BACHELOR'S THESIS ASSIGNMENT

I. Personal and study details

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Department / Institute: **Department of Electrical Power Engineering**

Study program: **Electrical Engineering and Computer Science**

II. Bachelor's thesis details

Bachelor's thesis title in English:

Bearing Failure Prediction

Bachelor's thesis title in Czech:

Predikce selhání ložisek

Guidelines:

In the thesis, the student will develop a method for prediction of bearing failure from a time series of measurements obtained on the machine. The data will be provided by a collaborating company. The company has agreed that the data can be published in the thesis.
1. Review the literature on bearing failure prediction.
2. Formalize the bearing failure prediction task. This requires establishing the cost of prediction failures and of false alarms. The predictions can be made with different time horizons and the cost might reflect this.
3. Prepare a representative training and test sets.
4. Implement a ball bearing failure prediction method, probably using a neural network.
5: Evaulate the solution on the test set and analyse the potential economic benefits of its deployment.

Bibliography / sources:

[1] Jin, Xin, et al. "Failure prediction, monitoring and diagnosis methods for slewing bearings of large-scale wind turbine: A review." Measurement 172 (2021): 108855.
[2] Zhao, Yuntian, et al. "An Adaptive Modeling Framework for Bearing Failure Prediction." Electronics 11.2 (2022): 257.
[3] Deep Learning (Adaptive Computation and Machine Learning series) by Ian Goodfellow, Yoshua Bengio, Aaron Courville, Francis Bach

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Date of bachelor's thesis assignment: **03.03.2023** Deadline for bachelor thesis submission: **14.08.2023**

Assignment valid until: **22.09.2024**

prof. Ing. Jiří Matas, Ph.D. Supervisor's signature	doc. Ing. Zdeněk Müller, Ph.D. Head of department's signature	prof. Mgr. Petr Páta, Ph.D. Dean's signature

III. Assignment receipt

The student acknowledges that the bachelor's thesis is an individual work. The student must produce his thesis without the assistance of others, with the exception of provided consultations. Within the bachelor's thesis, the author must state the names of consultants and include a list of references.

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Date of assignment receipt Student's signature

Czech Technical University in Prague
Faculty of Electrical Engineering

Bearing Failure Prediction

by

Daniil Grechany

A bachelor thesis submitted to
the Faculty of Electrical Engineering, Czech Technical University in Prague,
in partial fulfilment of the requirements for the Bachelor's degree.

Bachelor's degree study programme: Electrical Engineering and Computer Science

Prague, July 2023

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Declaration

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Abstrakt

Tato bakalářská práce zkoumá použití matematického modelu rozhodovacího stromu pro předpověď selhání ložisek v papírenských strojích pomocí analýzy amplitudy vibrací. Hlavní přínosy této práce zahrnují vývoj metodiky pro předpověď selhání ložisek s cílem zlepšit přesnost a efektivitu prediktivní údržby. To zahrnuje sběr a předzpracování dat, následně implementaci a testování modelu rozhodovacího stromu. Práce také zkoumá praktičnost nasazení takového modelu v průmyslovém prostředí, se zaměřením na ekonomické přínosy vyplývající z úspory času a zlepšení plánování údržby.
Přestože disertace poskytuje cenné poznatky o předpovědi selhání ložisek, uznává také, že je třeba udělat více práce. Návrhy pro budoucí výzkum zahrnují zdokonalení procesu sběru dat, úpravu citlivosti modelu pro zpracování v reálném čase a zkoumání implementace prediktoru selhání ložisek na základě frekvence.

Klíčová slova: Selhání Ložiska, Prediktivní Údržba, Analýza Vibrací, Rozhodovací Strom, Papírenský Stroj.

Abstract

This Bachelor's thesis examines the application of a mathematical decision tree model for predicting bearing failures in paper machines, using amplitude vibration analysis. The principal contributions of this thesis include the development of a methodology for predicting bearing failures, with a view to improving the accuracy and efficiency of predictive maintenance. This involves the collection and preprocessing of data, followed by the implementation and testing of a decision tree model. The thesis also explores the practicality of deploying such a model in an industrial setting, focusing on the economic benefits stemming from time savings and enhanced maintenance planning.
While the dissertation provides valuable insights into bearing failure prediction, it also acknowledges that more work needs to be done. Suggestions for future research include refining the data collection process, adjusting model sensitivity for real-time processing, and exploring the implementation of a frequency failure bearing predictor.

Keywords: Bearing Failure, Predictive Maintenance, Vibration Analysis, Decision Tree, Paper Machine.

Acknowledgements

First of all, I would like to express my gratitude to my bachelor thesis supervisor, prof. Ing. Jiří Matas, Ph.D. He has been a constant source of encouragement and insight during my research and helped me with numerous problems and professional advancements.
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Chapter **1**

Introduction

1.1 Motivation

Paper production is an essential sector with a substantial economic impact. The heart of this industry, the paper machine, contains numerous rolls whose functionality can be compromised due to wear, friction, and mechanical faults, particularly bearing faults. Undetected, these faults can induce costly downtime, reduced output, and potentially severe accidents. Therefore, the early detection of bearing faults in paper machine rolls is vital for maintaining operational efficiency and safety. The focus of this dissertation is the development of effective, reliable techniques for detecting bearing faults in paper machine rolls, aimed at minimizing the consequences of such faults on overall operation.

Roll bearings in paper machines are integral to maintaining streamlined production and preventing expensive shutdowns. A bearing failure can cause downtime ranging from several hours to multiple days, resulting in considerable production loss. This critical scenario underlines the importance of advanced knowledge about the equipment's condition, especially the crucial components.

Historically, preventive maintenance has been the strategy to manage potential faults in paper production machinery. However, this approach often incurs unnecessary maintenance activities leading to augmented costs and production disruptions. As a solution, machine learning techniques have gained traction for fault prediction across industries, including paper production, to overcome these challenges.

Machine learning-based fault prediction models use historical data, real-time monitoring, and sophisticated algorithms to detect potential bearing faults before they trigger unexpected breakdowns. Recognizing early signs of bearing faults allows for timely maintenance interventions, minimizing downtime, and optimizing production processes. Hence, bearing fault detection research in paper production has gained importance with the aim of developing effective techniques that enhance operational efficiency and productivity.

Bearing failures can have severe consequences, including expensive downtime, damage to other machine components, and potential safety hazards for operators. Predicting these failures in advance could avert these undesirable outcomes and potentially extend the machine's lifespan without the need for excessive maintenance.

The motivation for this research stems from the criticality of bearings in paper production, the need to prevent costly shutdowns, and the potential benefits of using machine learning-based fault detection techniques. By developing and applying advanced bearing fault detection methods, this research aims to contribute to the body of knowledge in the field of paper production, provide practical solutions for the industry, and advance the understanding of how machine learning can be effectively applied for predictive maintenance in the context of bearing faults in paper production machinery.

1.2 Problem Statement

The main aim of this study is to develop an effective method of detection and prediction of bearing failures, specifically for rolling bearings, which are applied to paper machine rolls. Bearing failures can lead to significant downtime and unexpected repair costs, so an effective predictive model offers the potential for substantial operational improvements and cost savings.
The challenge lies in analyzing complex and often incomplete vibration data, using amplitude vibration analysis techniques. This study focuses on the prediction of three primary types of failures. The complexity of the industrial setting, along with the limitations and specificity of available data, adds an additional layer of difficulty to the problem.

1.3 Structure of the Thesis

The thesis is organized into five chapters as follows:

1. *Introduction*: Describes the motivation for the research and presents the problem statement. This sets the context and outlines the challenge of predicting bearing failures.

2. *Background*: Provides necessary technical, theoretical, and practical background information, focusing on existing methodologies and their applicability in an industrial context.

3. *Data*: Introduces the data collection and pre-processing stages, which were performed for this study.

4. *Model*: Explanation of the implementation and testing of the predictive model. This chapter provides a detailed information of the model's creation using a mathematical decision tree algorithm and presents the outcomes of the model's application to real-world vibration data.

5. *Conclusion*: Summarizes the results of our research, suggests possible topics for further research, and concludes the thesis.

Chapter 2

Background

2.1 Technical Background

2.1.1 Paper Machine

Humanity has learned how to produce paper since ancient times, but the process was time-consuming and completely handcrafted. However, the history of paper machines starts just in the late 17th century with the invention of the French engineer Louis-Nicolas Robert, who developed and implemented the first continuous paper machine. But the fundamental principles such as division into sections and the use of rolls and of the web originate from another invention, Fourdrinier Machine. This machine can be seen as the precursor to modern machines.
The Mondi paper mill in Štětí currently operates five distinct paper machines, with plans to complete the construction of an additional machine in the coming year. Machines are complex and expansive industrial equipment used for manufacturing paper and paper products.
Each paper machine is designed with configurations and structures specified for the production of different paper types, as various paper types necessitate unique technological processes. As a result, each machine is dedicated to manufacturing a specific paper type. In this research, the focus will be primarily on two paper machines that have similarities in their structures and types of rolls employed.
Machines are separated into a variety of parts, according to different processes. Here is the description of the sections of both paper machines.

	I.PM	**II.PM**
1	Wire section	Wire section
2	Press part	Press part
3	Drying section	Drying section
4	Clupak	Calender section
5	Tambour section	Rewinder section
6	Rewinder section	Winder section
7	Winder section	

Table 2.1: Paper machines sections

Figure 2.1: Paper machine, Mondi Steti PM 1 [18]

Each process and its part is responsible for different stages of the papermaking process and has specific conditions:

1. Wire section:
    - The wire part is the initial section of the production process. The other name of this stage is forming, because here the pulp slurry shapes a wet sheet. The pulp is spread onto a moving wire or web. As the web moves along the section, the moisture is progressively removed from the paper fiber.
    - This all leads to the fact, that the critical condition of this process is high humidity, which can cause premature corrosion and rust.
2. Press section:
    - The press section includes various types of press rolls. Still, a wet sheet on the web goes throw a series of rolls, which effectively remove water from the fiber, squeezing the paper between. This increases the density and strength of the paper.
    - The press section operates under high pressure and temperature conditions.
3. Drying section:
    - The drying part consists of multiple groups of steam-heated cylinders, also known as drying rolls. As the web moves along the drying section, applied at the cylinders heat removes moisture from the paper.
    - This part also performs under high temperatures and pressures.
4. Calender and Tambour sections:
    - These sections are small parts, which are used to improve the smoothness, thickness, and gloss of the paper surface.
    - These sets of rolls operate under several conditions: temperature, pressure, and moisture.
5. Rewinder section:
    - In this section, dried paper is winded into a large roll.
    - No specific conditions, except for the high-speed rotation of rolls, but this one is applied to all the parts of the paper machine.
6. Winder section:

  - In the winder part, huge paper rolls from the rewinder part are cut into smaller ones of the desired width.
  - The same operating conditions as in the rewinder.

Paper machine components that will be mentioned during this research:

- Drive system: The drive system of a paper machine typically includes electric motors, gearboxes, and couplings that are used to provide power and control the speed of various sections of the machine, such as the headbox, forming section, press section, and drying section. These motors and drive components are responsible for powering the continuous operation of the machine.

- Rolls: Rolls are used in various sections of the paper machine to perform different functions. For example, the breast roll or headbox roll is used in the headbox section to spread the pulp evenly onto the forming wire. The forming rolls, also known as couch rolls or suction rolls, are used in the forming section to facilitate the dewatering of the wet paper sheet. Press rolls are used in the press section to compress the paper sheet and remove water, and dryer rolls are used in the drying section to remove remaining moisture from the paper sheet. These rolls are typically driven by motors and supported by bearings.

- Bearings: Bearings are critical components in a paper machine that support the rotating rolls and other moving parts. They are used to reduce friction and ensure smooth operation. Common types of bearings used in paper machines include ball bearings, roller bearings, and spherical roller bearings. Proper lubrication and maintenance of bearings are essential for reliable and efficient operation of the paper machine.

- Web: Also known as fabric or forming wire, is a continuous loop of woven mesh that carries the wet paper sheet through the forming section. It is typically made of synthetic materials, such as polyester, and plays a critical role in the formation of the paper sheet by allowing water to drain through while retaining the fibers. The fabric or wire is supported and guided by rolls and other components.

