data points into distinct categories, maximizing the margin between classes [9]. The Gaussian (RBF) kernel is used in Fine Gaussian SVMs to map data into a higher-dimensional space, allowing the model to capture non-linear relationships that may be present in maintenance data, where factors such as operating conditions and wear can introduce variability.

Fine Gaussian SVMs are especially beneficial in environments where early fault detection is essential. By adapting to the nuanced variations in data that indicate equipment wear or failure, this model can help maintenance teams detect issues at an early stage and take action before breakdowns occur. The Gaussian kernel's flexibility makes the Fine Gaussian SVM highly effective for classifying machine conditions, thus supporting more reliable maintenance planning [10].

## 1.8 Structure of the Thesis

This project is carried out in four main steps to accomplish all the objectives listed in the section 1.6: the description of the machine and the process of cane preparation, the preprocessing of the acquired data, the training and validation of the model assessing the condition indicators, and the cost-benefit ratio estimation.

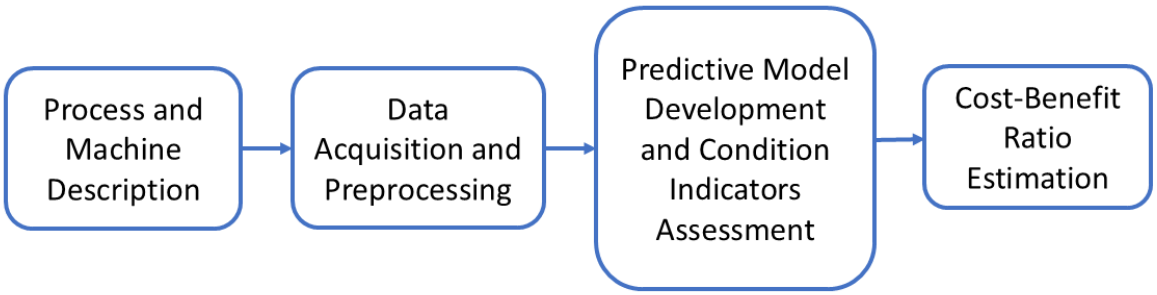


**Figure 1.3:** Project methodology

In Figure 1.3, a flowchart of the project can be observed, it gives a general idea of the structure of the project.

The thesis is organized into different chapters, each addressing a critical aspect of the study. Chapter 2 provides a descriptive methodology to understand the sugarcane preparation process and the wear mechanisms affecting shredder hammers. It examines the role of swinging hammers and grid plates in breaking down cane fibers, emphasizing operational factors such as rotor speed and grid clearance on sucrose extraction efficiency. Hammer wear is analyzed, focusing on abrasive and impact-induced damage, alongside the importance of welding-based recovery for maintaining efficiency and controlling costs. Chapter 3 focuses on data acquisition and preprocessing, detailing collaboration with Factory 1 to retrieve two years of operational data, including vibration, current, and speed signals, as well as hammer replacement logs. Preprocessing involved cleaning, filtering, and segmenting data using MATLAB to ensure reliability and accuracy.

Chapter 4 outlines the development of predictive models for hammer wear and remaining useful life (RUL). Critical signals, such as vibration levels and the 1st mill motor speed, are analyzed to establish their reliability as condition indicators. Regression and classification models are used to predict wear levels and RUL, with a comparison between two shredders included to highlight differences in signal behavior due to machine-specific characteristics. Chapter 5 evaluates the cost-benefit ratio of implementing the predictive maintenance model. Current hammer replacement costs are compared with estimated costs under the proposed model, demonstrating potential economic advantages through reduced downtime and optimized maintenance. Together, these chapters provide a comprehensive approach to understanding, modeling, and optimizing hammer maintenance in the sugarcane industry.

## 1.9 Methodology

### 1.9.1 Process and Machine Description

In the chapter 2 a descriptive methodology was used to understand the sugarcane preparation process and the wear of shredder hammers. Information was collected from technical literature and industry practices to outline the key characteristics of the shredding process and its impact on cane preparation.

The analysis focused on the operation of the sugarcane shredder, emphasizing the role of swinging hammers and grid plates in breaking down cane fibers to improve sucrose extraction. The influence of factors such as rotor speed, hammer arrangement, and grid clearance on the Percentage of Open Cells (POC) was described to highlight their importance in the milling process.

Hammer wear was examined by identifying two main mechanisms: abrasive wear caused by contact with cane fibers and impact-induced damage from repetitive collisions. The recovery of hammers through welding and reconditioning was also considered, illustrating its role in maintaining shredder efficiency and controlling operational costs.

This methodology provided a structured overview of how sugarcane is prepared for milling and the implications of hammer wear on machine performance, ensuring a foundational understanding of the process which is a very important factor when developing a predictive maintenance model on any machine, understanding its dynamics.

### 1.9.2 Data Acquisition and Preprocessing

In the chapter 3 the data acquisition and its preparation for the following processing is carried out. First, gaining access to the data required establishing cooperation with Factory 1. This involved presenting the project's objectives to the factory's director, obtaining permission to access the databases, and conducting interviews with the technical team, engineers, operators, and maintenance staff. These interviews were essential for understanding the machine's maintenance practices, hammer recovery processes, and critical operational variables.

With permission granted, historical data spanning two years were retrieved from the factory's databases. The extracted signals included the vibration, current, and speed of the first mill motor, all sampled at 1 Hz. Additionally, operational logs provided insights into the timing of hammer replacements and the amount of cane processed per run.

Data preprocessing was conducted to ensure reliability. Missing values were filled, and signals were segmented into operational runs based on maintenance schedules. MATLAB tools were utilized for cleaning and organizing the data, including removing periods when the machine was idle or generating outlier signals. A tailored filtering process, such as a third-order median filter, was applied to refine key signals like the 1st mill motor speed while maintaining accuracy.

### 1.9.3 Predictive Model Development and Condition Indicators Assessment

The process made in chapter 4 begins by identifying critical signals, such as the 1st mill motor speed, vibration levels, and power consumption, to establish their correlation with machine wear and operational efficiency. The approach taken involves processing the data to align signals with key operational stages and evaluate their reliability as condition indicators.

Regression and classification models are applied to predict hammer wear and remaining useful life (RUL). Regression analysis uses signals like vibration and power consumption to estimate weight loss, while classification models categorize wear levels and RUL based on predefined conditions. The study compares two shredders with different operational loads to demonstrate how machine-specific factors influence signals behavior and therefore predictive accuracy. Tailored maintenance strategies are proposed based on these findings.

The condition indicators assessment is made through a comparison of the performance of the different models, the condition indicators with the best trend are used to train the last classification models that estimate RUL.

### 1.9.4 Cost-benefit Ratio Estimation

The evaluation of cost-benefit ratio in the chapter 5, identified as the overall benefit for implementing the predictive model versus traditional strategies involves a comprehensive analysis. The initial step involves querying the current costs associated with hammer replacement in the sugarcane shredder at the mill, providing a baseline understanding of the existing expenditure. Subsequently, an estimation is made of the maintenance costs that would be incurred by the sugarcane shredder upon implementing the developed predictive model. Finally, the cost-benefit ratio of implementing the predictive model is calculated, comparing the anticipated benefits in terms of optimized maintenance and reduced downtime to the associated costs. This assessment allows for a thorough comparison of the economic impact and efficiency gains between the proposed predictive model and traditional strategies.

# Chapter 2

# The Sugar Cane Shredding Process and the Wear of the Hammers

## 2.1 Introduction

In the sugar industry, the performance of sugarcane shredders plays a critical role in the efficiency of sucrose extraction. These machines, responsible for breaking down the cane, use hammers that are subjected to significant wear due to the abrasive nature of the material and the mechanical stresses involved. This wear leads to frequent maintenance, with hammer replacements typically required every 15 days, resulting in costly downtime. To combat this, the hammers are regularly recovered through welded hardfacing, a process that restores their resistance to abrasion and impact. However, the wear of these hammers has direct implications for cane preparation quality and sucrose extraction efficiency, and excessive wear can cause machine imbalance, potentially accelerating the need for maintenance.

This chapter provides an overview of the sugar production process, focusing on the operation of sugarcane shredders and the preparation of the cane. It will also examine the wear mechanisms affecting shredder hammers and the recovery process used to extend their useful life.

## 2.2 Overview of Sugar Production

Sugar production from sugarcane involves several stages, each designed to maximize sucrose extraction and produce refined sugar efficiently. The key stages include cane preparation (the focus of this work), juice extraction, clarification, evaporation, crystallization, centrifugation, and drying. This process must be carefully managed to optimize sucrose recovery and ensure the quality of the final product. The figure 2.1 shows the stages involved in the sugar production process.

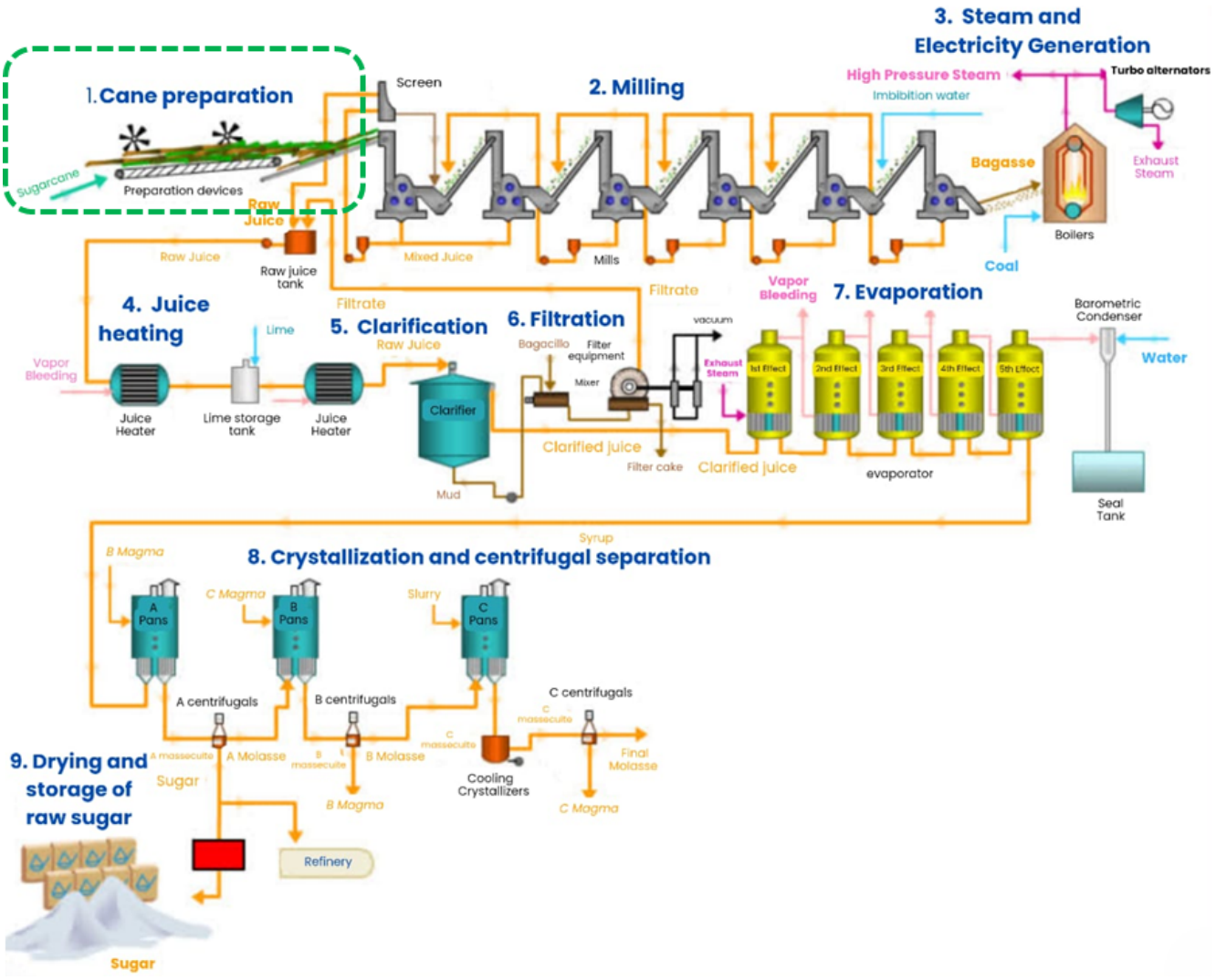


**Figure 2.1:** Sugar production process at the factory [11], process of focus in green

## Cane Preparation

Cane preparation is the initial stage in the sugar production process. After harvesting, the sugarcane is transported to the factory, where it undergoes shredding to facilitate efficient juice extraction. The use of sugarcane shredders breaks the cane into smaller particles, increasing the surface area for juice extraction during milling. This stage significantly influences the efficiency of milling and the recovery of sucrose [1, pp. 102-106]. Proper cane preparation is crucial to ensure that the subsequent milling stage operates at maximum efficiency, minimizing fiber retention and maximizing sucrose recovery. In the following sections the cane preparation and the sugarcane shredder will be discussed more in depth.

## Milling

Following cane preparation, the shredded cane is fed into a series of mills where heavy-duty rollers apply pressure to extract the juice. The milling process plays a crucial role in determining the amount of sucrose recovered from the cane [1, pp. 113-118]. The extracted juice contains sucrose,

water, and impurities, while the remaining fiber, known as bagasse, is separated and often used as fuel in the factory's boilers.

In modern sugar mills, imbibition is commonly practiced. This involves adding water or diluted juice between the milling stages to improve extraction efficiency. Imbibition helps dissolve the sucrose that remains in the bagasse after the initial milling process, significantly increasing the amount of juice recovered [1, pp. 117].

## Steam and Electricity Generation

The sugar mill is largely self-sufficient in energy due to the use of bagasse as a biofuel in the factory's boilers. After juice extraction, the bagasse is burned in boilers to produce steam, which serves two important purposes: it provides heat for various processes in the sugar mill and powers the factory's turbines, which generate electricity [1, pp. 195-199]. This cogeneration process ensures that both steam and electricity are continuously available, making the operation more efficient and cost-effective.

## Juice Heating

Once the juice is extracted, it is heated before moving into the clarification stage. Heating the juice is necessary to help remove impurities and prepare it for further processing. Lime is often added during this phase to aid in coagulating the impurities that will be separated in the clarification process [1, pp. 139-141]. The heated juice facilitates the removal of non-sucrose materials in the next stage.

## Clarification

The clarification process is designed to remove impurities from the extracted juice. During this stage, the heated juice is treated with lime to neutralize acids and promote the coagulation of non-sucrose substances [1, pp. 139-144]. The mixture is then heated further, causing the impurities to settle at the bottom as sludge. The clarified juice is drawn off for further processing, while the sludge is either discarded or processed to recover any residual sugar.

## Filtration

Following clarification, the juice is filtered to remove any remaining fine solids and suspended particles. Filtration plays a crucial role in ensuring that the juice is free of impurities before it undergoes evaporation [1, pp. 147-148]. This step helps improve the quality of the juice, ensuring that no solid particles remain that could negatively impact the final sugar product.

## Evaporation

In the evaporation stage, the clarified juice is concentrated by removing water. This process is carried out using a series of multiple-effect evaporators, where the juice is boiled at progressively lower pressures and temperatures [1, pp. 153-159]. The goal is to increase the sucrose concentration in the juice, reducing it to a thick syrup that is ready for crystallization. Efficient evaporation helps minimize energy use while achieving the desired sucrose concentration.

### Crystallization and Centrifugal Separation

The concentrated syrup from the evaporation process is transferred to vacuum pans for crystallization, where it is boiled under reduced pressure to form sugar crystals. Careful control over the temperature and pressure ensures that the crystals grow to the desired size and uniformity [1, pp. 174-178]. The resulting mixture of crystals and syrup, known as massecuite, is then moved to centrifuges.

In the centrifugal separation process, the massecuite is spun at high speeds to separate the sugar crystals from the molasses. The molasses is either recycled or used for other purposes, while the sugar crystals are dried to remove any remaining moisture [1, pp. 179-182]. Once dried, the sugar is ready for packaging or further refining, depending on the product's final specifications.

## 2.3 Cane Preparation

Cane preparation is a critical stage that directly influences the efficiency of the milling process. It aims to maximize the amount of sucrose available for extraction by mechanically disrupting the fibrous structure of the sugarcane. The primary tool used for cane preparation is the cane shredder, which tears the cane into finer particles, thereby increasing the surface area available for juice extraction. Figure 2.2 shows the general state at which the cane enters the shredder and comes out in finer particles.

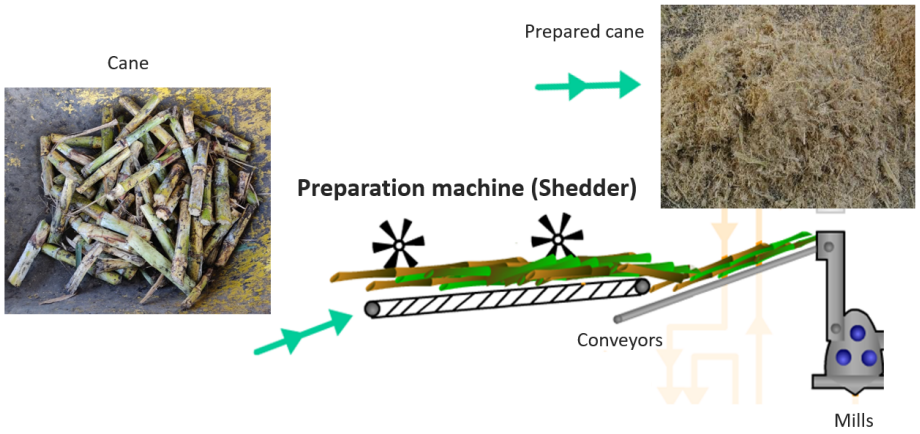


**Figure 2.2:** Cane preparation [11]

Moreover, it's worth noting that the equipment used for cane preparation can consume over 25% of the entire power supply in a sugar factory. Therefore, the choice of drive mechanisms and the efficiency with which power is utilized become critical factors in this context [1]. Shredders are responsible for breaking open the sucrose-containing cells within the cane, making it easier for milling rollers to extract juice during the crushing process. Without proper shredding, many cells remain intact, trapping valuable sucrose and leading to reduced extraction efficiency.

According to Cane Sugar Engineering by Peter Rein, the efficiency of shredding can be quantified by measuring the Percentage of Open Cells (POC). POC represents the extent to which the cane cells have been ruptured during preparation, allowing the sucrose within them to be more readily extracted. The formula for calculating POC is as follows:

$$POC = \frac{100 \cdot \frac{w_{S,T}}{w_{S,D}} \cdot \frac{m_{W,D}}{m_{C,D}}}{\frac{m_{W,D}}{m_{C,D}} + \left(1 - \frac{w_{S,T}}{w_{S,D}}\right) \cdot (1 - 1.25 \cdot w_{F,C})}, \tag{2.1}$$

where:

- $w_{S,T}$ = weight of sucrose extracted by tumbling.
- $w_{S,D}$ = weight of sucrose extracted by disintegration.
- $m_{W,D}$ = mass of water in the disintegrator.
- $m_{C,D}$ = mass of cane in the disintegrator.
- $w_{F,C}$ = fiber content of the cane (assumes 25% Brix-free water on fiber).

Generally speaking, the measures of POC can be higher if the hammers in the shredder are in good condition and the cane is therefore well prepared. The shredding process increases the surface area of the cane, making it easier for imbibition water to penetrate and dilute the remaining juice, leading to more efficient extraction during milling. Research cited in "Desgaste de máquinas de preparación y molienda de caña de azúcar" shows that proper shredding can improve extraction efficiency by reducing bagasse moisture and increasing the amount of juice extracted from the cane [12].

A high POC indicates that the shredder is working effectively, ensuring that most of the cane's cells are ruptured. This not only improves sucrose extraction but also reduces energy consumption by easing the load on the milling equipment, as the fibers are already significantly broken down. Mills using advanced shredders typically achieve POC values in the range of 85-90%, which is optimal for modern sugar mills.

## 2.4 Heavy Duty Cane Shredders

The shredder is the machine responsible for preparing the sugarcane. It operates by using swinging hammers that rotate on a rotor at a speed between 1000 to 1200 rpm . These hammers have a sweeping diameter that falls within the range of 1.4 to over 1.9 meters, resulting in tip speeds of approximately 100 meters per second, with variations between 65 to 110 meters per second. Figure 2.3 shows a 3D model of a sugar cane rotor in the industry and how the hammer would be oriented while the rotor is spinning and figure 2.4 shows the arrangement commonly seen in the Colombian sugar industry with horizontal feeding in the shredder.

