Machine Condition Monitoring of Production Equipment

Alexander Olsson

Henrik Persson Caesar

LUND UNIVERSITY

Department of Automatic Control

MSc Thesis
TFRT-6203
ISSN 0280-5316

Department of Automatic Control
Lund University
Box 118
SE-221 00 LUND
Sweden

Printed in Sweden by Tryckeriet i E-huset
Lund 2023

Abstract

This study investigates the possibility of implementing a machine monitoring system on IBAS2, a production machine responsible for aligning an optical lens with an image sensor. A machine-monitoring system could possibly reduce downtime, costs, and production recalls. After examining IBAS2, vibration analysis emerged as a promising monitoring approach. The research aimed to capture the natural vibrations exhibited by the machine during normal operation, serving as a baseline for understanding its functioning under normal conditions. The results obtained from this investigation demonstrate repetitive vibration patterns associated with specific machine components. Moreover, altering the velocity of a machine component leads to a distinct variation in the vibration pattern observed from the collected data. Furthermore, the results obtained from vibration measurements exhibit promising potential for detecting indications of machine wear. By leveraging accurate data that establish the machine's normal vibration patterns, we propose a future implementation of an AI model designed to detect deviations from the norm. This could lead to a vibration-focused machine monitoring system that predicts upcoming failures in IBAS2.

Acknowledgements

We would like to express our sincere gratitude to several individuals who have contributed to the successful completion of this thesis paper.

First and foremost, we would like to thank our mentor at Axis Communication, Bengt Sirbelius, for his guidance and support throughout our research. His valuable insights and knowledge have been instrumental in shaping our ideas and in providing constructive feedback on our work.

We are also grateful to our manager at Axis Communications, Pernilla Allansson, for providing us with the necessary resources and for encouraging us to pursue this research. We would like to extend our appreciation to the entire engineering team at Axis for their technical support and for sharing their expertise with us.

We are deeply indebted to our supervisor at LTH, Olle Kjellqvist, for his invaluable feedback, guidance, and encouragement throughout the course of our research. His knowledge and expertise have been critical in shaping our research and in helping us to achieve our goals.

Finally, we would like to thank our examiner, Kristian Soltesz, for his thorough review and insightful feedback on our work. His constructive criticism and suggestions have helped to improve the quality of our research.

We would like to acknowledge and thank all these individuals for their support, guidance, and encouragement throughout our research journey. Their contributions have been invaluable, and we could not have accomplished this without them.

Contents

1
Introduction

1.1 Background

The need for machine monitoring in today's society has been driven by the demand for increased reliability in machine performance. To achieve an increasingly reliable environment, it is crucial to have knowledge of a machine's optimal conditions. That knowledge, in combination with real-time measurements of the machine's current condition, may reduce errors and unwanted production stops. To enable machine monitoring, one potential approach is to install sensors within the machine to gather data on its condition. There are many parameters that can be monitored, for example vibrations, sound, temperature, or light. The choice of method depends on what is appropriate to measure and may differ depending on what machine is being monitored. The collected data is then analyzed to detect abnormal behavior in the machine and make appropriate decisions on whether the machine should run, stop, or warn of unexpected errors. Recent research in machine monitoring has focused on analyzing collected data, with deep learning algorithms such as Artificial Neural Networks (ANNs). ANNs can help to identify complex patterns and relationships within the data, making it possible to detect potential problems earlier and with higher accuracy.

Axis Communications is a leading manufacturer of networking products, producing thousands of products every week. For certain steps during the production process, Axis uses their proprietary machines for accuracy, repeatability, and quality reasons. These machines need to run with high uptime and operate correctly all the time. Any undetected error can result in lost time, expensive materials and even product recalls. It is critical for Axis to prevent any unexpected stoppages in production by detecting machine failures before they happen. One possible solution to achieve this goal is machine monitoring. Therefore, this thesis was carried out as a case study to explore possible implementations of a machine monitoring system on one of Axis's production machines. This study aims to demonstrate how machine monitoring can benefit the company by enhancing the reliability and efficiency of their manufacturing process.

1.2 Purpose and Objective

The main focus of this master's thesis is to investigate the development of a machine monitoring system that can be integrated into one of Axis Communications' production machines. The aim is to explore and understand the process of creating an efficient monitoring system, utilizing Axis machines as the platform for our research. This overarching aim can be broken down into the following specific sub-objectives.

1. Identify possible machine monitoring methods that can be used for one of Axis production machines.

2. Investigate which methods that would give most value.

3. Chose one or two methods and implement a machine monitoring system on one of Axis productions machines.

4. Gather data and experiences in order to suggest a direction for Axis to pursuit.

The implementation of a machine monitoring system on a bespoke machine does not adhere to strict rules. Due to the fact that production machines are designed for specific tasks, they can vary considerably, with their own unique tolerances and critical components. Prior to commencing an implementation, there are numerous questions that need to be explored, several of which are listed below.

1. Which components of the investigated machine should be regarded as crucial to observe for monitoring purposes?

2. Which parameters can be observed to gain an understanding of the condition of the machine being investigated?

3. Which sensors can be utilized to measure the condition of the machine, and what are the appropriate locations to mount them?

To obtain accurate answers to these questions, a comprehensive investigation of the specific machine in question is necessary. The problem formulation for this paper is as follows. What components of the machine can be considered critical for monitoring? Are there any sensors that can be used to monitor the critical parts? Can these sensors be placed in the machine in a suitable and efficient way, with the intention to gather data of the machines health in order to avoid unexpected production stoppages and product recalls? This paper will contribute Axis to an increased understanding of how a machine monitoring system can be implemented in their machines.

1.3 Limitations

The study has certain limitations that need to be acknowledged. Firstly, due to the nature of the investigation, all implementations must be temporary, and no alterations can be made to the machine of interest, IBAS2. These limitations were imposed to maintain the machine's performance and original design. However, this led to restrictions in the mounting method used for the sensors and where the sensors could be placed.

Additionally, this study is limited to a single machine, and there is no guarantee that the results obtained will be consistent with other IBAS2 machines. The study was conducted in a laboratory environment, which differs from a production facility. The study also lacks access to historical data on the machine's performance. These factors may impact the accuracy and generalizability of the study's findings. It is essential to acknowledge these limitations to ensure the appropriate interpretation and application of the study's results.

1.4 Report Outline

The primary objective of Chapter 2, entitled "Conceptual Framework", is to shed light on the concept of machine monitoring and its practical applications. The machine under investigation, IBAS2, is also presented and described. Moreover, it outlines key considerations that need to be taken into account when implementing machine monitoring systems. This chapter offers guidance on how to determine critical areas that might require monitoring, as well as highlighting the relevant parameters to measure and the appropriate sensors to use in a monitoring system. Furthermore, it discusses signal processing techniques and machine learning algorithms that can be utilized to extract useful information from sensor data.

Chapter 3, entitled "Critical Areas, Monitoring Approaches, and Suitable Sensors", presents the methodology employed to determine the specific areas of IBAS2 that require monitoring, the parameters to be measured, and the most appropriate sensors to be used. This chapter provides a comprehensive account of the process of identifying and selecting critical areas, highlighting the considerations taken into account when selecting the most suitable monitoring approaches based on the significance of the areas. Additionally, the chapter delves into the process of selecting the sensors to be utilized in the monitoring system, discussing the reasoning behind the choice of sensors. Lastly, the chapter presents the outcomes of the methodology employed, including the identified critical areas, the parameters to be measured, and the sensors selected for the monitoring system.

Based on the findings of Chapter 3, which identified vibration as a promising parameter for monitoring the machine's condition, Chapter 4, "Implementation of a Vibration Monitoring System", outlines the methodology and equipment used to implement the vibration monitoring system. This chapter details the process of designing and deploying a sensor-based monitoring system to measure, collect, transmit, store, and analyze vibration data. This system is built around the Raspberry Pi Pico W and leverages the MQTT protocol for communication.

Chapter 5, entitled "Vibration Monitoring Tests and Experiments on IBAS2," details the tests and experiments performed on IBAS2 using the vibration monitoring system developed in Chapter 4. The chapter describes a three-step process: firstly, verifying the monitoring system using controlled vibrations; secondly, testing the equipment on the machine during normal operations to assess its ability to provide useful data on the machine's performance; and lastly, conducting tests to see if the system can detect abnormal machine operations. The chapter presents the results, including observations and measurements gathered from the vibration monitoring system. The results provide insights into the system's effectiveness in monitoring IBAS2's vibrations.

Chapter 6, entitled "Discussion," delves into a comprehensive analysis of the results presented in the previous chapters. This chapter critically examines and interprets the findings in relation to the research objectives. Furthermore, the discussion chapter sheds light on the limitations encountered during the research process. It addresses any constraints or challenges that may have impacted the study's validity, reliability, or generalizability. In light of the limitations identified, the discussion chapter also provides thoughtful suggestions for future work. It outlines potential areas for improvement or extension of the study, offering recommendations for researchers who may wish to build upon the current research to address unanswered questions or explore related aspects.

Chapter 7, entitled "Conclusion," serves as the final chapter of the thesis, summarizing the key findings and insights from the research presented. It provides a comprehensive overview of the study's objectives and how they were achieved. Additionally, it may address any remaining questions or areas of uncertainty while offering suggestions for further research.

The Appendix, included at the end of the thesis, contains additional results that were obtained during the project but not utilized for the main analysis. It provides supplementary information and data that may be of interest to readers seeking a more comprehensive understanding of the research process and outcomes.

2

Conceptual Framework

2.1 IBAS2

The Image Based Alignment System 2 (IBAS2) is a production machine used to align an image sensor with a camera's optical lens for optimal image quality. This process is crucial for ensuring that the picture generated by the image sensor is of high quality. The purpose of this section is to provide a comprehensive understanding of the machine that is currently under investigation. This understanding will facilitate comprehension of the reasoning behind the experiments that were carried out on the machine.

IBAS2 operates by establishing a connection between an image sensor and the machine itself, which then extracts the image it produces. Collimators are then used to replicate a target image focused at an infinite distance, and the produced image is evaluated and calibrated for focus. The machine then aligns the sensor and lens to achieve optimal sharpness. The system's effectiveness lies in its ability to provide real-time image feedback, allowing for precise adjustments to be made during the alignment process. This results in high-quality images that meet industry standards. Figure 2.1 shows the IBAS2 machine design.

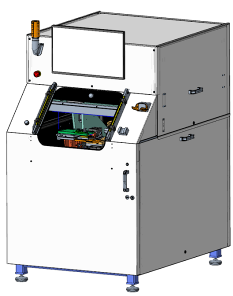


Figure 2.1 The Image-Based Alignment System 2. Image courtesy of Axis from an internal presentation in 2022.

The machine adjusts the distance between the image sensor and the optical lens by moving the optical lens, this can be seen as a translation in the Z-direction in a 3D-space. IBAS2 also has the ability to move the sensor in two additional directions, this can be seen as translations in the X- and Y-direction. The orientation of the sensor can also be altered around the X- and Y-axis. Figure 2.2 illustrates the described motions for alignment. Each motion in the active alignment is generated by an individual stepper motor equipped with actuators to control the precise movement.

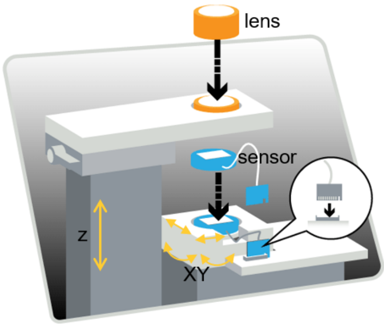


Figure 2.2 Overview of the motion capabilities of the alignment system. Image courtesy of Axis from an internal presentation in 2022.

The fixture where the alignment system is installed is referred to as a cart. There are two separate carts installed in the machine. Each cart is placed on a circular rail letting the carts move around in a controlled circular motion. This motion is generated by a stepper motor rotating a shaft that is equipped with a gear. The carts are moved to three main positions, the load position, the coarse alignment position and the main alignment position. The cart is positioned in the load position for the operator to place the optical lens and image sensor to the cart and connect the sensor to the system. At the coarse alignment position, a coarse alignment in the Z-direction of the sensor and lens is performed. A blemish test is also performed. At the main alignment position, the active alignment in the five described motions are performed. IBAS2 can align a wide range of used lenses and sensors. However, each type of lens and sensor requires specific positions of the collimators in order to replicate a target accurately. To accomplish this, the target stand, the fixture where the collimators are installed, can adjust its height position. With the target stand's flexibility, IBAS2 is capable of aligning image sensors for a variety of camera lenses.

2.2 Machine Monitoring

Machine monitoring has been utilized in various industries for a long time. The conventional approach to monitoring machinery involves visual inspection, where a human operator determines the health status of the machine. However, due to human limitations, this approach may not always accurately detect the machine's condition, as some aspects may be beyond human sensing capabilities [Hashemian, 2011]. In the upcoming section, a summary of machine monitoring will be presented, its significance, and the critical factors associated with it.

In order to overcome the limitations of human visual inspection, sensors are often utilized in machine monitoring. These sensors provide precise measurements and can detect subtle changes in the machine's performance. By combining sensor data with predictive maintenance techniques, companies can avoid unnecessary equipment replacement, reduce costs, improve safety, and increase efficiency. This integration allows for proactive maintenance, where potential problems can be identified and addressed before they result in unplanned downtime or costly repairs. Overall, the use of sensors and predictive maintenance techniques can significantly improve the performance and reliability of industrial machinery [Hashemian, 2011].

In 2007, a study was conducted to investigate the effectiveness of hands-on maintenance techniques [Hale, 2007]. In 1998 another study was conducted to investigate the effectiveness of online or predictive maintenance [Hashemian, 1998]. A comparison of these two studies revealed that machinery under hands-on maintenance experienced problems 20% more frequently than machinery under online maintenance. Additionally, seemingly identical copies of the same equipment maintained using hands-on techniques were found to fail at different rates, making it less reliable compared to equipment maintained using online techniques. These findings underscore the importance of implementing online or predictive maintenance techniques, as they can significantly reduce the likelihood of equipment failure and subsequent downtime. By utilizing real-time data from sensors and other sources, predictive maintenance allows for the identification of potential issues before they become significant problems, which can save time, money, and resources. In contrast, hands-on maintenance relies on scheduled inspections and reactive repairs, which may not catch all potential issues and can lead to costly equipment failures [Hashemian, 2011].

Today, maintenance is expensive which makes the choice of maintenance method important. There are three different types of maintenance according to Hashemian.

1. Run-to-failure
2. Preventive maintenance
3. Predictive maintenance

Run-to-failure is simply that no maintenance will be done until equipment or system failure occurs. As long as the machine is able to operate there will be no maintenance, except for small adjustments.

Preventive maintenance is a time-driven method. It involves performing routine maintenance tasks on a scheduled basis, typically compared to the equipment's expected lifetime. By following a regular maintenance schedule, potential problems can be identified and addressed before they become major issues that could result in costly repairs or even equipment failure. However, this method has some limitations. Since it is a time driven method, this can result in maintenance being performed too frequently, leading to unnecessary downtime and increased costs. Alternatively, if maintenance is performed too infrequently, the risk of equipment failure increases. Another limitation is that preventive maintenance does not account for unforeseen issues that may arise. Even with regular maintenance, unexpected problems can still occur, which may require unscheduled repairs and result in downtime.

Predictive maintenance involves the continuous monitoring of a system to prevent any potential breakdowns. This type of monitoring ensures that the equipment's condition is constantly visible and can be compared to historical conditions and behaviors during operation. As long as the equipment's condition is satisfactory for the operation to proceed, no maintenance is required. Maintenance will only take place when the system is on the verge of failure [Motaghare et al., 2018].

Predictive maintenance can be applied using three different techniques:

1. Existing-sensor-based maintenance
2. Test-sensor-based maintenance
3. Test-signal-based maintenance

Existing-sensor-based maintenance involves using an already existing sensor to collect data on the status of the equipment. For instance, in a nuclear power plant, blocked pressure transmitters can be detected by existing sensors. This allows for the replacement of only the blocked pressure transmitters, rather than all of them.

Test-sensor-based maintenance, on the other hand, requires the implementation of new sensors to collect data when existing sensors cannot provide the necessary information.

Test-signal-based maintenance involves sending a signal, such as a step response, to measure the response time of existing sensors. This technique can be used to confirm that sensors and other equipment in the machine are properly installed [Hashemian, 2011].

The diagram in Figure 2.3 portrays an example of a framework used in a predictive-maintenance-based machine-monitoring system. For a predictive-maintenance-based machine-monitoring system to function, several distinct steps are required. Firstly, to perform an analysis of a system, collecting data is crucial. This data can be collected using multiple sensors and stored in a database. For predictive maintenance to be possible, the system must be continuously monitored. The monitoring process must be designed to detect faults accurately, and the system should be equipped with suitable sensors. However, there is no single sensor solution that can work for every system. The sensor selection will depend on the unique requirements of each system. Ideally, the sensors should be capable of collecting data during both normal operation and when failure approaches. The ultimate goal is to have sensors that can detect faults as early as possible to minimize downtime. Generally, predictive maintenance systems require high-performance sensors, which will depend on the equipment's criticality [Murphy, 2020].

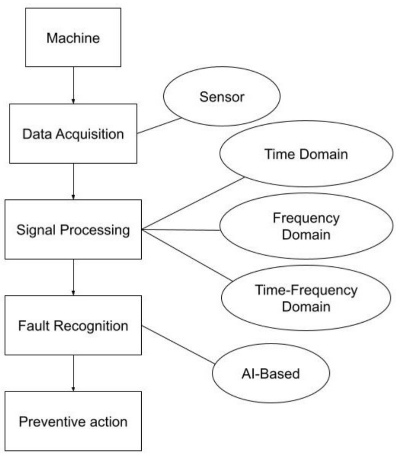


Figure 2.3 Example of a framework for a machine monitoring system. The squares represent the action flow of a machine monitoring system. The ellipses represent the solutions to accomplice the action

Secondly, the data acquired from the sensors needs to be processed in order to perform a useful analysis. First of all, the signal needs to be cleaned and filtered, by a pre-processing process. With the filtered signal, feature extraction can be performed. Features can be extracted from different domains. For example, time, frequency and time-frequency domain. There can be a large amount of features acquired from these domains. More features will lead to a greater computation time and complexity. To minimize, feature fusion and feature selection can be applied. With feature fusion, a set of multiple features can be merged together to obtain a new parameter, which is later used to analyze the machine's condition. Another way to solve this problem is to select the features which are most relevant for the monitoring. A downside to this selection is prediction accuracy. The limitations of features will decrease computation time although it might miss relevant features for higher prediction accuracy. Therefore, it is important to optimize the selection of features to analyze [Iliyas Ahmad et al., 2020].

Finally, the accumulated data is analyzed and compared to the historical states of the system. This analysis allows for determining whether the machine is operating as expected or potentially detect early machine errors that may result in failure. To perform this analysis, artificial neural networks can be utilized, taking into account the various states of the system during its operation. In simpler terms, the predictive analysis can anticipate the future states of the system and determine whether maintenance is necessary or not [Motaghare et al., 2018].

2.3 Determining Critical Areas in Machine to Monitor

To determine the areas of a machine that require monitoring for its condition, one may consider various factors such as:

1. Consequences of failure
2. Historical data
3. Expert opinion

When determining critical areas in a machine to monitor, evaluating the consequences of machine failure can be an effective approach in assessing the potential impact of various failures on the machinery. By comprehending the consequences of a particular machine failure, it becomes possible to grasp the significance of component reliability. This understanding sheds light on the criticality of ensuring the dependability and robustness of individual components within the machine. Analyzing historical data can also provide insights into critical areas and components that may require monitoring based on patterns and trends in past performance. Additionally, seeking advice from subject matter experts, such as development teams, can provide valuable insights into common failure points and recommendations for effective monitoring strategies [Automation24, 2020].