- Steam and condensate system: The steam and condensate system is used in the drying section of the paper machine to supply heat for evaporating water from the paper sheet. It typically includes steam supply pipes, steam showers, steam boxes, and condensate removal systems, such as steam traps and condensate pumps.

- Control system: The control system of a paper machine consists of various sensors, actuators, and automation equipment that are used to monitor and control the operation of the machine. This includes controlling motor speeds, adjusting tension, monitoring temperatures and pressures, and managing the overall process parameters to optimize paper quality and machine performance.

Throughout the paper machine, various control systems and sensors monitor and adjust parameters such as speed, temperature, and moisture content to ensure consistent and high-quality paper production. Additionally, there are numerous auxiliary systems, such as steam and water systems, vacuum systems, and air systems, that support the papermaking process and maintain the proper conditions for paper production.

A modern paper machine is a sophisticated piece of equipment that requires skilled operators and engineers to operate and maintain. It is capable of producing a wide range of paper grades, sizes, and finishes to meet diverse customer needs in industries such as printing, packaging, and specialty applications.

2.1.2 Rolls

Rolls, in some parts of the machine, also referred to as cylinders, are essential and indispensable components of paper machines. They are designed to withstand harsh operating conditions, such as high pressure, temperatures, and speed. Consequently, they are typically made of high-strength materials, such as cast iron, steel, or rubber.[33]

2.1.2.1 Parts of Rolls

- **Shell**: The shell is the cylindrical outer surface of the roll. It provides structural integrity and acts as a support for the paper web. The shell is typically made of metal, such as steel, and its surface may be coated or treated to enhance its durability and surface characteristics.

- **Core**: The core, also known as the shaft or mandrel, is the central cylindrical structure around which the roll is built. It provides stability and strength to the roll. The core is usually made of metal and is designed to withstand the load and stress exerted during the operation of the paper machine.

- **Journals**: Journals are the sections of the roll that extend beyond the bearings. They provide additional support for the roll and help distribute the load evenly. Also, journals act as a connection point for the bearing and transmit the rotational force from the machine's drive system to the roll.

- **Surface Treatment**: The surface of the roll may undergo various treatments depending on its specific function. For example, a drying roll may have a heat-resistant coating to withstand high temperatures, while a functional roll involved in pressing or sizing may have a specialized surface texture to impart desired characteristics to the paper web.

- **Bearings**: Bearings are one of the most critical mechanisms, which can be found throughout the paper machine. With nearly thousands of them dispersed all around the paper machine, they play an indispensable role in smooth rotation and movement. By minimizing friction, bearings ensure optimal alignment, reduce wear, and provide essential support for the rotation of rolls, motors, and other crucial mechanisms within the paper machine. Their proper functioning is vital for maintaining operational efficiency and preventing potential disruptions due to friction-related issues.

2.1.2.2 Rolls Classification

All types of rolls play significant roles in the overall process of paper-making but serve different purposes and work in different conditions. Based on their variety of purposes, they can be divided into three major groups: guiding rolls, functional rolls, and drying rolls.

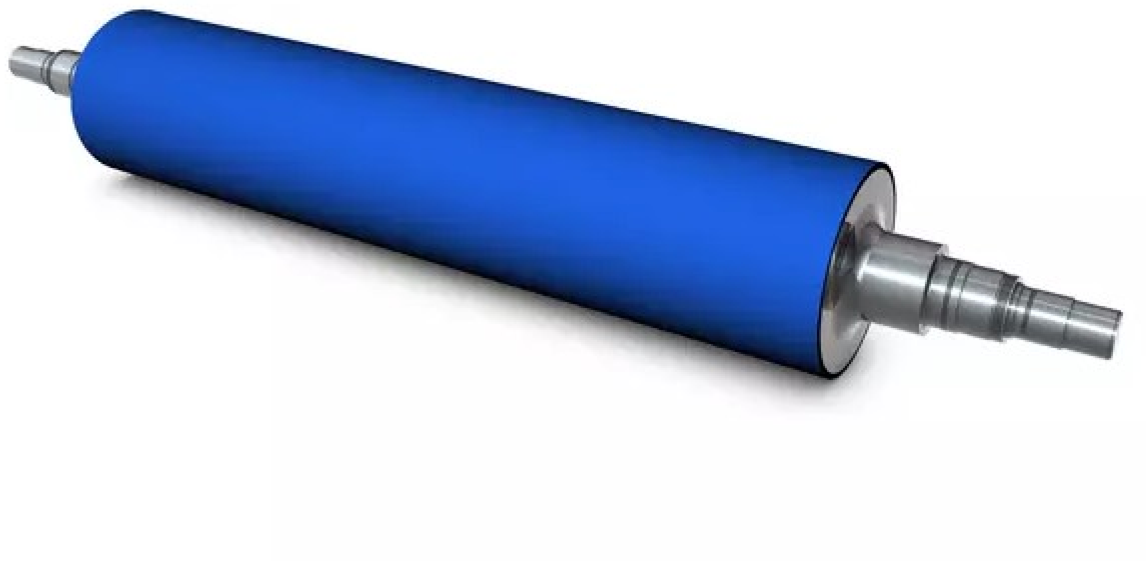


Figure 2.2: Voith Guiding Roll [32]

- **Guiding Rolls**: Guiding rolls play a critical role in the paper machine by directing and guiding the paper web throughout its journey from one section to another. Their primary function is to maintain proper alignment and tension of the paper web. Although guiding rolls may vary in weight and size, due to their similar functionality they do not require further subgroup classification.

- **Functional Rolls**: Functional rolls have specific roles in the papermaking process and directly influence the properties of the paper web. These rolls serve distinct purposes, such as pressing, spreading, or sizing the paper web. To analyze bearing faults effectively, it is necessary to categorize functional rolls into subgroups based on their specific functions.

- **Drying Cylinders(or Drying Rolls)**: Drying cylinders, also known as drying rolls, are crucial components responsible for removing moisture from the paper web. They are typically heated and work in conjunction with the dryer section of the paper machine to achieve the desired moisture content in the paper. Similar to guiding rolls, drying rolls may vary in weight and size, but they do not require further subgroup classification due to their shared functionality.

2.1.3 Bearings

Bearings are mechanical components, which play one of the most critical roles in any equipment, as well as in paper machines. They implement two major functions: reduction of friction and supporting the correct position of the rotating shaft. Vehicles require hundreds

of bearings.[14] But when we are talking about more sophisticated mechanisms like paper machines count goes on thousand.
Bearings of different types and sizes are used in almost every part of the paper machine. They allow to perform smooth rotation of rolls and motor shafts, which in return decreases energy consumption. Due to that, it is crucial to choose a proper bearing, that will be suitable for the specific load and operating requirements of the application.

2.1.3.1 Types of Bearings

There are hundreds of different types of bearings, which have unique designs and which are applicable for diverse purposes. But they can be generally categorized into two main groups: friction or plain, and antifriction or rolling bearings; each of these groups has subcategories. However, it is important to note that all bearings, whether rolling or sliding, technically manage friction, they just do it in different ways. The term "friction bearings" is used to distinguish plain bearings from "antifriction bearings", which reduce friction through rolling contact.[15]
This way of classifying is necessary, due to the assumption that different types and subtypes have different damage signals. Hypotheses of such kind are based on the fact, that bearings have different structures and areas of contact.

Bearings			
Friction		**Antifriction**	
Radial spherical plain bearing(RSP)	GE	Spherical roller bearing(SR)	2
		Tapered roller bearing(TR)	3
		Thrust Ball Bearing(TB)	5
		Deep groove ball bearing(DGB)	6
		Cylindrical roller bearing(CR)	N

Table 2.2: Types and IDs

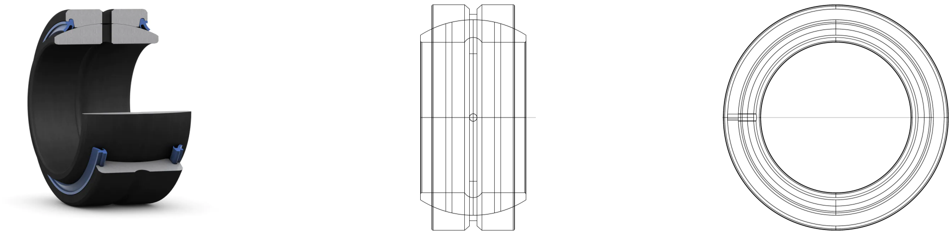
2.1.3.2 Friction bearings

This type is also known as plain or sliding bearings. They are called so because of the use of a sliding motion between shells of it, and simple design in comparison with rolling bearings. Plain bearings consist of a stationary outer ring and a rotating inner ring. Such a simple structure makes them a cost-effective solution to adjust alignment movements between the rolls shaft and housing, and applicable for heavy dynamic loads at low rotational speeds.[20]
Nevertheless, the design also has several disadvantages. One of them is the necessity of frequent lubrication because the moving parts in a sliding bearing are in direct contact. Lack of lubrication can cause severe problems including heightened wear and elevated heat production. with a lubricating film in between to reduce friction.[19]
Due to the fact that friction bearings are suitable for low-speed rotation, it requires a different(off-line) type of vibration monitoring process and this type will not be included in further study.

Radial spherical plain bearing

RSP bearing is one of the types of sliding bearings. Same as all sliding bearings it consists

just of two elements: inner and outer ring. But an inner ring of RSP bearings has a convex outer surface and an outer ring has a concave inner area.[4, 8]
Based on the specifications of RSP bearings, which are used on the considered paper machines, it is possible to notice that they have a steel/steel sliding contact area and that they are suitable for radial and axial loads.



(a) 3D Model [27] (b) Top-View (c) Side-View

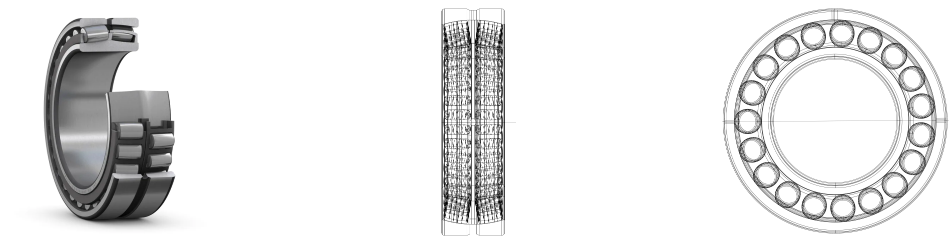
Figure 2.3: Radial spherical plain bearing, SKF GE 100 ES-2RS [4]

2.1.3.3 Antifriction bearings

Antifriction bearings, also called rolling, are used to reduce friction between moving parts and facilitate smooth motion. Bearings of this type consist of an inner ring, an outer ring, rolling elements, and a cage to hold the rolling elements in place. They are designed to handle high load-carrying capacities and high speed, because of low friction. Hence, this makes them suitable for high-speed rotating parts of paper machine rolls, which are rolls and cylinders.[37, 34]

Spherical Roller Bearing

SR bearing consists of an inner ring with two raceways, an outer ring with spherical-shaped inner raceways, barrel-shaped or spherical rolling elements, and a cage that keeps the rollers evenly spaced around the raceways. SR bearing's design allows them to accommodate misalignment and shaft inclination, making them suitable for guiding rolls and drying cylinders.[1, 11] Therefore in paper machines, SR bearings are commonly used in wire, press, and drying sections.

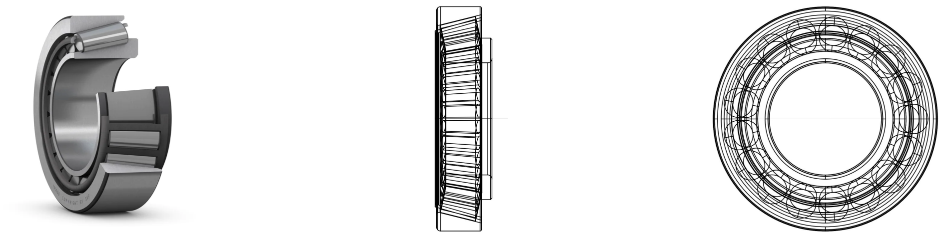


(a) 3D Model [24] (b) Top-View (c) Side-View

Figure 2.4: Spherical Roller Bearing, SKF 22234 CCK/W33 [1]

Tapered Roller Bearing

The unique feature of TR bearings is the tapered shape of rolling elements, which means that raceways of inner and outer rings are also conical. The conical shape allows TR bearings effectively support forces in several directions.[2, 12] Handling both axial and radial loads makes them applicable for supporting guiding and suction rolls of wire and press sections.