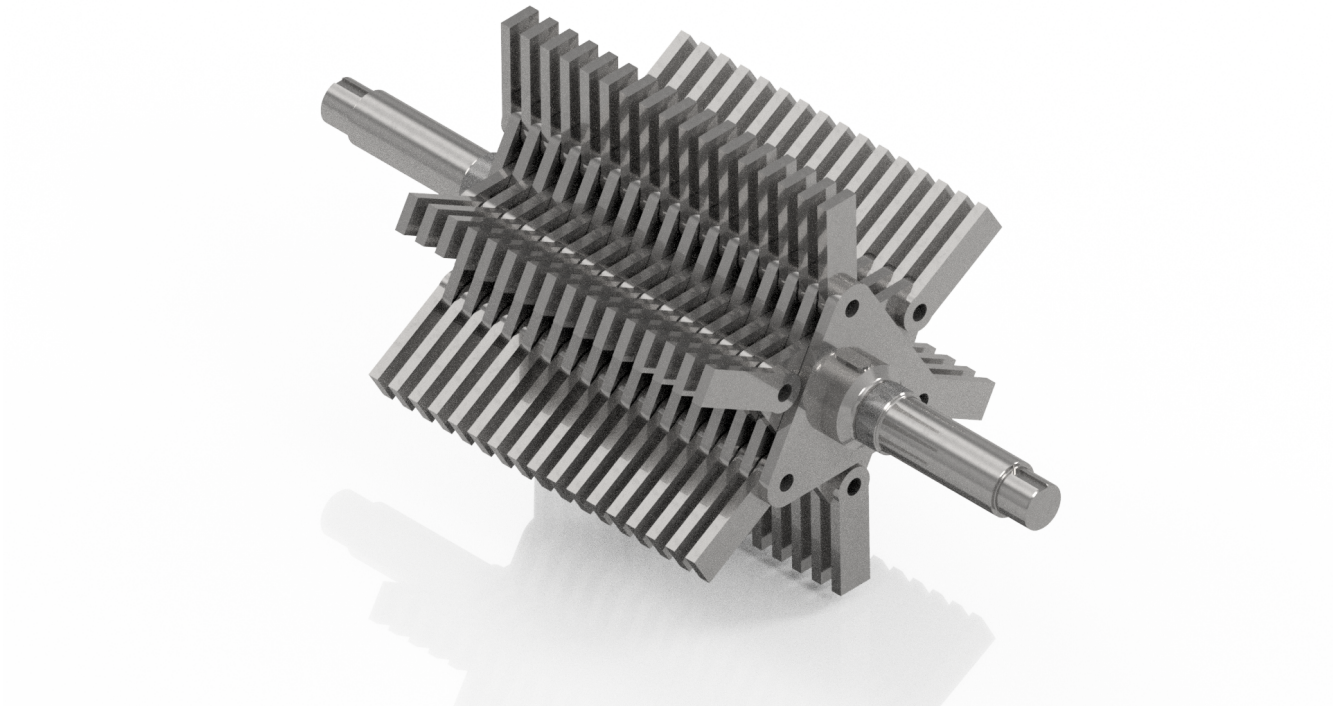

**Figure 2.3:** Shredder rotor and hammers [11]

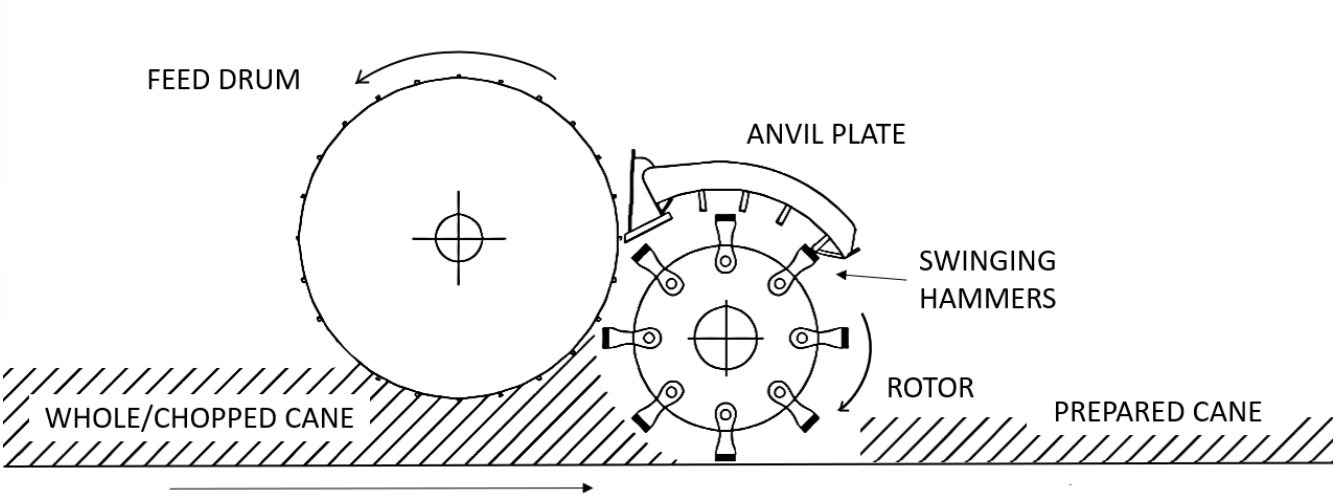


**Figure 2.4:** Sugar cane shredder. Adapted from [13]

The critical aspect of this setup is the close proximity (usually less than 10 mm) between the tips of the hammers and a grid plate or washboard made of anvil grid bars. These bars are positioned at right angles to the rotation of the hammers. Maintaining these tight clearances is essential for achieving the desired type of cane preparation, which involves producing long strands of finely shredded fibers. The figure 2.5 depicts this clearance and the trajectory the cane follows between the hammers and the grid plate.

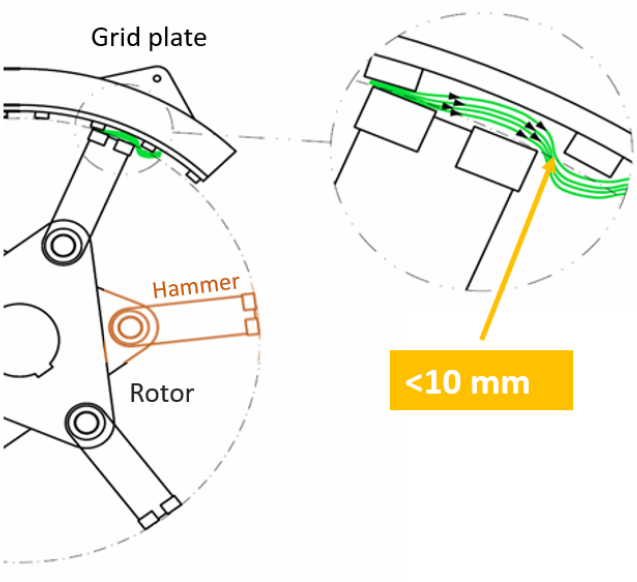


**Figure 2.5:** Clearance between the hammers and the grid plate and cane trajectory (green lines) [11]

The primary role of the grid bars is to redirect the particles back into the path of the swinging hammers. This redirection ensures that further "strikes" or impacts can occur, contributing to the effective shredding of the cane fibers [1]. Figure 2.6 shows a grid plate and a set of hammers used in a sugar factory in the Colombian sector.



**Figure 2.6:** Grid plate and hammers from a sugar factory in the Colombian sector [11]

## 2.5 Sugarcane Shredder Hammers

Due to the abrasive environment inside the shredder, where hammers are constantly interacting with cane fibers and other materials, they wear down quickly. On average, hammers need to be replaced every 15 days, and this replacement process typically requires around 4 hours of labor. Regular maintenance is necessary to prevent hammer degradation, which would otherwise lead to reduced shredding efficiency and mechanical issues. Mills are forced to stop the milling process approximately

20 times per year—equivalent to 3-4 effective days of milling just to service the shredder hammers. Although this downtime impacts productivity, it is essential to maintain consistent cane preparation levels. Failure to address hammer wear could lead to inefficient shredding, directly affecting sucrose extraction rates [12].

Hammer wear plays a significant role in the effectiveness of cane preparation, which in turn affects the overall milling efficiency. As hammers degrade, their ability to break down cane fibers diminishes, leading to a lower POC, a key indicator of the cane preparation level. A lower POC means that fewer sucrose-containing cells are opened, resulting in reduced sucrose extraction.

There are two primary types of wear that affect hammer performance:

- Abrasive wear: This occurs as the hammer surface interacts with cane fibers and foreign matter like dirt or small stones. Over time, this abrasion reduces the hammer's effectiveness, causing uneven cane particle sizes and lower preparation quality.

- Fractures and detachments: Continuous impacts between the hammer and incoming cane can lead to cracks or even hammer fragments breaking off. This type of damage not only reduces the hammer's efficiency but also causes imbalance in the shredder [12].

Figure 2.7 shows the two types of wear in a hammer that had not yet been recovered after its use.

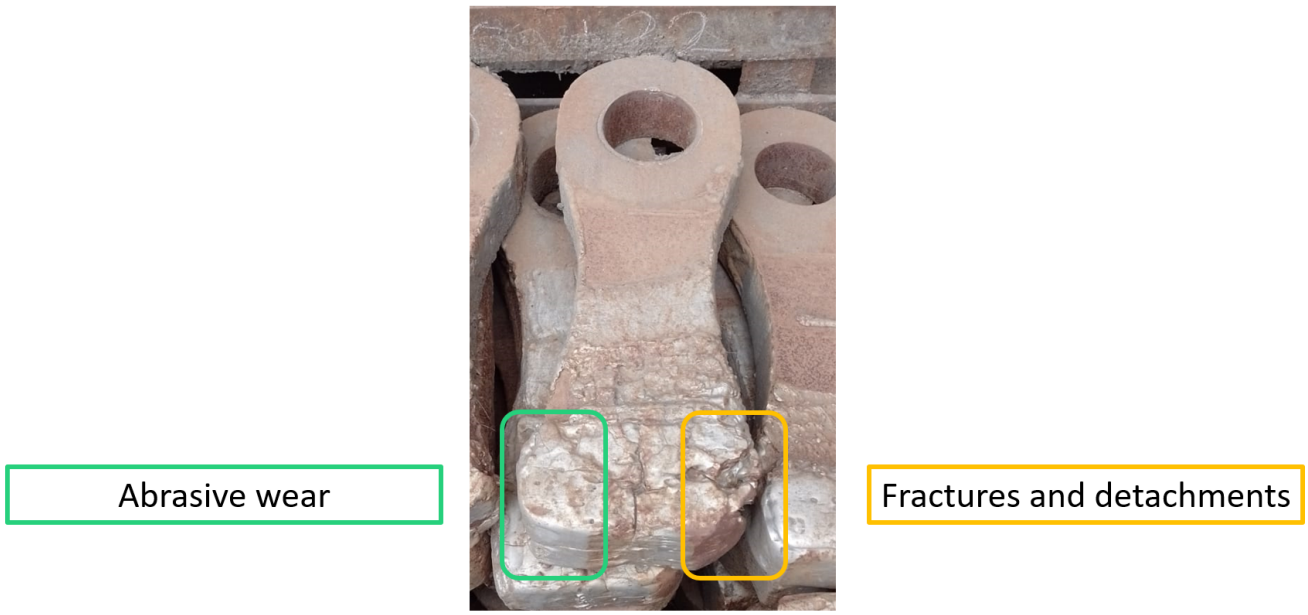


**Figure 2.7:** Types of wear in a shredder hammer [11]

Uneven hammer wear creates imbalance within the shredder, which in turn generates vibrations that can quickly escalate. This imbalance accelerates wear on other components such as bearings, shafts, and other mechanical parts, leading to costly, premature breakdowns. When the shredder vibrates excessively, it becomes less efficient in processing the cane, resulting in lower quality cane preparation, which in turn impacts sucrose extraction rates. Additionally, the change in hammer geometry as they wear affects the dynamics of the machine and the interaction between the hammers and the cane, leading to increased power consumption. As the hammers lose their

optimal shape, the shredder requires more energy to process the cane, which directly impacts the motor's consumption.

To manage this, modern sugar mills have adopted vibration monitoring systems. These systems use strategically placed sensors to track the shredder's vibration levels in real time. By monitoring vibrations, mills can detect subtle signs of imbalance early on, enabling maintenance teams to replace the hammers at the right time, rather than following a fixed schedule. **Vibration monitoring has now become the primary factor in deciding when to replace hammers**. Figure 2.8 shows a hammer before and after recovery.

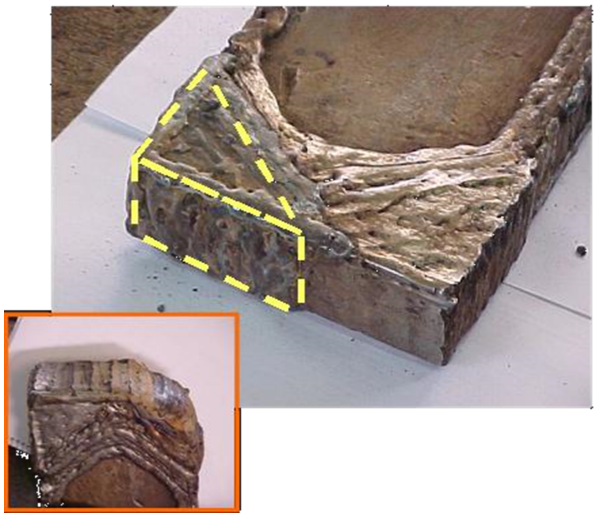

**Figure 2.8:** Hammer before and after Recovery [11]

The economic impact of hammer wear extends beyond just the cost of replacing the hammers themselves. Every year, mills consume around 12,000 kg of welding material for hammer recovery and reinforcement (hardfacing), which represents an annual cost of approximately 600 million pesos (as of 2024). This high cost due to the materials underscores the importance of maximizing hammer life and ensuring efficient maintenance practices.

In addition to material costs, the downtime required for hammer maintenance affects the overall productivity of the mill. However, by using vibration monitoring systems and optimizing hammer replacement schedules, mills can minimize this downtime and reduce overall maintenance costs. Despite the significant investment in hammer upkeep, this maintenance is essential to prevent even more costly losses in sucrose recovery due to inefficient cane preparation [12].

## 2.6 Case Study: Sugar Cane Shredder at Factory 1

The machine in question is a heavy-duty sugar cane shredder capable of processing around 500 tons per hour. Its motor boasts a power of 5300 HP and operates at a speed of 1000 rpm. To accommodate the inertia of the shaft and hammers, a steam turbine is utilized to power it up, ensuring that the current remains within safe limits. Consequently, even when there is no cane ready for processing in the factory, the machine remains operational to avoid the inconvenience of restarting it. This sugar cane shredder is equipped with 144 hammers, each weighing approximately 20 kg to 23 kg. The sugar cane is shown in figure 2.9.



**Figure 2.9:** Sugar cane heavy-duty shredder, motor side. Photo taken by the author

The interior of the sugar cane shredder has a configuration of swinging hammers arranged in 8 rows, with 18 hammers per row. Wear on the hammers primarily manifests at the front, where over time they become rounded or may even be fractured, especially in cases where stones accidentally enter the shredder coming from the harvesting process. Additionally, there are instances where the hammers lose material from behind due to heavy impacts. Figure 2.10 depicts the interior of the sugar cane shredder.



**Figure 2.10:** Interior of the shredder. Photo taken by the author

## 2.7 Conclusions

Hammers in sugarcane shredders are critical to achieving efficient cane preparation, but they are also subject to significant wear due to constant impact with cane fibers and foreign materials. The wear of hammers has direct implications for sucrose extraction efficiency, as well as the mechanical integrity of the shredder. Through regular maintenance and the use of modern tools like vibration monitoring, mills can optimize hammer replacement, reduce downtime, and maintain high levels of cane preparation.

Though hammer maintenance carries substantial costs, both in terms of materials and labor, the alternative of inefficient cane shredding would result in even greater losses. By adopting strategies to mitigate wear and using advanced monitoring technologies, mills can enhance operational efficiency and extend the lifespan of their shredders.

# Chapter 3

# Data Acquisition and Preprocessing

## 3.1 Introduction

In this section of the thesis, every aspect of data acquisition and preprocessing is addressed comprehensively. This includes detailed information about the process to get the factory's permission to access the data machine used, such as motor specifications and the average machine wear expressed in terms of weight loss per hammer. Additionally, it encompasses all the information provided by the sugar cane factory to facilitate the development of the model. The flowchart in figure 3.1 shows the steps carried out in this chapter.

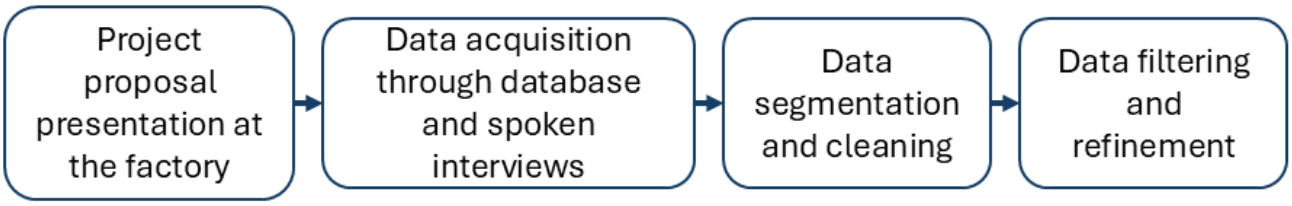


**Figure 3.1:** Flowchart of the data acquisition and preprocessing stage

## 3.2 Information Gathering Management

For the successful development of this project, it was necessary to obtain field data from the sugar factory's operational systems, at the beginning of the project, it was known which variables in the sugar cane shredder were measured, but not at what frequency or how large their databases were for storing historical data from various operational runs. A formal project proposal presentation had to be made at the factory, during which the main objectives of the project were presented to gather the opinion of the mill director. Access to the databases and permission to extract information from them were requested, and an initial interview with the director was conducted to understand the maintenance process of this specific shredder and how the factory manages the overall maintenance of the equipment. Additionally, the interview sought to determine which variables they believed were the most crucial for the operation of the machine.

Once permission was granted, coordination with the factory's technical team was necessary to ensure proper access to the data while complying with the company's confidentiality and data protection protocols. Not only was the factory director interviewed, but a series of visits to the mill

were also carried out, where interviews were conducted not only with the chief engineer but also with the mill operators, who spend entire shifts operating the mill and monitoring the operational signals, and are therefore very familiar with the sugarcane shredder.
The process of hammer recovery is not carried out by the mill operators but by the welders in the cane yards. Information such as the amount of metal used to repair the hammers through welding and the total amount of cane milled per run was obtained thanks to the head of the cane yards.
Throughout this process, regular communication with the factory's staff was maintained to address any concerns and ensure the smooth collection of information, while adhering to the agreed-upon data access policies. This collaboration was crucial for the accuracy and integrity of the data collected.

## 3.3 Data Acquisition

To successfully develop a predictive model, a substantial amount of data is required. Each operational cycle of the machine can span up to 19 consecutive days before maintenance and replacement of the hammers are necessary. As stated before in the section 3.2 with permission and access granted to the sugar cane factory's two-year database, the following signals, were acquired at the maximum sample rate possible, which is 1Hz:

- RMS Vibration Signal Motor Side in the X-axis (mm/s)
- RMS Vibration Signal Turbine Side in the X-axis (mm/s)
- RMS Current Signal of the Motor (A)
- Speed of the 1st Mill Motor (RPM)

The database was accessed through an Excel extension called Historian. Data retrieval involved a series of queries, each limited to half a day per query. The retrieved data was then stored in a collection of Excel files, each containing the signals as depicted in the figure 3.2.

One of the things that needed to be done was to fill missing values and segment the signals according to the periods of operation between hammer replacements. For this purpose, the sugar cane factory supplied two Excel files. One contained the mean weight loss across all the hammers per operational cycle along with the dates of the recovery process start and finish as shown in figure 3.3. The other Excel file contained the exact dates the hammers were replaced along with the amount of cane processed shown in figure 3.4.

It was noted that the dates corresponding to the replacement of the hammers didn't align with the dates corresponding to the hammers' recovery process. This misalignment complicated the process of gathering all the weight losses. However, the reference number of the set along with the dates when the hammers were completely recovered served as a guide. Consequently, the mean weight loss per hammer per run was determined.