2.4 Physical Quantities Considered for Machine Monitoring

There are various parameters that can be monitored to ensure optimal performance and prevent downtime in machines. For instance, pressure, vibration, electric current, position, sound, speed, temperature, motor function, fluid properties, and humidity are some of the parameters that could be monitored. Measuring electric current and voltage can provide information about the load and operation status of the machine. Electrical monitoring can also be used to determine the condition of the insulation, which is crucial for ensuring safety. The environment can affect the machine's condition, with factors such as moisture, surface contamination, and chemicals playing a significant role. Thus, monitoring parameters like humidity, oil from bearings or seals, and chemicals can help investigate and prevent such issues [Haq et al., 2021].

2.4.1 Temperature Monitoring

Temperature is a parameter that can be monitored to detect overloading or local overheating in machines. For instance, bearings have specific temperature limits that should not be exceeded. The temperature of a bearing can increase due to various factors such as winding temperature rise, motor operating speed, and temperature distribution within the motor. Measuring the bearing temperature can also provide valuable information about the other parts of the machine. However, one challenge of monitoring temperature is locating the source of the temperature increase [Zhou et al., 2007].

When electrical motors are operated, thermal stress can occur due to losses in copper conductors and heat generation. Operating motors at high temperatures can cause oxidation, leading to brittle insulation, de-lamination, and eventual failure. Hence, monitoring temperature is crucial in preventing such issues and ensuring optimal machine performance [Haq et al., 2021].

2.4.2 Vibration Monitoring

All production machines which have moving parts generate vibrations. This holds for machines that produce rotational, back-and-forth or linear motion, in fact it holds for all type of machinery motion. Therefore, vibration has become a popular, powerful and suitable parameter to monitor. Vibration is a mechanical phenomena where oscillations occur about a equilibrium point of a machine or component. The oscillations can be periodic or they can be stochastic and vary in amplitude. A machine may contain several elements that generate vibrations such as, electrical motors, rotating shafts and rolling bearing elements. Vibrations in a machine are normal since the motion that causes them are intended and each element contributes a characteristic vibration signature. However, vibrations can also be generated in a machine from different problems. For example, they can be caused by a lose bolt, worn equipment or misaligned shafts. Vibrations caused by problems in the machine can be seen as abnormal and to successfully use vibrations analysis for predictive maintenance it is important to differentiate the normal vibrations from abnormal vibrations. By monitoring vibration signatures over time, it is possible to predict machine failure [Mobley, 2002].

A predictive-maintenance-based machine-monitoring system, with the use of vibration analysis is based on the following facts [Mobley, 2002].

1. All common machinery problems and failure modes have distinct vibration frequency components that can be isolated and identified.

2. A frequency-domain vibration-signature is generally used for analysis because it consists of discrete peaks, each representing a specific vibration source.

3. There is a cause, referred to as a forcing function, for every frequency component in a machine's vibration signature.

4. When the signature of a machine is compared over time, it will repeat until some event changes the vibration pattern (i.e., the amplitude of each distinct vibration component will remain constant until the operating dynamics of the machine-train change).

2.4.3 Condition-Based Monitoring of Stepper Motors

Stepper motors are used to acquire high accuracy motion control. Common faults for a stepper motor are motor shaft misalignment and step loss. Misaligned shafts are generally caused by mechanical installation, impact and external force. The step loss is commonly caused by operation during high velocity and mechanical load. An increased mechanical load or misalignment of the rotating shaft will not cause vibrations in either the motor or load. In contrast to the first item mentioned in Section 2.4.2, which highlights that machinery issues and failures exhibit distinctive vibration frequency components, stepper motors do not align with this statement. At the same time, the current is constant. Therefore, it is difficult to detect faults when measuring vibrations and current. Instead the mechanical load and motor running position can be monitored. This can be done by analyzing the voltage and current data of the stepper motor coil [Liu et al., 2020].

Electric motors, including stepper motors, rely on the interaction of magnetic fields to generate rotational motion. In a stepper motor, the rotor moves in discrete steps based on the sequential energization of the stator coils, rather than continuous rotation. The stator's magnetic field interacts with the rotor, resulting in controlled movement.

Back-electromotive force (back-EMF), is a voltage generated in a motor due to the rotor's rotation and the interaction between magnetic fields. Back-EMF is primarily influenced by the motor's speed rather than the mechanical load. However, according to [Trinamic, 2023], the back-EMF can indicate the mechanical load on the motor, meaning it can be used to monitor actual load-conditions of a drive system.

When viewed from the rotor's perspective, the electromagnetic field of the stator either attracts or repels the rotor, which creates a phase shift between the rotor's magnetic field and the rotating field of the stator. This phase shift is commonly referred to as the load-angle, or the angle between the two magnetic field directions of the motor's rotor and stator. Under typical load conditions, the load-angle remains low and a portion of the energy supplied to the motor is returned to the power supply, resulting in back-EMF [Trinamic, 2023].

2.5 Selecting Sensors for Machine Monitoring

When selecting a sensor for the purpose of monitoring a machine event, several important factors need to be carefully considered. These factors include the sensor's performance, size, reliability, price and the characteristics of the sensor's output signal. The psychical quantity chosen to monitor plays a crucial role in determining the most appropriate sensor for the task at hand. This involves considering factors such as the physical magnitude of the event and the environmental conditions in which it occurs.

A range of different sensors may be employed to gather useful data. For instance, when monitoring the performance of a cutting tool some examples of sensors are a dynamometer, an accelerometer, an acoustic emission sensor, a current sensor, a power/voltage sensor, a thermal sensor, or a pressure and sound sensor [Mehdi, 2021].

Ultimately, the selection of a sensor for a given task will depend on a range of complex factors, including the nature of the event being monitored, the desired level of precision and accuracy, and the cost constraints that may be in play. Nevertheless, by carefully considering these various factors, it is possible to choose a sensor that will deliver reliable and meaningful data, enabling an efficient monitoring of a wide range of industrial processes and applications [Mehdi, 2021].

2.5.1 Vibration-Measuring Equipment

Vibration detection and measurement are often carried out using a sensor or transducer. Various types of sensors may be employed. Accelerometers, velocity transducers, and displacement sensors being the most widely used. The selection of an appropriate sensor type is usually influenced by factors such as frequency range, sensitivity, design, and operational constraints [Mohd Ghazali and Rahiman, 2021].

An accelerometer is a sensor that can be used to measure acceleration or vibration. Most accelerometers rely on the use of the piezoelectric effect, which occurs when a voltage is generated across certain types of crystals as they are stressed. The acceleration of the test structure is transmitted to a seismic mass inside the accelerometer, which generates a proportional force on the piezoelectric crystal. This external stress on the crystal then generates a high-impedance, electrical charge proportional to the applied force and, thus, proportional to the acceleration [*Measuring vibration with accelerometers* 2022].

Accelerometers that exploits the piezoelectric effect are used together with an external charge amplifier or in-line impedance converter to amplify the charge, lower the impedance for compatibility with measurement tools and reduce external noise. Some piezoelectric accelerometers have integrated amplifiers or impedance converters, these are called integrated electronic piezoelectric (IEPE) accelerometers [*Measuring vibration with accelerometers* 2022].

An alternative accelerometer is the micro-electro-mechanical system (MEMS) accelerometer. It usually consists of movable proof mass with plates, supported by a mechanical suspension system to the frame. When exposed to acceleration the proof mass is prone to oppose motion due to its internal inertia. Consequently the spring is stretched or compressed and as a result the force created in the spring can be converted to acceleration since they are proportional [Mohd Ghazali and Rahiman, 2021].

Velocity Transducers measure velocity. It does so by measuring voltage generated from the velocity of motion of the object it is attached to. As the surface where the transducer is mounted vibrates, a magnet in the sensor moves. This magnet has a coil around it and the motion of the magnet will generate a voltage that is proportional to the vibration causing it [Mohd Ghazali and Rahiman, 2021].

A displacement sensor is used to measure the relative position between the sensor and a fixed point, in terms of linear movement, rotational angle or three-dimensional space. There are several different types of displacement sensors. Optical displacement sensors, linear proximity sensors and ultrasonic displacement sensors are some examples [Mohd Ghazali and Rahiman, 2021].

The presented equipment to measure vibrations in this section have different advantages and disadvantages and are suitable to detect vibrations of different frequency ranges. Piezoelectric accelerometers have a wide frequency and dynamic range, are often of lightweight character and have high sensitivity. The disadvantages is that they need external electronic equipment to operate and are sensitive to its external environment [Mohd Ghazali and Rahiman, 2021]. The MEMS accelerometer are suitable to measure low frequency vibration but can also measure vibrations above 10 kHz and give usable data. It can process data quickly with a high sensitivity. Its disadvantages is that it has a substandard signal-to-noise ratio [Mohd Ghazali and Rahiman, 2021]. Velocity transducers have a limited frequency range of around 10 Hz to 2 kHz. They operate without any external devices and are generally favoured in monitoring rotating machinery. Displacement sensors are commonly used to measure vibrations below 10 Hz. They are good for detecting unbalanced rotating parts and misalignment problems. It is also fairly easy to change the measurement point if needed. The drawbacks is that they are susceptible to shocks. The advantages, disadvantages and common frequency range for the different vibration measuring equipment are collected in Table 2.1.

Table 2.1 Advantages and disadvantages of vibration-measure equipment and common frequency ranges.

Sensor	Advantages	Disadvantages	Frequency Range
Piezoelectric	Wide frequency and dynamic range, are often of lightweight character and have high sensitivity	Need external electronic equipment to operate and are sensitive to its external environment	1 Hz–10 kHz
MEMS	Wide frequency range, can process data quickly and have a high sensitivity	Has a substandard signal-to-noise ratio	1 Hz–10 kHz
Velocity Transducer	Can operate without any external device, generally used in monitoring rotating machinery	Limited frequency range	10 Hz–2 kHz
Displacement Sensor	Good for detecting unbalance and misalignment, easy to change measurement point	Susceptible to shock	<10 Hz

2.5.2 Sensor Mounting and Placement

The effectiveness of the sensor system also depends on the sensor placement. Optimal sensor locations can be determined by having a good understanding of how the machine works or by engineering judgement and iteration with collected data. It is rare that one location is enough to detect all disturbances. Therefore, it is important to determine which locations are superior to others to obtain the best available data. An example of a location problem is monitoring a tool tip. It is not feasible to place sensors at the tool tip. Therefore, locations around the critical area must be found and evaluated. The objective is to use a minimal number of sensors and at the same time obtain the required vibration spectra to monitor the tool tip [Er et al., 2016].

For the data gathered from sensors to be considered highly reliable, it is critical that the sensors are mounted properly. This makes the choice for mounting the sensor to the machine crucial to obtain accurate data. For example, slight deviations in the link between the sensor and the machine may cause errors in the amplitude and frequency readings in vibration measurement, making the reading unreliable [Mobley, 2002].

Accelerometers' frequency ranges differ a lot depending on how they are mounted. For accelerometers, there are typically four methods to consider:

1. Stud mount (screws/bolts)
2. Adhesive (epoxy, wax, tape)
3. Magnetic
4. Handheld or probe tips

Stud mounting is considered to be the superior method because it minimizes the sensor movement, which results in a higher frequency range. The sensor is mounted to the surface by the help of screws/bolts. It is often a permanent installation of the sensor since it requires drilling in the machine. The rest of the methods are more likely to be used for a temporary installation. Regardless of what accelerometer is used, the rule of thumb is, the stiffer the mounting is, the higher frequency range and reading accuracy will be [*Measuring vibration with accelerometers* 2022].

2.6 Signal-processing techniques

There are three important domains within signal processing, time domain, frequency domain and time-frequency domain. The data in these three different domains, can be analysed with different features. For example, from the time domain features such as average, magnitude, root mean square can be used. From the time domain, the signal can be transformed to the frequency domain with help of Fourier transform. The signal can then be transformed to the time-frequency domain with help of for example, Wavelet transform. These type of signal transformations might be needed to make a decision for the condition maintenance [Iliyas Ahmad et al., 2020]. In this section, features from these three domains are explained and motivates how analysing these features can favor a machine monitoring system.

2.6.1 Time-domain analysis

One of the most common ways to analyze signals is through the time domain. In this domain, proximity, velocity, and acceleration measurements are taken, and the resulting data is plotted against time. This provides information about the amplitude modulation, shaft unbalance, transient, and higher-frequency components of the vibration without the need for signal processing. However, the time domain method can be limited by noisy signals, making it difficult to detect various machine failures.

To obtain more relevant information from the signals, signal processing is necessary. Features such as peak, mean, root mean square, crest factor, and kurtosis can be used to analyze the signals and determine the machine's health status. By using these features, it is possible to identify specific faults and predict the remaining useful life of the machine. Overall, signal processing is a crucial step in machine monitoring that can provide valuable insights to the condition of the machine.

The peak is the greatest amplitude during a certain time window and can be calculated using (2.1), where v(t) is the signal and max means the greatest value during the time span T_1 to T_2.

$$peak = \max_{T_1 \leq t \leq T_2} |v(t)| \tag{2.1}$$

When operating in a faulty condition, the peak value is usually increased. The peak value can be helpful in detecting faults or abnormalities in signals or measurements. By monitoring the peak value of a parameter, such as vibration amplitude or current spikes, deviations from normal operation can be identified, indicating potential faults or malfunctions. Root mean square or RMS is useful for analyzing rotating machinery. It is often used when analyzing steady-state applications and single sinusoidal waveform. RMS is valued more than peak because peak is more affected by noise. The RMS can be calculated using (2.2), where T is the time duration and v(t) the signal,

$$RMS = \sqrt{\frac{1}{T} \int_{T_1}^{T_2} v^2(t)dt}. \tag{2.2}$$

The RMS value is not affected by the isolated peaks in the signal or short bursts of low-intensity vibrations. This makes the method more unreliable. With RMS it is possible to determine the energy of the vibration. Both the peak and RMS values pose challenges in detecting faults at the early stage. The crest factor is the ratio between the peak and RMS values and can be calculated using (2.3).

$$CrestFactor = \frac{peak}{RMS}. \tag{2.3}$$

The crest factor is often used when speed is irrelevant, when the measurements are from different speeds. Kurtosis is a measurement that is non-dimensional. It quantifies the number of outliers in distribution and in vibration data. Kurtosis can be seen as the number of transient peaks. An increasing value of the kurtosis can indicate wear. One downside to kurtosis analysis is that it is not always correct [Mohd Ghazali and Rahiman, 2021].

2.6.2 Frequency-domain analysis

The frequency-domain is utilized to analyze and represent signals by breaking them down into their unique sine waves. Instead of describing a signal solely in the time-domain, where it consists of unique sine waves, the frequency-domain analyzes the signal and displays each sine wave as a distinct peak at its corresponding frequency. This enables a comprehensive understanding of the signal's frequency composition and facilitates the identification and analysis of individual components contributing to the overall signal. The height of the peak will describe the amplitude of the sine wave and its position the frequency. Compared to the time-domain, the frequency-domain provides higher resolution for analyzing signal frequency components. It enables a thorough exploration of individual frequencies present in a signal, making it valuable for applications like audio processing and vibration analysis. Consequently, when pinpointing the source of a machine failure, the frequency domain is advantageous due to its ability to provide detailed insights into the specific frequencies associated with the failure.

If using frequency analysis, for a signal with with a frequency that varies over time, there will be information loss. To convert the signal from the time-domain to the frequency-domain fast Fourier transform (FFT) can be used. Fourier transform of a signal in the time-domain to the frequency-domain, in discrete time, can be seen in (2.4).

$$X[k] = \sum_{n=0}^{N-1} x[n]e^{-j2\pi kn/N}. \tag{2.4}$$

Where $X[k]$ represent the $'k'th$ frequency component, $x[n]$ the input signal at the $'n'th$ sample and N the total number of samples. It is also possible to convert a signal from the frequency domain, in discrete time, to the time domain using (2.5)

$$x[n] = \frac{1}{N}\sum_{k=0}^{N-1} X[k]e^{j2\pi kn/N} \tag{2.5}$$

FFT is a common and efficient algorithm to obtain the FT of time signals. A FFT plot of a machine without faults will result in one peak, which is the natural frequency of the machine. The presence of other peaks, different from the natural frequency, can indicate signs of faults in the machine. However, the transformation might result in a small loss of time information. Also, transient features can not be detected with FFT as well the importance of the fault. The algorithm is the most efficient one to separate the frequencies of the signal [Mohd Ghazali and Rahiman, 2021]. When using a excessively low sampling rate, aliasing can occur. Aliasing is when faulty frequency components appear. The reason is that the sampling frequency is not high enough. According to the Nyquist theorem, the sampling frequency should be at least twice as large as the maximum frequency available in the signal. If that can be achieved, aliasing will not occur [Goyal and Pabla, 2016].

Some features obtained from the frequency-domain are Cepstrum analysis, Envelope analysis and Spectrum analysis. Cepstrum analysis is when computing the logarithm of the estimated signal spectrum. The method is useful for detecting period structure in the frequency spectrum. Envelope analysis works by first using a bandpass filter to analyze the interesting frequencies and then a demodulation step. This might lead to the desired diagnostic information. For envelope analysis to work a sharp filter and information about the frequency band are needed. The last mentioned feature in the frequency domain is spectrum analysis. The signal should be converted to a logarithmic amplitude scale where changes can determine the state of the vibration. It is useful for determine signals that have a significant change during a short time period. Although, literature is available, spectrum analysis is a complex method and expert skills are required [Mohd Ghazali and Rahiman, 2021].

2.6.3 Time-frequency domain analysis

In the time-frequency domain, both time and frequency can be analyzed simultaneously. Compared to the time- or frequency-domain, where only one dimension is analyzed at the time. Methods from the time-frequency domain are appropriate for nonstationary signal analysis. Examples of features are spectrogram, wavelet transform (WT), Hilbert-Huang transform (HHT) and short-time Fourier transform (STFT).

Spectrogram is a visual way to display the energy of a signal with a certain frequency at time. It is possible to see how the energy of a signal is distributed over frequency components and time. WT is a linear transformation that decomposes a time signal into wavelets. Wavelets are local functions of time. The wavelets have a predetermined frequency. Instead of sinusoidal functions these wavelets are used as a basis for the analysis. To avoid misleading results, a suitable wavelet basis should be selected according to the signal structure [Mohd Ghazali and Rahiman, 2021].

With WT, it is possible to detect abrupt changes in the signal and sudden changes in acceleration data [Goyal and Pabla, 2016].

At high frequencies, WT can provide superior time localization compared to STFT. When dealing with nonstationary and transient signals from a measured vibration, WT is preferable. STFT can counter the limitations of FFT. Mostly, it is used to extract the narrowband frequency content in noisy or nonstationary signals [Mohd Ghazali and Rahiman, 2021]. The idea is to divide the signal into windows and then perform FT each segment [Goyal and Pabla, 2016]. A window function minimizes the spectral leakage. Spectral leakage is a phenomenon where the energy of a signal spreads out into neighboring frequencies during frequency analysis, causing distortion and making it harder to accurately identify the true frequency components of the signal. The function modifies the signal with zeros at the edges and amplifies it in the middle. This eliminates the discontinuities [Instruments, 2016]. The width of the window will lead to accuracy in different areas. A large width will lead to greater accuracy in frequency while a smaller width will lead to a greater accuracy in time. The drawback of this is that a high accuracy can not be obtained for frequency and time domain simultaneously [Mohd Ghazali and Rahiman, 2021].

2.7 Fault Detection and Diagnostics

After collecting data, it is often represented in either the time, frequency, or time-frequency domain. Frequency analysis is a common approach to extract relevant information about a machine's health by monitoring its vibrations. However, it can be challenging to detect faults since the vibration spectra contain numerous frequencies. To address this issue, dynamic signal analyzers can track changes in the vibration spectra over time, while intelligent FFT analyzers can compare characteristic frequencies to a reference model of a healthy machine to identify faults. While these methods can be useful, they may not capture all possible defects and may also include extraneous frequencies that do not provide any information on the machine's health.