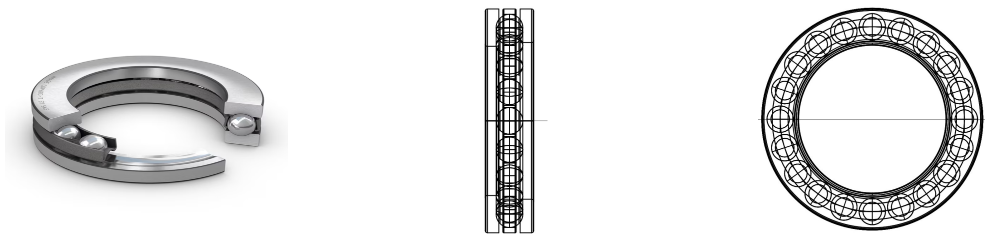


(a) 3D Model [25] (b) Top-View (c) Side-View

Figure 2.5: Tapered roller bearing, SKF 30208 [2]

Thrust Ball Bearing

In contrast to the previous bearings, the TB bearing is designed to handle only axial loads. The reason for the disability to accommodate radial load lies in the location of raceways. They are located on the side of rings. Therefore, it would not be correct to call rings outer and inner, that is why they call them shaft and housing rings, based on the side of application. TB bearing uses balls as rolling elements, which are also spread by a cage.[3] Due to such distinctive characteristics, only one shoe press roll at the I. PM uses this type of bearing.



(a) 3D Model [26] (b) Top-View (c) Side-View

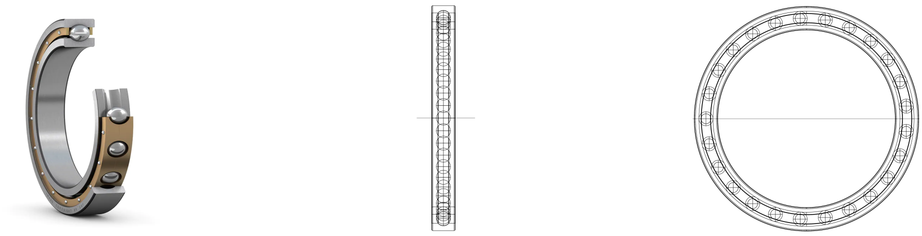
Figure 2.6: Thrust ball bearing, SKF 51108 [3]

Deep Groove Ball Bearing

Rolling elements of DGB bearings are also balls, but unlike the TB bearings, deep groove raceways of DGB bearings are located on the outer diameter of the inner ring and the inner side of the outer ring.[5] As well as SRB and TR bearings, they are developed to withstand radial and axial loads; and are suitable for high-speed rotations. Thus, this bearings are applied to guiding, spreading, and shoe press rolls.

Cylindrical Roller Bearing

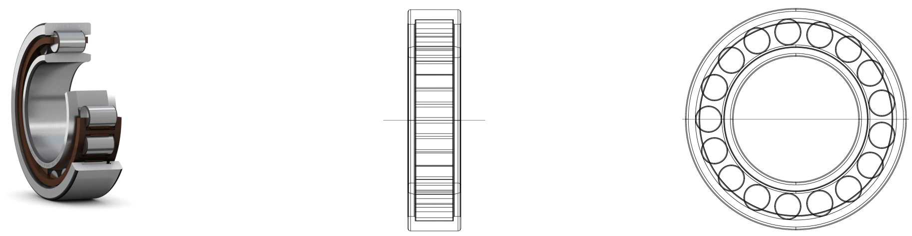
CR bearings have the ability to handle high radial loads and moderate axial loads, as well as high speeds. These bearings consist of cylindrical-shaped rollers, which give the rolling element a larger contact area, consequently, a higher carrying capacity. enabling smooth



(a) 3D Model [28] (b) Top-View (c) Side-View

Figure 2.7: Deep groove ball bearing, SKF 61830 MA [5]

rolling motion.[6, 9] Due to the ability to operate at high-speed rotations, CR bearings are mainly used on guiding rolls at the wire part.



(a) 3D Model [29] (b) Top-View (c) Side-View

Figure 2.8: Cylindrical roller bearing, SKF NU 2217 ECP [6]

The selection of the type of bearing is mostly based on the type and magnitude of load, which will act on the bearing. Due to that, it is very important to select the appropriate type that can handle the acting magnitude of the load.

2.2 Theoretical Background

2.2.1 Predictive Maintenance

Predictive maintenance represents a proactive approach that leverages data analysis and predictive modeling to identify potential equipment failures before they occur. The aim of predictive maintenance is to anticipate and prevent equipment failure to improve efficiency, reduce downtime, and extend machinery lifespan.
Techniques used in predictive maintenance often include condition monitoring, statistical process control, equipment performance modeling, and other predictive tools and techniques. Many of these methods are increasingly being integrated with advanced technologies like machine learning, improving their ability to predict and prevent potential equipment failure.
Predictive maintenance provides a multitude of benefits. It minimizes unplanned downtime, enhances operational efficiency, reduces maintenance costs, and improves product quality and overall safety. All these improvements contribute to increasing the overall profitability of the enterprise.

2.2.2 Vibration Analysis

Vibration is regarded as the most effective indicator for evaluating low-frequency dynamic states. Due to the fact that issues of rotating parts of paper machines are mainly represented as different forms of vibration, the condition monitoring data primarily comprises vibration signals generated by accelerometers. Vibration analysis can be divided into two parts: frequency and amplitude.[10]
Frequency describes the rate of vibration of the bearing. The frequencies, at which some oscillations occur, allow to identify damages or faults because some of them appear at certain frequencies. For example, frequency analysis can help in determining rings and rolling elements defects.[38]
At the same time, amplitude gives an understanding of vibration magnitudes and indicates the degree of damage. This study is based on amplitude analysis.

Velocity

The velocity describes the rate of change in displacement of the vibration signal. It is obtained by integrating the accelerometer measurements, and it is measured in mm/s.
Velocity serves as an effective metric for medium-range frequency vibrations and is used for examining defects related to fatigue.

Acceleration

The acceleration is the rate of change in velocity, which is measured with the accelerometer. The acceleration unit is g-force, where 1g is gravitational acceleration on the planet Earth.
Continuous monitoring of vibration accelerations of bearings allows to indicate mechanical defects such as disbalance, wear of bearing, and misalignment. By analyzing the hourly values of acceleration over time, gradual increases in vibration levels can be associated with potential bearing faults.

Enveloped Acceleration

The enveloped acceleration trend is derived from the vibration acceleration. Implementation of enveloping algorithm consists of two steps.
First, it is necessary to apply at the acceleration signal band-pass filter, which filters out low-range frequencies.
Second, the filtered vibration signal passes to the enveloper. The enveloper is an electric circuit, which captures high frequencies of low-amplitude vibration spikes and enlarges them based on the repetition rate.
Then, values of enveloped acceleration are plotted over time, allowing for the detection of changes that may indicate developing bearing defects and even breakdowns.

Bias Voltage

The bias voltage is the characteristic, which describes DC voltage applied to an accelerometer. The stability of this characteristic allows to verify the quality of vibration trends values. This means that if the bias voltage trend is stable over time, then points of vibration trends are actual. Otherwise, there is some fault, which is probably caused by the condition of the accelerometer, wires, or their connection, and they have to be checked and exchanged to obtain proper values.

2.2.3 Standards

Standards serve as a fundamental reference point in industrial contexts, providing guidelines and best practices that ensure quality, reliability, and safety. A critical standard in the field of vibration analysis and predictive maintenance is ISO 10816-1:1995.
ISO 10816-1:1995 is a standard set forth by the International Organization for Standardization (ISO). It provides specific guidelines for evaluating the severity of mechanical vibration in non-reciprocating machines (rotating machines). The standard primarily applies to measurements taken on rotating machinery, coupled to its foundation or structure through bearings, observed under normal steady-state operating conditions.
According to ISO 10816-1:1995, the vibration values are divided into four zones:

1. Zone A (Vibration of the machine is normally considered satisfactory)

2. Zone B (The machine is acceptable for unrestricted long-term operation)

3. Zone C (The machine may require attention)

4. Zone D (The machine is unsatisfactory for long-term continued operation)

The standard helps in quantifying the 'severity' of a vibration, which is an important aspect of conducting a vibration analysis. By defining severity levels and providing clear guidelines, ISO 10816-1:1995 aids in making informed decisions regarding machinery maintenance and operation. This standard forms the foundation for the effective implementation of predictive maintenance strategies, ensuring the efficiency, longevity, and safety of machinery.

2.3 Practical Background

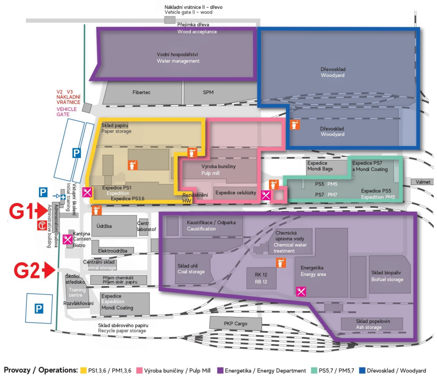
2.3.1 Paper Mill Overview

Mondi Štětí a.s. is a paper mill located in the town Štětí, which lies on the border of the region Ústí nad Labem, which is about 38 km north of Prague. This location was chosen because this town lies on the right bank of the river Labe(Elbe), and the water source is essential for the papermaking process. Mill in Štětí employs around 1000 workers and the approximate area is 1.2 km^2. Mondi Štětí a.s. is a part of the multinational packaging and paper Mondi plc., but this factory specializes in producing mostly packaging paper standards. The mill handles the entire process of producing paper, from raw materials to finished products, which means it is a full-cycle production.

A paper mill typically consists of several key components:

1. Woodyard: The woodyard is a component that handles the processing and storage of wood as the primary raw material. It serves as the entry point for logs brought to the mill. In the woodyard, logs are sorted based on their size and quality. The woodyard processes logs by cutting off the bark and chipping the logs into wood chips. Wood chips are then transported to the pulp mill for further processing.

(a) Photo



(b) Plan

Figure 2.9: Mondi Štětí a.s. [16]

2. Pulp Mill: The pulp mill is responsible for converting raw materials, such as wood chips or recycled paper, into pulp. It typically includes various stages and processes to break down the raw materials and separate the fibers. The pulp produced in the pulp mill is then transported to the paper machines for paper production.

3. Water Management: Water management is an important aspect of paper mill operations. Paper mills consume significant amounts of water for various processes, such as pulping, papermaking, and cooling. Effective water management systems are put in place to minimize water usage, recycle and treat wastewater, and ensure compliance with environmental regulations. Water treatment plants are used to treat and purify the wastewater generated during the papermaking process before it is discharged. Water conservation measures, such as reusing water and implementing efficient water technologies, are also implemented to minimize water consumption.

4. Energy Area: The energy area in a paper mill is responsible for generating and supplying the necessary energy to power the mill's operations, including the woodyard, paper machines, pulp mill, and other auxiliary equipment. In this case, the energy area goes a step further and produces enough power not only for the mill but also for the nearby town. The energy area typically consists of power generation units such as boilers, turbines, and cogeneration systems. These systems can utilize various fuel sources, including biomass, natural gas, or renewable energy sources, to produce electricity and thermal energy. The generated power is distributed throughout the mill, and the excess power is supplied to the local power grid to meet the energy needs of the surrounding community.

5. Paper Machines: Paper machines are the heart of the paper mill, responsible for transforming pulp into paper. These machines are typically large and complex. They receive the pulp from the pulp mill and initiate the papermaking process.