Subsequently, the signals were segmented based on the days of replacement, during which the current and voltage signals were observed to be zero.These adjustments enhance clarity and coherence in the description of the data processing steps.

| | A | B | C | D | E |
|---|---|---|---|---|---|
| 1 | DateTime | Current (A) | Vibration Motor Side (mm/s) | Vibration Turbine Side (mm/s) | 1st Mill Motor Speed (RPM) |
| 2 | 03/04/2023 14:04:16 | 126,935112 | 5,159180 | 3,690430 | 400,038849 |
| 3 | 03/04/2023 14:04:17 | 117,533867 | 5,159180 | 3,690430 | 400,038849 |
| 4 | 03/04/2023 14:04:18 | 136,367676 | 3,970215 | 3,364746 | 400,395874 |
| 5 | 03/04/2023 14:04:19 | 135,109848 | 3,970215 | 3,364746 | 400,395874 |
| 6 | 03/04/2023 14:04:20 | 134,345367 | 4,939941 | 3,606445 | 400,007019 |
| 7 | 03/04/2023 14:04:21 | 132,145126 | 4,939941 | 3,606445 | 400,007019 |
| 8 | 03/04/2023 14:04:22 | 124,215546 | 5,085449 | 3,905273 | 400,007019 |
| 9 | 03/04/2023 14:04:23 | 137,364304 | 5,085449 | 3,905273 | 400,007019 |
| 10 | 03/04/2023 14:04:24 | 132,789688 | 4,651367 | 3,511230 | 400,692078 |
| 11 | 03/04/2023 14:04:25 | 132,789688 | 4,651367 | 3,511230 | 400,692078 |
| 12 | 03/04/2023 14:04:26 | 133,916153 | 3,663086 | 3,714355 | 400,294098 |
| 13 | 03/04/2023 14:04:27 | 133,916153 | 3,663086 | 3,714355 | 400,294098 |
| 14 | 03/04/2023 14:04:28 | 131,279068 | 4,035156 | 3,193848 | 400,951447 |
| 15 | 03/04/2023 14:04:29 | 131,279068 | 4,035156 | 3,193848 | 400,951447 |
| 16 | 03/04/2023 14:04:30 | 133,229599 | 4,792480 | 3,589844 | 400,480835 |
| 17 | 03/04/2023 14:04:31 | 133,229599 | 4,792480 | 3,589844 | 400,480835 |
| 18 | 03/04/2023 14:04:32 | 138,785568 | 4,085449 | 3,374023 | 400,077454 |
| 19 | 03/04/2023 14:04:33 | 138,785568 | 4,085449 | 3,374023 | 400,077454 |
| 20 | 03/04/2023 14:04:34 | 133,870346 | 4,575195 | 3,530762 | 399,731720 |
| 21 | 03/04/2023 14:04:35 | 139,541626 | 4,575195 | 3,530762 | 399,731720 |
| 22 | 03/04/2023 14:04:36 | 135,102951 | 4,575195 | 3,287109 | 399,435364 |
| 23 | 03/04/2023 14:04:37 | 134,063553 | 4,575195 | 3,287109 | 399,435364 |
| 24 | 03/04/2023 14:04:38 | 119,436256 | 3,309570 | 2,894043 | 400,215393 |
| 25 | 03/04/2023 14:04:39 | 132,146652 | 3,309570 | 2,894043 | 400,215393 |
| 26 | 03/04/2023 14:04:40 | 118,917702 | 4,309082 | 3,213379 | 399,897369 |
| 27 | 03/04/2023 14:04:41 | 140,927002 | 4,309082 | 3,213379 | 399,897369 |

ABR2023_1

**Figure 3.2:** Final Excel file with the data

| | BU | BV | BW | BX | BY | BZ | CA | CB | CC | CD | CE | CF |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | | | SET 23 | | | | | | SET 24 | | | |
| 2 | 01/10/2021 | 12/10/2021 | | | TOTAL | | 06/02/2023 | 12/02/2023 | | | TOTAL | |
| 3 | Initial Weight | 0 | | | | | Initial Weight | 22.520 | | | | |
| 4 | Final Weight | 24.000 | | | | | Final Weight | 24.000 | | | | |
| 5 | Total difference (g) | 24.000 | | | | | Total difference (g) | 1.480 | | | | |
| 6 | Welder Hours | 248 | $ 8.346,00 | | $ 2.069.808,00 | | Welder Hours | 264 | $ 8.346,00 | | $ 2.203.344,00 | |
| 7 | Helper Hours | 32 | $ 6.633,00 | | $ 212.256,00 | | Helper Hours | 32 | $ 6.633,00 | | $ 212.256,00 | |
| 8 | | | 0 | $ 50.350,00 | $ 0,00 | | | | 0 | $ 75.900,00 | $ 0,00 | |
| 9 | | | 191,8 | $ 69.761,00 | $ 13.380.159,80 | | | | 238 | $ 50.350,00 | $ 11.983.300,00 | |
| 10 | | | 0 | $ 104.739,00 | $ 0,00 | | | | 0 | $ 114.260,00 | $ 0,00 | |
| 11 | | | 0 | $ 40.051,00 | $ 0,00 | | | | 0 | $ 70.889,00 | $ 0,00 | |
| 12 | | | 0 | $ 40.031,00 | $ 0,00 | | | | 0 | $ 66.013,00 | $ 0,00 | |
| 13 | | | 0 | $ 83.700,00 | $ 0,00 | | | | 0 | $ 0,00 | $ 0,00 | |
| 14 | | | 0 | $ 43.280,00 | $ 0,00 | | | | 0 | $ 0,00 | $ 0,00 | |
| 15 | CANE PROCESSED | 34.897,49 | | TOTAL | $ 15.662.223,80 | | CANE PROCESSED | 37.437,95 | | TOTAL | $ 14.398.900,00 | |
| 16 | DAYS OF MILLING | 4 | | | | | DAYS OF MILLING | 7 | | | | |
| 17 | | | | | | | | | | | | |
| 18 | | | SET 23 | | | | | | SET 24 | | | |
| 19 | 03/07/2022 | 08/07/2022 | | | TOTAL | | 22/03/2023 | 27/03/2023 | | | TOTAL | |
| 20 | Initial Weight | 23.800 | | | | | Initial Weight | 23.500 | | | | |
| 21 | Final Weight | 24.000 | | | | | Final Weight | 24.000 | | | | |
| 22 | Total difference (g) | 200 | | | | | Total difference (g) | 500 | | | | |
| 23 | Welder Hours | 224 | $ 8.346,00 | | $ 1.869.504,00 | | Welder Hours | 248 | $ 8.346,00 | | $ 2.069.808,00 | |
| 24 | Helper Hours | 48 | $ 6.633,00 | | $ 318.384,00 | | Helper Hours | 32 | $ 6.633,00 | | $ 212.256,00 | |
| 25 | | | 55,2 | $ 75.900,00 | $ 4.189.680,00 | | | | 60 | $ 75.900,00 | $ 4.554.000,00 | |
| 26 | | | 77,4 | $ 50.350,00 | $ 3.897.090,00 | | | | 126 | $ 50.350,00 | $ 6.344.100,00 | |
| 27 | | | 0 | $ 114.260,00 | $ 0,00 | | | | 0 | $ 114.260,00 | $ 0,00 | |
| 28 | | | 0 | $ 70.889,00 | $ 0,00 | | | | 0 | $ 70.889,00 | $ 0,00 | |
| 29 | | | 0 | $ 66.013,00 | $ 0,00 | | | | 0 | $ 66.013,00 | $ 0,00 | |
| 30 | | | 0 | $ 0,00 | $ 0,00 | | | | 0 | $ 0,00 | $ 0,00 | |
| 31 | | | 0 | $ 0,00 | $ 0,00 | | | | 0 | $ 0,00 | $ 0,00 | |
| 32 | CANE PROCESSED | 142.602,94 | | TOTAL | $ 10.274.658,00 | | CANE PROCESSED | 52.921,450 | | TOTAL | $ 13.180.164,00 | |
| 33 | DAYS OF MILLING | 14 | | | | | DAYS OF MILLING | 7 | | | | |

**Figure 3.3:** Portion of the final Excel file with the weights before and after operation (confidential information blurred)

| | A | B | C | D | G | H | I | J |
|---|---|---|---|---|---|---|---|---|
| 1 | | HAMMER SETS STATISTICS | | | | | | |
| 2 | | SET NUMBER | ENTRY DATE | RELEASE DATE | CANE PROCESSED | Initial Weight | Final Weight | AVERAGE WEIGHT LOSS KG |
| 4 | | SET 19 | 07-08-2021 | 30-08-2021 | 201.907 | | | |
| 5 | | SET 18 | 30-08-2021 | 06-09-2021 | 57.828 | | | |
| 6 | | SET 20 | 06-09-2021 | 23-09-2021 | 145.887 | | | |
| 7 | | SET 19 | 23-09-2021 | 05-10-2021 | 81.990 | | | |
| 8 | | SET 17 | 05-10-2021 | 17-10-2021 | 93.862 | | | |
| 11 | | SET 14 | 17-10-2021 | 01-11-2021 | 103.311 | | | |
| 12 | | SET 20 | 01-11-2021 | 24-11-2021 | 160.981 | | | |
| 15 | | SET 22 | 24-11-2021 | 07-12-2021 | 65.302 | | | |
| 16 | | SET 21 | 07-12-2021 | 21-12-2021 | 101.719 | | | |
| 19 | | SET 20 | 21-12-2021 | 03-01-2022 | 74.144 | 23,08 | 22,58 | 0,500 |
| 20 | | SET 19 | 03-01-2022 | 18-01-2022 | 113.469 | 21,50 | 20,00 | 1,500 |
| 23 | | SET 21 | 18-01-2022 | 23-01-2022 | 45.219 | 23,66 | 23,37 | 0,293 |
| 24 | | SET 17 | 23-01-2022 | 06-02-2022 | 111.845 | 21,33 | 20,24 | 1,094 |
| 27 | | SET 18 | 06-02-2022 | 17-02-2022 | 89.150 | 23,00 | 22,20 | 0,800 |
| 28 | | SET 19 | 17-02-2022 | 28-02-2022 | 84.974 | 21,42 | 20,25 | 1,170 |
| 31 | | SET 22 | 28-02-2022 | 15-03-2022 | 104.721 | 23,95 | 21,38 | 2,569 |
| 32 | | SET 20 | 15-03-2022 | 28-03-2022 | 98.039 | 22,90 | 21,00 | 1,900 |
| 33 | | SET 18 | 28-03-2022 | 18-04-2022 | 94.361 | 22,80 | 21,73 | 1,068 |
| 34 | | SET 22 | 18-04-2022 | 10-05-2022 | 102.364 | 23,86 | 22,87 | 0,992 |
| 35 | | SET 19 | 10-05-2022 | 01-06-2022 | 60.969 | 21,42 | 20,50 | 0,917 |
| 39 | | SET 20 | 01-06-2022 | 21-06-2022 | 49.671 | 22,90 | 21,52 | 1,379 |
| 40 | | SET 23 | 21-06-2022 | 25-06-2022 | 34.897,49 | 24,00 | 23,80 | 0,200 |
| 41 | | SET 22 | 25-06-2022 | 14-07-2022 | 137.158,88 | 23,86 | 22,73 | 1,128 |
| 42 | | SET 19 | 14-07-2022 | 24-07-2022 | 129.360,54 | 21,34 | 20,22 | 1,118 |
| 43 | | SET 23 | 24-07-2022 | 08-08-2022 | 142.602,94 | 24,00 | 22,58 | 1,422 |

**Figure 3.4:** Portion of the Excel file containing the dates of hammer replacements and some additional data

## 3.4 Data Preprocessing

As part of the signal preprocessing, data importation plays a crucial role. There is a large number of Excel files, approximately 3 per month, which are converted to CSV format and then must be imported into MATLAB. Importing the data can be tedious due to the sheer volume of files, but due to the significant amount of information they contain, it's a necessary step.
The process begins with MATLAB's Data Cleaner tool. This tool facilitates the importation of data from CSV format and enables the creation of MATLAB Timetables for analysis within the tool. Additionally, it allows for the removal of missing data points resulting from the importation process and eliminates duplicates, which are inevitable in the iterative acquisition process.
Figure 3.5 illustrates how this initial processing affects one of the signals obtained when importing milling speed and vibration data.

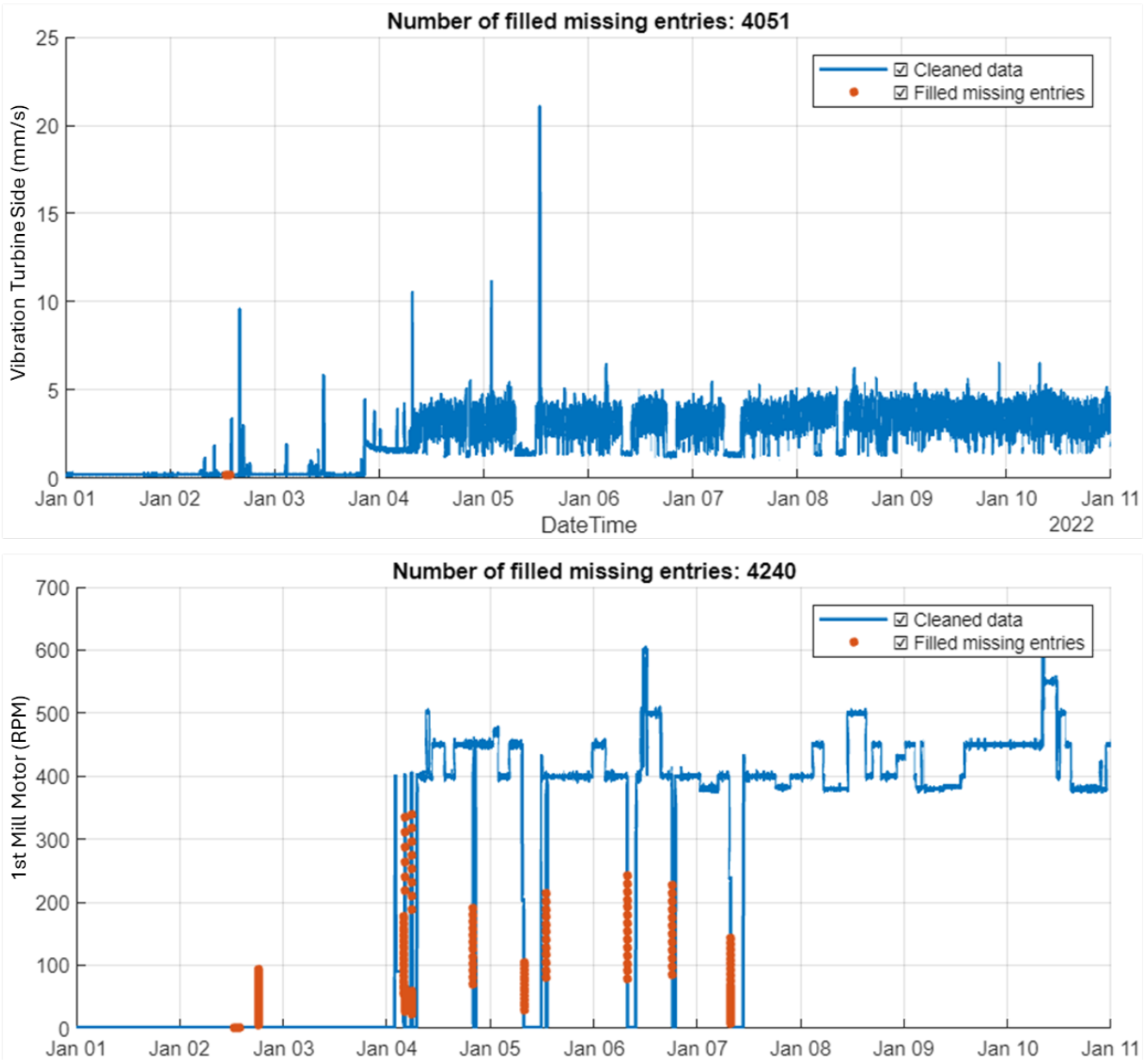


**Figure 3.5:** Missing values filling (vibration turbine side on the top and speed of the 1st Mill on the bottom)

After the data was cleaned the next step was to divide it into the different runs of the shredder, the sugar cane factory provided the day but not the exact moment of the hammer replacement, for this purpose the Feature Designer app from MATLAB was used as it has a very user friendly interface to zoom in and out the signal and visualize it. The signal used to determine the exact moment the machine was turned off to replace the hammers was the current signal, when the value is zero, it means that is the point where the machine was turned off for replacement. Figure 3.6 shows the current signal and vibration (Turbine Side) where the moment the hammers where replaced can be seen, not only by looking at the current signal, but also at the decrease of the vibration signal after a stop.

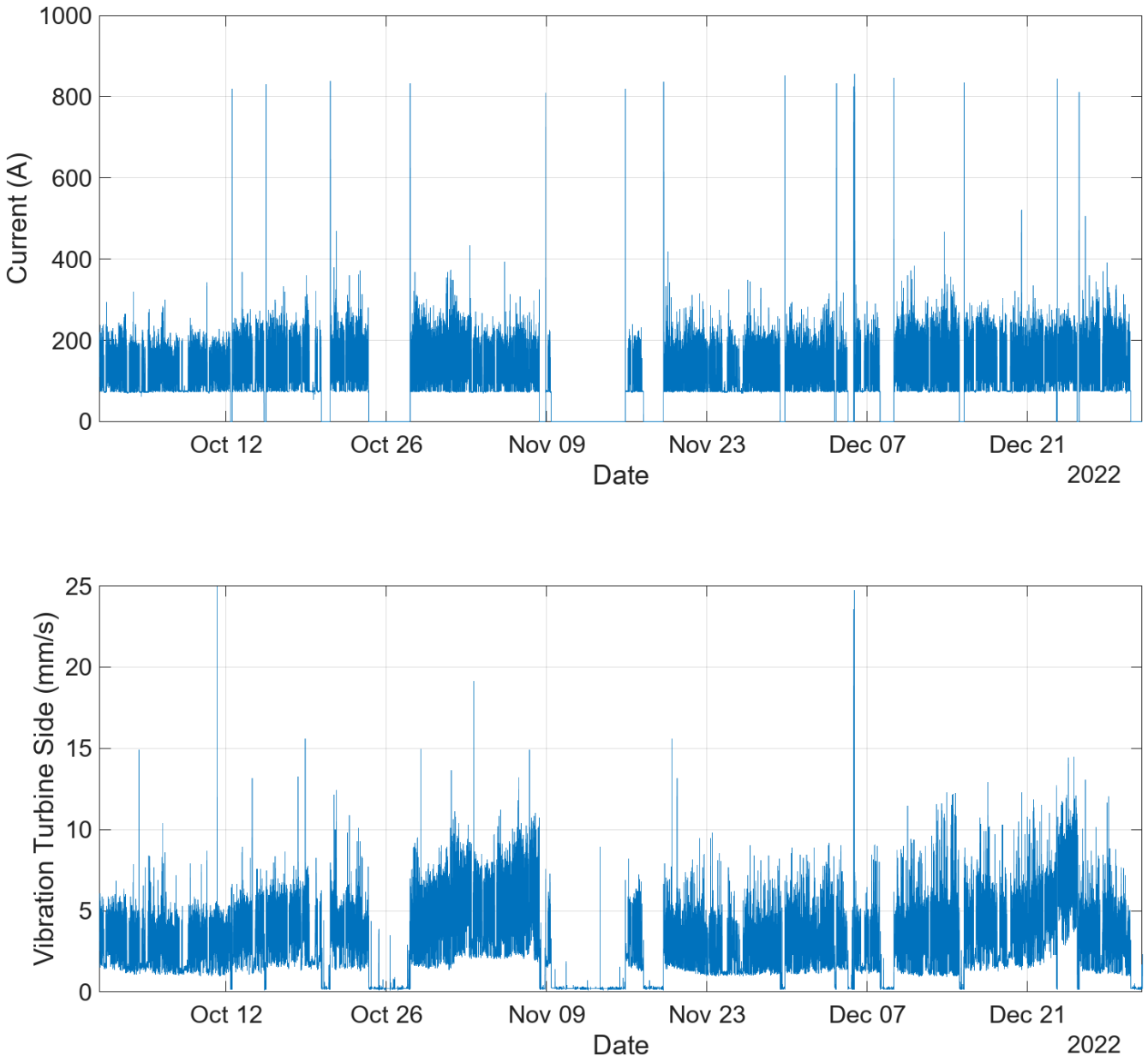


**Figure 3.6:** Current (top) and vibration turbine side (bottom) signals fragment (Oct 2022 - Dec 2022)

Once the signals were divided in every run of the machine the result was 43 different runs between December 2021 and September 2023. The figure 3.7 shows one of the runs of the machine with every signal acquired.