To overcome these limitations, a neural network can be implemented, which can effectively analyze complex systems and detect faults without prior knowledge of the system's structure. The neural network's model is established using data from healthy conditions, and once trained, it can analyze the system during both healthy and faulty conditions to predict the machine's future state [Su and Chong, 2007].

2.7.1 Machine Learning for Predictive Maintenance

Machine learning (ML) is a subcategory of artificial intelligence (AI) that has emerged as a powerful tool for predictive maintenance. ML algorithms analyze large datasets to identify patterns and trends that can help predict when a machine is likely to fail or require maintenance. Common ML models include neural networks, linear regression, logistic regression, clustering, decision trees, random forests, and support vector machines. These models can be trained on large datasets to learn patterns and relationships between variables, allowing them to make accurate predictions about future outcomes.

To build and deploy a machine monitoring system using ML, the process typically starts with data collection. Time-series data from sensors is collected and preprocessed, including filtering and feature extraction. The extracted features are then used to train the ML model, allowing it to learn from the data and make predictions about future events. The quality and quantity of data used to train the model can have a significant impact on its accuracy and effectiveness. Therefore, it is important to collect and curate high-quality data.

To further enhance the effectiveness of ML for predictive maintenance, additional techniques can be applied, such as anomaly detection, fault diagnosis, and prognosis. Anomaly detection can identify abnormal patterns in the data, which may indicate a potential fault or failure. Fault diagnosis can help pinpoint the root cause of a problem, while prognosis can predict the remaining useful life of a machine or component. These techniques can be combined with ML algorithms to create a more comprehensive predictive-maintenance system.

In addition, there are various challenges that need to be addressed when implementing ML for predictive maintenance, including data quality, model interpretability, and algorithm selection. It is important to ensure that the data used to train the model is accurate and representative of the real-world operating conditions. Model interpretability is also critical, as it enables stakeholders to understand how the model arrived at its predictions and to identify potential biases or errors. Finally, the selection of appropriate ML models is critical, as different models are better suited to different types of problems and datasets [Brown, 2021].

One suitable model class for predictive maintenance is autoencoders. Autoencoders are trained using data from normal conditions to identify and distinguish abnormal data in comparison to the normal training data. This is done by compering the input data to low dimensional data, with the help of a encoder. The low dimensional data is then converted back to high dimensional with a decoder. The purpose is to let the Neural Network learn a small set of informative features. After training, the autoencoder knows how to encode and decode healthy data to get similar input and output. When it acts on unhealthy data the input and output will not be similar and faults have been detected. This method does not provide any fault diagnostic that is, information of where the fault occured. However, it is a simple method and that only needs data from normal conditions, which simplifies the training of the model [Park et al., 2019].

3

Critical Areas, Monitoring Approaches, and Suitable Sensors

To enable successful implementation of the monitoring system, critical areas within the IBAS2 machine must be identified and mapped. Once the areas to monitor are identified, a suitable monitoring method is to be selected. Appropriate sensors can then be placed in these critical areas to gather useful data on the machine's status. The first section in this chapter presents the methodology that was used in this master's thesis to identify the critical parts that need monitoring, selecting an appropriate monitoring approach and choosing suitable sensors for data collection. The outcome of the approach is detailed in the second section of this chapter.

3.1 Identification of Critical Components

The initial stage of implementing a machine monitoring system involves identifying critical machine components. These components require monitoring to ensure optimal performance and prevent unexpected failures. Several techniques, such as historical data analysis, can be employed to identify these critical components, as discussed in Section 2.3. However, this project disregards the historical data analysis method due to the unavailability of the required data. Instead, the expert opinion approach was utilized to identify the critical components of the machine. In this approach, the engineers responsible for developing and designing the machine at Axis Communications provided their expert opinions on the key components that require monitoring.

To identify and map these critical components, a discussion was held with the development team at Axis Communications. Section 2.1 provides an overview of the function and purpose of the IBAS2 machine, which involved aligning an image sensor with an optical lens to achieve optimal picture sharpness and focus.

3.2 Selecting Monitoring Method

After completing the critical area identification process, the next important step is selecting an appropriate monitoring method. There are various monitoring techniques available, with commonly used methods including temperature and vibration monitoring. To determine the most suitable monitoring method for IBAS2, a review of established methods commonly used for monitoring machines was conducted. The review is presented in 2.4, and was utilized as a basis to select the most appropriate method for this project. The selection of a monitoring method is dependent on several factors, including the type of machine, its criticality, and ease of implementation. These factors were carefully considered during the process of selecting a suitable monitoring method for IBAS2 in this thesis.

3.3 Selection of Sensors for Monitoring Machine Condition

To ensure that the machine's health and performance are constantly monitored, appropriate sensors must be carefully chosen. These sensors has to be capable of providing precise and timely data on the machine's critical components. An evaluation of sensors that can provide the required information based on the chosen monitoring approach was conducted. When selecting sensors, several factors are considered such as their functionality, ease of implementation and price.

3.4 Critical Components Found in IBAS2

A discussion was held with the engineers responsible for designing, calibrating, and maintaining IBAS2 in order to identify its critical areas that require monitoring. During the discussion with the development team at Axis Communications, the engineers informed that the production machine had experienced problems in the past. The engineers have reported that contact with the carts has caused misalignment of the different sides of the target stand, leading to a tilted target stand that negatively affects calibration performed by the collimators used for alignment. Furthermore, the rail along which the carts move can sometimes cause increased friction, resulting in unintended variations in the cart's velocity that may cause problems for the machine over time. The engineers also noted that the carts may encounter higher resistance than usual, causing them to stop unexpectedly. In addition, the engineers have observed that the actuators controlling the X-tilt wear out after a period of usage.

From the discussions, it was found that the reported issues were all related to the active alignment process of IBAS2. It was concluded from both parts that the active alignment process is critical and may require monitoring since its performance is crucial for the machine's output. The active alignment process plays a crucial role in producing high-quality images with the expected sharpness for the final product. The precision of the alignment, which is controlled by precise movements on a scale of micrometers, greatly influences the sharpness of the resulting image. Therefore, implementing a machine monitoring system that focuses on the active alignment process is essential in this project.

As stated in Section 2.1, the equipment used to align the optical lens with the image sensor are located on two carts that carry out the necessary movements. These carts have been identified, in this study, as critical areas of the machine that require monitoring to ensure high-quality images from the produced cameras. Additionally, the target stand carrying the collimators used for calibration has also been identified as a critical area to monitor since it is directly involved in the alignment process. As indicated in Section 2.1, the active alignment process in IBAS2 is entirely controlled by stepper motors, making their reliability essential to the overall system performance. Each of the two carts in IBAS2 is equipped with six stepper motors, each responsible for its own specific movement. These motors are fitted with different parts such as gears, linear and rotary actuators, that are used for various transmissions to ensure precise movement. The accurate operation of these translations and rotations is crucial in achieving the required level of alignment accuracy. Therefore, the stepper motors and the equipment they control are considered critical components of the machine monitoring system, and their performance should be monitored. Table 3.1 provides a comprehensive list of all the different parts of the alignment system selected for monitoring on IBAS2.

Table 3.1 The components chosen to monitor and the function of each component.

Component	Function
Cart	The cart movement between different positions.
X-step	X-translation from motor and actuator.
Y-step	Y-translation from motor and actuator.
Z-step	Z-translation from motor and actuator.
X-tilt step	Rotation around the x-axis from motor and actuator.
Y-tilt step	Rotation around the y-axis from motor and actuator.
Target stand	Height adjustment from the target stand

3.5 Physical Quantity Chosen for Monitoring

As presented in Section 3.4, the analysis found that the components located in the two carts responsible for the movement used in IBAS2's active alignment system, along with the target stand, have been identified as critical components in the active alignment process.

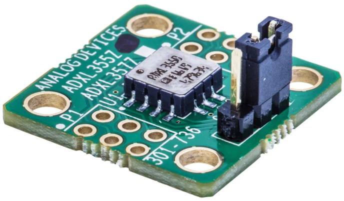
In Section 2.4.3, a monitoring method for stepper motors using the back-electromotive force (BEMF) was described, which appears to be compatible with the machine's mechanical structure. However, implementing this approach would require modifying or replacing the motor control driver, which is beyond the scope of this project. As a result, this method is not considered feasible. Instead, this project will focus on vibration analysis to monitor the condition of the carts and target stand in IBAS2. As discussed in Section 2.4.2, machines with moving parts generate vibrations, and the carts in IBAS2 consist of several moving elements that are vital to the final product's quality. Therefore, vibration analysis could be a suitable method for assessing the condition of the carts.Temperature tracking is another condition monitoring technique that could reveal potential areas of failure in IBAS2, such as improper lubrication, worn parts, or misalignment, due to excess heat. However, temperature monitoring will not be evaluated in this project.

3.6 Sensors Selected for Monitoring Machine Condition

The previous section highlighted that this thesis will focus on vibration analysis as the monitoring method. To measure vibrations, appropriate sensors are required. Section 2.5.1 discussed various types of sensors commonly used, such as accelerometers (MEMS and piezoelectric), velocity transducers, and displacement sensors, which provide data in different frequency ranges. Considering their wide frequency range, high sensitivity and small size, accelerometers have been selected for this thesis. Two accelerometers will be tested and evaluated for monitoring the carts' vibrations: the ADXL355 MEMS accelerometer from Analog Devices and the VS-BV203-B piezoelectric accelerometer from Tokin.

The ADXL355, seen in Figure 3.1a, is a three-axis accelerometer that comes with an integrated temperature sensor and offers selectable measurement ranges of ± 2 g, ± 4 g and ± 8 g, where $g = 9.81\text{m}/\text{s}^2$. The device provides digital output and offers communication with external devices through Serial Peripheral Interface (SPI) or Inter-Integrated Circuit (I^2C) interfaces. The ADXL355 offers a bandwidth of 1000 Hz and a noise density of $0.00025\ \text{m}/\text{s}^2/\sqrt{\text{Hz}}$, making it an ideal device for high precision measurement applications. Additionally, the ADXL355 features a 20-bit analog-to-digital converter (ADC) and comes equipped with programmable high- and low-pass digital filters.

The Tokin piezoelectric accelerometer, seen in Figure 3.1b, is an analog sensor equipped with a built-in amplifier and designed to measure a single axis of vibration. Its operational bandwidth ranges from 10 Hz to 15 kHz, with a measurement range of $\pm 50\ \mathrm{m/s^2}$. The accelerometer exhibits a sensitivity of $20\ \mathrm{mV/m/s^2}$ and a noise density of $0.003\ \mathrm{m/s^2/\sqrt{Hz}}$.



(a) The Eval-ADXL355-Z evaluation board for the ADXL355. Image sourced from [Analog-Devices, 2023].

(b) The piezoelectric accelerometer from Tokin. Image sourced from [KEMET-Electronics-Corporation, 2023].

Figure 3.1 The two accelerometers used for vibration measurement.

4

Implementation of a Vibration-Monitoring System

A comprehensive plan for data acquisition, storage, and analysis is crucial to ensure the effectiveness of the proposed vibration monitoring system. This includes determining the frequency of data collection, the format of the data, and the storage location. In this project, the sensors were connected to Raspberry Pi's Pico W microcontroller, seen in Figure 4.1, to acquire and handle the analog/digital output from the sensors. This microcontroller is capable of reading and handling sensor values and comes with WiFi connectivity, allowing for the construction of a wireless sensor network. Moreover, its dual-core processor architecture enables the simultaneous collection of data from sensors on one core and processing on the other core. The processed data can then be transmitted to a computer for further analysis, either via a cable or a wireless connection [Pi Ltd, 2023].

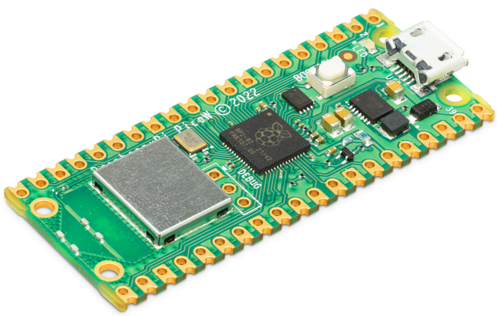


Figure 4.1 The Raspberry Pi Pico W. Image sourced from [Raspberry-Pi, 2023].

The present chapter provides a description of the data acquisition system employed in this study, focusing specifically on the communication between the Raspberry Pi Pico W microcontroller and the two different utilized sensors as well as the wireless transfer of the collected data to a computer for subsequent analysis. The chapter includes an overview of the technical specifications of the Pico W microcontroller, along with a description of the system. The chapter concludes with detail, the critical processes of signal processing and feature extraction, which were used to analyze the data collected from the sensors.

4.1 Design and Implementation of a Sensor Monitoring System with Raspberry Pi Pico W

This study aimed to develop a system for handling the Pico, which involved the utilization of the Pico-SDK designed for C/C++. The implementation is based on C code and leverages the Pico's WiFi capabilities by creating an MQTT client on each Pico. These clients connect to a message handling broker using the MQTT protocol, which allows for the transmission of sensor data from the Pico to a computer. In this regard, Eclipse Mosquitto, an open-source message broker that implements the MQTT protocol, is employed to facilitate communication between the Pico and the computer. To ensure effective communication with the message broker from the computer, an MQTT client was created using Paho MQTT in a Python script, which was executed on a local computer. Specifically, the Pico would collect sensor measurements and publish the data to a dedicated topic for the sensor, while a computer subscribed to the same topic, read the data and stored it in a text file. This setup enables the storage of data locally, where further analysis can be performed. The system overview can be seen in Figure 4.2.

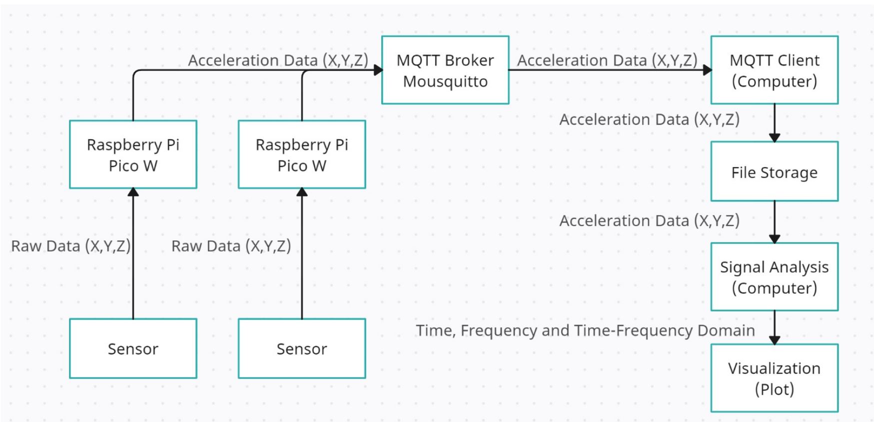


Figure 4.2 Overview of the data acquisition system.

The storage capacity of the Raspberry Pi Pico is limited to 2 MB on-board QSPI flash memory and 264 kB on-chip SRAM, which posed a challenge for storing sensor data on the device. To overcome this limitation, a data buffer was implemented to gather and store the sensor measurements. When the buffer reaches a set value of samples, the data is copied, transmitted, and then deleted to make room for new data. To manage this process efficiently, the Pico's dual-core architecture is utilized. One core is responsible for capturing the data and signaling a flag once the data has been successfully copied to another location. Meanwhile, the second core manages the copied data and communicates with the message broker to publish the data and signal a flag once it has been sent. This approach ensures that sensor measurements where collected and published without the risk of data loss.

The data buffer for the digital sensor is set up to hold 256 samples from each axis along with the corresponding time duration of the sample. As a result, each message transmitted from the Pico contains a total of 1024 measurements. The sampling period for the digital sensor is set to 600 μs. This sampling period was set to ensure a fixed sampling period. As a result, the frequency bandwidth is reduced to approximately 800 Hz. This decision was made based on the assumption that frequencies above 800 Hz are not crucial for the analysis of the machine under investigation. Additionally, an assumption that any higher frequencies that may be present could still be detected by the analog sensor. Communication between the Pico and the sensor was managed through an I^2C interface. The devices is connected as follows: the Pico's I^2C SDA pin (GP4 or physical pin 6) is connected to the SDA on the ADXL355 board, and the Pico's I^2C SCL pin (GP5 or physical pin 7) is connected to the SCL on the ADXL355 board. The ADXL355 is powered by the Pico, with the Pico's 3v3 pin (physical pin 36) connected to VDD on the ADXL355 board and the Pico's GND pin (physical pin 38) connected to GND on the ADXL355 board. The data obtained from the digital sensor is normalised by gravitational acceleration (g).

The data buffer for the piezoelectric analog accelerometer is configured to accommodate 512 measurements, each with a corresponding time duration of the sample. Consequently, each message transmitted from the Pico includes 1024 values. To ensure accurate measurements, the sampling period for the piezoelectric analog accelerometer is set to 200 μs. This sampling period was set to ensure a fixed sampling period. As a result, the frequency bandwidth is reduced to approximately 2400 Hz. This decision was made to establish a fixed sampling rate. The Pico powers the sensor thorugh a connection bewteen the input voltage cable of the sensor to the Pico's 3v3 pin and the ground cable to the Pico's GND pin. Additionally, the cable in the sensor carrying the output voltage is connected to Pico's GP26 A0 pin, which is capable of handling analog input. A 100 kΩ resistance is connected to the sensor output terminal, as stated in the provided instruction guide by Kemet Electronics.

The analog sensor provides a continuous signal that varies proportionally with the physical quantity it measures. The output signal is an analog representation of the input signal and can have an infinite number of values within a specific range, expressed as voltage. This signal passes through an ADC. An ADC converts an analog input signal into a digital output signal. The digital output signal consists of binary numbers that represent the analog signal's amplitude at a particular moment in time. The ADC samples the analog signal periodically and converts each sample into a binary number with a specified resolution. The Pico W utilizes the RP2040 microcontroller chip from Raspberry Pi, which has a built-in 12-bit resolution ADC. The digital output signal from the ADC is converted into a voltage between 0 V and 3.3 V. A signal value of 1.66 V should indicate that no vibration is detected by the sensor, and the sensor is stationary. The sensors can measure up to 3.3 V of positive acceleration and a maximum of 0 V of negative acceleration.

The RP2040 ADC does not include an on-chip voltage reference and instead utilizes its own power supply as a reference point. In the case of the Pico, the ADC supply is produced from the 3.3 V switching mode power supply (SMPS) by means of an R-C filter. Although this solution may seem feasible, it presents certain limitations, as indicated in the data sheet.

1. It is relying on the 3.3 V SMPS output accuracy, which is not great.
2. There can only be so much filtering and therefore ADC supply will be somewhat noisy.
3. The ADC draws current (about 150μA if the temperature sense diode is disabled, but it varies from chip to chip) and therefore there will be an inherent offset of about 150 μA·200 = 30 mV. There is a small difference in current draw when the ADC is sampling (about +20 μA) so that offset will also vary with sampling as well as operating temperature.

The data sheet, propose several options for addressing the issues. For example, to optimize the performance of the ADC, an external shunt reference (such as the *LM*4040) can be linked from the VREF pin of the ADC to ground.

4.2 Signal Processing and Analysis Techniques for Monitoring-System Evaluation

To confirm the effectiveness of the monitoring system, the collected data must be analyzed using signal processing and analysis techniques. There are several methods for visualizing and processing signals, including the time, frequency, and time-frequency domains as mentioned in Section 2.6. In this project, the analysis was focused on the time and frequency domains, rather than the time-frequency domain. However, if the data obtained from vibration monitoring does not exhibit a clear vibration pattern centered around a stationary line, the time-frequency domain was employed for further analysis. This approach is necessary because the Fourier Transform (FT) may fail to detect frequency patterns present in the data.