The whole production process can be expressed in the simplified scheme:

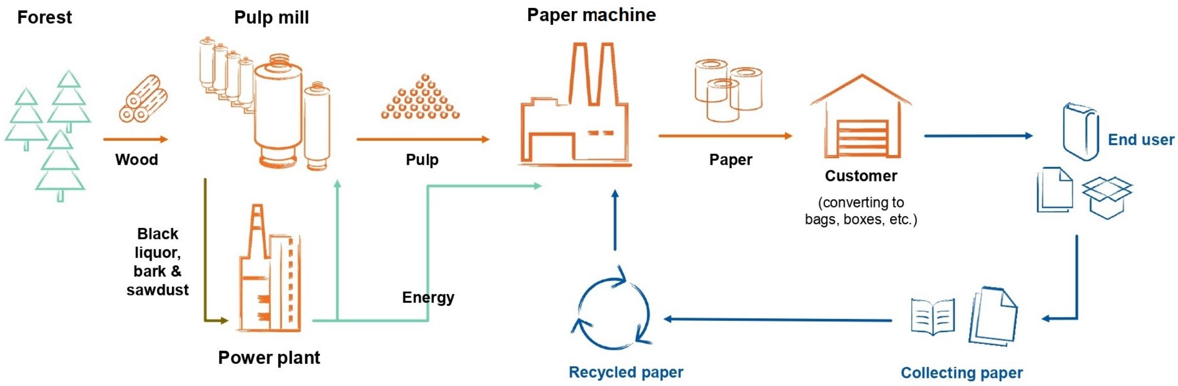


Figure 2.10: Simplified scheme of production process [16]

2.3.2 Bearing Failure Modes

2.3.3 Condition Monitoring in Paper Mill

As previously mentioned, each paper machine holds approximately a thousand bearings, and the condition of each has to be controlled. Hypothetically, it is possible to implement the system, which will be capable of collecting such a vast amount of data. But real-life solutions have resource limitations. In these circumstances, such limitation is the number of wires and their length. Therefore, companies separate bearing condition monitoring into two groups: on-line and off-line. The decision is done based on how critical is the breakdown of the bearing for production and whether can it cause a chain reaction of breakdowns or damage some other equipment.

2.3.3.1 Types of Monitoring systems

Off-line monitoring

Off-line monitoring involves periodic tests of equipment health by collecting data while the PM is running. The data collection process occurs in the way, that a collector or measurer goes throw all the sections of PM and makes two minutes length measurements. In case of inaccessibility or possible danger to the life of the measurer, a thermographic camera is used. Data collection is done by the portable analyzer to which the sensor is connected. The analyzer takes a vibration signal and immediately plots graphs, which allows to conclude the condition of the equipment.
Analyzer is capable of saving the measurements and transferring them to the PC, but the short-term measurements from an unknown axis can not be used for the model training and testing.

On-line monitoring

On-line monitoring is a real-time approach that involves continuous monitoring of equipment health during the operation of PM. Data collection is slightly similar to the off-line process, but the implementation is much more complex, for the reason that it has to handle continuous vibration signals from hundreds of bearings simultaneously.

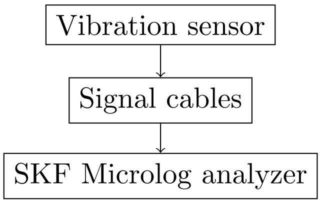


Figure 2.11: Off-line monitoring connection diagram

In the on-line monitoring system, sensors are strategically placed on the bearing housing in a horizontal-traverse direction. Such location is grounded by the International Standard ISO 10816-1:1995, which allows to measure axial vibrations. The standard provides different sensors positions These sensors constantly monitor the vibrations produced by the equipment. The sensor signals are then transmitted through wires to the processing unit.
The processing unit receives and processes the signals. Then the processed signal from different channels goes to the server. The communication between the processing unit and the server is established through a Modbus TCP/IP protocol.
Such system serves as a valuable tool in assessing the health status of bearings. It allows to detect developing faults or anomalies at an early stage, enabling timely intervention and proactive maintenance.
But as any system, this one also has some disadvantages, and one of them is the amount of human labor. Because each value that is above the set threshold requires to be checked and verified.

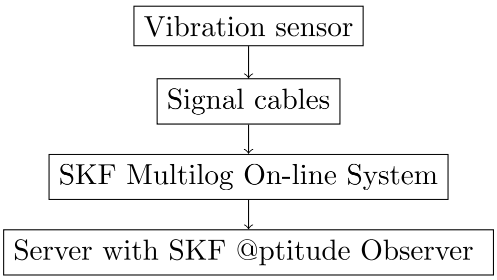


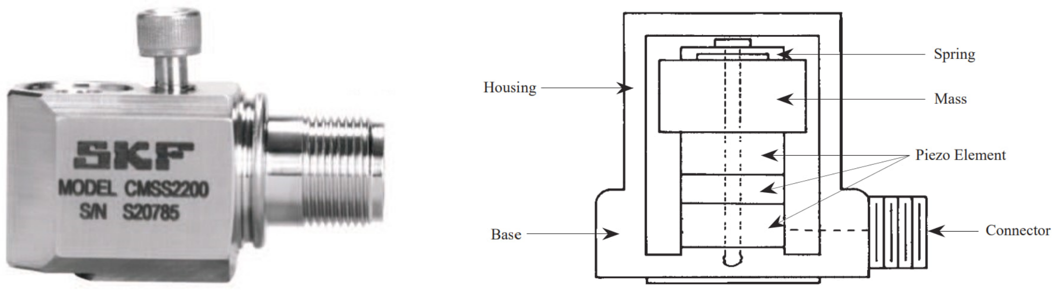
Figure 2.12: On-line monitoring connection diagram

2.3.3.2 Monitoring equipment

Vibration Sensor

Both types of monitoring use the same sensor. Basically, this is due to hardware compatibility. Vibration sensors are commonly used to measure the vibration levels of rotating machinery. One widely used vibration sensor is the Industrial accelerometer SKF CMSS 2200. This accelerometer is designed to withstand harsh operating conditions and can be easily installed on various types of equipment, including bearing housings. Due to manufacturing calibration, these sensors are able to provide accurate and reliable measurements of vibration parameters, including velocity and acceleration.[7] That is why, the vibration signal can not be collected by simple microphones.
Accelerometers usually consist of one or several piezoelectric crystal elements. The vibration

of the bearing stresses the mass, inside of the sensor; and the mass acts on piezo elements. Subsequently, crystals produce an electric output proportional to acceleration.
The number of piezo elements in the accelerometer SKF CMSS 2200 is unknown, due to the fact that this is not a piece of open-source information.
This accelerometer is a broadband vibration sensor because it covers a wide range of performing frequencies, including both low and high frequencies. The high-frequency range is significant for monitoring rolling bearings because it allows to detect early signs of bearing degradation.[38]



(a) Photo [30] (b) Scheme [38]

Figure 2.13: Industrial accelerometer, SKF CMSS 2200

Signal Cables

Signal cables are integral components of monitoring systems, connecting and transmitting the electrical signals generated by sensors to the processing equipment. The SKF CMSS 932-68 series of signal cables are specifically designed for reliable and high-quality signal transmission in industrial environments. These cables provide excellent noise immunity, ensuring accurate connection. The CMSS 932-68 series signal cables are designed with an IP68 standard, making them highly resistant to dust and water contacts. This rating ensures their reliable performance even in challenging environmental conditions, providing further protection and reliability for on-line monitoring systems.[13]

(a) IP68 sensor/connector/cable assembly (b) Photo

Figure 2.14: Cable SKF CMSS 942 [13]

SKF Microlog analyzer

The SKF Microlog Analyzer AX is a portable data collector and analyzer, which allows to check of the condition of rotating PM components during the performance. This device is an advanced vibration-monitoring tool with multiple useful features such as the collection and viewing of spectral and time domain data, and FFT analysis. These features allow to identify the root cause of any abnormal conditions or faults in the short term.[21, 35]

Figure 2.15: SKF Microlog analyzer AX [31]

SKF Multilog On-line System

The Multilog on-line system, also known as the IMx process unit, is designed to monitor the condition of rotating machinery in real-time. This unit digitizes and processes the signals, using advanced signal processing techniques, to extract meaningful information about the machine's condition.
The IMx process unit acts as an interface between the sensors and the server. It can receive up to sixteen analog signals, which means that it can process data from sixteen sensors simultaneously. The communication between the process unit and the server is established by the Ethernet cable and the Modbus TCP/IP protocol, which allows Modbus messages to be wrapped within TCP/IP packets. This feature greatly reduces the amount of wires and other expensive hardware.[17]

(a) Process Unit [22]

(b) Process Unit Box [23]

Figure 2.16: Process Unit IMx-16Plus

Server with SKF @ptitude Observer

The processed data from the SKF IMx unit is then transmitted to a server equipped with the SKF @ptitude Observer software. This software provides further analysis capabilities, including trending, alarm management, and diagnostic tools. It can generate various trends such as acceleration, velocity, and enveloped acceleration, providing valuable insights into the condition of the bearings.[36]

(a) Logo

Figure 2.17: SKF @ptitude Observer [36]

Chapter 3

Data

3.1 Collection and Description

Precise data collection, storage, and analysis are necessary for effective condition monitoring. All the data, used for the model implementation, was provided by the Mondi paper mill. The data in the paper mill is organized and partitioned based on departments. This structured approach ensures that each department can access relevant data.
The research depends not just on vibration signals but also on rolls and bearings maintenance data, which is necessary for the implementation of cost functions. Together, these datasets from Condition Monitoring and Mechanical Maintenance departments provide a comprehensive picture of the operational history and current conditions of the PMs.

3.1.1 Mechanical Maintenance Data

An essential element of our analysis involved the construction of cost functions. For that, it was necessary to find a meaningful metric for quantifying the effectiveness of the machine learning algorithm. Out of all possible factors such as the cost of spare parts, labor, or equipment, which is required for the replacement, the replacement time became the crucial variable of functions.
Replacement time, in this context, refers to the time interval required to replace a faulty bearing once it has been identified. This period is crucial as it directly affects the overall downtime of the production line. The interval itself is based on the information from Standard Operating Procedures (SOPs), which were provided by the Mechanical Maintenance Department, and depends on the location of the roll in the PM. An example of SOP can be found in Appendix.
There are three different scenarios of the replacement, which affect these intervals. The first one is a planned bearing replacement, which means that this happened in a predictive manner and there was no breakdown. The second scenario is an unplanned failure of the bearing, which did not cause any damage to other parts. The last one is the worst-case scenario, unexpected breakdown of bearing damaged housing or journal. All the intervals of these scenarios for different types of rolls and sections of PMs can be found in Table 3.1. But it is necessary to mention, that function rolls intervals have the same duration in all of the cases because they are replaced fully even if just one of the bearings is damaged. This is due to the preinstallation of bearing on rolls by the manufacturer.

Besides the replacement time intervals, data from the Mechanical Maintenance Department contains essential information about rolls, including the precise locations within the paper machine, specifications, and bearing models, which are mounted on these rolls. Thus, all the provided maintenance data allowed to generate the tables for both PMs, which became the base of the model structure.

Section	Group	Subgroup	RT 1.scenario	RT 2.scenario	RT 3.scenario
Wire	guiding		4-6 h.	8-10 h.	16-20 h.
	functional	suction	3-5 h.	3-5 h.	3-5 h.
Press	guiding		4-6 h.	6-8 h.	3-10 h.
	functional	press	8-10 h.	8-10 h.	8-10 h.
		suction	10-12 h.	10-12 h.	10-12 h.
		spreader	4-6 h.	4-6 h.	4-6 h.
		shoe press	12-14 h.	12-14 h.	12-14 h.
Drying	guiding		4-7 h.	6-10 h.	6-12 h.
	drying		6-8 h.	8-10 h.	10-12 h.
Tambour	functional	reel spool	0 h.	0 h.	0 h.
Calender	guiding		4-8 h.	6-10 h.	4-14 h.
	functional	press	8-10 h.	8-10 h.	8-10 h.
		spreader	8-12 h.	8-12 h.	8-12 h.
		shoe press	12-14 h.	12-14 h.	12-14 h.
Rewinder	guiding		3-5 h.	4-6 h.	4-6 h.
	functional	reel drum	24-30 h.	24-30 h.	24-30 h.
		spreader	8-12 h.	8-12 h.	8-12 h.
Winder	guiding		4-6 h.	8-10 h.	16-20 h.
	functional	reel drum	8-10 h.	8-10 h.	8-10 h.
		spreader	8-70 h.	8-70 h.	8-70 h.
		reel spool	0 h.	0 h.	0 h.