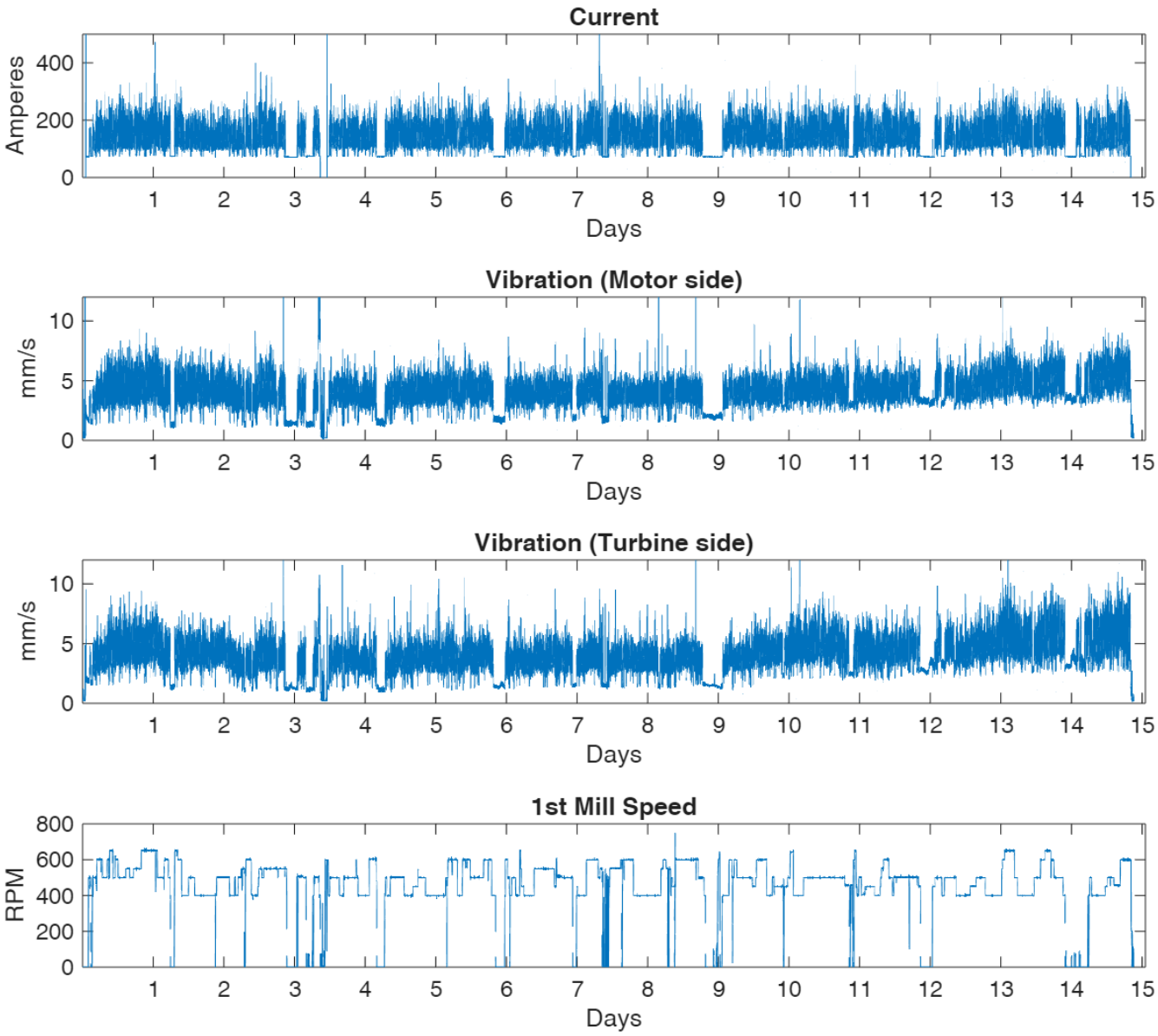


**Figure 3.7:** One of the machine runs with every signal available

As it can be noted in the figure 3.7, there are moments where the machine is turned off or not processing any cane and it shows especially in the current and vibration signal, also, there are times where the vibration signals have atypical values, this noise comes from the radios used in the sugar cane factory as reported by the head of instrumentation in the factory.
The next part of the preprocessing of the signals is to eliminate all this periods where no cane is being processed, where the current value is below 80 Amperes which is the current in these periods, also the vibration signals must be between 2 and 10 mm/s and the milling speed must be above 300 rpm which is the slowest speed the mill operates at. The 1st mill motor speed is a good indicator of the milling rate as the conveyors carrying the cane are all controlled depending on the milling speed of the 1st mill, how good of an indicator it is will be assessed in the next chapter.
The 1st mill motor speed signal has small variations as it is a physical system and can be disturbed from its set-point, to filter this signal for further processing without resourcing to time-frame based filters that give an offset to the processed signal from the original signal, a 3rd order median filter

was used with the signal previously rounded to the nearest multiple of 25, as these are the normal increments or decrements in the speed of the mill, to make this offset negligible while still being effective at filtering the signal. The figure 3.8 shows the 1st mill motor speed before and after this process.

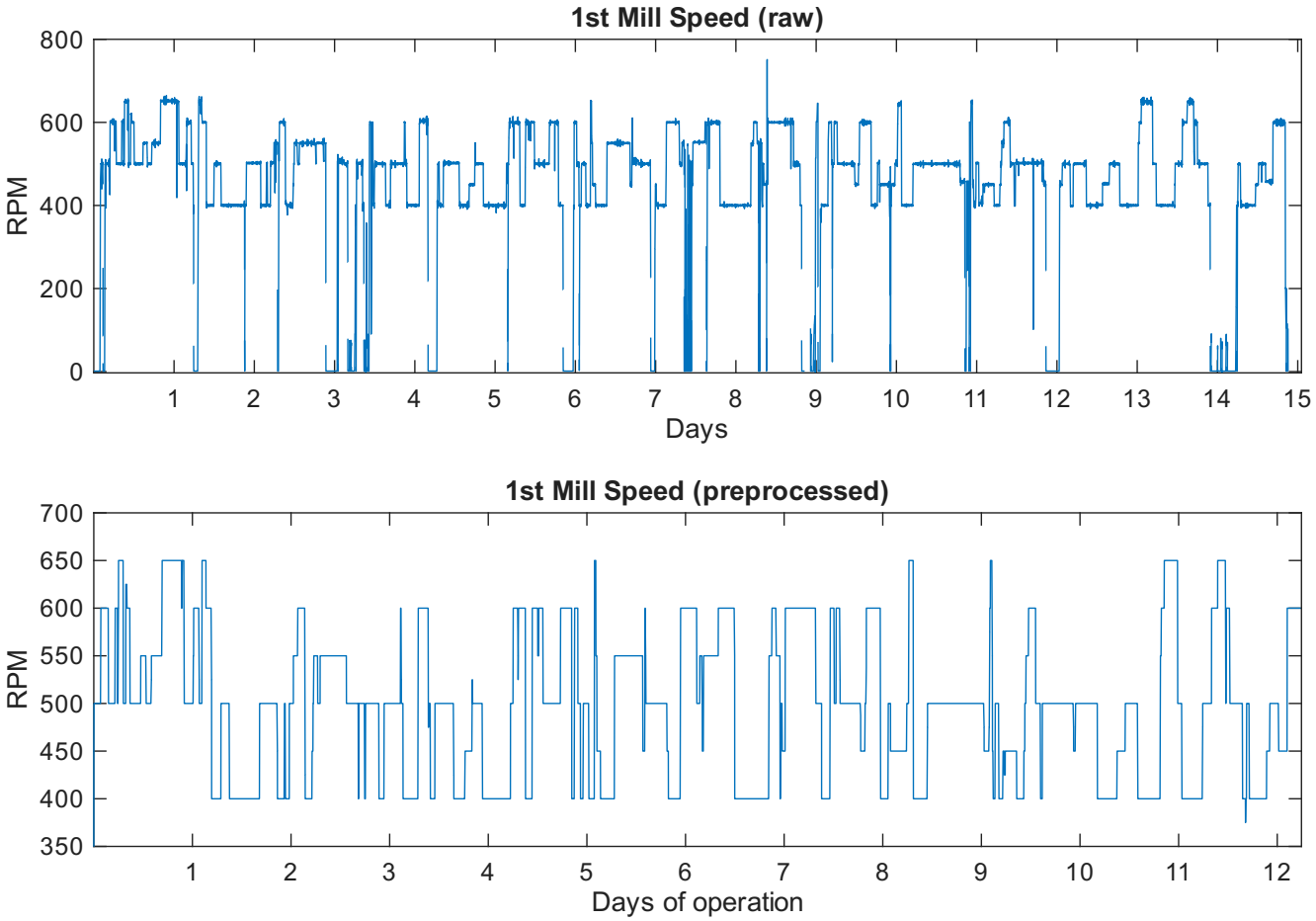


**Figure 3.8:** 1st mill speed signal preprocessing

The rest of the signals processed as stated before are shown in figure 3.9.

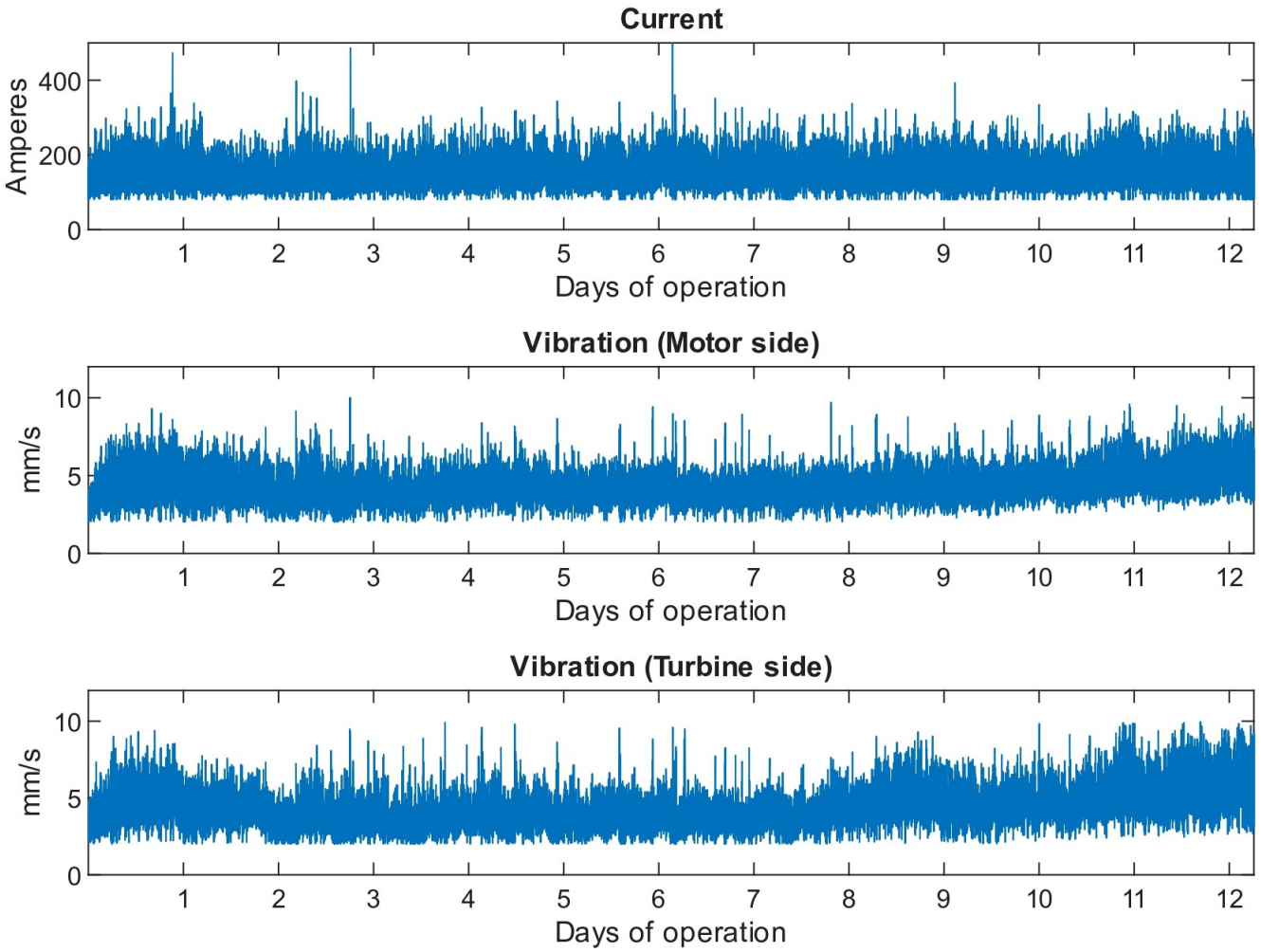


**Figure 3.9:** Processed signals except 1st mill speed

## 3.5 Conclusions

In summary, this chapter has outlined the critical steps involved in data acquisition and preprocessing, providing a foundation for the development of an effective predictive maintenance model and accomplishing the first specific objective of this thesis. The process of obtaining the factory's permission to access the machinery data and understanding the specifications, such as motor characteristics and average hammer wear, were essential for gathering accurate and relevant information. Additionally, the cooperation from the sugar cane factory, in providing detailed operational data, has been invaluable in ensuring that the data used for the model is both representative and robust. This groundwork allows for a more reliable model that can accurately reflect the operational conditions of the sugar cane factory's equipment, setting a solid basis for the predictive maintenance approach detailed in the subsequent chapters.

# Chapter 4

# Condition Indicators Assessment and Model Development

## 4.1 Introduction

This chapter focuses on assessing condition indicators and developing models for predictive maintenance, building on the data preprocessing discussed in the previous chapter. It emphasizes the importance of condition indicators in translating data into actionable insights for effective maintenance. Through evaluation and iterations, the chapter aims to enhance the predictive model accuracy and developing a model that can not only reflect the machine condition in real time but also be used to make maintenance decisions.

## 4.2 Milling Rate Importance

The milling rate in the operation of a sugar cane shredder holds significant importance for its residual useful life, as noted by both machine operators and intuitive understanding. This rate directly indicates the volume of material being processed: the higher the rate, the greater the vibration experienced by the machine, consequently leading to accelerated wear. The correlation between milling rate, vibration intensity, and machine wear shows the critical role this factor plays in determining the longevity of the equipment.
There was no time series of the cane being processed because at the moment of writing this paper there was no way of having that information in real time. The only signal that could be used as an indicator of the milling rate is the speed of the 1st mill motor. The cane conveyors carrying the cane to the sugar cane shredder have levelers that keep the height of the cane "mattress" being fed to machine, so, the cross section area at any given point is the same, this means that the mass flow which is the mass of cane processed is directly correlated to the speed of the 1st mill. To prove this assumption, a curve fitting was made to see the correlation between the overall cane processed per run of the machine as shared by the sugar factory and the integral of the 1st mill motor speed signal. The results are shown in the figure 4.1. It is important to disclaim that this correlation is only possible in **stationary state**, due to the dynamics of the machine and the separation of the 1st mill motor and the shredder.

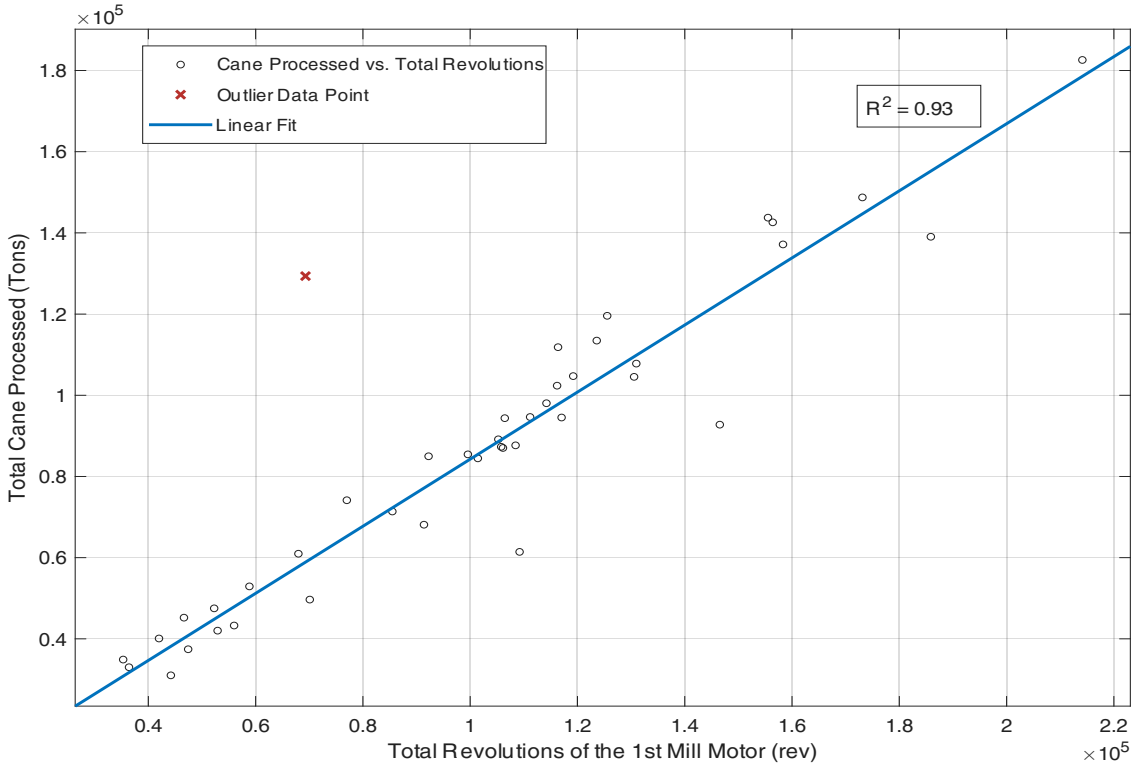


**Figure 4.1:** Linear fit between total cane processed per operational run and the total revolutions made by the 1st mill motor (applicable in stationary state)

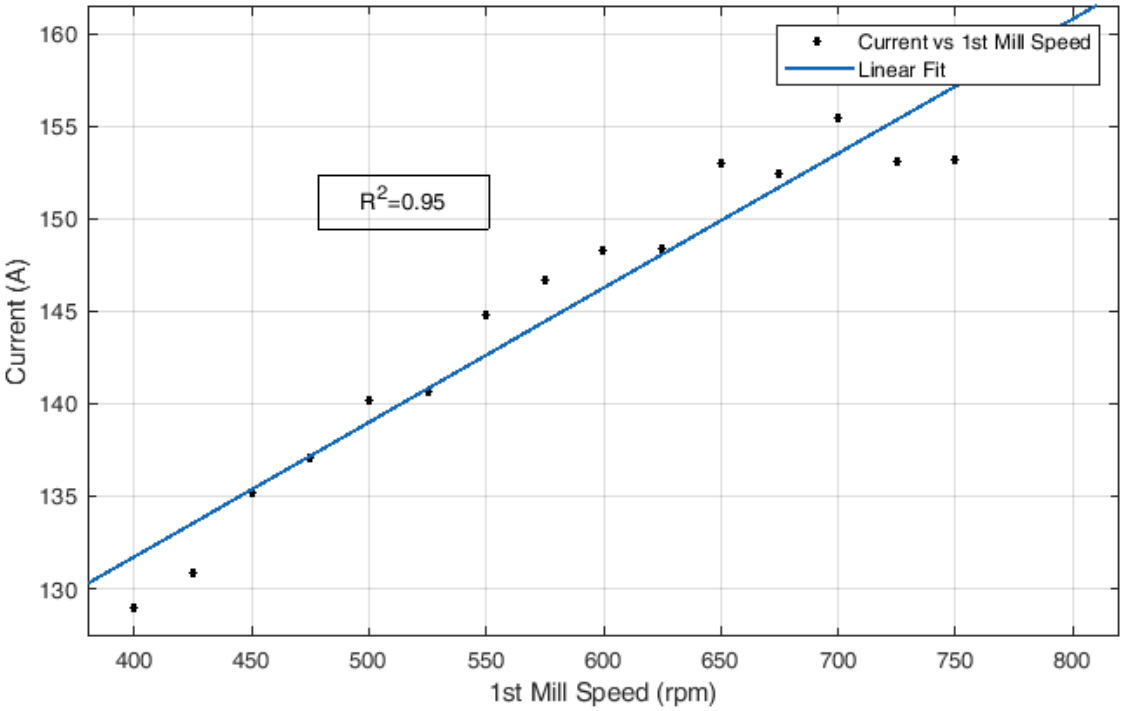


**Figure 4.2:** Linear fit between current and the 1st mill motor speed

As the figure 4.1 shows, the coefficient of determination is 0.93 a value that shows a strong correlation between the 1st mill speed and the milling rate and ensures that the 1st mill motor speed signal can be used as an estimation of the milling rate.
The sugar cane shredder runs at a constant speed; the only variation is the amount of cane fed into the machine; the more cane fed into the machine, the more the vibration and current increase. This is why the milling rate required to be predicted. A motor will draw greater current as the load is increased [14]. The correlation between the milling rate and the motor's current is depicted in figure 4.2, showing a coefficient of determination is 0.95.