4.2.1 Time-domain analysis

In Section 2.6, various features are explained that can be collected from the time domain, such as peak, root mean square, crest factor, and kurtosis. The acceleration data is obtained from the measurements over time. The sample rate, which is the time between measurements, needs to be known to visualize the data. The scripts that are running to collect data for each type of sensor has a fixed sample rate, which provides the necessary information. With a known sample rate the signal can be visualized in the time domain. Previously mentioned features in the time domain was not used since necessary information was given from the raw plot of the acceleration data.

4.2.2 Frequency-domain analysis

In the frequency-domain, sine waves present in the measured data are represented as straight lines, displaying their amplitude and frequency. Here, the amplitude is plotted against the frequency. For this project, FFT was used to transform the signal from the time domain to the frequency domain. The condition of the machine was then be determined by analyzing the number of peaks. A single peak indicates the natural frequency, whereas multiple peaks can signify faults. Envelope analysis can aid in analyzing the located peaks. This can be achieved with the help of a bandpass filter to determine which frequencies should be included in the spectra. For instance, the used accelerometers have a certain bandwidth. The Kemet sensor has a bandwidth of 10 – 15000 Hz, and ADXL355 has a bandwidth of about 0 – 1000 Hz. ADXL355 does not require a filter since the bandwidth is sufficient for detecting common frequencies in machinery. However, Kemet's bandwidth is extensive, and using both a low pass and high pass filter can envelop the signal to a similar spectrum as the ADXL355. This makes it easier to compare the two sensors, and at the same time, the signal is not outside of their bandwidth. By presenting the measured data in he frequency-domain, the natural frequency can be determined for various parts of the machine and compared to frequencies from faulty conditions to evaluate the machine monitoring system.

Python was utilized to execute the FFT of the sensor readings. The Scipy package is utilized to transform discrete data from the time domain to the frequency domain. This conversion is carried out by utilizing the *fft* method, which performs a discrete Fourier transform and returns a new data set when a data set is provided as input. To obtain the correct frequency, Scipy's *fftfreq* method is employed. This method necessitates the number of samples and the period time and returns the FFT sample frequency points. Matplotlib is employed to visualize the FFT. The absolute value of the FFT is plotted, but only for half of the values in the new data set since the other half corresponds to the negative frequencies, which are not interesting in this thesis. The data from the FFT is normalized using $2/N$, where N is the number of samples, as demonstrated by Scipy's examples [The Scipy Community, 2023].

Since the data sets can be extensive, data collection is always done in multiples of two to simplify the computation for the FFT. As a result, the data transmitted from the Pico W is always in multiples of two.

4.2.3 Time-Frequency-domain analysis

For non-stationary signals, spectrograms were used to visualize the data in the time-frequency domain, since FFT is not optimal to perform on a non-stationary signal. The spectrograms is plotted with help of Matplotlibs method *specgram*. As parameters it needs the data set, the sample frequency and what unit to display the intensity, which in this case was dB (Decibel). In this case the data is always sampled with a frequency of 1600 Hz.

5

Vibration-Monitoring Tests and Experiments on IBAS2

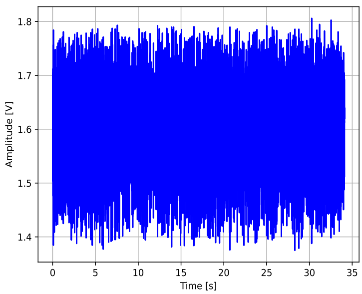
To evaluate the effectiveness of the monitoring system in identifying a normal machine operation and detecting faults, a series of tests and experiments was conducted that simulate normal machine operations and also some constructed abnormal behaviors. The resulting data from the operating machine was analyzed using various methods to evaluate the system's potential. This chapter provides a detailed description of the tests and experiments that were conducted, including their purposes, and how they were performed. The results are presented in this chapter and in Appendix A.

5.1 System Validation Using Controlled Vibrations

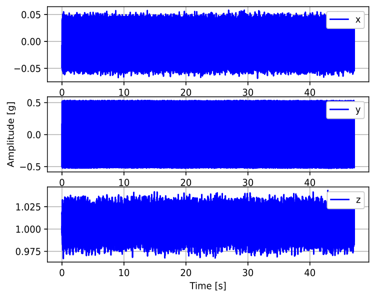
To validate the capability of the proposed data collection system in detecting vibrations, a validation test was performed using machinery capable of generating controlled vibrations. The testing equipment, located at the Axis facility, is designed to produce vibrations with predetermined amplitude and frequency, ensuring accurate and repeatable results. The machine is designed to generate vibrations on a cube, which is typically outfitted with cameras. However, for the present test, no cameras were attached to the cube.

The validation process was conducted through three separate tests, each of which featured a fixed amplitude of 0.5 g. The frequencies used in these tests were 50 Hz, 75 Hz, and 100 Hz. To validate the system further, it would have been preferable to use a vibration frequency exceeding 100 Hz, to validate more of the sensors bandwidth. However, the Axis team deemed it necessary to prioritize the safety of the equipment, therefore the test was limited to 100 Hz. In order to provide a more thorough evaluation, the frequencies of 50 and 75 Hz were also incorporated into the testing protocol. The cube vibrations were generated along a single axis, and to measure them, the digital sensor, ADXL355, was positioned on top of the cube, with its Y-axis running parallel to the vibration direction. The analog sensor, on the other hand, was placed on the side of the cube, with its single measurement axis parallel to the vibration direction. The sensors were mounted on the cube using tape, a method of adhesive mounting that, as discussed in Section 2.5.2, is not regarded as the optimal solution. Nevertheless, due to the inability to stud mount the sensors onto the cube, tape mounting was deemed to be sufficient for the present purpose.

Figure 5.1 visualizes the time-domain output obtained from the sensors when subjected to machinery vibrations at a frequency of 50 Hz. On the other hand, Figure 5.2 display the frequency-domain representation of the measured data from both the digital and analog sensors in this particular test. These figures clearly exhibit a distinct peak at the intended frequency of 50 Hz for both the digital and analog sensors. In all three tests, both the digital and analog sensors successfully detected the predetermined vibration frequency. However, it is worth noting that the results obtained from the analog sensor exhibit a higher level of noise, with frequencies exceeding those associated with the targeted vibration.



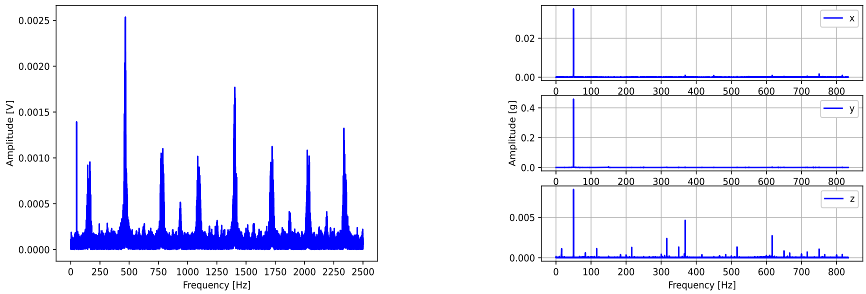
(a) Analog sensor.



(b) Digital sensor.

Figure 5.1 The time-domain representation of the measured vibrations from the controlled vibrations test at a frequency of 50 Hz and an amplitude of 0.5 g.

Furthermore, upon performing the FFT analysis on the data obtained from the digital sensor, the identified amplitudes at the frequencies of interest were determined to be 0.46 g for the 50 Hz test, 0.47 g for the 75 Hz test, and 0.49 g for the 100 Hz test. However, upon inspecting the time-domain representation of the data, as shown in Figure 5.1b, it becomes apparent that the vibration amplitude is closer to 0.5 g along the Y-axis, since it vibrates in that direction. This observation holds true for all three tests. For a comprehensive overview of the verification tests conducted, please refer to Appendix A, Section A.1.



(a) Analog sensor. **(b)** Digital sensor.

Figure 5.2 The Frequency-domain representation of the measured vibrations from the controlled vibrations test at a frequency of 50 Hz and an amplitude of 0.5 g. The results from the analog sensor corresponds to the Y-axis for the digital sensor.

5.2 Attempt to Reduce Noise in Analog Sensor

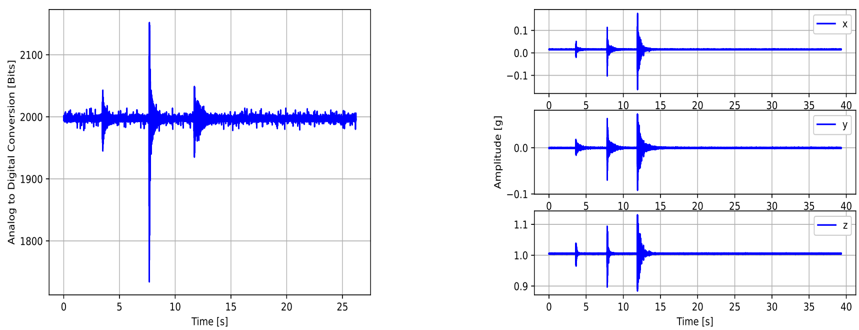
Based on the findings of the system validation tests outlined in Section 5.1, it was clear that the measurements obtained from the analog sensor exhibited a considerable amount of noise. This noise could potentially be attributed to the analog signals passing through the ADC in the Raspberry Pi Pico W, which is known to have certain limitations, as discussed in Section 4.1. Consequently, the converted data may not possess the desired level of quality. To address this issue, an effort was initiated to mitigate the noise.

As mentioned in Section 4.1, the data sheet provided by Raspberry Pi, for the Pico W, recommended the utilization of an external shunt voltage reference to optimize the performance of the ADC. Following this guidance, the LM4040 was selected as the appropriate shunt voltage reference, providing a steady voltage of 3V. The LM4040 was connected to the Raspberry Pi Pico W by positioning it between the ground and the ADC VREF pin, utilizing a resistance of 270 Ω. This configuration aimed to improve the accuracy and stability of the ADC readings.

In order to evaluate the potential improvement in the readings obtained from the analog sensor, two tests were conducted. The objective of the first test was to determine whether the analog sensor could detect three distinct levels of amplitude. To perform this test, the analog sensor was positioned on the chassis of the IBAS2, and a total of three knocks were delivered to the chassis next to the sensor. The force applied for each knock was incrementally increased. During this test, the digital sensor was also used. It was placed next to the analog sensor. The readings from the digital sensor were then considered for comparison with the measurements obtained from the analog sensor.

A second test was conducted with the intention of comparing the measurements obtained from both the analog and digital sensors. For this purpose, the sensors were positioned adjacent to each other on the cart, specifically at the location where the optical lens is typically placed. This placement was deemed suitable for capturing the vibrations resulting from the Z-translation of the alignment process. During the test, the sensors were employed to monitor the Z-translation, while the motor drove the setup up and down at the normal operating speed of the machine. This allowed for the collection of data regarding the vibrations generated during the Z-translation process. By simultaneously monitoring the vibrations using both the analog and digital sensors, a comparison could be performed of the two sensor types in capturing and measuring the Z-translation vibrations. In the system validation tests, the results obtained from the digital sensor were deemed to be accurate and reliable. As a result, the readings from the digital sensor served as a reference or benchmark against which the measurements from the analog sensor were compared.

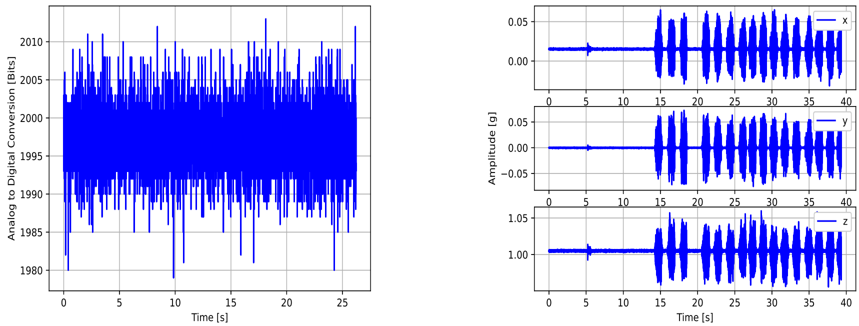
The results from the knocking next to the sensors are presented in Figure 5.3. It is evident that both the analog and digital sensors were able to detect the three distinct knocks delivered to the chassis. However, a notable discrepancy is observed in the results obtained from the analog sensor. In particular, as the force of the knocks increased for each hit, the expected outcome would be for the amplitudes measured by the analog sensor to also increase progressively. However, the results from the analog sensor show an inconsistency in this regard. The second hit exhibits a higher amplitude compared to the third hit, contrary to expectations. In contrast, the readings from the digital sensor align with the anticipated trend, with the third hit, which received the greatest force, showing the highest amplitude.



(a) Analog sensor. **(b)** Digital sensor.

Figure 5.3 Impact Testing with Increasing Force, as Sensors Recorded Three Knocks. The results from the analog sensor corresponds to the Z-axis for the digital sensor.

The results from the second test are depicted in Figure 5.4. These figures reveal that the digital sensor successfully detects the movement of the platform induced by the Z stepper motor. However, the analog sensor fails to accurately capture this movement, yielding noisy readings instead. Notably, the amplitude of this noise is comparable to or even greater than the actual vibrations produced by the movement. Consequently, the vibrations originating from common machine parts become indistinguishable within the pervasive noise detected by the analog sensor. Despite attempting to mitigate the noise by utilizing an LM4040 as a new reference voltage for the ADC in the Raspberry Pi Pico W, the reduction in noise from the analog readings remained insufficient. Consequently, it was determined that the analog sensor would not be further utilized in this project.



(a) Analog sensor. **(b)** Digital sensor.

Figure 5.4 Z-Translation drive results for noise evaluation. The results from the analog sensor corresponds to the Z-axis for the digital sensor.

5.3 Testing Methodology for Monitoring Machine Condition

This section details the different tests that were made. The tests were useful to evaluate the ability of the proposed system, to monitor the health of the machine and detect faults via vibration monitoring. During normal machine operations, data was collected to establish a healthy baseline, which was then used to compared to data gathered during periods of machine faults for potential future analysis. To assess the effectiveness of the monitoring system, constructed faults were introduced into the machine, and comprehensive analysis of the data collected during both healthy and unhealthy states was performed.

Accurate data collection requires the placement of sensors in close proximity to critical components within the machine. These critical components has been discussed in Section 3.4 and summarized in Table 3.1. As outlined in Section 2.5.2, the positioning of the sensor has a significant impact on the obtained results. While mounting the sensor using screws or bolts are the most precise approach, this is not a feasible option for a temporary implementation. Instead, tape and cable ties were used to mount the sensors. Only the digital sensor, ADXL355, was utilized in the tests presented in this section, as the measurements obtained from the analog sensor were found to be noisy.

5.3.1 Normal Machine Operations

5.3.1.1 Vibration Testing for Cart Movement. As detailed in Section 2.1, IBAS2 consists of two carts onto which the alignment system has been integrated. The individual carts can be maneuvered to distinct locations to facilitate diverse stages of the alignment process. A dedicated stepper motor controls the movement of each cart via a rotating gear mechanism, which enables the carts to traverse along a stationary circular gear rail by means of gear transmission. The gear that is rotated by the motor consists of 32 teeth, and during normal machine operations, the motor rotates at a rate of 37.5 revolutions per minute (RPM).

Tests were made to monitor and identify the characteristic vibrations resulting from the movement of carts within the machine. To this end, individual tests was conducted on each cart to facilitate a comparative analysis of their similarities and differences. In order to conduct the test, the cart was moved back and forth between the load position and the main alignment position at normal speed. Multiple iterations of this test were performed, with sensors placed at different locations to ensure a comprehensive investigation of the system's behavior. The objective of this approach was to identify the characteristic vibrations generated by the cart's movement. Two distinct sensor placements were employed for the tests. In one configuration, a sensor was positioned on each cart, as depicted in Figure A.27. Additionally, tests were conducted with one sensor placed directly on the gear rail, around which the cart moves, while the other sensor was positioned at the same location as previously described, on the right cart. By conducting a series of tests with varying sensor placements, the study aimed to improve the understanding of the system's dynamics and behavior. As previously stated, tape and cable ties were used to mount the sensors to the cart.

5.3.1.2 Vibration Testing for X-, Y- and Z-Translations. As outlined in Section 2.1, critical movements involved in the active alignment process are the translation executed in the X-, Y- and Z-direction. Each of these movements is controlled by a separate stepper motor that drives a linear actuator to facilitate the necessary motion. These precise movements enable accurate alignment and calibration of the system by allowing for the precise positioning of the sensors relative to the optical lens. During standard machine operations, the motors controlling the X- and Y-translation rotates at a rate of 125 RPM and the motor controlling the translation in Z-direction rotates with a speed of 200 RPM.

To identify and monitor the characteristic vibrations generated by the X-, Y- and Z-translations, tests were conducted on each individual cart responsible for its respective translation. These tests involved driving the motor and actuator back and forth at normal speed to characterise the vibrations resulting from each translation. The tests were performed for the X-, Y- and Z-translations. The sensor placement for the tests in X- and Y-direction is shown in A.28 and the sensor placement for Z-direction is shown in A.29.

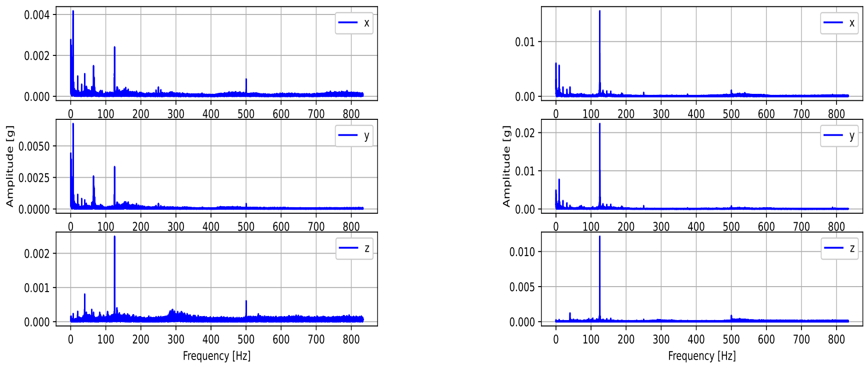
5.3.1.3 Vibration Testing for X and Y Tilting Movement. As mentioned in Section 2.1, the alignment system has the capability rotate the image sensor along the X- and Y-axis. To achieve this, two stepper motors, one for each rotation, are employed to control the movement involved in both rotations. The motors drives actuators, able to adjust its orientation. The motor drives at normal speed at 250 RPM. Tests were performed to identify the characteristic vibration pattern that is generated by the described movement. To test this, the motor was utilized to drive the actuator back and forth at normal speed. These tests were conducted independently for both rotations on each cart. The sensor placement for these test is shown in A.28.

5.3.1.4 Vibration Testing for Target stand. Section 2.1 mentions that the height of the target stand can be adjusted via a stepper motor. However, the engineers responsible for developing the machine have reported issues with misalignment of the different sides of the target stand due to contact with the carts as discussed in Section 3.4. Such misalignment can lead to a tilted target stand, which can negatively impact the calibration performed by the collimators used for alignment.

Tests were conducted to investigate the vibration pattern generated by the movement of the target stand. Apart from identifying the characteristic vibration pattern, these tests aimed to compare the vibration patterns of the different sides of the target stand. This was tested by comparing sensor data from both sides to determine whether the sides vibrate in the same way or not. The goal was to determine if the monitoring system can be used to detect whether the target stand is tilted or not. During these tests, the target stand was moving up and down as it does during normal operation. In one test the sensors were mounted next to each other to determine weather they measure the same values or not. In a second test the sensors were mounted on one side each.