Table 3.1: Types of Rolls and Time for Replacement Scenarios

3.1.2 Condition Monitoring Data

The Condition Monitoring Department deals with different types of operation status analyses across the entire paper mill. In the case of PMs, vibration analysis is used as the method for assessing the performance condition. By monitoring and analyzing various trends derived from vibration signals, potential faults can be detected and addressed in a proactive manner. Three types of vibration trends are used for validation. These trends represent hourly mean or sometimes peak values of vibration parameters such as acceleration, velocity, and enveloped acceleration. The peak value is stored in case of crossing the preset threshold. If this happens several times in one hour, then all the values, which exceeded the boundary, are stored. If it happens that none of the magnitudes overstepped the limit, the hourly average is taken.
The primary tool, which is used for analysis and holds monitoring data, is the SKF @ptitude Observer. This application holds all vibration trends with additional information. The additional information notes, which were done by monitoring department specialists, contain descriptions of decisions and actions taken based on abnormal bearing behavior. The content of notes is not exportable with trends but in Observer it is visible and the information about

replacements is recorded. Therefore, it was required to download these trends and tables with replacements. With replacements, there were no complications but unfortunately, the Observer does not give direct access to the whole database, which means that it does not allow the exportation of trends simultaneously. This is most likely done for security purposes. However, in the case of obtaining the data, this meant that it was necessary to download trends manually. In addition to the fact that this is a time-consuming process, it also poses the risk of confounding an indefinite number of trends.
Trends from the Observer are exported as Excel files(.xls) but initially, they are stored as XML files(.xml). This mismatch raises the warning of Excel, leading to additional steps during data pre-processing. Raw trend files consist of eighty columns but for the research, just six are used. These columns hold the date and time, when the values were stored, the magnitude of the vibration parameter, middle and upper boundaries of the threshold, cycles per minute, and bias voltage. Therefore, each bearing is represented by three files, one for each of the vibration parameters.
Due to the fact, that this study uses trends from two distinct paper machines, a decision was made to partition the data into training and testing sets based on the paper machines. Consequently, the data from the first paper machine forms the training set, while the data from the second paper machine comprises the testing set.
Alongside the datasets, the Condition Monitoring Department also supplied additional information regarding the distribution of failures, which could be used as ground truths. These ground truths, which are approximate distributions expressed in percentages, are based on years of experience of the department's specialists. It is important to note that these distributions were not derived from statistical analysis but are rooted just from practical experience. This distribution is illustrated in Figure 3.1.
Tables 3.3 are examples of the content of files in the dataset.

Failure	Abb.	in %
Signal Failure	A	45%
Noise	B	50%
Bearing Failure	C	5%

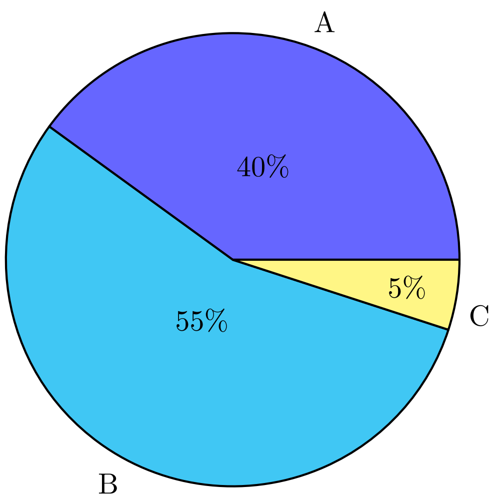


Figure 3.1: Failures Distribution

Date/Time	Value(mm/s)	MID Threshold	MAX Threshold	CPMs	Bias(V)
2020-02-12 20:00:02	0.9	4.0	3.0	507.026	13.328
2020-02-13 01:00:00	0.93	4.0	3.0	507.022	13.459
2020-02-14 01:00:03	0.84	4.0	3.0	507.027	13.358
2021-02-17 06:00:00	0.63	4.0	3.0	536.608	12.967
2021-02-17 07:00:00	0.71	4.0	3.0	505.059	12.976
2021-02-17 08:00:00	0.69	4.0	3.0	505.035	12.983

(a) Velocity

Date/Time	Value(g)	MID Thr	MAX Thr	CPMs	Bias(V)
2020-02-12 20:00:00	0.19	3.0	2.0	570.414	13.323
2020-02-13 01:00:01	0.19	3.0	2.0	507.026	13.459
2020-02-14 01:00:01	0.14	3.0	2.0	507.028	13.358
2021-02-27 00:00:01	0.21	1.5	1.0	454.542	13.339
2021-02-27 01:00:01	0.21	1.5	1.0	454.528	13.342
2021-02-27 02:00:00	0.21	1.5	1.0	505.037	13.331

(b) Acceleration

Date/Time	Value(gE)	MID Thr	MAX Thr	CPMs	Bias(V)
2020-02-12 20:00:03	0.16	3.0	2.0	507.023	13.328
2020-02-13 01:00:03	0.12	3.0	2.0	538.717	13.327
2020-02-14 01:00:00	0.11	3.0	2.0	507.019	13.358
2021-02-06 02:00:01	0.16	1.5	1.0	505.042	12.99
2021-02-06 03:00:00	0.18	1.5	1.0	505.037	12.989
2021-02-06 04:00:03	0.16	1.5	1.0	454.531	12.987

(c) Enveloped Acceleration

Table 3.2: Files Content, MC 1 Operational Side

3.2 Pre-processing

As well as the collection process, the pre-processing of data was separated into two major stages.
The first one was to pre-process maintenance data, which consisted just of merging 3 tables into one, to have information regarding rolls and bearings in one file.
The second stage was a pre-processing of vibration trends. This part is done in several steps. As it is previously mentioned, files with trends are exported as .xls files but because of the original format, Excel raises a warning. Due to the same reason, it was not possible to open and process the file. So, I decided to resave all the files as text files(.txt) and to work with the content as with text. XML is a markup language, which is used to store and transport data. This means, that columns and rows are divided by tags. Counting the right number of tags allowed me to find the necessary columns in each file, which were after stored in the Comma Separated Values file(.csv). After performing the previous steps, I had the same three files but already of much lower weight. To finalize pre-processing of trends it was also necessary to merge them, to have all the points aligned by the date and time. For hourly points, it was relatively easy but the main issue was with peak values. I made an assumption that taking the mean of these values will affect the shape of the trend more rather than taking just the highest out of them. Consequently, every time there was more than one value, I was taking the highest, and this rule worked not just for magnitudes of vibration parameters but also for cycles per minute and bias voltage. But there were also cases when the vibration parameters at the same hour had less than three values. In such circumstances, I had to neglect such points.
Therefore, after performing these steps I managed to decrease the number of vibration trend files three times, and the total weight twenty-five times. From almost 53 gigabytes to a bit more than 2 gigabytes.
Table 3.3 holds the example of a merged vibration trends file but shows just the primary columns. As you can notice, the values of the second columns in Tables 3.2 (a-c) are the same values as the magnitudes of the first three rows in Table 3.3, and CPMs and bias voltage columns have the max values.

Hour ID	Date/Time	Acceleration(g)	Enveloped Acceleration(gE)	Velocity(mm/s)	Bias(V)	CPMs
0	2020-02-12 20:00:00	0.19	0.16	0.9	13.328	570.414
5	2020-02-13 01:00:00	0.19	0.12	0.93	13.459	538.717
29	2020-02-14 01:00:00	0.14	0.11	0.84	13.358	507.028
9124	2021-02-27 00:00:00	0.21	0.48	0.8	13.339	454.543
9125	2021-02-27 01:00:00	0.21	0.44	0.72	13.342	454.542
9126	2021-02-27 02:00:00	0.21	0.43	0.62	13.331	505.044

Table 3.3: Pre-processed file, MC 1 Operational Side

Chapter **4**

Model

4.1 Implementation

Having just a few actual examples of breakdown or pre-breakdown states of bearings for both paper machines, the decision was made in favor of a mathematical model rather than a probabilistic one. Due to the assumption, that such a low-probability outcome will be considered very unlikely. While in reality there always is a possibility of such an event, just monthly maintenance and preventive replacements allow to avoid this.
The initial step of the implementation of any model is the development of the structure. The design of the structure has to describe the production process in a detailed and comprehensive way. Due to this, I choose the top-down approach, starting with macro objects of the mill and delving into smaller objects. Such a systematic methodology ensures that no crucial details were overlooked.

Each class within the model plays a specific role:

- **Machine**: Serves as a fundamental node, this class represents the entirety of paper machines, further containing a list of Roll class objects within it.

- **Roll**: This class is responsible for tracking the various rolls within the machines. Each instance of the Roll class is exactly two instances of the Bearing class.

- **Bearing**: This class symbolizes the individual bearings present in each side of the roll. It retains information about the bearing and the roll to which it has been applied. Furthermore, it accommodates lists of all segments.

- **Segments**: This class subdivides a list of bearing points into segments for a more detailed monitoring process. Segmentation of bearings enables the identification of specific problem areas within each bearing. For research purposes, the duration of each segment has been set to one calendar month. This timespan does not interfere with the computation of coefficients.

- **Points**: This class represents the specific point in time where all the values of the vibration trends and their related calculations are recorded.

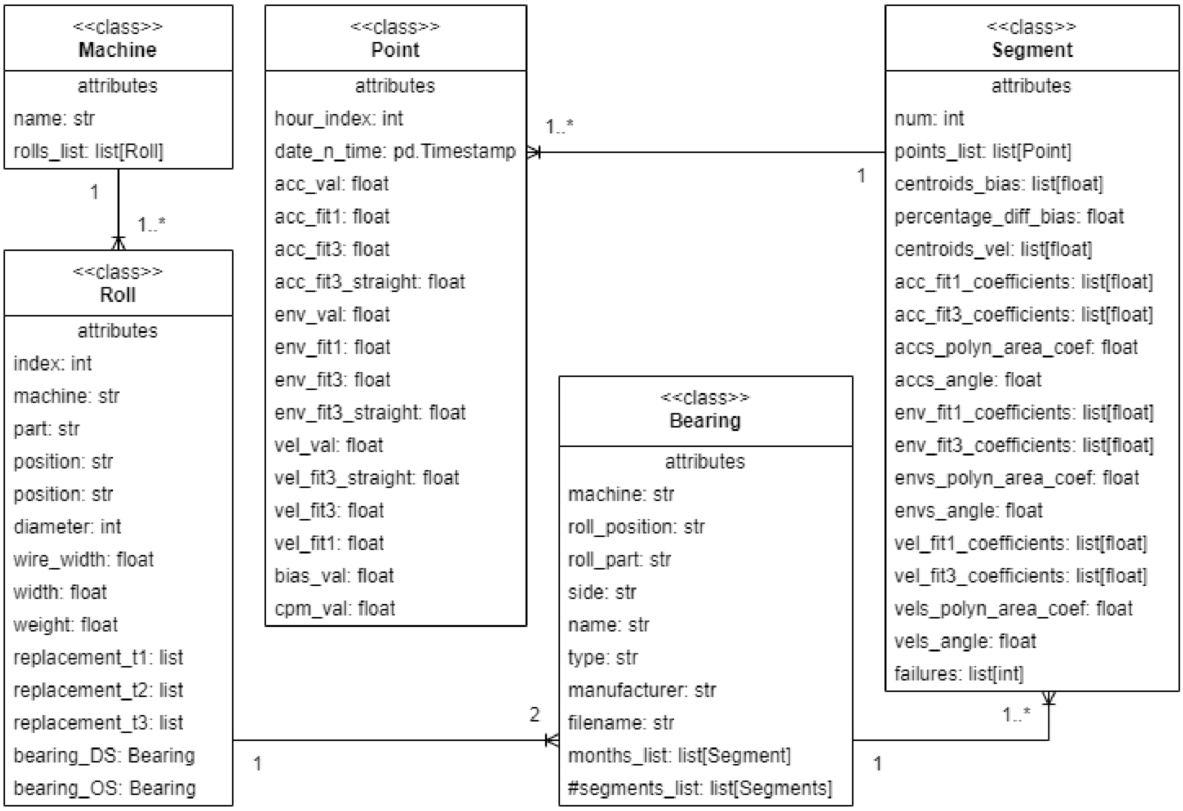


Figure 4.1: Classes Structure

With the implemented structure I started to apply various algorithms to these trends to study magnitude changes. At first, I considered trends as noisy due to the swift fluctuations between adjacent points. To address this, I experimented with different data smoothing techniques such as moving average and exponential smoothing. However, as I delved deeper into the study of trends and vibration analysis techniques, I was starting to realize the crucial importance of preserving magnitudes. Smoothing algorithms were suppressing actual noise and modifying the shape of the trend in the signal, complicating the differentiation between noise and actual damage in the bearing.