The same was done with the mean vibration of the two sides of the machine. The figure 4.3 shows the coefficient of determination of the linear fit between these two variables.

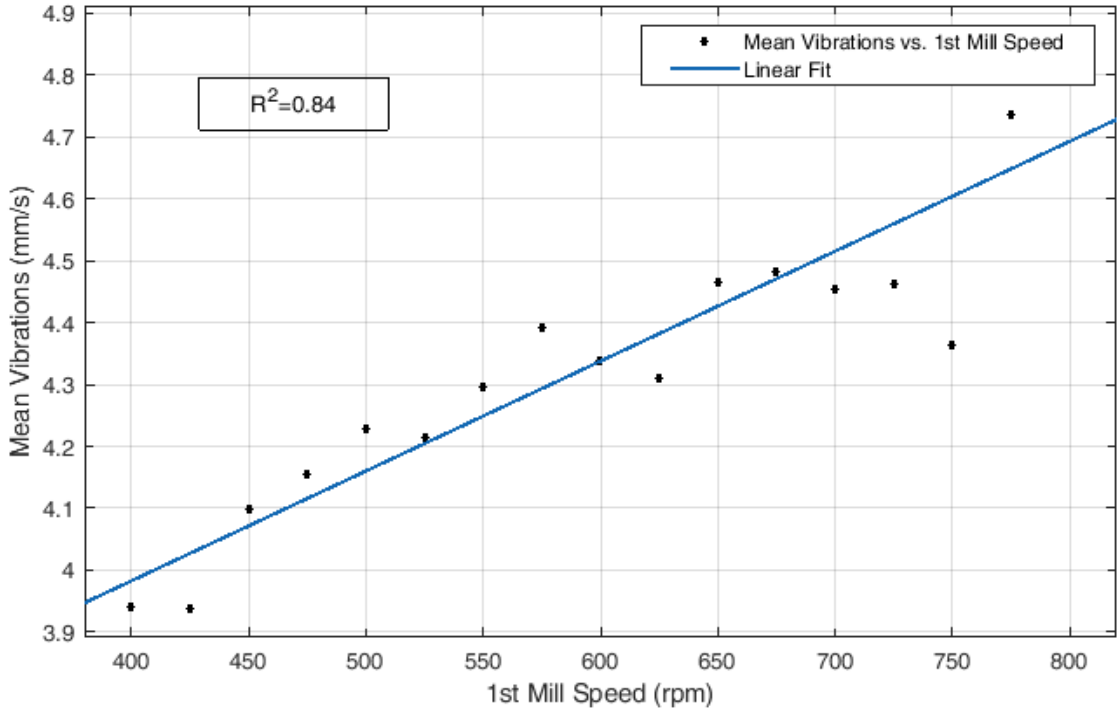


**Figure 4.3:** Linear fit between vibrations and the 1st mill speed

Given the significant impact of the milling rate on other signals, the predictive model will be developed with the milling rate as a reference point, as stated before, the cane flow is proportional to this value in stationary state conditions. This approach will consider how variables such as vibration and current signals evolve in relation to the milling rate over time.

## 4.3 Condition Indicators Assessment through Model's Performance

A condition indicator can describe the current state of a machine and track its degradation over time. These indicators are not only useful for training regression machine learning models but also classification models. The primary goal of these models is to facilitate maintenance decisions and to enable the deduction of additional information, such as the mean weight loss per hammer, from

the machine's signals.
In a first attempt to see how the different signals could describe the machine's degradation the mean weight loss prediction was the main objective. The mean of the vibration, current and 1st mill motor speed signal was computed at the last and first 24 hours of operation, the increase of each signal was used to train different regression models in the Matlab regression learner environment. The model with the lowest root mean square error (RMSE) was a linear vector support machine model with root mean square error of around 591 grams. The figure 4.4 shows the prediction plot of the model.

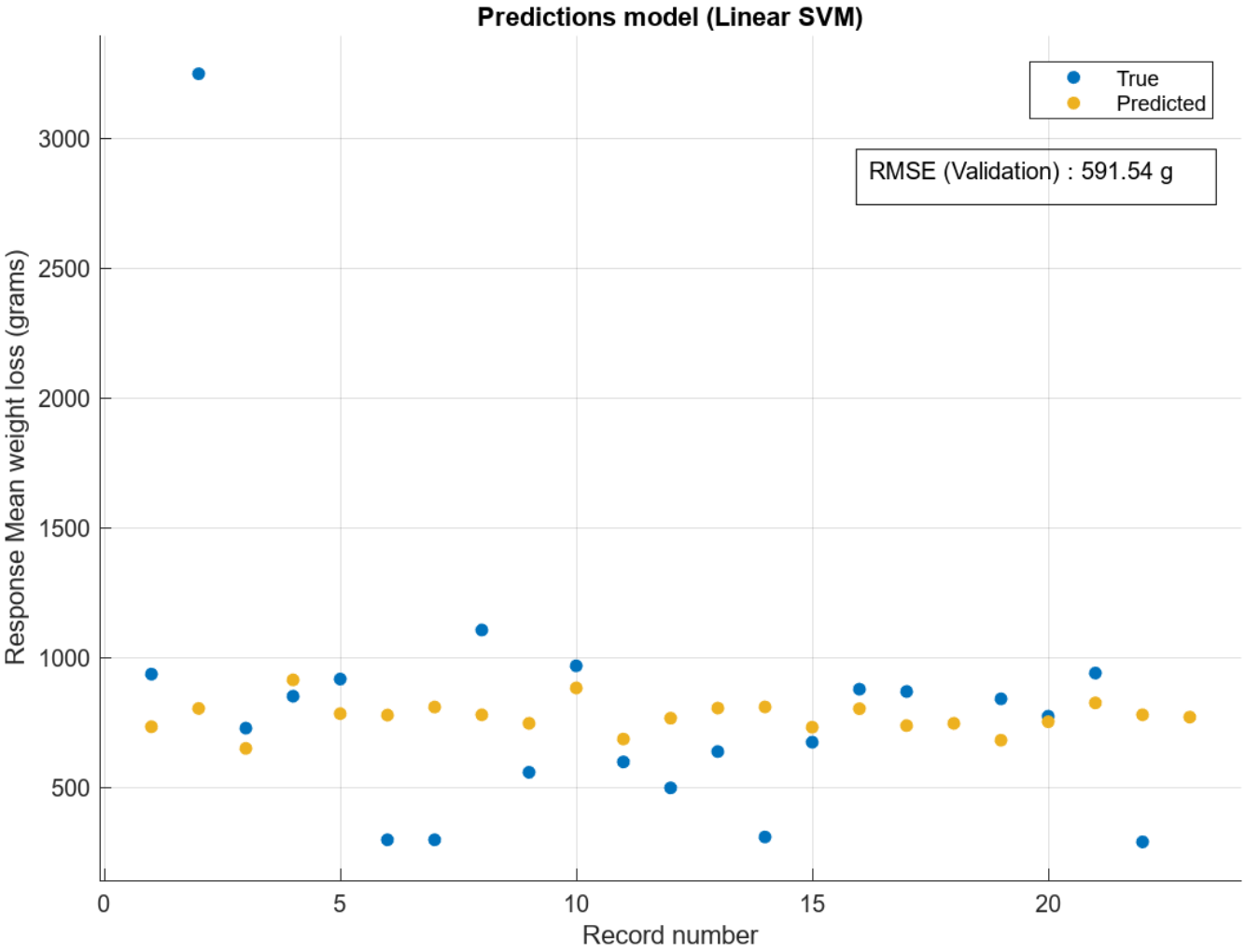


**Figure 4.4:** Response plot for the first regression model to predict mean weight loss

For a better interpretation of this RMSE result, it is essential to understand the distribution of the mean weight loss data. Figure 4.5 shows the mean weight loss distribution. As depicted in the figure 4.5, in almost 86% of the cases the mean weight loss was between 200 and 1500 grams.A root mean square error of 591 grams would be equal to a 39% error in the best case. The main objective is gonna be to reduce this error to the lowest possible.
For the training of any machine learning model, more data allows the model to be trained to higher levels of accuracy, thereby improving the performance. One way to do this is splitting the signals into different subsets that represent the machine state at given points, for example, at the beginning of the shredder's operation the wear is negligible, and, at the final stage, it is approximately the

weight loss reported by the factory, so if the signal is split into the different time frames where the 1st mill motor speed is constant, the number of data points can be increased to a significant amount, this time the number increased from 23 to 1189 observations (data points). The regression model that showed the best performance had an RMSE of 366.85 grams. The figure 4.6 shows the response plot for this model.

Although the results of this model show a lower RMSE, the response plot exhibits a large dispersion with respect to the weight loss points and a shift at the zero wear point.
A regression model to estimate the mean weight loss without stopping the machine could benefit the sugar cane factory but it is not the only possible approach. A classification model where the classes correspond to a certain level of wear established with the quartiles or the median of the weight loss is also a possible approach that could have a better accuracy. In this particular case, the median was 853 grams, there will be 3 classes, the class 0 represents a state with no wear, the class 1 represents a state where the mean weight loss is less than 853 grams, and the class 2 where it is more than 853 grams. The data set used for this purpose was extracted using 15 time domain features over the first and last 12 hours of the machine's operation splitting the signals where the 1st Mill speed was constant, these features were extracted using the diagnostic feature designer tool from Matlab. The features extracted are listed below:

- Mean (Vibration Motor side)
- Peak Value (Vibration Motor side)
- RMS (Vibration Motor side)
- Standard Deviation (Vibration Motor side)
- Mean (Vibration Turbine side)
- Peak Value (Vibration Turbine side)
- RMS (Vibration Turbine side)
- Standard Deviation (Vibration Turbine side)
- Clearance Factor (1st Mill Motor Speed)
- Crest Factor (1st Mill Motor Speed)
- Impulse Factor (1st Mill Motor Speed)
- Peak Value (1st Mill Motor Speed)
- Standard Deviation (1st Mill Motor Speed)
- Mean (Current)
- RMS (Current)

Using this features as explained before, the results of the classification model are shown in the confusion matrix in figure 4.7.

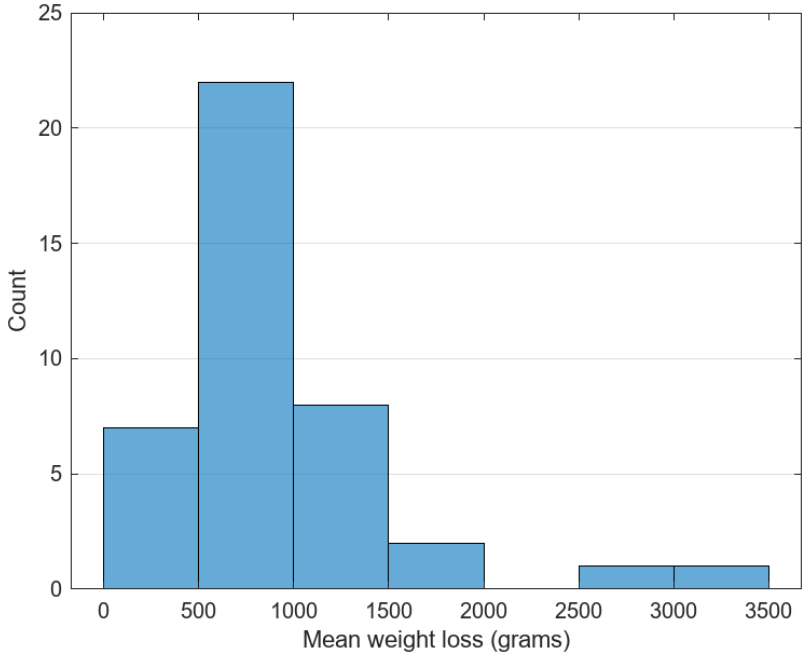


**Figure 4.5:** Mean weight loss histogram

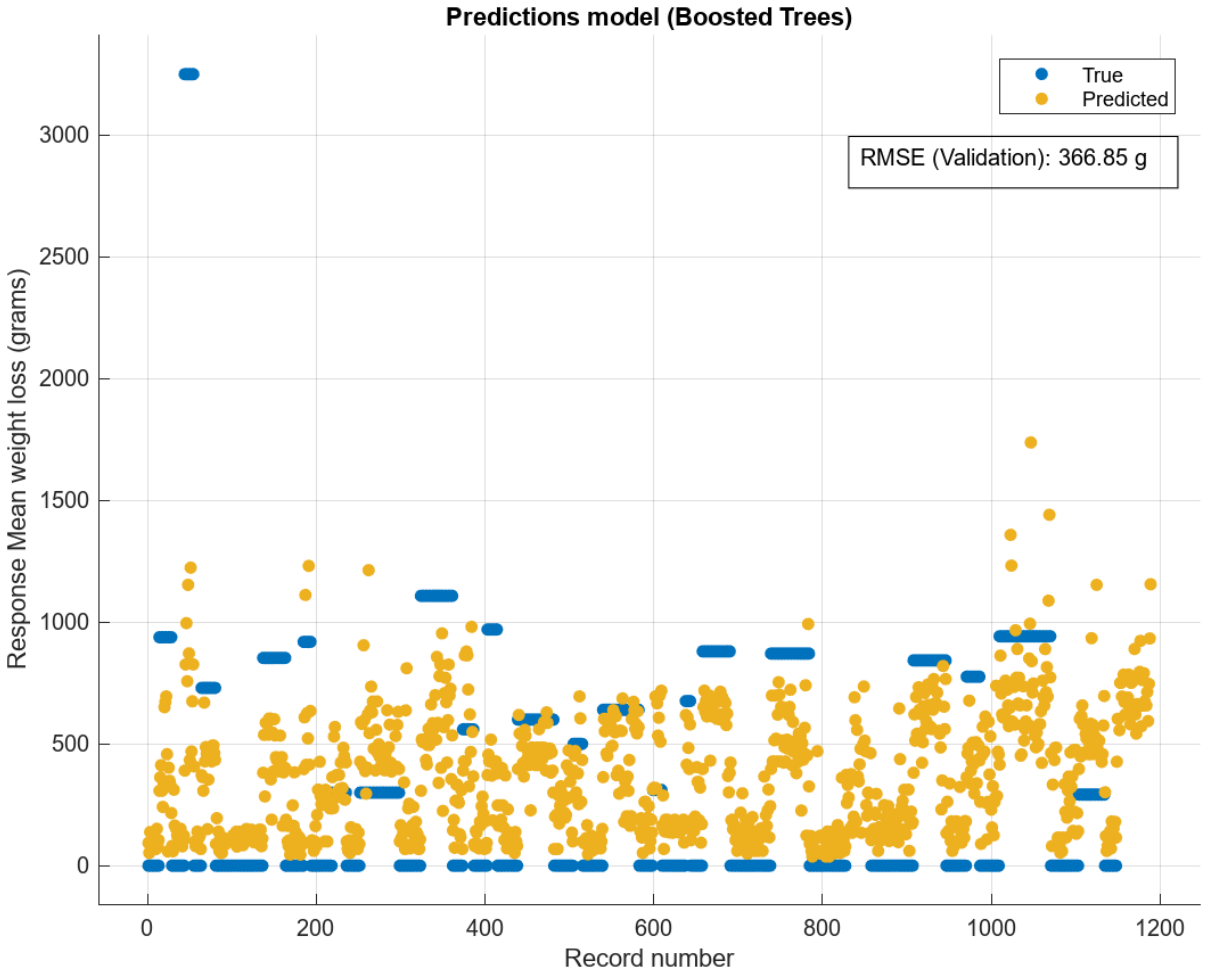


**Figure 4.6:** Response plot for the second regression model to predict mean weight loss

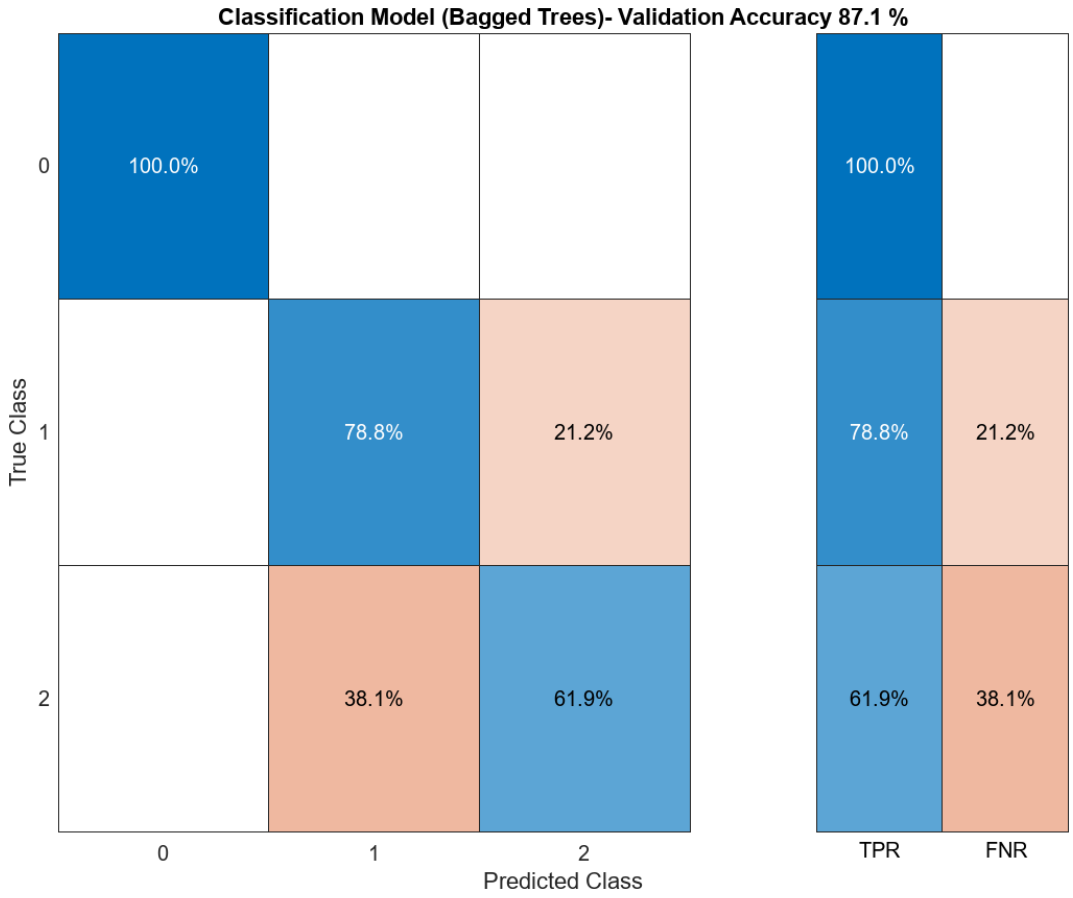


**Figure 4.7:** Confusion matrix of the 1st weight loss classification model

This model had an overall accuracy at validation of 87.1% and showed a specific accuracy at identifying the moment where the wear was negligible at the beginning of the machine's operation of 100%. These results are promising for an initial model but the main objective is to develop a model that can be used to make maintenance decisions beforehand, this involves a variable to be estimated, time. A classification model can be used to predict time to failure of a machine, the classes can represent a certain time frame and reflect machine health, like the one John Atherfold and Christopher van der Berg developed in the example shown in the webinar "Predicting Boiler Trips with Machine Learning" [15].
For training machine learning models, having more data typically leads to better performance. In this study, to increase the amount of data available from the 43 machine runs, the following approach was implemented: each machine run was segmented into days based on the level of anticipation required. Afterward, the data from each day was further divided into periods where the milling rate remained stable, as determined by analyzing the speed signal of the 1st mill motor. These stable periods were then split into sections lasting between 10 and 30 minutes, significantly increasing the number of signals available for analysis. From each of these sections, time-domain features were extracted. These extracted features were then labeled according to the day of operation they originated from. For instance, features derived from signals collected during the last day of operation were labeled as "Class 1," those from the second-to-last day as "Class 2," and so forth. The model obtained would have the class as an output that states the number of days remaining for hammers replacement. This method effectively expanded the dataset, enabling more robust model training by providing additional labeled data as shown in Figure 4.8.