5.3.2 Results from Monitoring Normal Machine Operations

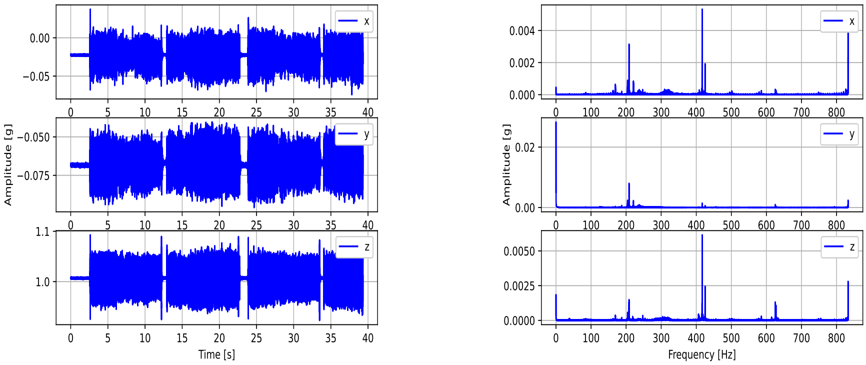
5.3.2.1 Results from Monitoring Cart Movement. The results obtained from monitoring the movement of the two carts during regular machine operations are presented in this section. Figure 5.5 shows the outcomes of the FFT analysis performed on the acceleration data acquired while driving the carts back and forth under normal condition, when the carts were equipped with one sensor each. The peak frequency observed is approximately 125 Hz for both carts. The amplitude of the left cart is smaller than for the right cart. In the alternative sensor placement configuration, a similar peak frequency of approximately 125 Hz was observed from both sensors. However, it is worth noting that the amplitude recorded by the sensor positioned on the gear rail was comparatively smaller than that of the sensor placed on the cart. For a visual representation of the results not included in this section, please refer to Section A.2 in Appendix A.



(a) Left cart. **(b)** Right cart.

Figure 5.5 Frequency-Domain Representation of Vibrations: Monitoring Cart Movement under Normal Operations.

5.3.2.2 Results from Monitoring X-, Y- and Z-Translations. This section presents the findings obtained from the conducted tests aimed at monitoring the three distinct linear translation movements that IBAS2 can generate. Figure 5.6 displays the result from monitoring the Y-translation on the left cart. Specifically, 5.6b shows the absolute values of the frequency domain coefficients of the acceleration data corresponding to the Y-motor translation. In all three axes, a noticeable frequency peak at 200 Hz is observed, despite its relatively small amplitude. Additionally, peaks at 400 Hz are found in both the X- and Z-axes. When measuring the Y-motor of the right cart, a peak of 200 Hz is also detected in the Z-axis. However, for the X- and Y-axes, the highest peaks were identified at 100 Hz.



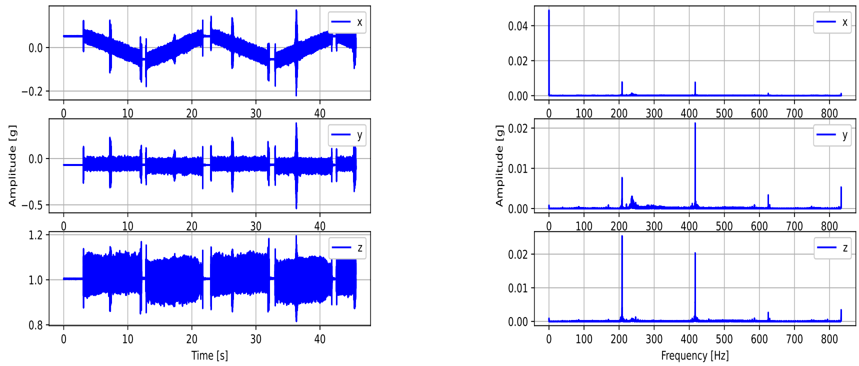
(a) Time-domain. **(b)** Frequency-domain.

Figure 5.6 Results from Monitoring Y-translation on left cart under Normal Operations.

From the monitoring of the X-translation, four distinct peaks were identified at approximately 100 Hz, 200 Hz, 300 Hz, and 400 Hz for each cart. Notably, the amplitude of the vibration measured in the sensor's X-axis, which was parallel to the translation, exhibited higher values for the right cart compared to the left cart.

The results obtained from the Z-translation analysis revealed peaks at approximately 170 Hz for the left cart. In contrast, a peak exceeding 650 Hz was observed for the right cart. Furthermore, it is noteworthy that the amplitude of vibrations originating from the right cart is significantly higher than that of the left cart, particularly during the beginning and ending phases of the translation. An additional observation was made regarding the operational noise, with the right cart emitting noticeably louder sounds compared to the left cart. Visual representation of the results from all three translations can be seen in Appendix A in Section A.3.

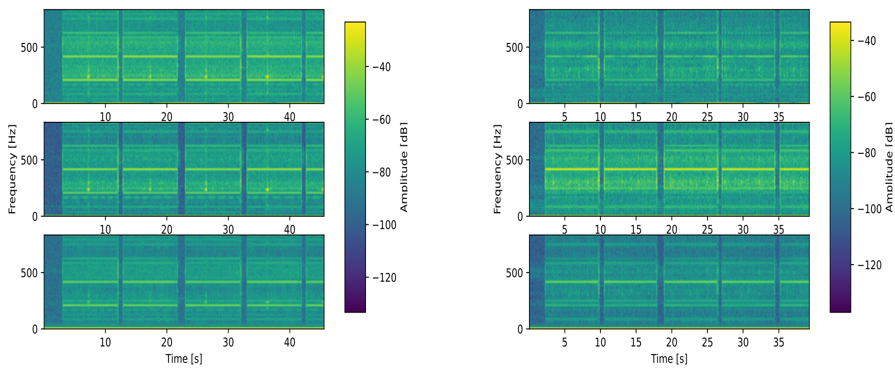
5.3.2.3 Results from Monitoring Tilt Movement. The findings of the test involving the X- tilt motor on the left cart are illustrated in Figure 5.7. When analyzing the measurements from the sensors Y- and Z-axes, peaks at around 200 Hz and 400 Hz was observed. However, as showed in the figure, the vibrations measured along the X-axis do not exhibit oscillations around a stationary line. This makes the frequency-domain representation of that data to fall in at 0 Hz. Therefore the data is also represented as a spectrogram for the gathered data of the x and y tilt motors. This can be seen in Figure 5.8 for the X-tilt movement. For the right cart a peak at around 400 Hz was found. Regarding the other tilt movement, around the Y-axis, frequency-domain peaks were identified at approximately 200 Hz and 400 Hz for both carts, with varying amplitude. Visual results of the X- and Y-tilt motor movements can be found in Section A.4 in Appendix A.



(a) Time-Domain.

(b) Frequency-Domain.

Figure 5.7 Results from monitoring the movement of X-Tilt on left cart under Normal Operations.

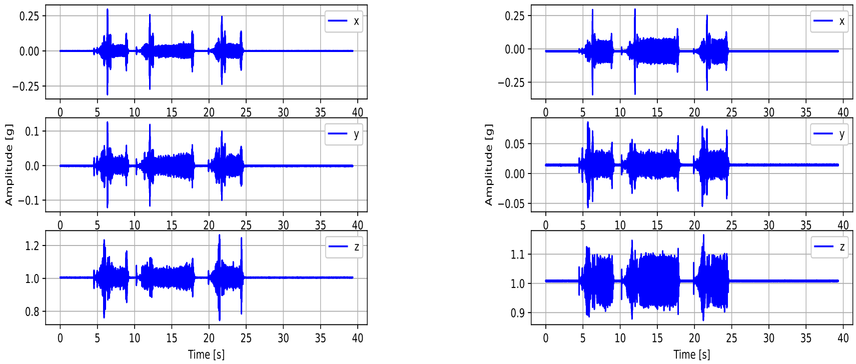


(a) The left X-tilt motor.

(b) The right X-tilt motor.

Figure 5.8 Results from monitoring the movement of the X-Tilt motors under Normal Operations presented in the time-frequency domain.

5.3.2.4 Results from Monitoring Target Stand. The outcome of monitoring vibrations from the target stand is showed in Figure 5.9. The figure illustrates the results obtained when two digital sensors were installed on different sides of the target stands. The result shows that both sides vibrate during the same duration but with varying amplitude. In the frequency-domain peaks at around 400 Hz are observed for both sides. The remaining results from monitoring the target stand can be seen in Section A.5 in Appendix A.



(a) Left side. **(b)** Right side.

Figure 5.9 Results from Monitoring the Target Stand under Normal Operations. One sensor is mounted on the right side and one on the left side of the target stand.

5.3.3 Abnormal Machine Operations

5.3.3.1 Investigating the Effect of Changing Cart Velocity. As stated in Section 3.4, the engineers at Axis Communication have reported that the rail along which the carts move sometimes causes increased friction. This can lead to unintended variations in the cart's velocity, potentially causing problems for the machine over time. To investigate whether the proposed monitoring system can detect changes in the cart's velocity, tests were conducted where the velocity parameter of the machine is set to both lower and higher values than the normal velocity. The goal of these tests were to determine whether the monitoring system is capable of detecting lower and/or higher velocities. The tests to investigate changes in the cart's velocity were conducted in the same manner as the tests described in 5.3.1.1. The motors were set to drive the carts back and forth between the load position and the main alignment position at a speed of 25 RPM for one test, and 50 RPM for the other test.

5.3.3.2 Testing the Response to Increased Resistance on the Carts. As mentioned in Section 3.4, Axis Communication engineers have reported that the carts may experience higher resistance than usual, causing them to stop unexpectedly. To validate the performance of the proposed monitoring system in such a scenario, a test was conducted where a force was applied to the cart while it is in motion. During the test, the cart was moving, at normal speed, back and forth between the load position and the main alignment position. A human was at one point pushing the cart until it comes to a stop. During this test, a sensor was mounted on the cart.

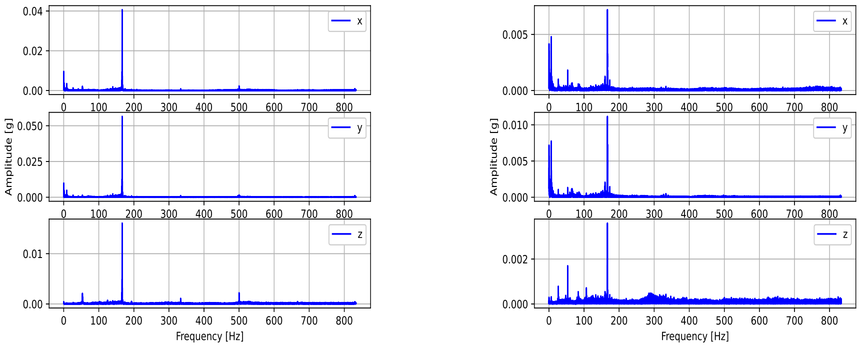
5.3.3.3 Tests to Identify Wear in X-Tilt Actuators. From the result in Section 3.4, it was found that experts at Axis Communications have observed that after a period of usage, the actuators controlling the X-tilt begin to wear out. It was believed to be caused in the movement path of the actuator, which is worn out by the beads used in the path to ensure smooth movement. The beads are thought to cause pits in the path. These pits were hypothesized to be located near the point where the system experiences zero tilt. This hypothesis was based on the fact that the beams mostly reside in this position, resulting in maximum scuffing along that particular path. Over time, these pits can become deeper, resulting in more vibrations and a rougher movement.

Tests were performed to investigate if the vibrations from these pits can be detected. The sensor was placed on the X-tilt actuators as shown in Figure A.28 in Appendix A. The actuators were then increasing and decreasing in degrees, from the minimal to the maximum value. This was done with the normal speed of 250 rpm for the tilt motors and also with a higher velocity of 375 rpm. Each respective cart was tested.

5.3.3.4 Testing the Importance of Sensor Mounting for Accurate Measurements. As discussed in Section 2.5.2, the way in which the sensors are mounted can have a significant impact on the quality of the measurements obtained. To assess the importance of proper sensor mounting, a test was conducted in which the sensor was not mounted at all. In this test the sensor was placed and not mounted on a cart. The cart was then driving back and forth between the load position and the main alignment position at the normal speed.

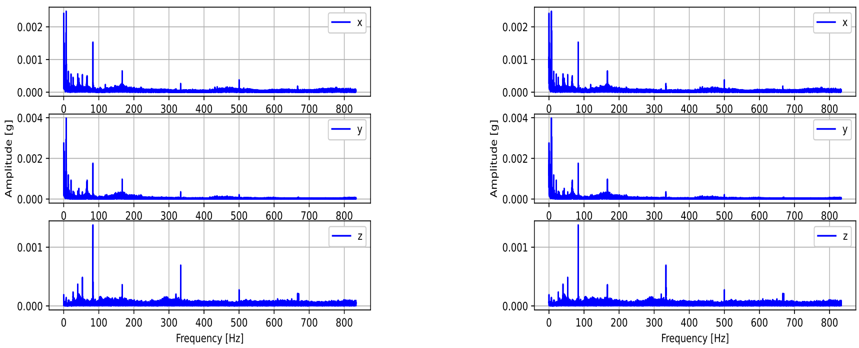
5.3.4 Results from Abnormal Machine Operations

5.3.4.1 Result of Changing Cart Velocity. The frequency-domain representation of the results obtained from driving the cart motors at 50 RPM, with one sensor placed on each cart, is presented in Figure 5.10. Notably, both carts exhibit a peak frequency of approximately 165 Hz. The results from driving the cart motors at 25 RPM are illustrated in Figure 5.11. In this case, the peak frequency observed for both carts is approximately 80 Hz. For the normal speed test, the identified peak frequency for the carts was 125 Hz. This finding indicates that the monitoring system is capable of detecting changes in cart velocity. Visual representation of the remaining results, involving changes in cart velocity, can be found in Appendix A, specifically in Section A.6.



(a) Right cart. **(b)** Left cart.

Figure 5.10 Frequency-Domain Representation of Vibrations: Monitoring Cart Movement with Higher Cart Velocity.



(a) Right cart. **(b)** Left cart.

Figure 5.11 Frequency-Domain Representation of Vibrations: Monitoring Cart Movement with Lower Cart Velocity.

5.3.4.2 Results from Increased Resistance on Cart. During the experiment where external resistance was applied to the cart while it was in motion, an interesting observation was made. The cart came to a halt due to the resistance but continued to exert effort to move until it was eventually turned off. Figure 5.12 illustrates the monitoring of this event in the time-domain. The resistance or force was applied approximately 35 seconds into the experiment. Notably, from the visualisation of the results all three patterns that occurred: normal driving, abrupt stop, and the moment when the machine was turned off are distinguished.

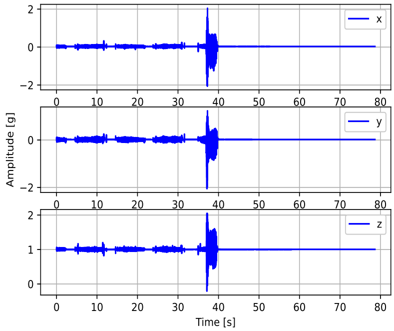
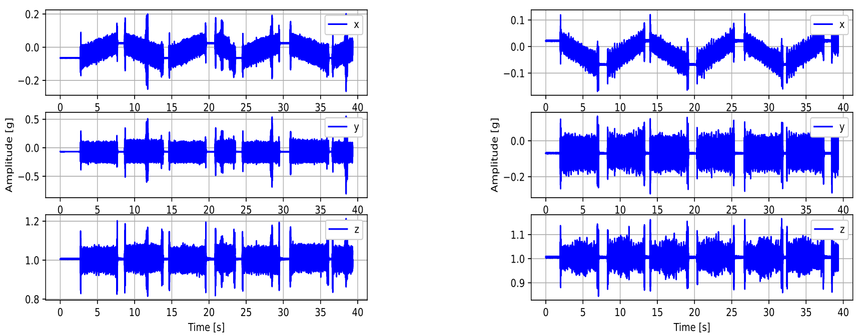


Figure 5.12 Results from Increased Resistance on Cart. A force was applied to the cart forcing it to stop.

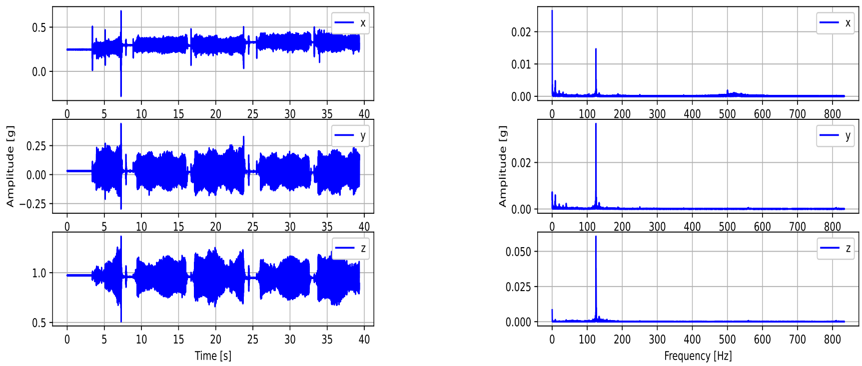
5.3.4.3 Results of Identifying Wear in X-Tilt Actuators. An attempt was made to detect possible pits in the movement path of the actuators responsible for the X-tilt. The monitoring system was employed to observe the X-tilt actuator. The acceleration over time is shown in Figure 5.13, which involved a higher velocity than usual. During the test, certain peaks emerged in the middle of the movement for the left cart. These peaks aligned with the hypothesis that wear would manifest in the region where no tilt is applied to the system. Furthermore, Figure 5.7a exhibited peaks at the same location for the left cart, supporting this observation. Consequently, these results suggest that the X-tilt actuator might be somewhat worn in the left cart. On the other hand, no distinct peaks were identified for the right cart. This lack of peaks could imply that the actuator is not worn out.



(a) Left cart. **(b)** Right cart.

Figure 5.13 Time-Domain Analysis: Measured Vibrations Captured during High-Speed Monitoring of X-Tilt Actuator Movement.

5.3.4.4 Results Obtained from Bad Mounting. The results of the test described in Section 5.3.3.4 are presented in Figure 5.14 for the left cart. The first figure displays the acceleration data in the time-domain, while the second figure shows it in the frequency-domain. In Figure 5.14b, a peak frequency of 125 Hz can be observed. Interestingly, this frequency matches the one recorded when the sensor was mounted using tape. However, the time-domain graph reveals that the vibration amplitude differs from the tests where tape was used. This suggests that proper mounting is crucial for obtaining accurate data on vibration amplitude, while still being able to identify the correct frequency.



(a) Time-domain. **(b)** Frequency-domain.

Figure 5.14 Result from monitoring the cart movement when the sensor was not mounted.

6

Discussion

The objective of this study was to explore the feasibility of implementing a machine monitoring system on the IBAS2 production machine. To achieve this, the machine structure was investigated to identify areas that were crucial for monitoring. The analysis revealed that the components responsible for active alignment were particularly important to monitor. After evaluating various monitoring approaches, it was concluded that measuring the machine's vibrations, generated from the alignment system, showed promising potential as a monitoring method. Based on the findings from the analysis, the study focused on deploying a vibration monitoring system inside the machine to gather useful data on its condition. Accelerometers were utilized to collect the vibration data and to evaluate the performance of the machine's alignment system. Tests were conducted to identify the natural vibrations generated during normal machine operations. The results showed that the system was able to recognize distinct patterns in the vibrations generated from the machine for the different components. This allowed a baseline to be established for normal machine behavior. A baseline that could be used to detect deviations. In addition, tests were conducted to evaluate how the monitoring system responded to abnormal machine behavior. The results showed that the system was able to identify deviations in the operating speed of the machine. Also, it is hypothesized that the system was capable of detecting wear in the machine's components. These findings suggest that the vibration monitoring system is a potential tool for detecting and diagnosing machine issues, helping to prevent unplanned downtime and reduce maintenance costs.

In this chapter, an analysis and interpretation of the research findings, discussing their significance and implications for theory and practice, is provided. Finally, a discussion of the limitations of the study and some recommendations for future research is given.