Instead of smoothing the data, I made an assumption that implementing a polynomial fit could be a solution because in the case of fitting every magnitude would influence the polynomial. However, before fitting it is necessary to ensure that the segment does not contain any anomalous data, such as enormous velocity values and an unstable bias trend. The presence of such data would indicate signal failure. To verify the stability of bias voltage and eliminate impossible velocity magnitudes, I performed a check on the signal using k-means clustering with two centroids. By analyzing the comparative magnitude between the two centroids, we are able to verify the stability of a bias voltage and impossible magnitudes of velocity.

After checking the signal, I started testing various polynomial degrees, from which I made several conclusions. The first one was, that polynomials of higher degrees have a better fitting but the number of coefficients, that such polynomials generate, is not very convenient for making any decision. This led to a choice between the simplicity of the model using lower-degree polynomials and its capacity to accurately fit the data with higher-degree poly-

nomials. For this reason, I decided to use polynomials of low degrees. Due to the study of the growth of trends, quadratic polynomials were also not suitable. Consequently, for further implementation, I utilized polynomials of first and third degrees.
Already having coefficients and both discrete polynomial fits, I performed several additional computations before the implementation of the decision tree. Using the coefficient of the first-degree polynomial I estimated the angle of the polynomial, to generate a descriptive variable that would allow to verify the degree of inclination. Due to the high number of points in each segment, the angle in degrees was represented by extremely small decimal fractions, so for convenience, it was necessary to convert them to seconds. To have a more comprehensive representation of the third-degree polynomial rather than just coefficients, I chose to calculate the area of the space between the polynomial and a straight line, drawn from the polynomial's first and last values. This area is used to calculate the second coefficient. Consequently, this gives us two meaningful coefficients for each type of vibration signal. With the help of these coefficients, it is possible to design the decision tree.

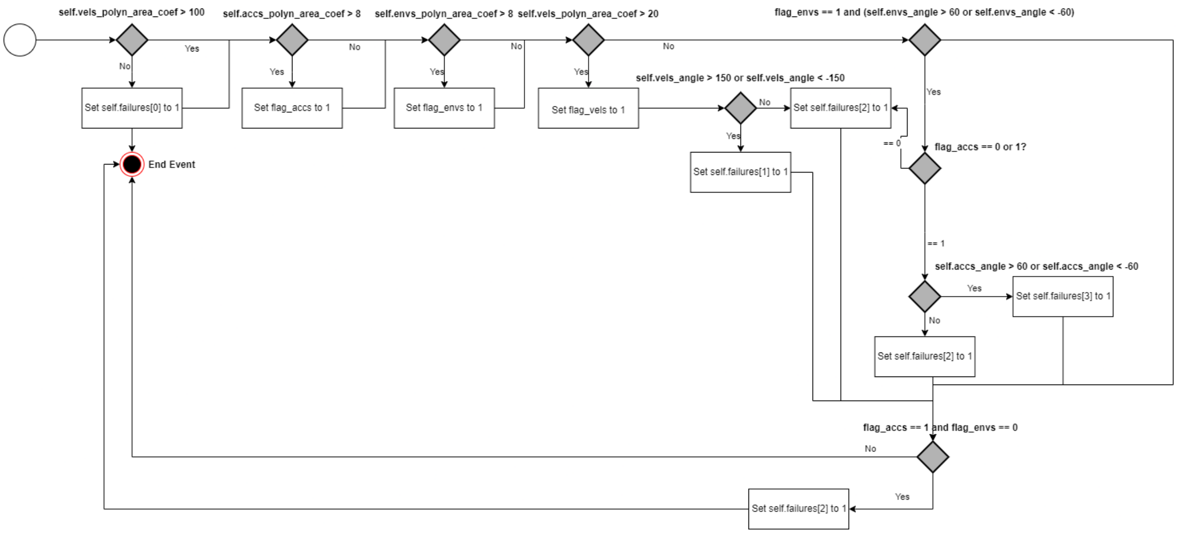


Figure 4.2: Decision Tree

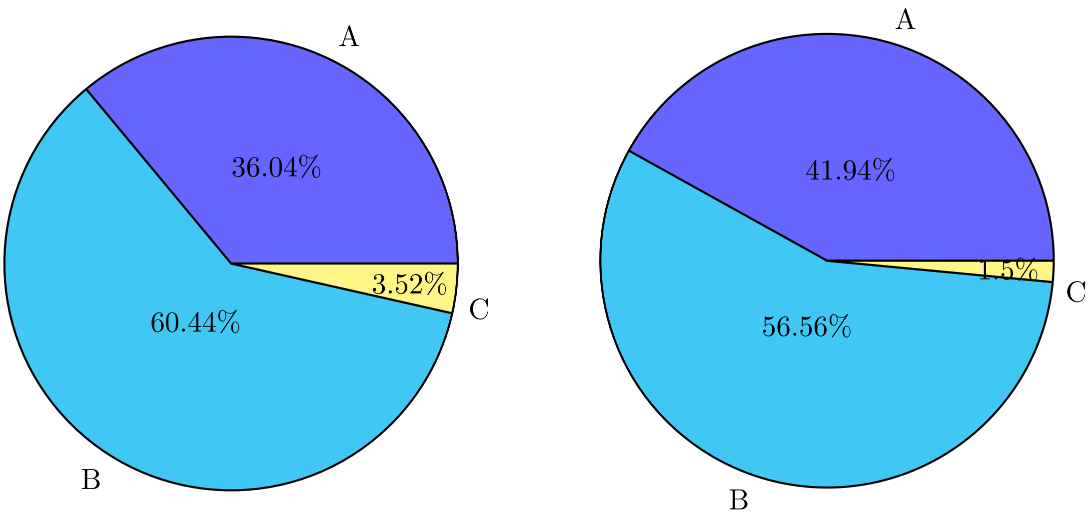
4.2 Testing

Due to the lack of statistically proven ground truths I decided to perform verification of the correctness of the choice of decision model using several methods. Initially, a comparison was made between the obtained statistics of each machine and the provided approximations. The outcomes of this comparison are shown in Table 4.1 and Figure 4.3.
Statistics of PMs demonstrated comparable outcomes, both close to approximate ground truths. However, the comparison of failure distributions of machines provides just a broad understanding and could not be seen as a definitive validation. But making some comparisons between sections and some other groups could provide additional confirmations. The statistics supporting this observation can be found in Table 4.2.
The study of condition distributions across paper machine sections provides several conclusions. Primarily, Signal Failures accrue in the Wire Section more frequently rather than in others. The logical explanation for this can be the high humidity levels prevalent in this part

of the PM that can affect electronic circuits and devices. Secondly, Noise accrues more often in the Drying Section, this situation can be explained, that this happens due to one specific type of noise, which is quite common for the drying section. This noise is called steam head noise, it accrues due to the high-temperature steam inside of the drying rolls, which goes throw them and sometimes produces a high-pitched buzzing sound.
Comparisons between types of bearings were also done. But unfortunately, just one of the types of bearings, Spherical Roller Bearings(SR), is represented by the high number of examples in these datasets. Therefore, it is not possible to draw any conclusions on the types of bearings and find confirmation or refutation of the hypothesis. After statistical validation, it is necessary to visually inspect trends and decisions regarding them, comparing them with the conclusions of specialists from the Condition Monitoring Department. Examples of the bearing of failures are provided in Figures 4.4 and 4.5.

Condition	Abb.	Paper Machine I. segments		Paper Machine II. segments	
		number	in %	number	in %
Normal		2819	42.49%	1648	48.80%
Signal Failure	A	1375	20.73%	725	21.47%
Noise	B	2306	34.76%	978	28.96%
Bearing Failure	C	134	2.02%	26	0.77%
Overall		6634	100%	3377	100%

Table 4.1: Conditions Distribution for Training and Testing Datasets

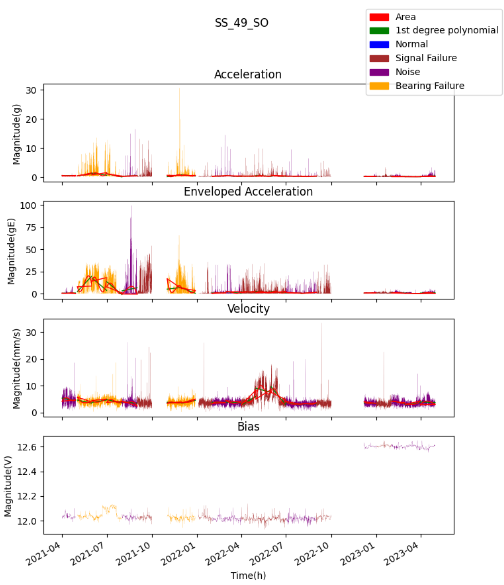


(a) I.PM (b) II.PM

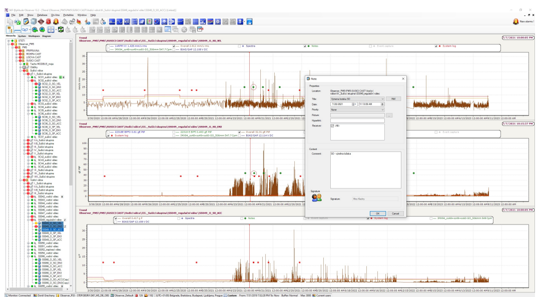
Figure 4.3: Failures Distribution;
A - Signal Failures, B - Noise, C - Bearing Failures

Section	Condition	Abb.	Paper Machine I. segments		Paper Machine II. segments	
			number	in %	number	in %
MC	Normal		114	27.67%	480	58.11%
	Signal Failure	A	206	50.0%	184	22.28%
	Noise	B	77	18.69%	159	19.25%
	Bearing Failure	C	15	3.64%	3	0.36%
	Overall		412	100%	826	100%
LC	Normal		190	82.60%	267	60.14%
	Signal Failure	A	21	9.13%	77	17.34%
	Noise	B	16	6.96%	90	20.27%
	Bearing Failure	C	3	1.30%	10	2.25%
	Overall		230	100%	444	100%
SS	Normal		2515	41.97%	901	42.76%
	Signal Failure	A	1148	19.16%	464	22.02%
	Noise	B	2213	36.93%	729	34.60%
	Bearing Failure	C	116	1.94%	13	0.62%
	Overall		5992	100%	2107	100%

Table 4.2: Conditions Distribution for Sections of Paper Machines, MC - Mokrá část/Wire section, LC - Lisova část/Press section, SS - Sušící sekce/Drying section