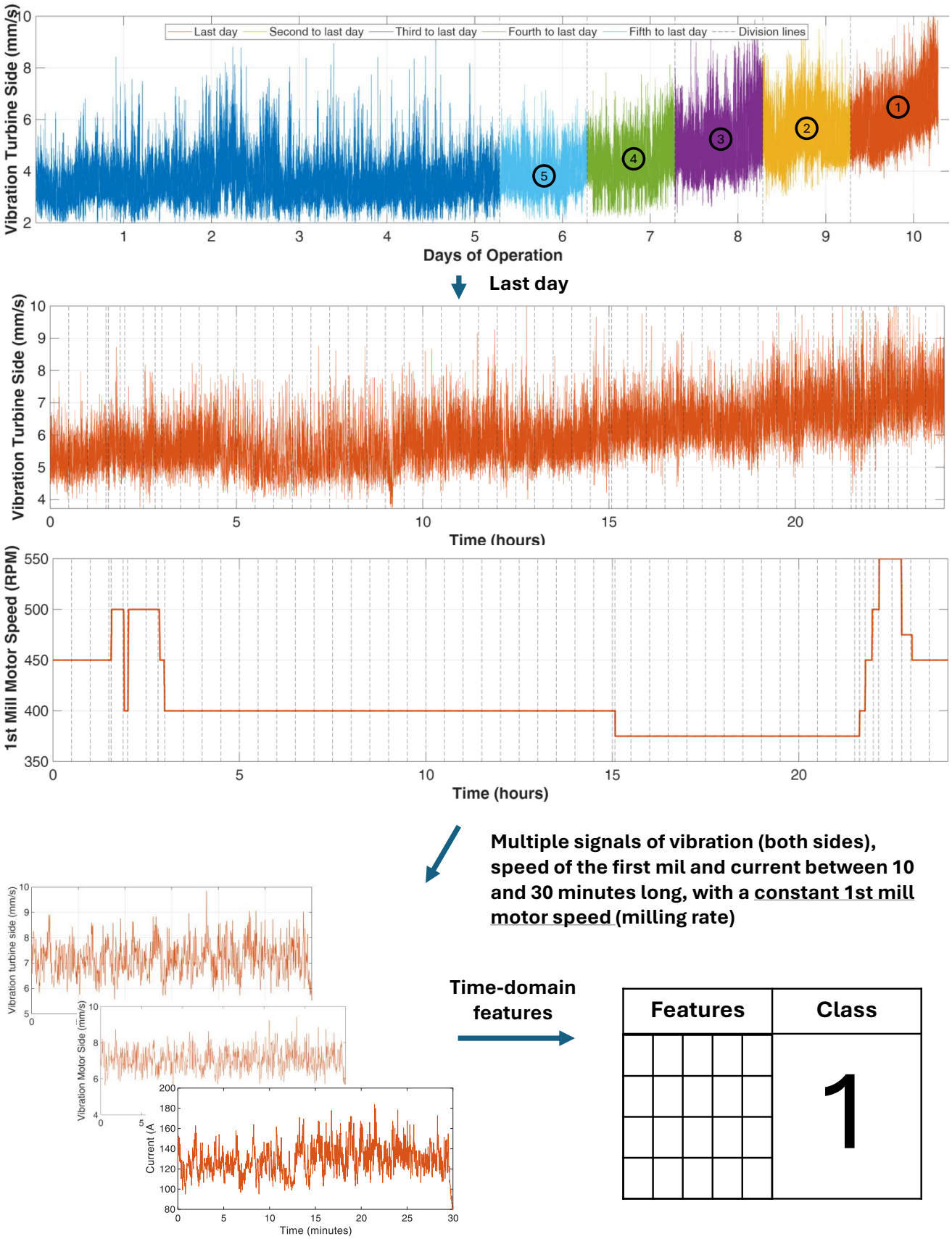


**Figure 4.8:** Data processing for the RUL classification model approach using 5 days in this example, increasing the number of data points for training

When training different classification models a trend was found, the best accuracies were obtained by extracting the following features from the signals.

- Mean (Vibration Motor side)
- RMS (Vibration Motor side)
- Standard Deviation (Vibration Motor side)
- Mean (Vibration Turbine side)
- RMS (Vibration Turbine side)
- Standard Deviation (Vibration Turbine side)
- Mean (1st Mill Motor Speed)
- Mean (Current)
- Standard Deviation (Current)

As stated before the signals were extracted using time frames between 10 and 30 minutes of constant milling rate, therefore constant 1st mill speed. Using the runs of the machine where the mean of the last 12 hours of vibrations on the turbine side was greater than 4.5 mm/s and the non stop operation time was longer that 7 days a first classification model for time to hammer replacement was trained. In this model the class represents the number of days remaining before a replacement of the hammers is needed. The confusion matrix in the figure 4.9 shows the model's performance through different accuracies obtained in validation according to the class to be predicted.

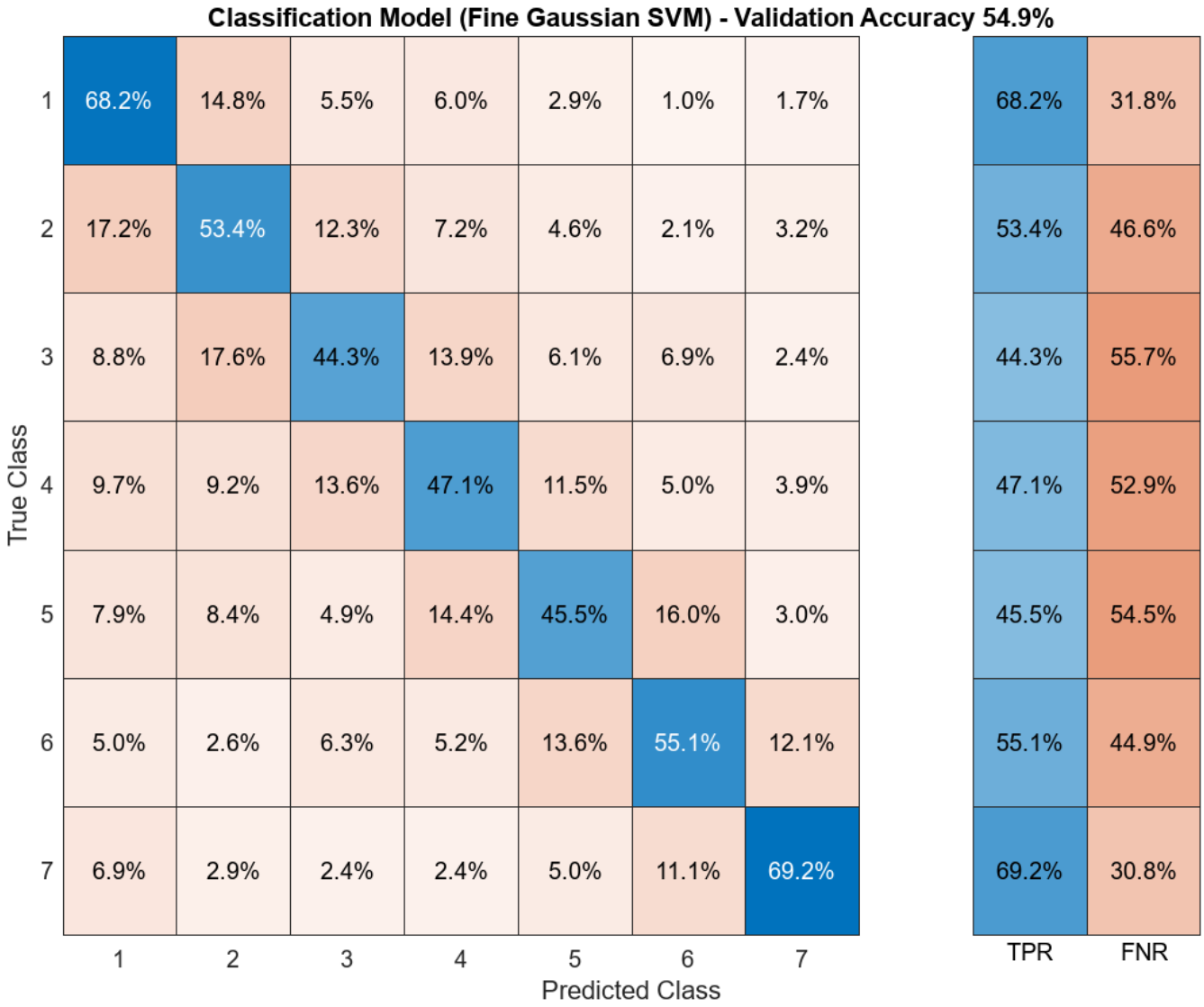


**Figure 4.9:** Confusion matrix of the second classification model for RUL estimation using data for training of 2675 points

The accuracy of the model using 7 days was 54.9%. In an attempt to improve the accuracy sacrificing the time span, the same was done but with 5 days this time. Every run longer than 5 days and where the mean of the last 12 hours of vibrations on the turbine side was greater than 4.5 mm/s was used to train this model. The confusion matrix using 5 days is shown in figure 4.10.

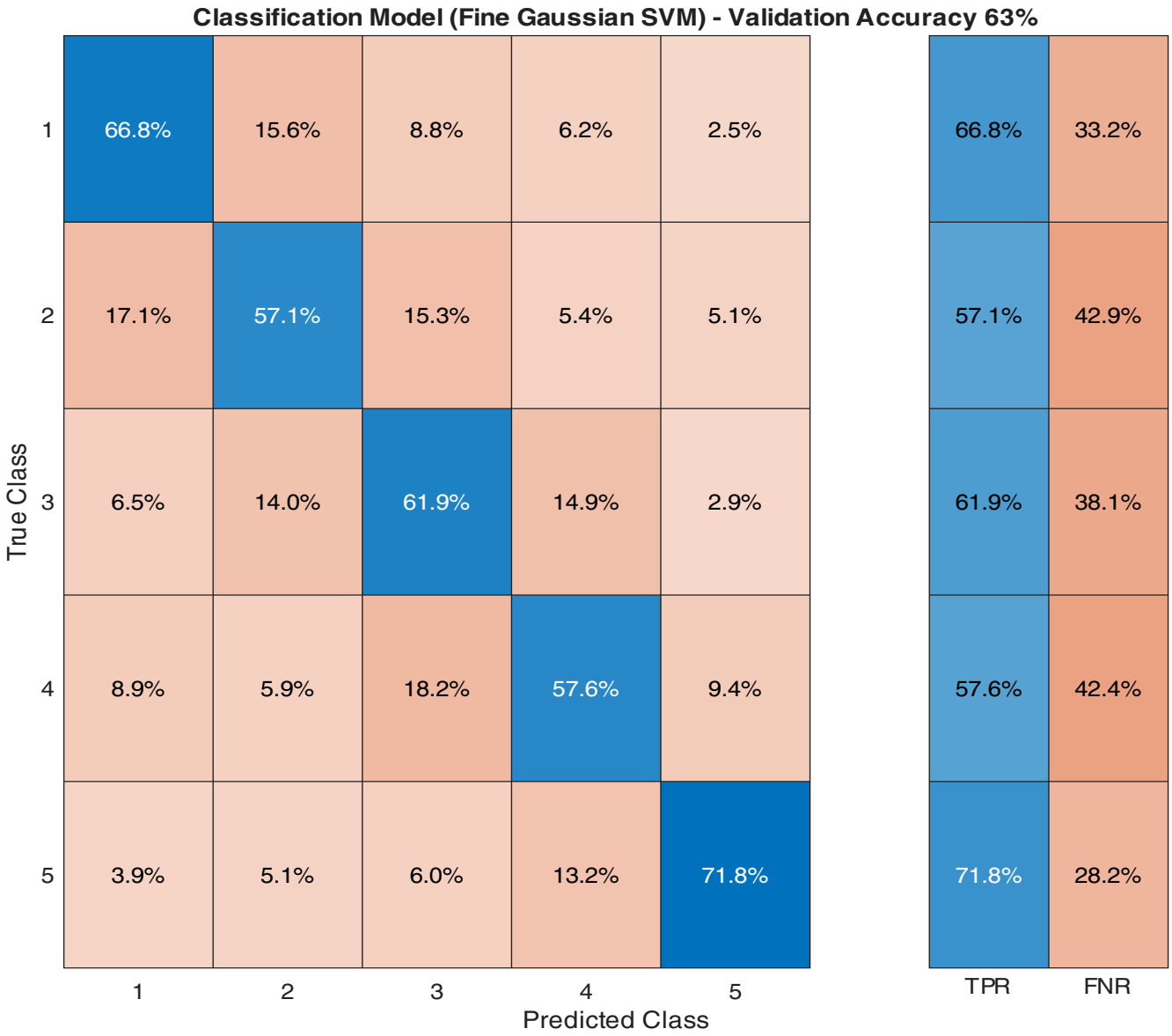


**Figure 4.10:** Confusion matrix of the third classification model for RUL estimation using data for training of 3313 points from 14 operational runs

The 5 days classification model showed and improvement and reached a 63% accuracy at validation, but, taking into account the confusion values at the classes nearby the true classes, this accuracy is even bigger sacrificing time precision. For this specific approach using 5 classes, 10% of the labeled data was reserved for testing the model. Figure 4.11 shows the results of the model using the test data with a 64.4% accuracy.

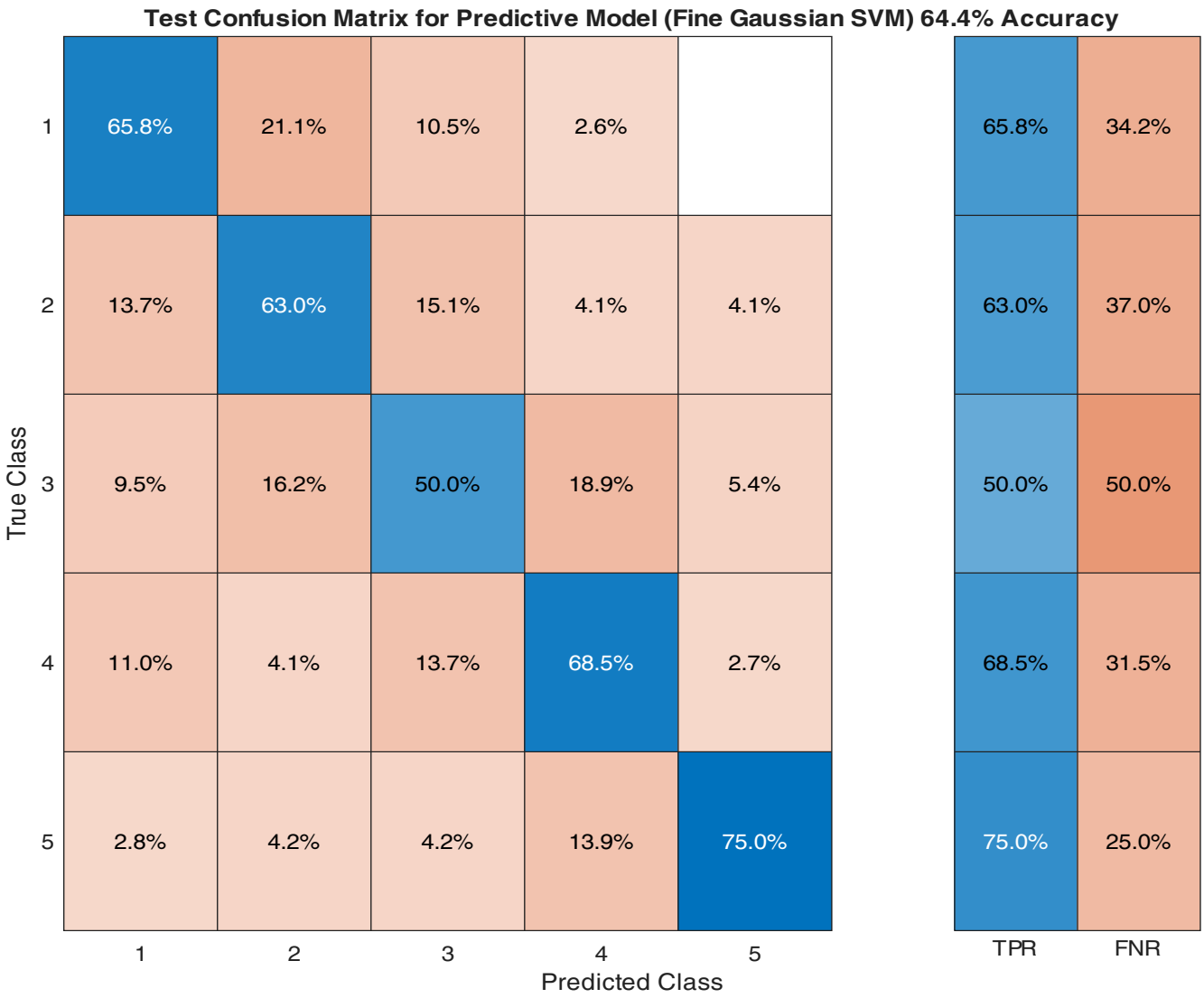


**Figure 4.11:** Confusion matrix using a separate set of 368 labeled points from the same 14 operational runs

The best way to estimate residual useful life is to combine condition indicators into a health indicator that reflects the current state of the machine as a time series for a prognostics model. However, the data obtained from the sugar factory at the beginning of this study did not yield good results when trying to derive a health indicator (this process explored with another sugar cane shredder in the future work section at the end of this document). A possible explanation for this could be the behavior of the energy consumption in the sugar cane shredder; although it was proven in this study that the amount of cane being fed to the machine impacts its current, the wear and tear do not affect it as much as it was assumed beforehand . For this specific sugar cane shredder in this specific sugar factory the main reason to change the hammers is the increase in vibrations, through the different interviews carried out in the sugar factory that was the only thing pointed out. Even though the wear and tear of the hammers change their geometry it may be possible that due to the specifics of this sugar cane shredder operation, its energy consumption doesn't get to a critical point or even increase noticeably. An increment in the energy consumption could be a key condition indicator and a potential predictor for the hammers replacement that may yield better results. A further analysis of this behavior is made in the next section.

## 4.4 Power Consumption and Vibration Behavior

After collecting over a year of operational data from a sugar cane shredder at Factory 1, analysis revealed unexpected behavior in its vibration and power consumption patterns. While it was initially assumed that the power consumption would increase as the hammers wore down due to changes in their geometry, the signals showed no such trend. Instead, only the vibration levels consistently increased over time, correlating with the wear of the hammers. Consequently, Factory 1 has implemented a maintenance strategy that uses vibration levels as a key indicator, or alarm, to determine when the hammers need replacement while other sugar cane factories use the energy consumption or power as the main decision factor.To further investigate this behavior, it was necessary to analyze signals from another sugarcane shredder at a different Factory, Factory 2. Although it was not possible to gather as much detailed information from Factory 2 as from Factory 1, a limited dataset from Shredder 2, with a one-hour sampling frequency over a single operational run, was sufficient to highlight the differences in vibration and energy consumption behaviors between the two shredders. This data was adequate to illustrate the contrasting trends between the machines, which are operated under different load conditions. In this case the operational runs take even longer, this means that there is more time between the hammers replacements in this Factory compared to the Factory 1.
For comparing purposes the normalized specific energy consumption was estimated in each one of the shredders dividing the total energy consumed by the total amount of cane processed in 6 hour time lapses and then normalizing it with the overall mean of the data. For the shredder at Factory 1 the 1st Mill speed was used as it works as an indicator of the amount of cane being processed as shown in section 4.2, and for the shredder at Factory 2 the juice flow signal was the mass flow indicator. The figures 4.12 and 4.13 show the behavior of the specific energy consumed in both shredders. As it can be noted, the energy consumption of the sugar cane shredder at Factory 1 doesn't have an increasing trend over the 43 runs analyzed, the sugar cane shredder at Factory 2 on the other hand shows a notorious trend with the energy consumption increasing more than 50% in one of the 3 runs.