6.1 Interpretation of the results

Engineers at Axis highlighted some typical issues that the machine has encountered and helped the study pinpointing the essential components that must be functional at all times for the machine to give a result that is expected. The result of this discussion landed in that the alignment system is the most important part of the machine and that it has to function at all time. Upon examining the alignment system, it became apparent that multiple components are utilized for proper alignment. This investigation deemed each of these individual components to be critical, implying that all vital parts susceptible to mechanical wear were accounted for in the machine. However, while the previous discussion emphasized the criticality of the components used during alignment, it is important to note that monitoring the wear of machine components is not the only way to determine the status of the machine. Other parts of the machine, such as the control system or electrical load, can also provide valuable information on its overall condition. Therefore, it is necessary to consider various factors and approaches when assessing the health of the machine.

The method chosen to determine the status of the machine in this study was through monitoring vibrations. This decision was based on the assumption that the alignment system components would generate natural vibrations during motion, which can be used as a baseline for measurement. The tests conducted during normal operation confirmed that each component did generate a distinct natural vibration pattern, indicating that measuring vibrations could be a suitable way to monitor machine health. However, it should be noted that there may be other physical quantities to monitor that could potentially provide information about the machine's status. For instance, measuring the temperature could be a viable option, as many machine failures generate heat. However, the challenge of locating the heat source prevented further investigation in this study. Furthermore, it would be strategically wise to monitor the condition of the stepper motors since they control all motion in the machine. However, this study did not explore the option of monitoring the back-EMF, as it would require replacing the drivers controlling the stepper motors.

In this study, two accelerometers were chosen to measure vibrations in the machine. The digital ADXL355 accelerometer, with three axes, was found to work well and provide reliable data. The bandwidth of the digital sensor, 1000 Hz, was sufficient to detect the vibration frequencies present in the machine. However, to further validate the system, it would have been beneficial to compare measurements from both the digital and analog sensors. This would ensure that both sensors detect the same frequencies and amplitudes and accurately capture all signals.

The analog sensor used in this study, the Tokin VS-BV203-B, is capable of measuring frequencies up to 15,000 Hz with excellent sensitivity, making it a suitable candidate to capture a wider bandwidth of machine vibrations. However, as discussed in Section 5.2, the sensor produced extensive noise, and attempts to reduce the noise to a usable level were unsuccessful. It was initially believed that the analog-to-digital conversion process occurring within the microcontroller might have contributed to the noise. An attempt was made to stabilize the ADC by using an external voltage reference, but this approach did not yield the desired results. External interference from electromagnetic fields or mechanical vibrations is a common cause of noise in measurement data obtained from analog accelerometers. Such interference can generate unwanted signals that distort the measurement data, which may be the reason for the noise observed in this study.

The monitoring system's results for normal conditions are presented in Section 5.3.2. These results indicate that the machine generates specific vibration patterns and frequency peaks that correspond to particular movements, which can then serve as a baseline for detecting deviations from normal conditions. In addition to detecting specific vibration patterns, a comparison of the results from both carts, each holding one alignment system, is explored. The results from Section 5.3.2.1 reveals that both carts exhibit a peak at the same frequency, but the measured vibration amplitude differs between them. The same holds for the X- and Y-translation, where the peak frequencies match but the amplitudes differ. One possible explanation for the difference in amplitude could be the variation in the mountings of the sensors. A poorly mounted sensor may not sense the vibration amplitude as well as a properly mounted one, resulting in varying amplitude measurements between carts and test rounds. The study showed that the monitoring system is capable of detecting the same frequency generated from the cart movement even when the sensor is not mounted properly, but with a smaller amplitude. This suggests that the difference in amplitude between the carts is related to how well the sensor is mounted to the cart. However, it is also possible that differences exist between the carts and their components, such as varying operating hours and installation methods, which could account for some of the variation observed in the results obtained from monitoring their components. Despite these differences, both alignment systems function well for manufacturing products.

The evaluation of the results from monitoring the Z-translation reveals significant differences between the different carts. The results exhibit a large variation, and there are no shared frequency peaks between the two individual z-translations. During the tests, the right translation produced a sound significantly higher than the left, and it is hypothesized that the sound came from a source that may have an impact on the results. However, it is unclear what causes the sound and whether it affects the alignment quality. Despite this, the monitoring system can detect the variations, and with clear data on how a properly functioning Z-motor should sound and vibrate, deviations can be detected.

Although the results show variations when comparing the corresponding components of the two carts, the data remains consistent within each round when comparing data gathered from the same part. This indicates that a normal vibration pattern for each part of the alignment system can be established. Therefore, when implementing a real monitoring system on the IBAS2, it may be more appropriate to focus on building a baseline for each individual component on both carts, rather than comparing corresponding components on the carts to each other.

It's important to consider that there may be differences in the vibration patterns of a machine when it's brand new compared to after a few years of use. When using historical data to understand the machine's current condition, it's necessary to determine how far back in time the data should be compared. While the vibration patterns may have changed over the machine's lifetime, it may still function properly. Therefore, it may be more effective for the monitoring system to focus on detecting recent changes rather than changes that have occurred over a longer period of time. However, analyzing historical data over a longer time span can still be valuable in understanding how the machine has performed over time.

Some of the results gathered during testing show unexpected peaks in the frequency-domain, which are likely caused by the test setup and signal processing. These peaks are primarily observed in the translations along the X-, Y-, and Z-directions. During all tests, the motor that drives the movement being investigated is moved back and forth between its start and end positions. At each position, it briefly stops before moving in the opposite direction. This stop-and-go movement is included in the FFT analysis, which may lead to extra peaks in the results. To avoid this issue, a more suitable approach would be to perform the FFT only on the measured data while the selected object is in motion, thereby eliminating the noise caused by the stops.

Section 5.3.4 presents results obtained from abnormal conditions. One of the tests involved adjusting the velocity of the cart, which led to a change in the frequency peak. When the friction between the carts and the rail increases, the velocity may change. When comparing the results of this test to those obtained under normal conditions, it shows that the frequency peaks are shifted, as a consequence of the velocity change.

If the stepper motor driving the cart is subjected to a certain amount of force, it may stop moving and start vibrating at its current position due to a step loss in the motor. This is also a phenomenon that has been reported to occur during normal operation at production sites. In Figure 5.12, a significant increase in amplitude can be observed after approximately 36 seconds, when the cart stops and vibrates at its current position. Prior to stopping, the cart moves back and forth between its maximum and minimum positions. There is a clear difference in amplitude between the normal movement and when it stops. The system was shut down at 40 seconds, which can also be seen as the amplitude variation becomes small. Based on the results presented in the study, it can be concluded that the monitoring system deployed has the capability to accurately detect the fault caused by the stepper motor losing its steps.

Based on the results presented in the study, there might also be signs of wear in the machine under investigation. Specifically, during the X-tilt movement of the left cart, there is a repeating change in amplitude in the middle of its movement. This change occurs in the middle of every X-tilt movement, which suggests that it is not due to a fault in the test setup or signal processing. The home position for the x-tilt actuator is at 0 degrees, which is in between the two positions the actuator was driven under the tests investigating it. The observed repeating change of amplitude in the middle of the left cart's X-tilt movement corresponds with the wear location that engineers at Axis suspected. Based on the location of the repeating change of amplitude in the middle of the left cart's X-tilt movement, which corresponds with the suspected wear location by Axis engineers, it is possible that this amplitude change is caused by pits or other wear in the path of the actuator.

Axis engineers provided an old X-tilt actuator that was previously used in a machine and deemed defective. Upon manually moving the actuator, a noticeable roughness or jaggedness was felt in the movement. However, this sensation was not detected when manually moving the actuator on the left cart. Therefore, it cannot be concluded with certainty whether the observed amplitude change is due to pits in the actuator's path or not. However, upon comparing the left and right actuators, it can be observed that the right actuator shows no signs of wear in the middle of its movement. This suggests that the left X-tilt actuator is in a worse state compared to the right one.

The data obtained from the digital sensor's X-axis during X-tilt movement and Y-axis during Y-tilt monitoring exhibit non-stationary behavior, which affects the frequency-domain analysis. As shown in Figure 5.7b, a peak at 0 Hz in the frequency domain is observed for the X-axis, which is due to FFT analysis on a non-stationary signal. To handle this issue, the data can be processed and visualized in the time-frequency domain, such as using a spectrogram. In Figures 5.8 and A.16, spectrograms of the X- and Y-tilt motors are presented, respectively. The intensity of the color in the spectrogram represents the amplitude of the vibrations. It is evident that the same frequency peaks as in the stationary signals can be observed in the non-stationary signals. This is in contrast to the FFT results in the previous plot, where the frequency peaks were not clearly visible for the non-stationary signal.

In Figure 5.7b, a frequency peak can be observed at around 800 Hz, which is the maximum frequency that the monitoring system can measure. This suggests that the frequency range used may be too small, and a larger frequency range may be required to accurately display the peak. This can be achieved by altering the sampling period when acquiring data from the accelerometer. During the test, the sampling frequency is approximately 1600 Hz, which enables detection of frequencies ranging from 0 Hz to around 800 Hz. The sensor has a bandwidth of 1000 Hz, and thus it may be possible to accurately represent the detected peak of the Y-tilt motor by adjusting the sampling period time. The reason for using a sampling frequency of 1600 Hz was to ensure a fixed period time or sampling frequency. Collecting data at higher sampling frequencies often resulted in irregularities in the time it took to gather a single sample, leading to non-constant period times.

The target stand was evaluated during the tests under normal conditions, and two sensors were mounted on each side to measure acceleration data. The obtained data was found to be quite similar, although slight differences in mounting may have led to small variations. However, when adjusting the height of the target stand, the vibration pattern observed on both sides was similar. This suggests that digital sensors could be used to determine whether the movement of each side of the target stand has been performed similarly.

6.2 Limitations

This thesis work has encountered certain limitations that have constrained its scope. Firstly, the monitoring system was tested in a laboratory setting instead of the actual manufacturing environment where the products are produced. This raises doubts about whether the sensors used would be reliable in an environment with more ambient noise. For instance, trucks passing by the machine could cause it to vibrate differently. The second limitation of this thesis work is that the sensors were mounted temporarily between tests, resulting in inconsistent mounting quality between tests. This may have resulted in varying data and affected the accuracy of the results obtained. For improved accuracy of results, it is recommended to mount the sensors in close proximity to the vibrating objects permanently. Although the sensors can detect vibrations from larger distances, the optimal amplitude measurement can be obtained by mounting them closer.

Furthermore, the machinery under test could not be modified during this thesis, which limited the ability to permanently mount sensors. This also impacted the type of fault conditions that could be introduced to the machine, as tests were selected to avoid causing harm to the machine's health. To further validate the effectiveness of the monitoring system in detecting faults, it would be beneficial to monitor a machine with known problems, such as shaft misalignment, loose bolts, or heavy wear on machine components. By analyzing the data collected from the monitoring system in this scenario and comparing it to that of a healthy machine, the system's ability to detect faults can be assessed.

In addition, due to the required modifications with the control system, it was not feasible to directly monitor the stepper motors. However, in a future implementation, it may be beneficial to monitor additional parameters, including the stepper motors, given their significant role in the machine's operation.

6.3 Future Work

If further investigation into implementing a machine monitoring system focusing on measuring vibrations in the IBAS2 is to be conducted, several considerations should be made. Firstly, the sensor used to measure the system should be evaluated further. Although the digital sensor used in this thesis managed to detect almost all vibration frequencies present in the machine, it may be necessary to choose a sensor with a higher bandwidth to ensure accurate detection of all signals. The analog sensor has a wider bandwidth and may be suitable for the task, but the extensive noise in its measurements must be removed. A recommended sensor choice would be a three-axis vibration sensor with a bandwidth higher than 1000 Hz. If using the Pico W as the microcontroller with an analog sensor, an external ADC may be necessary.

Additionally, strategic sensor placement is crucial to ensure accurate and reliable readings. If the sensors are to be permanently installed in the machine, it is recommended to conduct an investigation to determine optimal sensor placement for detecting vibrations. Based on this study, it appears that the X-translation, Y-translation, X-tilt, and Y-tilt on one cart can be monitored using the same sensor. However, separate sensors are necessary for monitoring the Z-translation, cart movement, and target stand to obtain sufficient readings. Moreover, if the sensors are permanently installed, stud mounting should be utilized to ensure consistent measurements between tests.

To utilize vibration as a quantity for monitoring Axis production machines, a more comprehensive database of normal conditions is required. This master's thesis has established a small baseline to investigate this possibility. With a larger dataset of normal conditions, a neural network, like an autoencoder, can be trained to identify abnormalities. Ideally, training the neural network should only require data from healthy conditions, eliminating the need for any changes or manipulations in the monitored machine. However, unhealthy data is still necessary to validate the neural network's performance, but not to the same extent as for healthy conditions.

Tests can be performed to evaluate the neural network's ability to make a decision based on unhealthy data or data that differs from the healthy trained data. These tests may involve introducing known faults to the machine and monitoring the output of the neural network to see if it correctly identifies the abnormal behavior. By testing with different fault types and severities, the performance of the neural network can be evaluated and improved. Overall, the goal is to develop a robust monitoring system that can accurately detect abnormal behavior and provide early warnings to prevent potential machine failure.

Testing the system in a real production environment would be crucial to validate its effectiveness in detecting abnormalities in actual operating conditions. This would also allow for an assessment of how much the surrounding noise, in the production environment, affects the measurements.

In a real production environment, the system would be exposed to a range of different vibrations and sounds that may not have been present in the lab environment where the system was tested initially. For instance, the presence of nearby machinery, conveyor belts, or even foot traffic could create additional noise that may interfere with the system's ability to detect abnormalities accurately.

To account for this, the system should be tested extensively in the actual production environment, with careful consideration given to the placement of the sensors to ensure they are optimally positioned for accurate readings. Additionally, the system should be calibrated to account for any noise or interference in the production environment, and any necessary adjustments made to improve its performance in detecting abnormalities.

By testing the system in a real production environment, any limitations or areas for improvement can be identified and addressed, making it possible to develop a more robust and reliable monitoring system for Axis production machines.

7

Conclusion

The aim of this thesis was to explore the potential benefits of a machine monitoring system for Axis. Specifically, the research delved into the IBAS2 to identify critical components that could be monitored. It also investigated whether suitable sensors exist for monitoring these components and whether it is feasible to implement a machine monitoring system in the IBAS2 to collect data on machine health. Furthermore, an investigation was conducted to determine if the collected data could establish a baseline for normal conditions and detect any deviations from this normal state.

According to the study, the critical components in the machine being investigated are those involved in the alignment process, which control movements on a scale of micrometers. These components share a common feature in that they all generate movement, which led this research to conclude that vibrations is the primary monitoring parameter. To measure these vibrations, the study suggests using an accelerometer, as all moving elements in the machinery can generate vibrations that can be detected using this device. The deployed monitoring system has successfully established a small baseline for the machine's healthy state based on measured vibrations. The vibrations generated by each component exhibit a repetitive pattern, and adjustments made to the component configurations are reflected in the measurements. Hence, the researchers believe that a monitoring system based on vibrations can be utilized in the IBAS2 to identify variations from normal conditions in the critical components.

It is important to acknowledge the limitations of this study. Firstly, the machine under investigation was located in a laboratory, rather than a production site, which limits the generalizability of the findings to real-world industrial settings where environmental conditions may affect the performance of the monitoring system. Additionally, adjustments could not be made to the machine and only temporary solutions could be implemented to monitor its status, and no real data on faulty conditions were collected. Future research should consider conducting similar studies in industrial settings to address these limitations.

In the future, it may be advisable to consider the utilization of an artificial neural network. Such a network could employ acceleration data to determine whether a machine requires maintenance or not. The ANN could benefit from incorporating more of the described features, such as peak and RMS measurements in the time domain. For instance, if the peak value exceeds a certain threshold, it may indicate an issue with the machine. Similarly, changes in vibration frequency in the frequency domain are worth exploring. To obtain valuable training data, it is important to improve the accuracy of the measurements.

In order to achieve greater accuracy, it would be necessary to mount the sensors at a fixed location. Additionally, a wider range of sensors could be employed to capture a broader frequency spectrum and to verify amplitudes and frequencies from multiple sensors. It would also be worthwhile to investigate whether digital or analog sensors are more suitable for a real-world implementation.

In conclusion, the successful implementation of a monitoring system in the IBAS2 has demonstrated the feasibility of using vibrations as a primary parameter for identifying variations from normal conditions in critical machine components. While limitations exist, future research can build on these findings and explore the use of artificial networks and a larger variety of sensors to enhance the monitoring system's effectiveness. By improving the reliability of the machine monitoring system, it could reduce the risk of unexpected production stops and product recalls, leading to more efficient and safer industrial operations. As such, this thesis represents a step forward in the quest for smarter and more effective production at Axis Communications.

Bibliography

Analog-Devices (2023). *Eval-adxl355-z*. Available at: https://www.mouser.se/ProductDetail/Analog-Devices/EVAL-ADXL355Z?qs=vcbl%252BK4rRld3rqhNJZ6Vfg%3D%3D, visited on 2023-03-12.

Automation24, I. (2020). *Understanding the key elements for machine condition monitoring*. URL: https://www.manufacturingtomorrow.com/article/2020/06/understanding-the-key-elements-for-machine-condition-monitoring/15359, visited on 2023-04-02.

Brown, S. (2021). *Machine learning, explained*. URL: https://mitsloan.mit.edu/ideas-made-to-matter/machine-learning-explained.

Er, P. V., C. S. Teo, and K. K. Tan (2016). "Approach towards sensor placement, selection and fusion for real-time condition monitoring of precision machines". *Mechanical Systems and Signal Processing* **68-69**, pp. 105–124. ISSN: 0888-3270. DOI: 10.1016/j.ymssp.2015.07.008.

Goyal, D. and B. S. Pabla (2016). "The vibration monitoring methods and signal processing techniques for structural health monitoring: a review". *Archives of Computational Methods in Engineering* **23**:4, pp. 585–594. ISSN: 1886-1784. DOI: 10.1007/s11831-015-9145-0.

Hale, G. (2007). "Intech survey: predictive maintenance top technology challenge in 2007". *InTech*.

Haq, S. U., C. Schartner, and M. T. Moorthy (2021). "Understanding alternative methods of machine online condition monitoring; an investigation based on years of experience and field case studies". In: *2021 IEEE Electrical Insulation Conference (EIC)*, pp. 30–33. DOI: 10.1109/EIC49891.2021.9612306.

Hashemian, H. M. (1998). "Advanced instrumentation and maintenance technologies for nuclear power plants".

Hashemian, H. M. (2011). "State-of-the-art predictive maintenance techniques". *IEEE Transactions on Instrumentation and Measurement* **60**:1, pp. 226–236. DOI: 10.1109/TIM.2010.2047662.

Iliyas Ahmad, M., Y. Yusof, M. E. Daud, K. Latiff, A. Z. Abdul Kadir, and Y. Saif (2020). "Machine monitoring system: a decade in review". en. *Int. J. Adv. Manuf. Technol.* **108**:11-12, pp. 3645–3659.

Instruments, N. (2016). *White paper engineer's guide to accurate sensor measurements*. URL: `http://sezaitaskin.cbu.edu.tr/wp-content/uploads/2016/09/25188_Sensor_WhitePaper_IA.pdf`.

KEMET-Electronics-Corporation (2023). *Vs-bv203-b*. Available at: `https://www.mouser.se/datasheet/2/212/1/KEM_SE0209_VS-1830215.pdf`, visited on 2023-03-12.

Liu, Z., T. Yuan, X. Zhou, X. Yuan, Y. Wang, and X. Zhang (2020). "Research on predictive maintenance technology of stepping motor based on load value analysis". In: *2020 Chinese Automation Congress (CAC)*, pp. 7122–7125. DOI: `10.1109/CAC51589.2020.9327408`.

Measuring vibration with accelerometers (2022). en. `http://www.ni.com/white-paper/3807/en/`. Accessed: 2023-1-18.