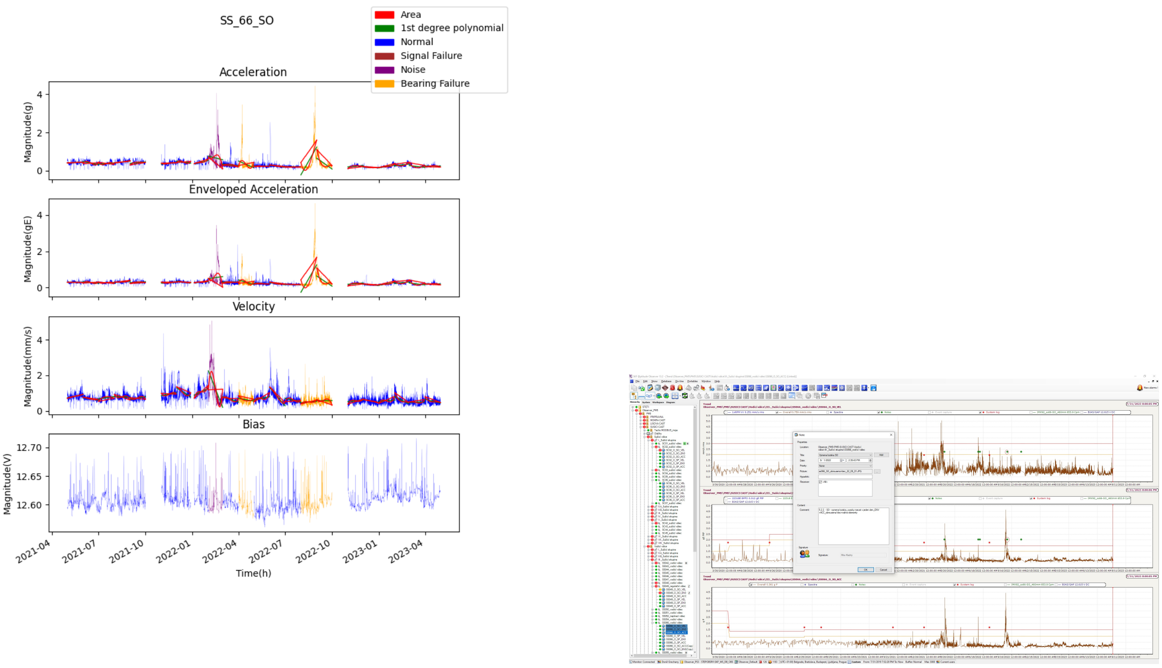


(a) Plot of the Model



(b) Plot of Observer and Note

Figure 4.4: First Example of Bearing Failure



(a) Plot of the Model

(b) Plot of Observer and Note

Figure 4.5: Second Example of Bearing Failure

CHAPTER 5

Conclusion

5.1 Summary

Given the comprehensive exploration conducted in this study and the various observations derived, the research concludes that the mathematical decision tree algorithm offers a promising approach for the detection and prediction of bearing failures. The implemented model exhibits reliable performance, and the failure prediction task has been effectively formalized, taking into account the costs of prediction failures and false alarms.
However, the decision tree model is not without its limitations and areas for improvement. Specifically, there remains the critical task of setting the sensitivity of the coefficients. The analysis revealed that both overfitting and underfitting can significantly impact the quality of predictions, and thus, the model's overall performance. Thus, further research should focus on tuning the model to better manage these challenges.
While the initial goal of the study was to implement a failure prediction method using a neural network, the course of the study steered towards the use of a mathematical decision tree. This decision was based on the specific characteristics of the data set and the need for a more flexible model that can accommodate complex non-linear relationships in the data.
In terms of the prepared training and test sets, these were appropriately separated and utilized, enabling an accurate evaluation of the model's performance. However, a limitation here lies in the imbalance of the bearing types represented in the data sets. Only one type, Spherical Roller Bearings (SR), is significantly represented, which inhibits the possibility of drawing any definitive conclusions about different types of bearings.
Finally, while the research has not specifically quantified the potential economic benefits of this decision tree model, it's clear that an effective prediction and detection system for bearing failures could lead to considerable cost savings. By enabling early detection and alerting, the system could potentially minimize unplanned downtime, avoid catastrophic failures, and optimize maintenance scheduling. Moreover, the time saved from manually sorting failures can be better utilized, resulting in greater operational efficiency.
Therefore, as a next step, it would be beneficial to focus on further refining the model and possibly expanding the types of bearings included in the data sets. Additionally, a thorough cost-benefit analysis could be conducted to more concretely quantify the economic benefits of deploying such a model. Ultimately, with these improvements, the research offers a promising step forward in the realm of predictive maintenance for bearing failures.

5.2 Contributions of the Dissertation Thesis

This dissertation thesis contributes to the existing body of knowledge in several significant ways:

- **Formalization of Bearing Failure Prediction Task**: The research formalized the bearing failure prediction task, offering a practical framework for future studies. It emphasized the importance of establishing the cost of prediction failures and false alarms, crucial for industrial implementation.
- **Development of a Mathematical Decision Tree**: The study introduces the innovative use of a mathematical decision tree for bearing failure prediction, as opposed to conventional methods like neural networks. This novel approach offers a simpler, yet effective, method to handle complex non-linear data.
- **Real-world Application and Evaluation**: The research applied the model to real-world datasets from two different paper machines. This practical application provides valuable insights and demonstrates the potential usability of the model in industrial settings.
- **Sensitivity Analysis of Coefficients**: The study presents insightful findings on the influence of coefficient sensitivity on prediction quality. It underscores the careful balance needed between underfitting and overfitting in predictive models, which is particularly crucial in bearing failure prediction.
- **Novel Data Segmentation Approach**: The dissertation introduces an innovative approach to data segmentation, dividing bearing data into time-limited segments, highlighting that the optimal segmentation should be between maintenance periods rather than arbitrary calendar months. This method enhances failure prediction by enabling specific problem area identification within each bearing.
- **Exploration of Different Real-Life Implementation Approaches**: The thesis demonstrates that various real-life implementation approaches are feasible based on magnitude (amplitude) vibration analysis. This flexibility is vital for industries with diverse operational needs and constraints.
- **Operational Efficiency Improvement**: The research suggests that automated bearing failure detection and prediction can significantly enhance operational efficiency. This contribution has broad implications for machinery-dependent industries, where timely detection and preventive action can lead to considerable cost and time savings.

The collective impact of these contributions is a significant advancement in our understanding and capabilities in predictive maintenance, particularly bearing failure prediction. The dissertation also highlights the need for further research and model refinement to optimize these contributions and realize their potential benefits fully.

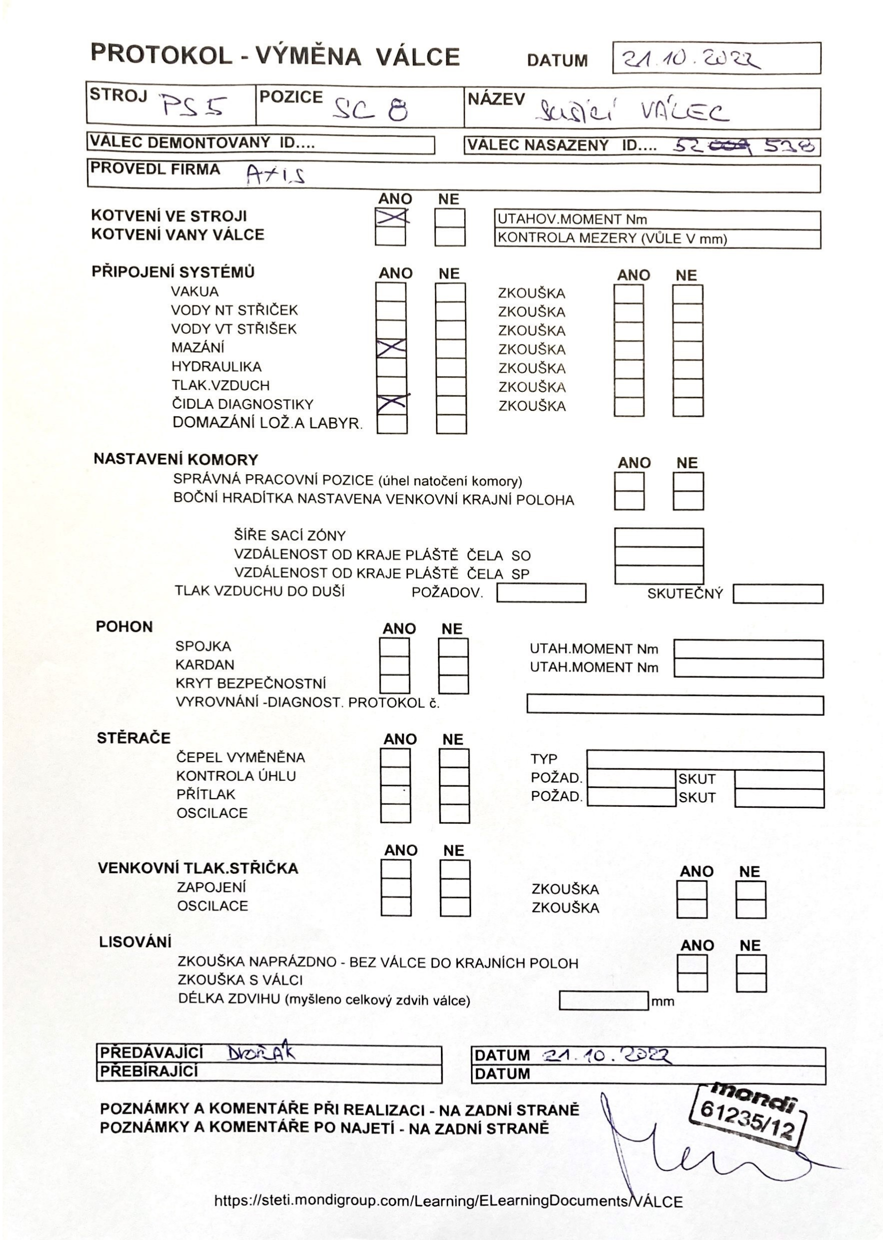
5.3 Future Work

Future research directions and potential improvements suggested by this dissertation are:

- **Data Collection Improvement**: The data collection process could be optimized to ensure that vibration parameter values are recorded simultaneously. This enhancement will help eliminate gaps and missed data, thereby improving the quality and reliability of the input for the prediction models.
- **Sensitivity Correction for Real-Time Operation**: Future work should focus on fine-tuning the sensitivity of the prediction model for real-time operation. The objective would be to enable the model to work effectively for segments between maintenance periods, rather than calendar months, thereby enhancing its relevance and applicability in a real-world industrial setting.
- **Real-time Model Implementation**: Once the model's sensitivity is optimally adjusted for real-time operations, its implementation and testing in a live environment will be the next step. This implementation would allow for more robust testing and verification of the model's performance.
- **Development of Prediction Models**: In line with the ultimate goal of predictive maintenance, future studies could focus on the development of advanced prediction models. Collecting more examples of bearing failures can drive this. These models could provide early warning of potential failures, facilitating preventative maintenance and avoiding costly machine downtimes.
- **Frequency-Based Bearing Failure Prediction**: There's a potential to broaden the research scope by considering frequency-based bearing failure predictors. Given the wide range of failures that frequency analysis can detect compared to amplitude analysis, this could open up new avenues for enhancing the effectiveness of bearing failure prediction.

In conclusion, while this dissertation makes significant strides toward effective bearing failure prediction, these future research directions suggest there is still substantial potential for further exploration and improvement in this crucial area of industrial machinery maintenance.

.1 Appendix


PROTOKOL - VÝMĚNA VÁLCE DATUM 21.10.2022

STROJ PS5 POZICE SC 8 NÁZEV Sušící VÁLEC

VÁLEC DEMONTOVANÝ ID....

VÁLEC NASAZENY ID.... 52 ~~...~~ 528

PROVEDL FIRMA AXIS

	ANO	NE	
KOTVENÍ VE STROJI	X		UTAHOV.MOMENT Nm
KOTVENÍ VANY VÁLCE			KONTROLA MEZERY (VŮLE V mm)

PŘIPOJENÍ SYSTÉMŮ	ANO	NE		ANO	NE
VAKUA			ZKOUŠKA		
VODY NT STŘIČEK			ZKOUŠKA		
VODY VT STŘIŠEK			ZKOUŠKA		
MAZÁNÍ	X		ZKOUŠKA		
HYDRAULIKA			ZKOUŠKA		
TLAK.VZDUCH			ZKOUŠKA		
ČIDLA DIAGNOSTIKY	X		ZKOUŠKA		
DOMAZÁNÍ LOŽ.A LABYR.					