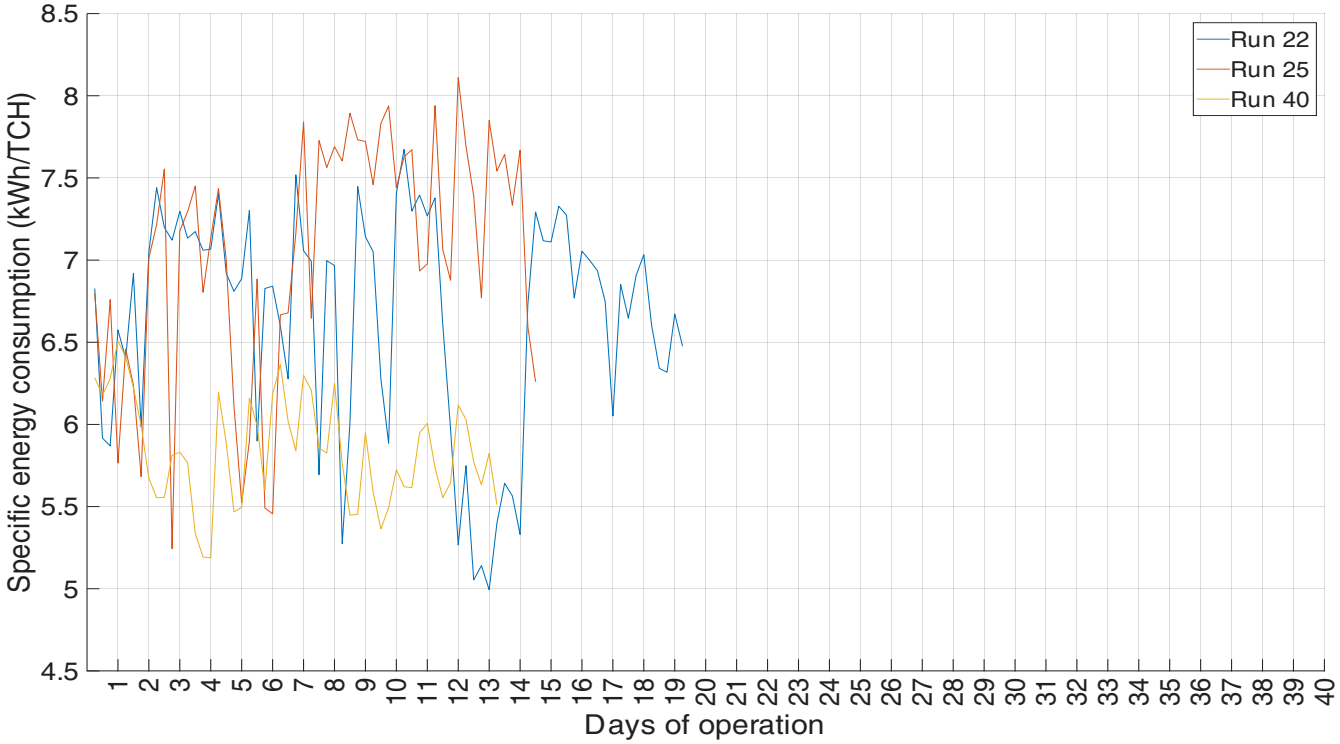


**Figure 4.12:** Specific energy consumption through the three longer runs gathered at the factory 1

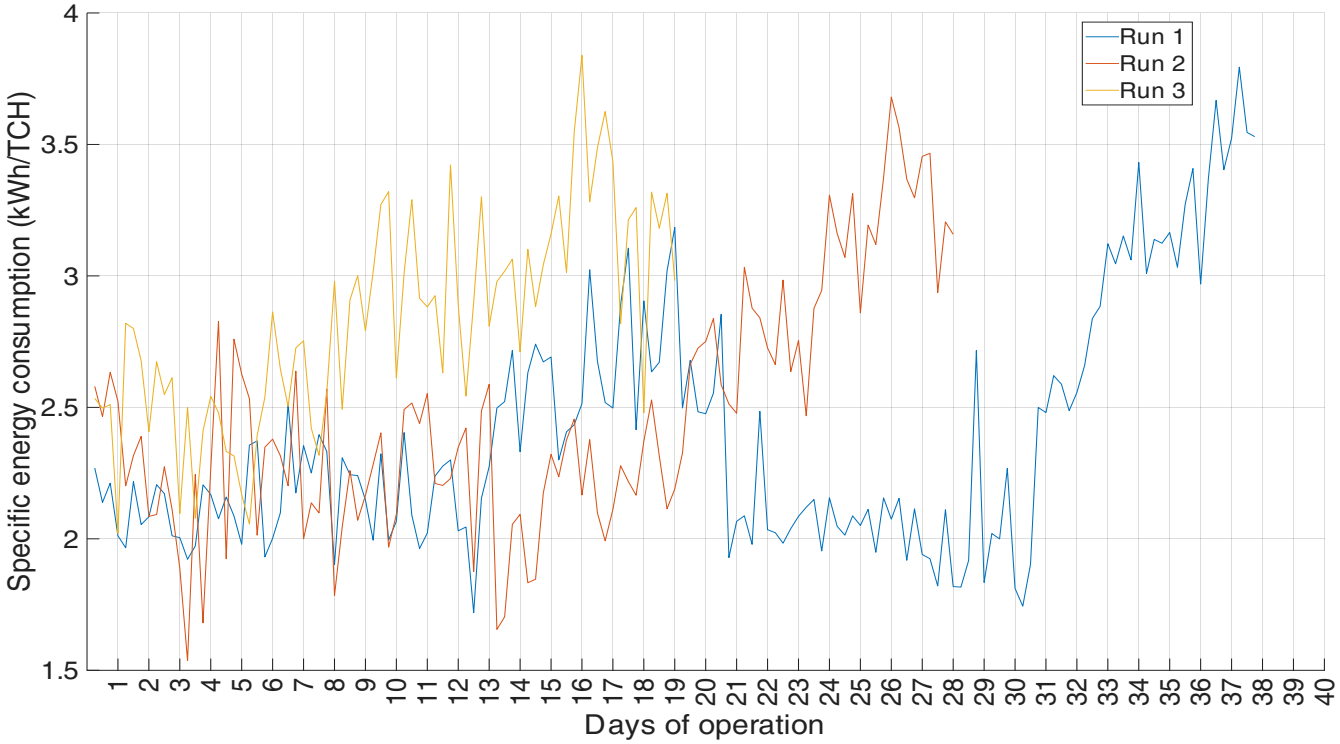


**Figure 4.13:** Specific energy consumption through all the runs gathered at the factory 2

It is important to note that the second shredder at Factory 2 was manufactured by the same company as the one at Factory 1 (Fives Cail). Despite having similar widths, 2.13 m and a 2.08 m

for the Shredder 1 and 2 respectively, which according to the manufacturer means being designed for the same capacity (as shown in Figure 4.14), Shredder 2 exhibited a different pattern of behavior. While Shredder 1 operates near its maximum design capacity, Shredder 2 processes roughly half of its intended mass flow and for longer periods of time between hammers replacement. In this case, as the hammers wore down, an increase in power consumption was observed rather than a rise in vibration levels. This contrast suggests that each shredder's response to wear is significantly influenced by its operational load in relation to its design specifications. The difference in load conditions likely explains the distinct behaviors observed: Shredder 1, operating at full capacity, experiences increased mechanical strain, which manifests as rising vibration levels. On the other hand, Shredder 2, processing a smaller load, shows increased power consumption as the primary indicator of hammer wear. This distinction implies that vibration monitoring is a more effective maintenance indicator for shredders running at high capacity, while power consumption serves as a better indicator for machines operating under capacity.

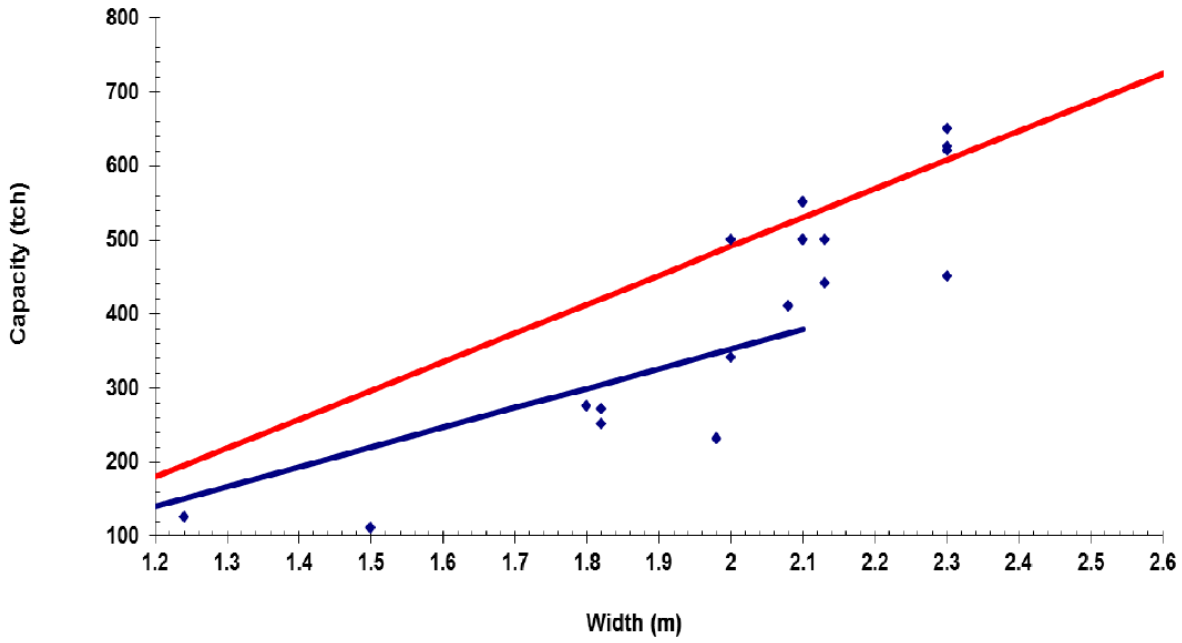


**Figure 4.14:** Correlation between capacity and width from sugar cane shredders. Taken from Fives Cail portfolio (2014)

These findings highlight the importance of tailoring maintenance strategies to specific operational conditions. By understanding the unique behavior of each shredder, the data and its trend can be further used to develop a precise predictive maintenance model that has into account the increment in vibration, energy consumption, milling rate (mass flow) or any signal that is affected by the shredder's degradation.

## 4.5 Conclusions

This chapter focused on assessing condition indicators and developing predictive models for the maintenance of sugar cane shredders, highlighting the differences in their behavior under varying operational conditions. The primary objective was to explore various approaches for estimating hammer wear and residual useful life (RUL) using available signals such as vibration, motor current, and milling rate.

The results showed that the milling rate, as approximated by the speed of the 1st mill motor, significantly influenced vibration and current signals. These correlations enabled the extraction of features used for regression and classification models. The regression models achieved moderate success, with the best performing model reducing the root mean square error (RMSE) to approximately 366 grams. However, the accuracy was still limited due to the inherent noise and variability in the data. The classification models demonstrated more promise, with a 5-day RUL estimation achieving 63% accuracy at validation and 64.4% on a separate test dataset. Through the different models tried out in this chapter an iterative process was made varying the features used as condition indicators, this process made clear which features worked best and had the best trend, accomplishing therefore the second specific objective of this thesis.

Despite these promising results, the accuracy and precision of the models leave room for improvement. One key limitation was the availability of data, which restricted the ability to train more robust models. The splitting and labeling techniques expanded the dataset, but the variability in operational conditions across runs likely influenced the models' performance. Incorporating more diverse and larger datasets, particularly from different shredders or longer runs, could provide the variability and richness needed to train more robust and accurate models.

The analysis of power consumption and vibration trends further emphasized the complexity of predictive modeling. The contrasting behaviors of shredders at Factory 1 and Factory 2 demonstrated how operational load significantly impacts degradation indicators. While vibration levels proved to be a reliable indicator for the high-capacity shredder at Factory 1, power consumption trends were more informative for the underloaded shredder at Factory 2. This finding underscores the importance of tailoring predictive maintenance strategies to the specific operational context of each machine.

In conclusion, while the chapter achieved meaningful insights and a foundation for predictive modeling, the development of more robust and generalized models will require additional data. This includes real-time cane flow measurements, extended operational data from multiple shredders, and a more comprehensive understanding of the factors influencing power consumption and vibration. Future work should aim to collect and analyze these data points to enhance the accuracy and reliability of predictive maintenance models.

# Chapter 5

# Cost-benefit Ratio Estimation

## 5.1 Introduction

This chapter estimates the cost-benefit ratio of using a predictive maintenance model for the sugar cane shredder compared to the traditional maintenance strategies used in the Factory 1. By preventing early hammers replacements, predictive maintenance reduces downtime, labor, and maintenance costs, while also improving juice extraction efficiency. This increased efficiency enables higher sugar yields by processing more cane with less disruption. The analysis will consider both the costs of implementing predictive maintenance and the economic gains from reduced operational costs and enhanced production. Ultimately, this evaluation highlights the potential financial and operational advantages of predictive maintenance in the milling process.

## 5.2 The Cost Equation

In order to estimate the cost of repairing and maintaining operative a cane preparation machine a number of things in the machines degradation need to be considered[12]. The main variables to be considered are:

- Drop in the preparation index and reduction in extraction.
- Time of use of blades or hammers elapsed between repairs.
- Excess energy consumed, above the initial nominal value.
- Metal lost or removed due to wear.
- Reduced component lifespan due to increased dynamic forces, especially on rolling-contact bearings.
- Change time (repair duration). This variable depends on the design and number of elements the machine uses, the personnel required for the operation, and the difficulty and precision required for assembly.

The general equation has the following structure [12]:

$$C_t = C_n + C_{mmo} + C_{pe} + C_e + C_d, \tag{5.1}$$

where:

- $C_t$: Total cost.
- $C_n$: Cost of new inserts and their preparation.
- $C_{mmo}$: Cost of replacement material and labor.
- $C_{pe}$: Cost due to decreased extraction.
- $C_e$: Cost of excess energy.
- $C_d$: Cost of damage caused by imbalance in service.

The cost associated with decreased extraction depends on how frequently the anvil plate in the shredder is adjusted and on the performance of the subsequent milling process. In the industry, some factories frequently adjust the milling process to maintain a stable POC, preventing significant changes and the data available is insufficient to accurately estimate this cost. The same applies to excess energy costs, as this shredder shows no significant change or trend in energy consumption. Furthermore, assessing the cost of damage due to imbalance would require a more in-depth analysis. Therefore, for this research, only the costs of replacement materials and labor, as well as the costs of potential additional sugar cane required for processing, are considered. These costs will provide a sufficient basis for a comparative analysis.
The main approach of this chapter is gonna be the analysis of how the model would impact down time and therefore effective milling time.

## 5.3 Impact of the Model on Effective Milling Time

The analysis is gonna consider a time frame of approximately one year, for this purpose the last year of data gathered from the factory 1 which contains the data of 24 operational runs was used. In one year the hammers were replaced 24 times, that means that each operational run of the hammers before the model's implementation takes around 15 days. These times include effective milling time, stops, scheduled and unscheduled maintenance, and other situations in the factory that may result in machine downtime. For each one of these runs the classification model trained in the previous chapter was applied to estimate wether or not the set of hammers could keep operating for an additional amount of time reducing the number of stops for maintenance and adding effective milling time. The mean potential additional days per run are computed by applying the model to the last set of data from each run. On average the prediction showed that the hammers could keep working 1.75 days more.

If the effective milling days increase, the frequency of hammer replacements required per year decreases, leading to higher sugar production. The approach to estimating the cost-benefit ratio will account for these two aspects. As mentioned earlier, the analysis focuses on a one-year period, meaning that the number of runs per year is reduced compared to before the model's implementation from 24 to 22. The potential additional milling time will now be considered as effective milling time for the purpose of cost computation.

## 5.4 Cost-benefit Ratio Estimation

According to Factory 1, the following costs are incurred for each hammer recovery at the time of doing this research (2024), and these will be considered as the costs associated with each machine

stoppage:

- Mean cost of material for each hammers recovery : 11'870.000 COP
- Mean cost of labor for each hammers recovery : 4'580.000 COP

With two fewer stops, the maintenance savings are calculated as follows:

$$TotalSavings = 2 \times (11870000 + 4580000) = 32'900,000\ COP \tag{5.2}$$

To estimate the overall benefits of increased effective milling days, the following parameters, which are the usual parameters in the sugar industry and this factory, at the time of doing this research (2024), are considered:

- Mean milling rate : 470 Tons/hour
- Mean Sucrose in the cane : 12%
- Mean Extraction in the mill : 96.5%
- Mean Elaboration efficiency : 89%
- Price of a quintal in the market (50 kg) : 160.000 COP
- Mean net margin at the factory= 14% (At the time of doing this research)

Assuming that the time saved in less maintenance is used as effective milling time with around 3 hours of mean time per hammers replacement, the additional sugar and its benefits are computed as follows:

$$\begin{aligned} AdditionalSugar &= CaneProcessed \times Sucrose \times MillExtraction \times ElaborationEfficiency \\ &= (470 \times 6 \times 1000 \times 0.12 \times 0.965 \times 0.89) \\ &= 290635\ kg = 5813\ q. \end{aligned} \tag{5.3}$$

$$AdditionalBenefits = 5813 \times 160000 \times 0.14 = 130'211,000 COP. \tag{5.4}$$

The overall potential benefit of implementing the model is then the sum of the total savings and the additional benefits of milling more sugar:

$$OverallBenefit = 163'111,000 COP. \tag{5.5}$$

## 5.5 Conclusions

This chapter presented a detailed cost-benefit analysis for implementing a predictive maintenance model in the sugar cane shredder at Factory 1 accomplishing the third specific objective of this thesis. By extending the effective milling time and reducing the frequency of hammer replacements, the model significantly decreases both downtime and maintenance costs. The reduced number of stops for hammer replacements translates into fewer labor and material expenses, amounting to substantial savings. Additionally, the increased operational time lead to higher sugar production, which contributes considerably to the overall benefit.

Through the cost-benefit estimation, it was determined that the model provides a dual advantage: a direct reduction in maintenance expenses and an increase in revenue from additional sugar production. This analysis demonstrates that the implementation of a predictive maintenance model not only improves operational efficiency but also yields a financial return. The total estimated benefit of 163'111,200 COP underlines the value of adopting predictive maintenance strategies in enhancing productivity and profitability in the milling process.

# Chapter 6

# Conclusions and Future Work

This research demonstrates the potential of implementing predictive maintenance models for sugarcane shredders, particularly in improving operational efficiency and reducing maintenance costs. Through extensive analysis of hammer wear and machine performance, key insights into the degradation processes and condition indicators were identified. However, the results emphasize that the predictive model's performance is highly influenced by the clarity and consistency of the trends observed in the collected signals.

In the sugarcane shredder analyzed, energy consumption did not show a sufficiently strong trend, limiting its effectiveness as a condition indicator. Additionally, it was observed that the timing of maintenance stops plays a crucial role in the predictive model's utility. When the shredder is consistently stopped at a similar health level, often dictated by external factors unrelated to the machine's condition, such as other parts of the factory, the predictive model's ability to reflect true degradation is constrained.

To fully leverage predictive maintenance, it is essential to adjust the operational strategy, ensuring that stops are determined primarily by the actual health of the machine. This adjustment would allow for better alignment of machine-specific indicators, such as energy consumption and vibrations, with predictive maintenance algorithms. Moreover, integrating additional monitoring tools, such as real-time condition indicators for an accurate mass flow signal of cane and cane preparation quality, could further refine the model's predictions. Vibration signals at a higher sample frequency could also be extremely beneficial as some information might be lost when lowering the sample frequency using RMS values, a common practice in the industry.

The research provides a solid foundation for the development of more effective predictive maintenance strategies in sugarcane shredders. However, for widespread adoption, future efforts should focus on optimizing the collection of condition data, improving instrumentation, reducing external dependencies on maintenance schedules, and ensuring that machine behavior trends are consistently captured. These improvements will contribute to achieving a predictive model capable of reliably guiding maintenance decisions and maximizing operational efficiency. The study also aims to fill the identified gap by contributing a predictive model for the timely replacement of hammers in cane shredders, a critical component of sugar production. The absence of such models in the sector underscores the novelty and importance of this work. The project aligns with the Industry 4.0 initiative, specifically addressing the needs of the Cenicaña Research Center. Ultimately, the project aims to contribute not only to the academic knowledge base but also to practical advancements in the sugar industry.

# Future Work

## Health Indicator Development

The classification model developed in this work is one of the approaches to the predictive maintenance of the shredder, other feasible approach is the development of a health indicator that uses a number of condition indicators combined in a dimension reduction process to estimate the machines health in real time. This health indicator can also be used to train a prognostics model.