Mehdi, K. (2021). "Review work on automatic monitoring systems in machining process: means and methods". In: *2021 12th International Conference on Mechanical and Aerospace Engineering (ICMAE)*, pp. 505–510. DOI: `10.1109/ICMAE52228.2021.9522429`.

Mobley, R. K. (2002). "7 - vibration monitoring and analysis". In: Mobley, R. K. (Ed.). *An Introduction to Predictive Maintenance (Second Edition)*. Second Edition. Plant Engineering. Butterworth-Heinemann, Burlington, pp. 114–171. ISBN: 978-0-7506-7531-4. DOI: `https://doi.org/10.1016/B978-075067531-4/50007-5`. URL: `https://www.sciencedirect.com/science/article/pii/B9780750675314500075`.

Mohd Ghazali, M. H. and W. Rahiman (2021). "Vibration analysis for machine monitoring and diagnosis: a systematic review". en. *Shock Vib.* **2021**, pp. 1–25.

Motaghare, O., A. S. Pillai, and K. Ramachandran (2018). "Predictive maintenance architecture". In: *2018 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC)*, pp. 1–4. DOI: `10.1109/ICCIC.2018.8782406`.

Murphy, C. (2020). *Choosing the most suitable predictive maintenance sensor*. URL: `https://www.analog.com/en/technical-articles/choosing-the-most-suitable-predictive-maintenance-sensor.html`, visited on 2023-01-18.

Park, P., P. D. Marco, H. Shin, and J. Bang (2019). *Fault detection and diagnosis using combined autoencoder and long short-term memory network*. URL: `https://www.mdpi.com/1424-8220/19/21/4612`.

Pi Ltd, R. (2023). *Raspberry pi documentation*. URL: `https://www.raspberrypi.com/documentation/microcontrollers/raspberry-pi-pico.html`, visited on 2023-04-02.

Raspberry-Pi (2023). *Raspberry pi pico w*. Available at: https://www.electrokit.com/en/product/raspberry-pi-pico-w/, visited on 2023-03-14.

Su, H. and K. T. Chong (2007). "Induction machine condition monitoring using neural network modeling". *IEEE Transactions on Industrial Electronics* **54**:1, pp. 241–249. DOI: 10.1109/TIE.2006.888786.

The Scipy Community, N. (2023). *Fourier transforms (scipy.fft)*. URL: https://docs.scipy.org/doc/scipy/tutorial/fft.html, visited on 2023-04-02.

Trinamic, A. (2023). *Stallguard and coolstep*. URL: https://www.trinamic.com/technology/motor-control-technology/stallguard-and-coolstep/, visited on 2023-02-14.

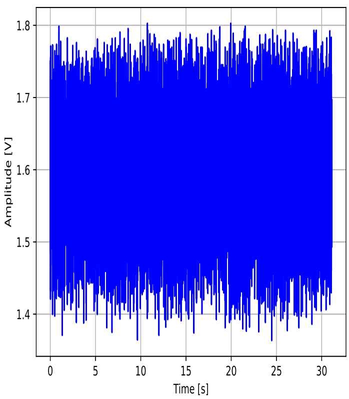
Zhou, W., T. G. Habetler, and R. G. Harley (2007). "Bearing condition monitoring methods for electric machines: a general review". In: *2007 IEEE International Symposium on Diagnostics for Electric Machines, Power Electronics and Drives*, pp. 3–6. DOI: 10.1109/DEMPED.2007.4393062.

A

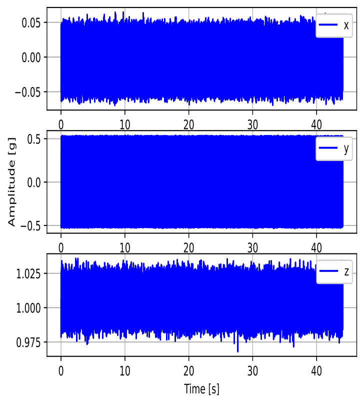
Appendix

A.1 System Validation Using Controlled Vibrations

The precision of the monitoring system was evaluated through experimentation using the available vibration equipment at Axis. Specifically, the system's accuracy was assessed by measuring a constant frequency generated by a vibrating cube in the laboratory. The cube was set to oscillate at 50 Hz, 75 Hz, and 100 Hz with an amplitude of 0.5 g. To measure the vibrations, the digital sensor was positioned to detect vibrations along its y-axis, while the analog sensor was situated to detect vibrations along its z-axis. The results of the experiment for the 75 Hz and 100 Hz tests are presented in Figures A.1 through A.4.

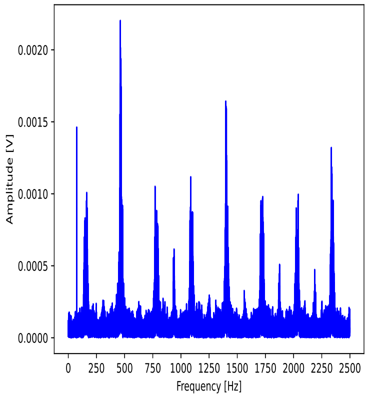


(a) Analog sensor.

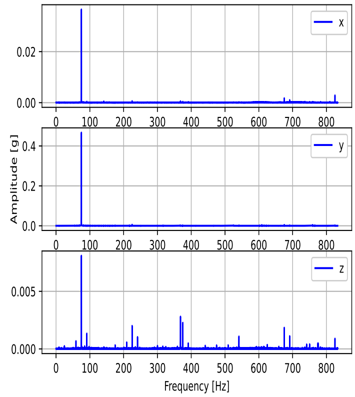


(b) Digital sensor.

Figure A.1 The time-domain representation of the measured vibrations from the controlled vibrations test at a frequency of 75 Hz and an amplitude of 0.5 g.

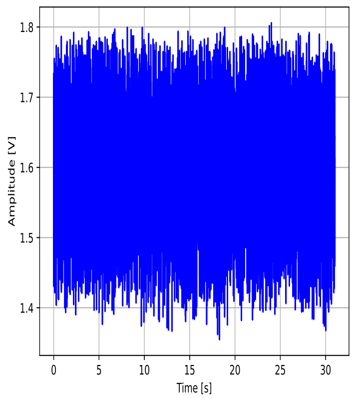


(a) Analog sensor.

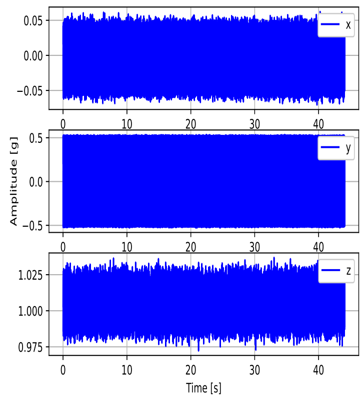


(b) Digital sensor.

Figure A.2 The frequency-domain representation of the measured vibrations from the controlled vibrations test at a frequency of 75 Hz and an amplitude of 0.5 g. The results from the analog sensor corresponds to the Y-axis for the digital sensor.

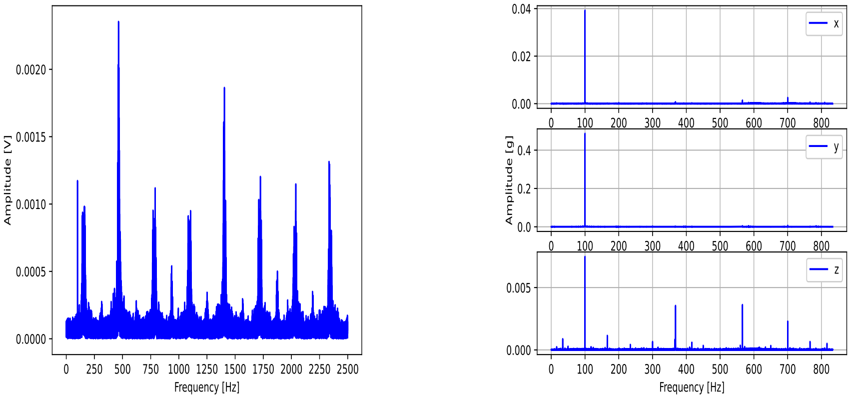


(a) Analog sensor.



(b) Digital sensor.

Figure A.3 The time-domain representation of the measured vibrations from the controlled vibrations test at a frequency of 100 Hz and an amplitude of 0.5 g.

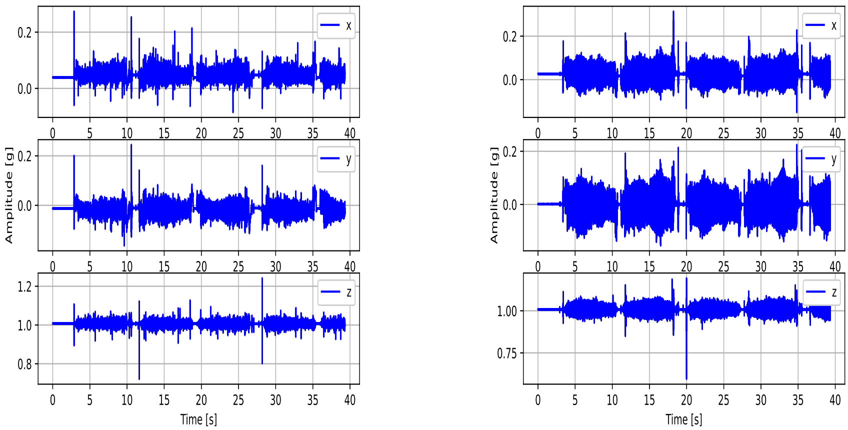


(a) Analog sensor. **(b)** Digital sensor.

Figure A.4 The frequency-domain representation of the measured vibrations from the controlled vibrations test at a frequency of 100 Hz and an amplitude of 0.5 g. The results from the analog sensor corresponds to the Y-axis for the digital sensor.

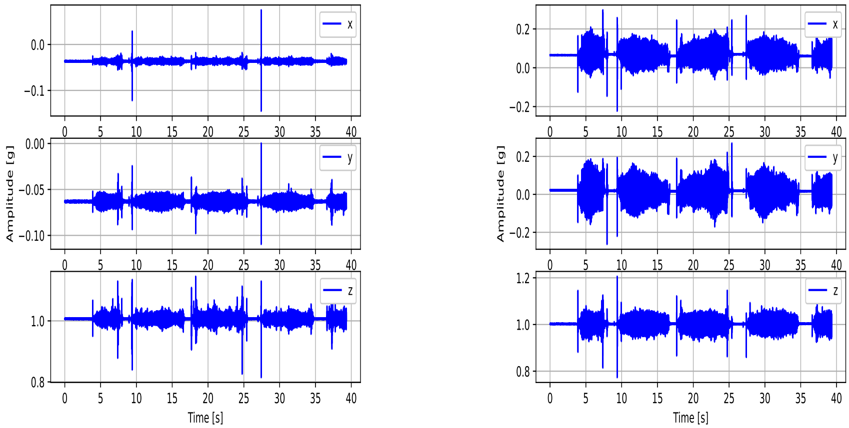
A.2 Monitoring Cart Movement under Normal Operations

Tests with the objective of monitoring and identifying the characteristic vibrations generated when driving the carts under normal machine conditions were conducted. Figure A.5 showcases the vibration data captured in the time-domain, where a sensor was placed on each cart. Figure A.6 shows the measured vibrations of the cart movement when one sensor was placed on directly on the gear rail and the other sensor on the right cart. The frequency-domain representation on the of this sensor configuration is showed in Figure A.7.



(a) Left cart. **(b)** Right cart.

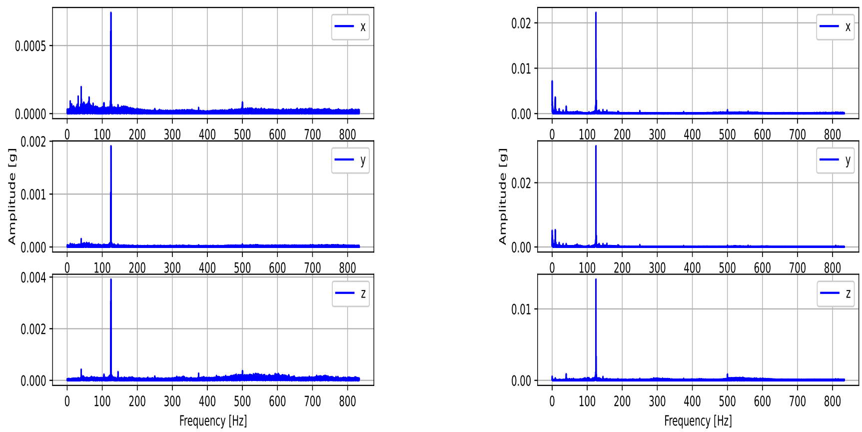
Figure A.5 Time-Domain Representation of Vibrations: Monitoring Cart Movement under Normal Operations.



(a) Data captured from sensor placed on the rail.

(b) Data captured from sensor placed on right cart.

Figure A.6 Time-Domain Representation of Vibrations: Monitoring Cart Movement under Normal Operations, one sensor placed on the circular rail.

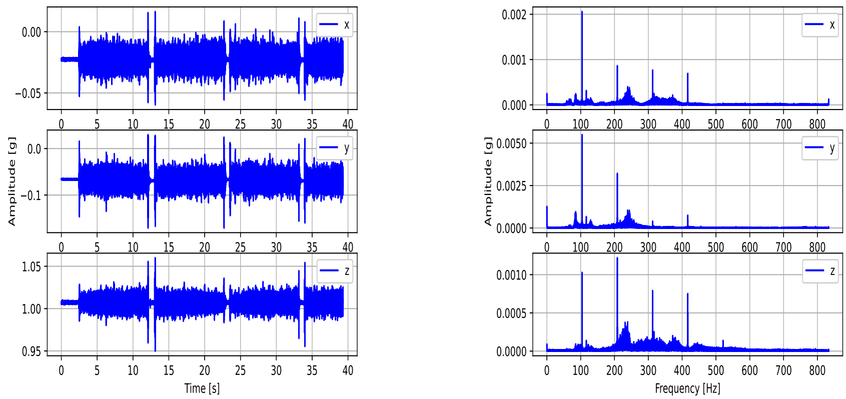


(a) Data captured from sensor placed on gear.

(b) Data captured from sensor placed on right cart.

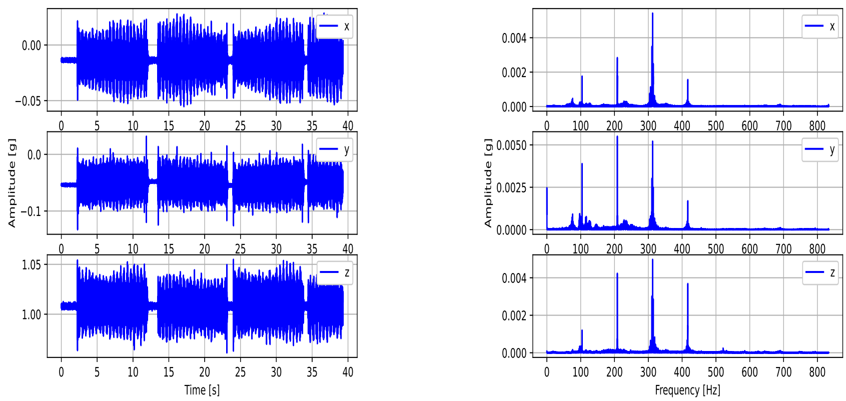
Figure A.7 Frequency-Domain Representation of Vibrations: Monitoring Cart Movement under Normal Operations, one sensor placed on the circular rail.

A.3 Monitoring X-, Y- and Z-Translations under Normal Operations



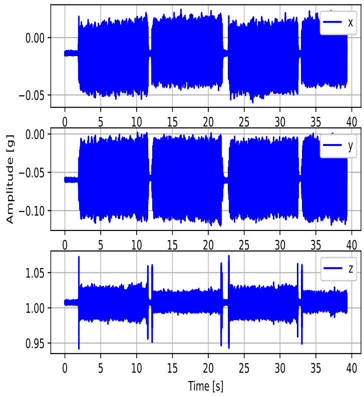
(a) Time-domain. **(b)** Frequency-domain.

Figure A.8 Results from Monitoring X-translation on left cart under Normal Operations.

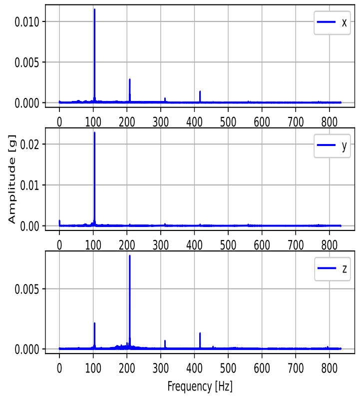


(a) Time-domain. **(b)** Frequency-domain.

Figure A.9 Results from Monitoring X-translation on right cart under Normal Operations.

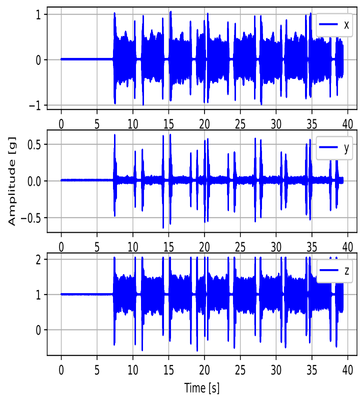


(a) Time-domain.

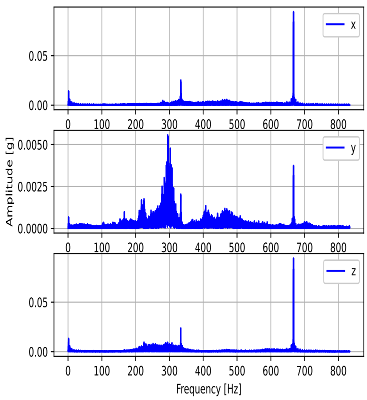


(b) Frequency-domain.

Figure A.10 Results from Monitoring Y-translation on right cart under Normal Operations.

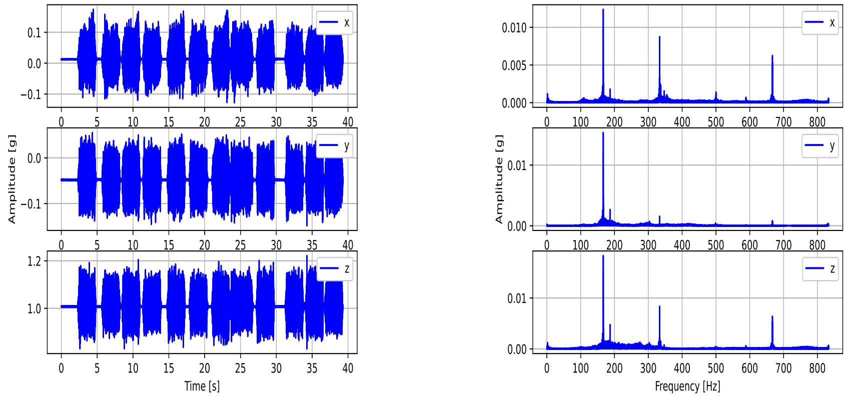


(a) Time-domain.



(b) Frequency-domain.

Figure A.11 Results from Monitoring Z-translation on right cart under Normal Operations.

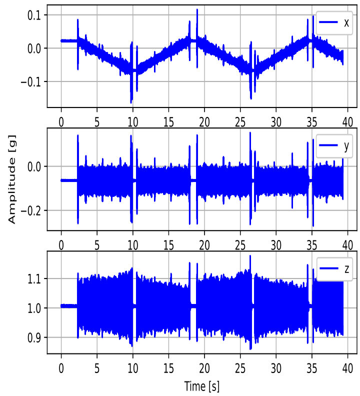


(a) Time-domain.