NASTAVENÍ KOMORY — ANO NE

SPRÁVNÁ PRACOVNÍ POZICE (úhel natočení komory)

BOČNÍ HRADÍTKA NASTAVENA VENKOVNÍ KRAJNÍ POLOHA

ŠÍŘE SACÍ ZÓNY

VZDÁLENOST OD KRAJE PLÁŠTĚ ČELA SO

VZDÁLENOST OD KRAJE PLÁŠTĚ ČELA SP

TLAK VZDUCHU DO DUŠÍ POŽADOV. SKUTEČNÝ

POHON — ANO NE

SPOJKA — UTAH.MOMENT Nm

KARDAN — UTAH.MOMENT Nm

KRYT BEZPEČNOSTNÍ

VYROVNÁNÍ -DIAGNOST. PROTOKOL č.

STĚRAČE — ANO NE

ČEPEL VYMĚNĚNA — TYP

KONTROLA ÚHLU — POŽAD. SKUT

PŘÍTLAK — POŽAD. SKUT

OSCILACE

VENKOVNÍ TLAK.STŘIČKA — ANO NE

ZAPOJENÍ — ZKOUŠKA — ANO NE

OSCILACE — ZKOUŠKA

LISOVÁNÍ — ANO NE

ZKOUŠKA NAPRÁZDNO - BEZ VÁLCE DO KRAJNÍCH POLOH

ZKOUŠKA S VÁLCI

DÉLKA ZDVIHU (myšleno celkový zdvih válce) mm

PŘEDÁVAJÍCÍ Dvořák — DATUM 21.10.2022

PŘEBÍRAJÍCÍ — DATUM

POZNÁMKY A KOMENTÁŘE PŘI REALIZACI - NA ZADNÍ STRANĚ

POZNÁMKY A KOMENTÁŘE PO NAJETÍ - NA ZADNÍ STRANĚ

mondi 61235/12

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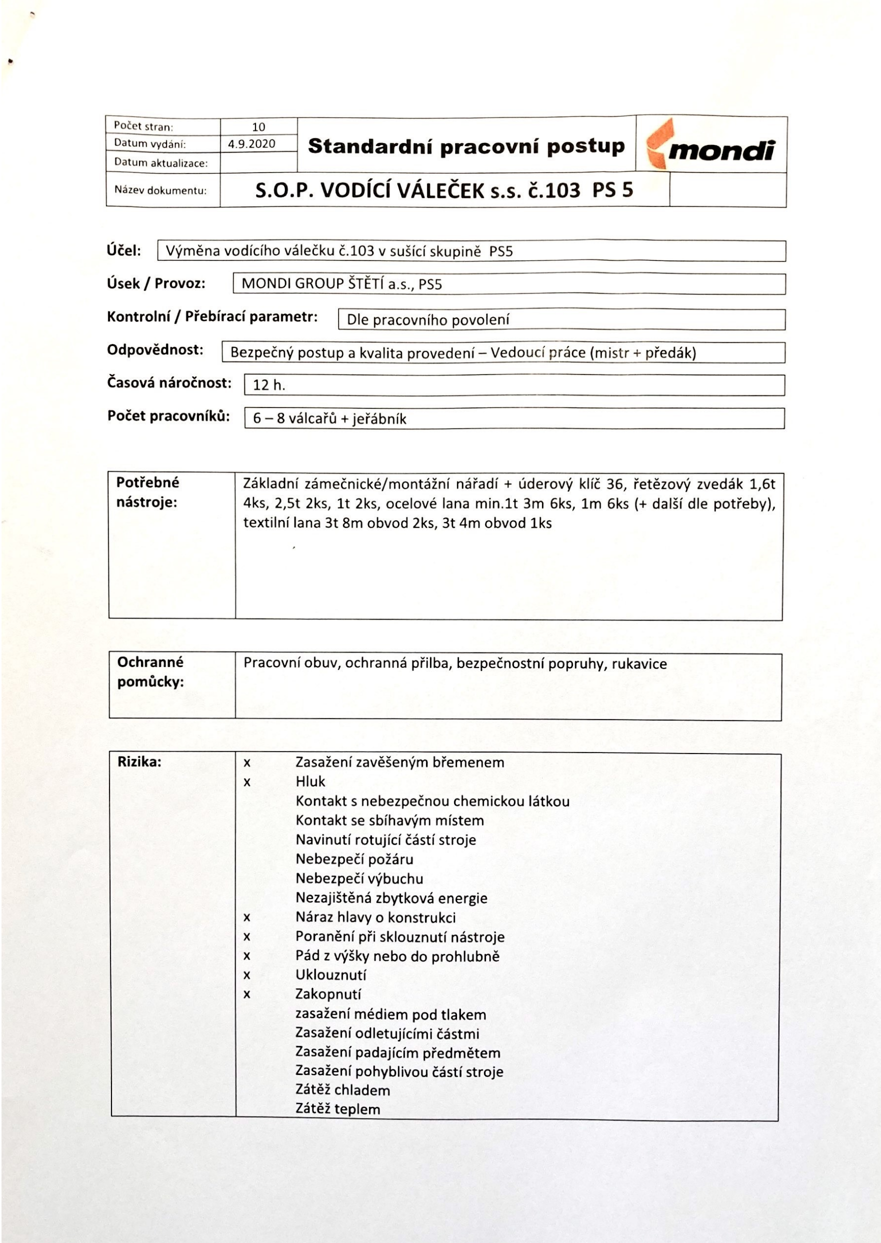
Figure .1: Roll Exchange Protocol

.2 Appendix



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Datum vydání:	4.9.2020		
Datum aktualizace:			
Název dokumentu:	**S.O.P. VODÍCÍ VÁLEČEK s.s. č.103 PS 5**		

Účel: Výměna vodícího válečku č.103 v sušící skupině PS5

Úsek / Provoz: MONDI GROUP ŠTĚTÍ a.s., PS5

Kontrolní / Přebírací parametr: Dle pracovního povolení

Odpovědnost: Bezpečný postup a kvalita provedení – Vedoucí práce (mistr + předák)

Časová náročnost: 12 h.

Počet pracovníků: 6 – 8 válcařů + jeřábník

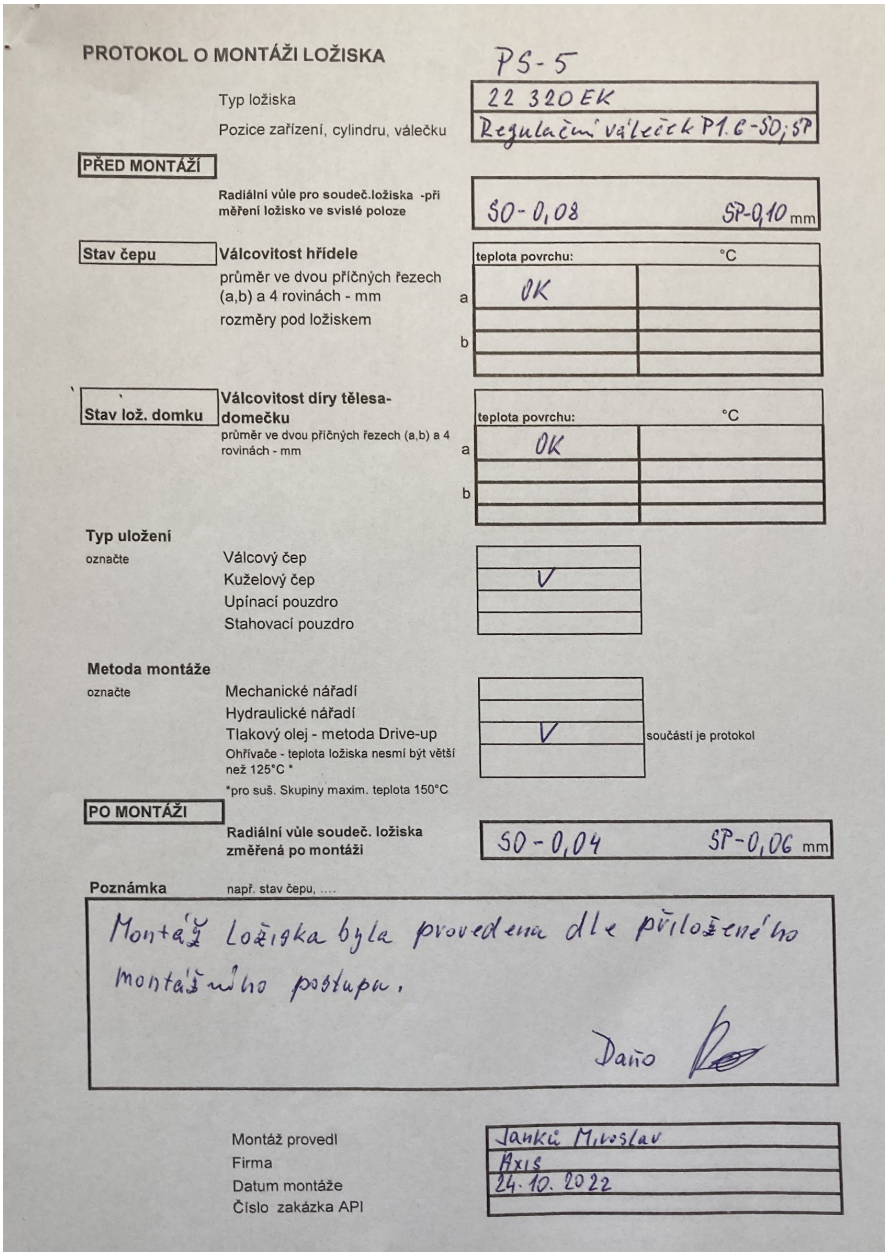
Potřebné nástroje:	Základní zámečnické/montážní nářadí + úderový klíč 36, řetězový zvedák 1,6t 4ks, 2,5t 2ks, 1t 2ks, ocelové lana min.1t 3m 6ks, 1m 6ks (+ další dle potřeby), textilní lana 3t 8m obvod 2ks, 3t 4m obvod 1ks

Ochranné pomůcky:	Pracovní obuv, ochranná přilba, bezpečnostní popruhy, rukavice

Rizika:		
	x	Zasažení zavěšeným břemenem
	x	Hluk
		Kontakt s nebezpečnou chemickou látkou
		Kontakt se sbíhavým místem
		Navinutí rotující částí stroje
		Nebezpečí požáru
		Nebezpečí výbuchu
		Nezajištěná zbytková energie
	x	Náraz hlavy o konstrukci
	x	Poranění při sklouznutí nástroje
	x	Pád z výšky nebo do prohlubně
	x	Uklouznutí
	x	Zakopnutí
		zasažení médiem pod tlakem
		Zasažení odletujícími částmi
		Zasažení padajícím předmětem
		Zasažení pohyblivou částí stroje
		Zátěž chladem
		Zátěž teplem

Figure .2: Standard Operating Procedures (SOP)

.3 Appendix



PROTOKOL O MONTÁŽI LOŽISKA

PS-5

Typ ložiska: 22 320 EK

Pozice zařízení, cylindru, válečku: Regulační váleček P1.6-SO; SP

PŘED MONTÁŽÍ

Radiální vůle pro soudeč.ložiska -při měření ložisko ve svislé poloze: SO-0,08 SP-0,10 mm

Stav čepu

Válcovitost hřídele
průměr ve dvou příčných řezech (a,b) a 4 rovinách - mm
rozměry pod ložiskem

teplota povrchu: °C

a: OK

b:

Stav lož. domku

Válcovitost díry tělesa-domečku
průměr ve dvou příčných řezech (a,b) a 4 rovinách - mm

teplota povrchu: °C

a: OK

b:

Typ uložení

označte

Válcový čep	
Kuželový čep	V
Upínací pouzdro	
Stahovací pouzdro	

Metoda montáže

označte

Mechanické nářadí		
Hydraulické nářadí		
Tlakový olej - metoda Drive-up	V	součástí je protokol
Ohřívače - teplota ložiska nesmí být větší než 125°C *		

*pro suš. Skupiny maxim. teplota 150°C

PO MONTÁŽI

Radiální vůle soudeč. ložiska změřená po montáži: SO-0,04 SP-0,06 mm

Poznámka: např. stav čepu, ...

Montáž ložiska byla provedena dle přiloženého montážního postupu.

Daňo

Montáž provedl	Janků Miroslav
Firma	Axis
Datum montáže	24.10.2022
Číslo zakázka API	

Figure .3: Bearing Exchange Protocol

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