The sugar cane at Factory 2 and its data used to compare the behavior of the specific energy consumption where used for the initial exploration of a health indicator development. Ideally, data on not only power but also vibrations and some indicator of the amount of cane entering the machine are needed. In this case the data used from the available is the energy consumed (RMS) and the speed of the turbine that powers the first mill (RMS), both with a sample period of 1 hour. The figure 6.1 shows the power signal of each of the runs.

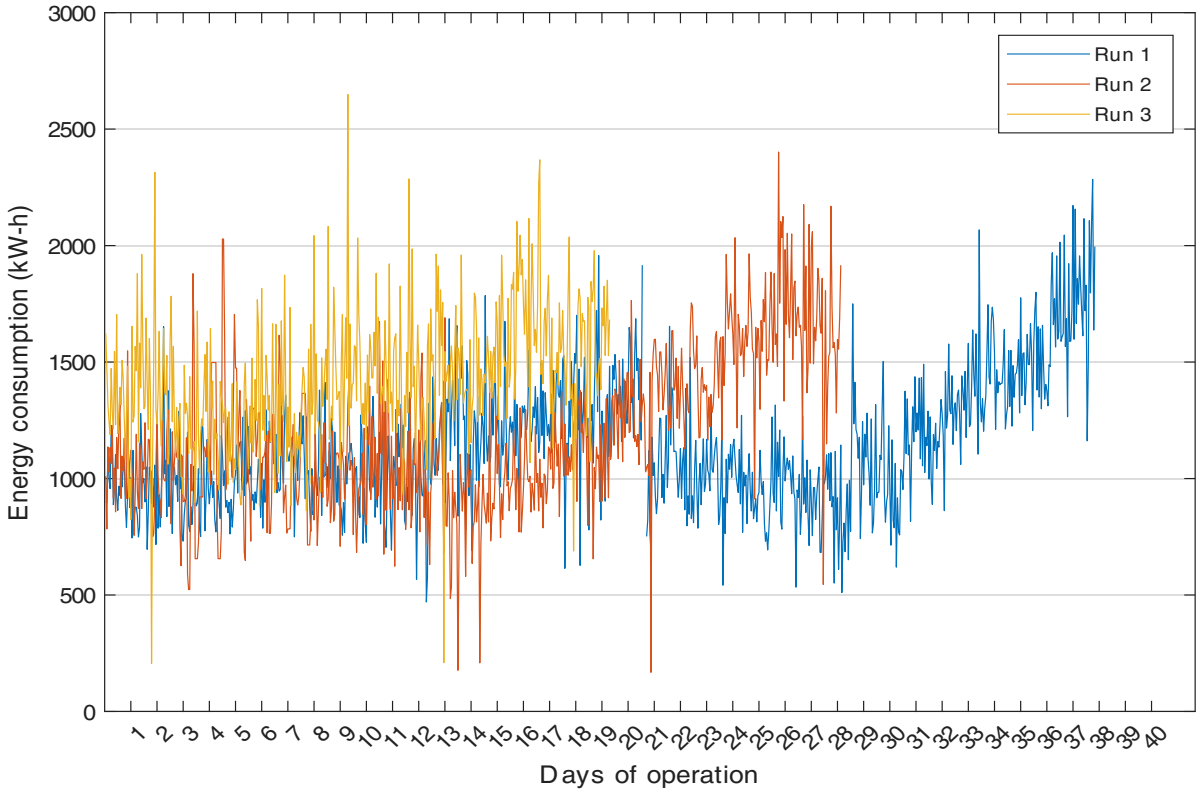


**Figure 6.1:** Power behavior of the three runs (Sugar factory 2)

During the first run there was an intervention on the machine, the details are unknown but it affected the energy consumption and thus the reliability that this run had to be used for a health indicator development where all the runs involved need to be regular runs of the machine with no particular events or interventions. Using the diagnostic feature designer from Matlab, the following features of the speed of the turbine from the first mill and the energy consumption were extracted from the remaining two runs:

- Clearance factor

- Crest factor
- Impulse factor
- Kurtosis
- Mean
- Peak value
- RMS
- Shape factor
- Skewness
- Standard deviation

The previous features were extracted in one-day time frames and then used to assess the feasibility of a health indicator by analyzing energy consumption and cane flow in another sugarcane shredder, which may yield better results.
Matlab provides a useful tool to develop a health indicator once all the features are extracted, the Health indicator designer App (available since version R2024a). This tool generates a health indicator that has the general form of a scalar linear regression equation, there are two main parameters that can be adjusted: the tuning parameter and the feature density. They are both used to obtain the best results with the minimum amount of features.
In a first attempt to develop a health indicator the features extracted from the three runs of the machine were used. The best results were obtained using the run 3, the health indicator obtained in this case shows a linear degradation with a very minimal error at the end of life point (EOL) which is one of the main goals besides an overall minimal error. 16 features were used to develop the health indicator with the crest factor both for the turbine speed and energy consumption being the most important feature. The figure 6.2 shows the potential health indicator for this sugar cane shredder using the power consumption and the speed of the turbine in the first mill.

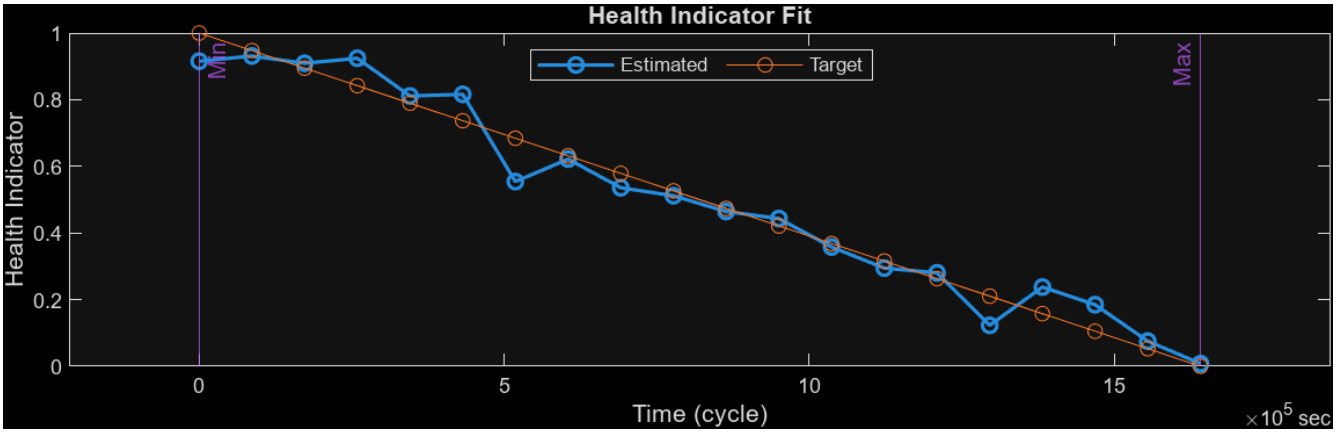


**Figure 6.2:** Health indicator exploration using the energy consumption and speed of the turbine at the first mill

The generation of a health indicator that works for almost every run of the machine requires more than one run of data as well as information regarding the details of each run. For example,

in this case the run number 1 didn't represent a normal operation cycle of the machine and was therefore not used in the development of this health indicator. Not every run of the machine goes under the same amount of degradation and each run has its own characteristics and different duration. This Sugar cane will be the next one to be analyzed using primarily its power consumption and another indicators related to its degradation.

## RUL Estimation through statistical regression models

When a reliable health indicator is developed, one that consistently exhibits a discernible linear or exponential trend, it becomes feasible to train predictive models based on statistical regression techniques. These models, which utilize linear or exponential regression, can leverage the real-time progression of the health indicator to forecast its future values.

The predictive process involves identifying the trajectory of the health indicator over time, enabling the model to project its evolution under current operational conditions. By analyzing the health indicator's trend, the model determines when it is likely to intersect with a predefined threshold. This threshold represents a critical point that signifies the necessity for maintenance or intervention.

By predicting this intersection point, the model effectively estimates the Remaining Useful Life (RUL) of the machine. The RUL prediction highlights the moment at which the machine's health will deteriorate to a level requiring maintenance, thus facilitating proactive decision-making. This methodology, rooted in trend analysis, ensures that maintenance activities can be planned in advance, reducing unexpected downtimes and optimizing operational efficiency. The potential model would perform as shown in the figure 6.3.

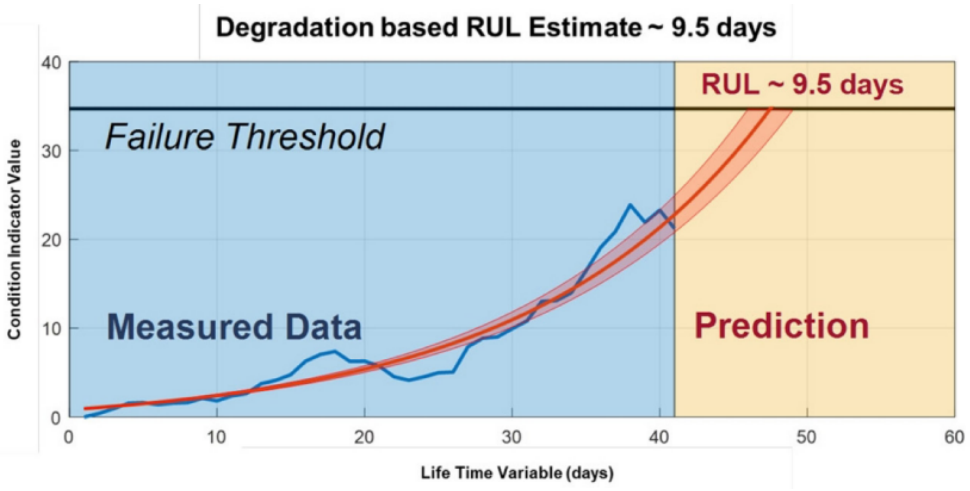


**Figure 6.3:** Exponential regression model used for RUL prediction [16]

## Cane preparation estimation using image processing

As described in section 2.3 a crucial factor in the efficiency of the milling process is the Preparation Index or Percentage of Open Cells (POC) of the sugar cane. This index is currently measured through laboratory analysis, which involves sampling cane and processing it. While this method is accurate, it demands resources and time, and the measurements are not frequent enough to provide continuous monitoring. Consequently, there is a growing interest in developing an in-line system that can estimate POC in real-time, offering significant benefits to the operation and maintenance of sugar mills.

A promising approach to achieving this real-time estimation is through image recognition technology. Preliminary results from ongoing research indicate that image processing techniques can classify cane particles by size, which correlates with the cane's POC. Figure 6.4 shows the pictures of two different samples of shredded cane and their corresponding values of POC obtained in the laboratory, by processing the image to detect and classify the particles in the surface as shown in figure 6.5. By mounting a camera over a conveyor belt and analyzing the particle size distribution as the shredded cane passes, it is possible to estimate the POC continuously and in real time. This method involves using image recognition algorithms to categorize particles into different size classes and then comparing this data with laboratory-obtained POC values to build a predictive model for POC estimation.

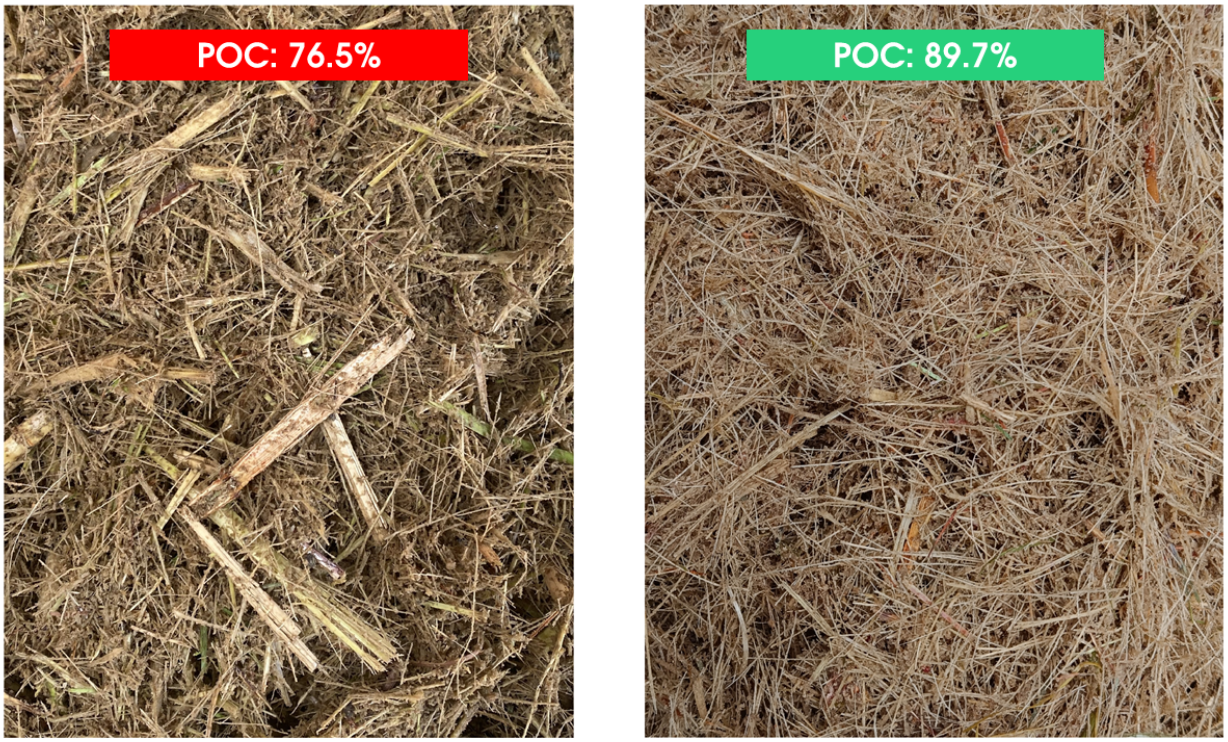


**Figure 6.4:** Shredded cane images and their respective POC

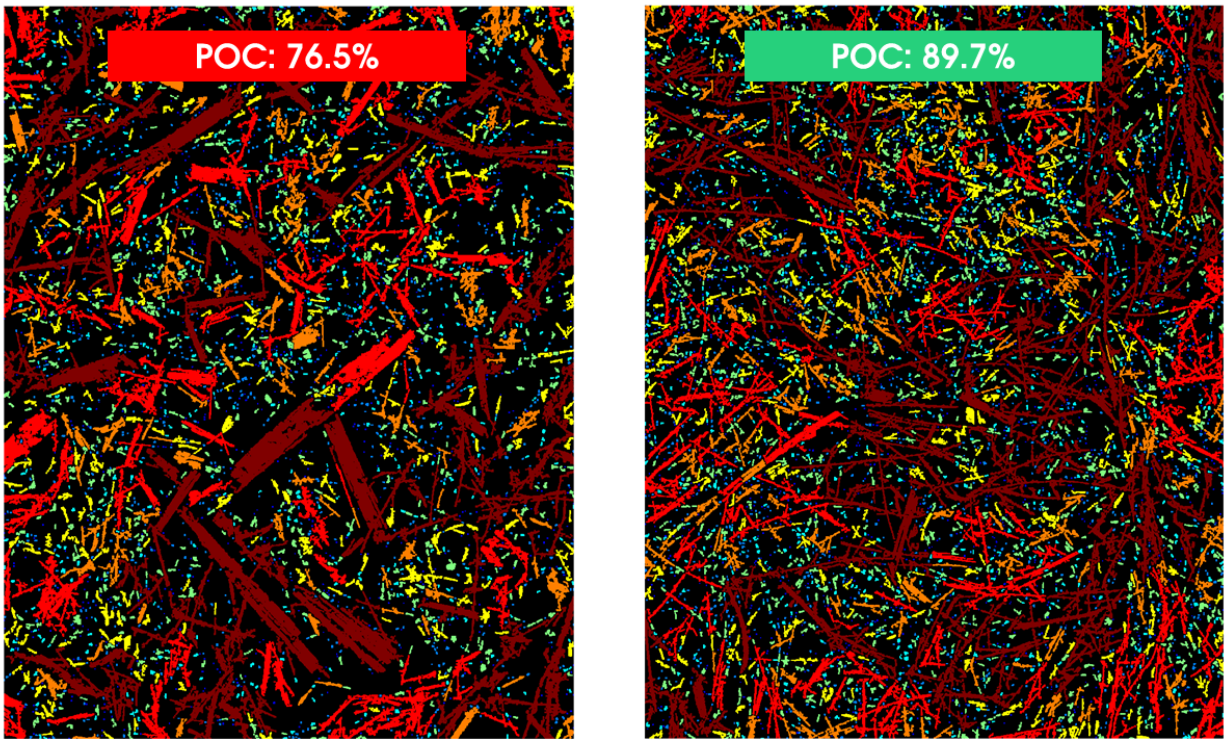


**Figure 6.5:** Shredded cane images with particles defined and classified by image processing

Implementing such an image-based system could provide several advantages for the sugar factory. Firstly, it would allow in-line monitoring of cane preparation, enabling operators to assess the effectiveness of the shredding process instantaneously without the need for laboratory analysis. This real-time feedback loop could facilitate immediate adjustments in shredding intensity or hammer maintenance schedules, ensuring optimal cane preparation for milling. This approach could also play a pivotal role in predictive maintenance models. One of the main indicators of hammer degradation in sugar cane shredders is a reduction in cane preparation quality. However, due to the infrequent POC measurements currently used, it is challenging to correlate hammer wear directly with preparation quality over time. An in-line POC estimation system would provide continuous data, allowing for a more detailed analysis of how hammer wear affects cane preparation. This data could be incorporated into predictive maintenance algorithms, enhancing their accuracy in forecasting hammer replacement needs based on actual operational performance.

# References


[1] Peter Rein and RG Attard. "Cane sugar engineering". In: (2007).

[2] Hong Thom Pham et al. "Prognosis of Machine Health Condition Using ARMA-GARCH Model". PhD thesis., 2010.

[3] Minghang Zhao, Baoping Tang, and Qian Tan. "Bearing remaining useful life estimation based on time–frequency representation and supervised dimensionality reduction". In: *Measurement* 86 (2016), pp. 41–55.

[4] Lei Xiao et al. "A novel approach for bearing remaining useful life estimation under neither failure nor suspension histories condition". In: *Journal of Intelligent Manufacturing* 28 (2017), pp. 1893–1914.

[5] Miguel Ángel Bermeo-Ayerbe et al. "Remaining useful life estimation of ball-bearings based on motor current signature analysis". In: *Reliability Engineering & System Safety* 235 (2023), p. 109209.

[6] RK Mobley. "An Introduction to Predictive Maintenance". In: *Elsevier Science google schola* 2 (2002), pp. 485–520.

[7] Y Lei. *Intelligent Fault Diagnosis and Remaining Useful Life Prediction of Rotating Machinery*. Elsevier Inc, 2016.

[8] Andrew KS Jardine, Daming Lin, and Dragan Banjevic. "A review on machinery diagnostics and prognostics implementing condition-based maintenance". In: *Mechanical systems and signal processing* 20.7 (2006), pp. 1483–1510.

[9] Corinna Cortes. "Support-Vector Networks". In: *Machine Learning* (1995).

[10] Achmad Widodo and Bo-Suk Yang. "Support vector machine in machine condition monitoring and fault diagnosis". In: *Mechanical systems and signal processing* 21.6 (2007), pp. 2560–2574.

[11] Cenicaña. *Cenicaña Research Center. Image Repository*. 2024.

[12] Gómez Perlaza et al. *Desgaste de máquinas de preparación y molienda de caña de azúcar*. Serie de Procesos industriales. Cenicaña, 2008.

[13] ST Inskip et al. "Cane preparation-optimised technology." In: *International Society of Sugar Cane Technologists: Proceedings of the XXVIIth Congress, March 7-March 11, 2010, Veracruz, Mexico*. Asociación de Técnicos Azucareros de México, AC (ATAM) & The XXVIIth ISSCT ... 2010.

[14] EJ Moyer and U Chicago. "Basics on electric motors". In: *University of Chicago* (2010).

[15] Christopher van der Berg John Atherfold. *Predicting Boiler Trips with Machine Learning (Webinar)*. `https://la.mathworks.com/videos/predicting-boiler-trips-with-machine-learning-1629926764579.html`. 2021.

[16] Rachel Johnson Aditya Baru. *Three Ways to Estimate Remaining Useful Life for Predictive Maintenance*. https://la.mathworks.com/company/newsletters/articles/three-ways-to-estimate-remaining-useful-life-for-predictive-maintenance.html.