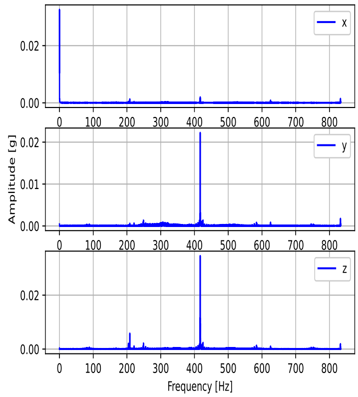
(b) Frequency-domain.

Figure A.12 Results from Monitoring Z-translation on left cart under Normal Operations.

A.4 Monitoring Tilt Movement under Normal Operations

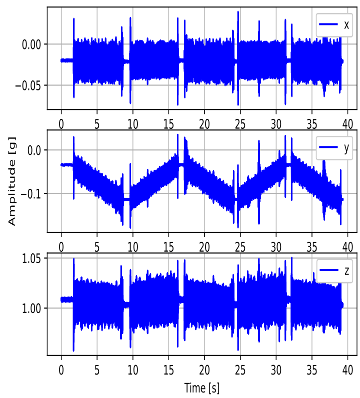


(a) Time-domain.

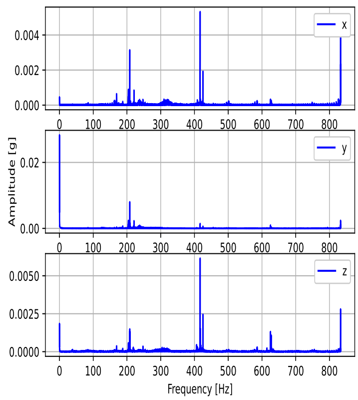


(b) Frequency-domain.

Figure A.13 Results from Monitoring X-tilt on right cart under Normal Operations.

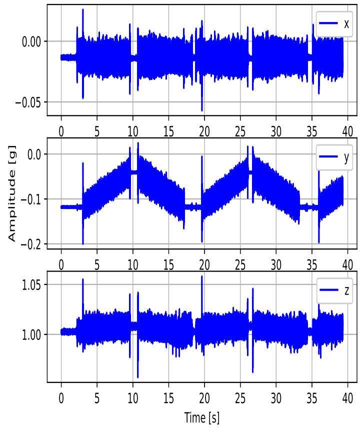


(a) Time-domain.

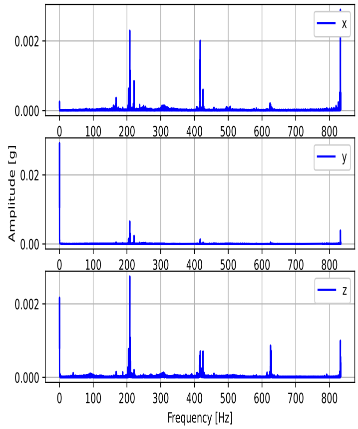


(b) Frequency-domain.

Figure A.14 Results from Monitoring Y-tilt on left cart under Normal Operations.

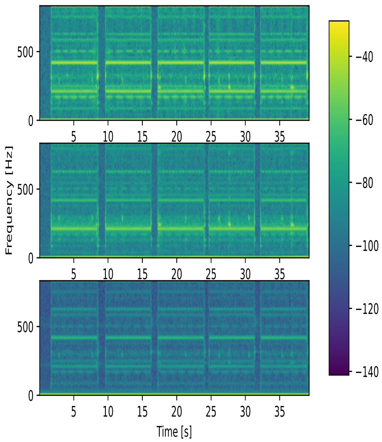


(a) Time-domain.

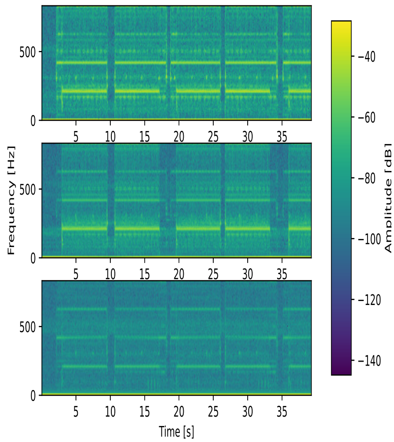


(b) Frequency-domain.

Figure A.15 Results from Monitoring Y-tilt on right cart under Normal Operations.



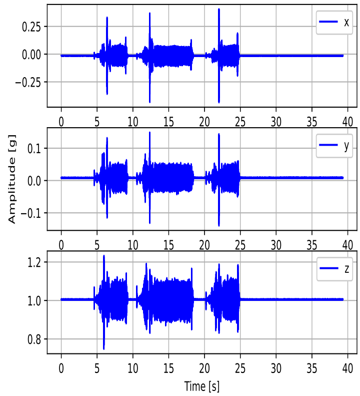
(a) The left Y-tilt motor.



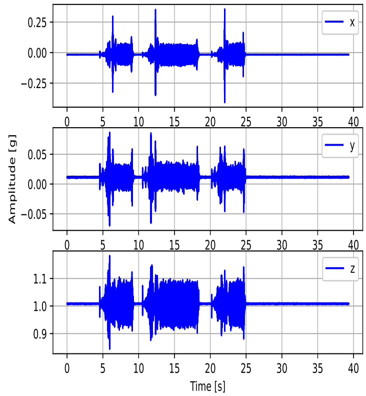
(b) The right Y-tilt motor.

Figure A.16 Results from monitoring the movement of the Y-Tilt motors under Normal Operations presented in the time-frequency domain.

A.5 Monitoring The Target Stand under Normal Operations

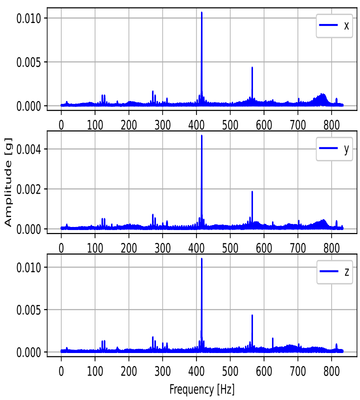


(a) First sensor.

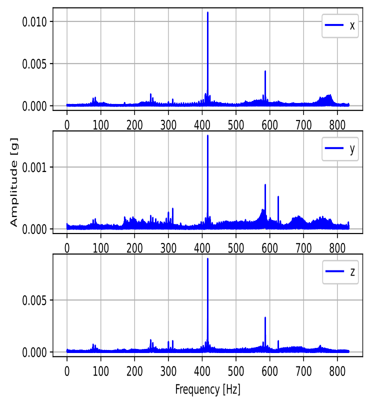


(b) Second sensor.

Figure A.17 Time-Domain Representation of Vibrations: Monitoring Target stand under Normal Operations. The sensors are mounted next to each other.

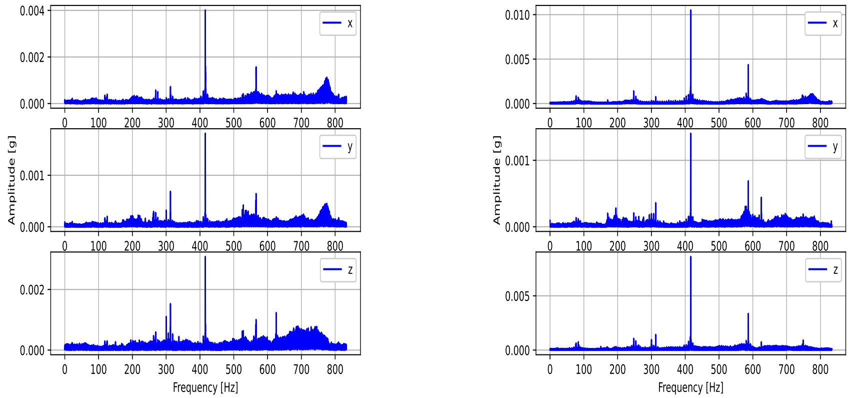


(a) First sensor.



(b) Second sensor.

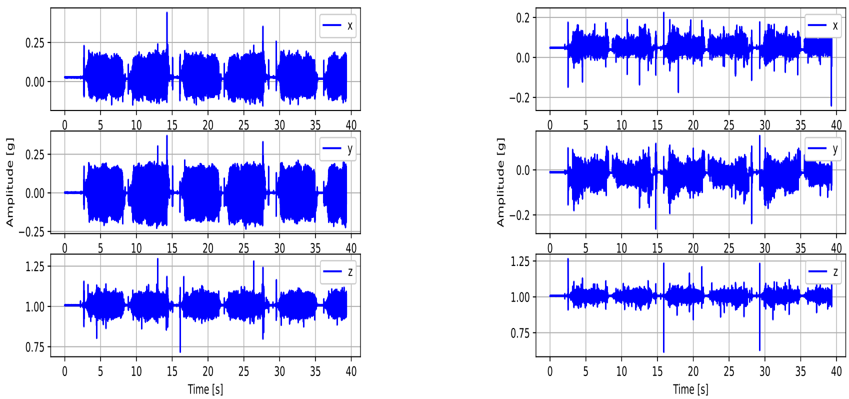
Figure A.18 Frequency-Domain Representation of Vibrations: Monitoring Target stand under Normal Operations. The sensors are mounted next to each other.



(a) First sensor. **(b)** Second sensor.

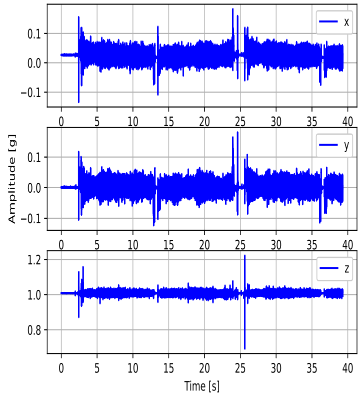
Figure A.19 Frequency-Domain Representation of Vibrations: Monitoring Target stand under Normal Operations. The sensors are mounted on different sides.

A.6 Investigating the Effect of Changing Cart Velocity

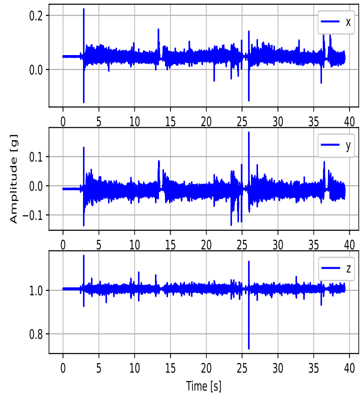


(a) Right cart **(b)** Left cart

Figure A.20 Time-Domain Representation of Vibrations: Monitoring Cart Movement with Higher Cart Velocity.

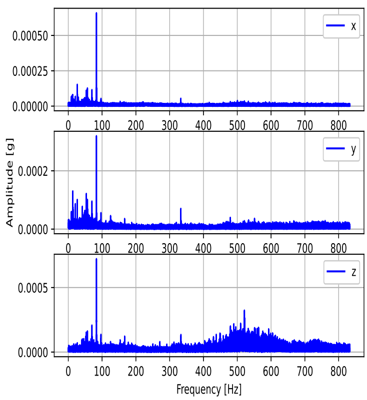


(a) Right cart.

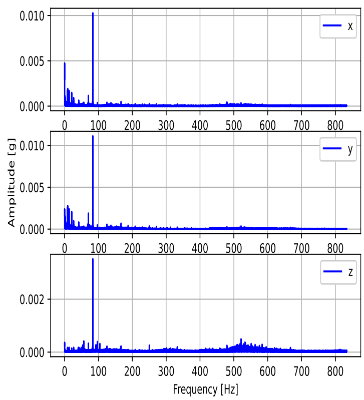


(b) Left cart.

Figure A.21 Time-Domain Representation of Vibrations: Monitoring Cart Movement with lower Cart Velocity.

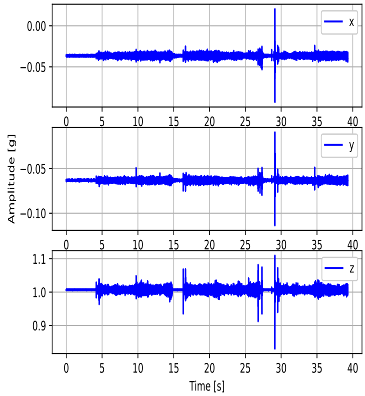


(a) Data captured at circular rail.

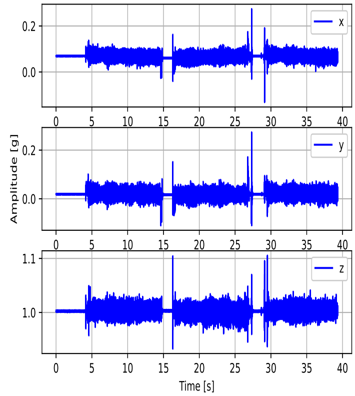


(b) Data captured at right cart.

Figure A.22 Frequency-Domain Representation of Vibrations: Monitoring Cart Movement with lower Cart Velocity. One sensor placed on the circular rail and other on the right cart.

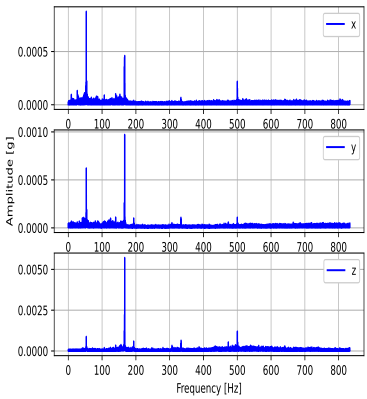


(a) Data captured at circular rail.

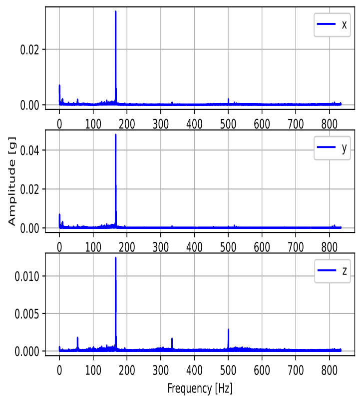


(b) Data captured at right cart.

Figure A.23 Time-Domain Representation of Vibrations: Monitoring Cart Movement with lower Cart Velocity. One sensor placed on the circular rail and other on the right cart.

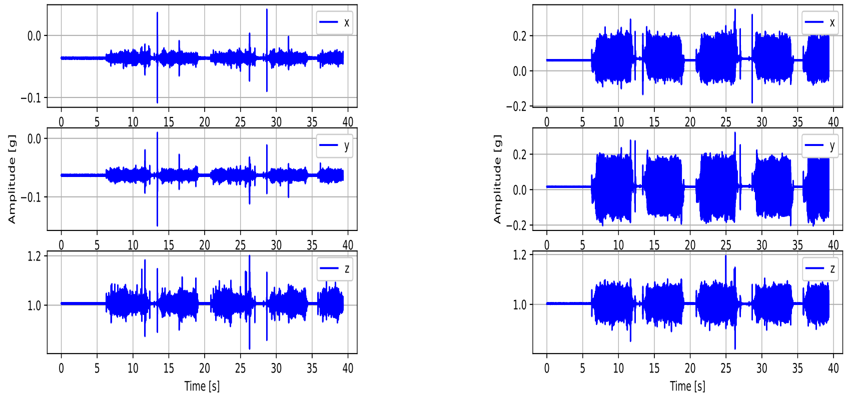


(a) Data captured at circular rail.



(b) Data captured at right cart.

Figure A.24 Frequency-Domain Representation of Vibrations: Monitoring Cart Movement with Higher Cart Velocity. One sensor placed on the circular rail and other on the right cart.

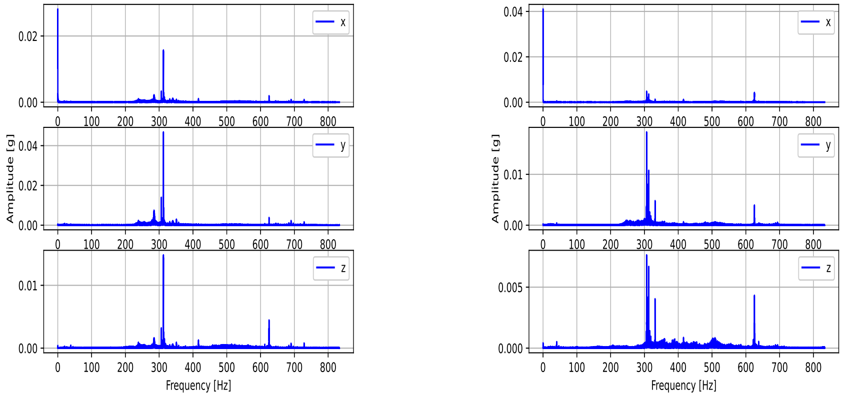


(a) Data captured at circular rail.

(b) Data captured at right cart.

Figure A.25 Time-Domain Representation of Vibrations: Monitoring Cart Movement with Higher Cart Velocity. One sensor placed on the circular rail and other on the right cart.

A.7 Tests to Identify Wear in X-tilt Actuators



(a) Left x-tilt motor.

(b) The right cart.

Figure A.26 Frequency-Domain Representation of Vibrations: Trying to identify wear in X-tilt Actuators. Higher speed than normal machine operations.

A.8 Mounting Locations of Sensors

This section showcases a series of images depicting the installation of sensors in various testing scenarios. In Figure A.27, the sensor is positioned on the cart to detect vibrations resulting from its movement. Figure A.28 displays the sensor placement for monitoring X and Y translations, as well as X and Y tilts. Lastly, Figure A.29 illustrates the sensor location utilized when monitoring vibrations caused by Z translations.

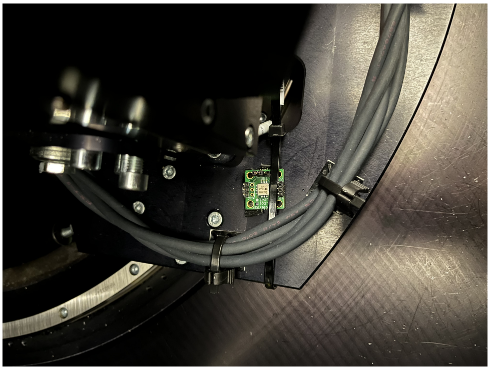


Figure A.27 The sensor is positioned on the cart to detect vibrations resulting from its movement.

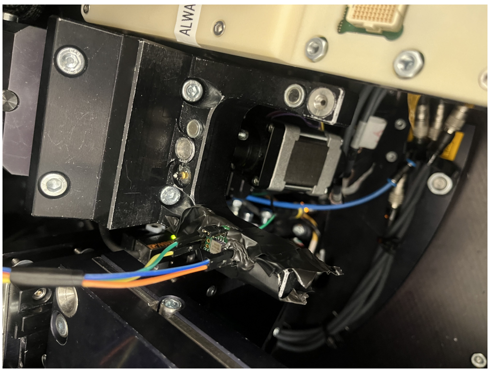


Figure A.28 The sensor placement for monitoring X and Y translations, as well as X and Y tilts.

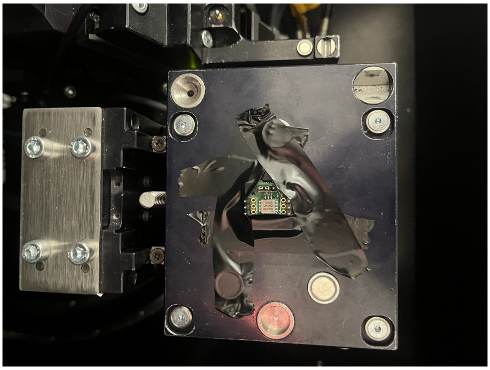


Figure A.29 The sensor location utilized when monitoring vibrations caused by Z translations.

Lund University
Department of Automatic Control
Box 118
SE-221 00 Lund Sweden

Document name
MASTER'S THESIS

Date of issue
June 2023

Document Number
TFRT-6203

Author(s)
Alexander Olsson
Henrik Persson Caesar

Supervisor
Bengt Sirbelius, Axis Communication, Sweden
Olle Kjellqvist, Dept. of Automatic Control, Lund University, Sweden
Kristian Soltesz, Dept. of Automatic Control, Lund University, Sweden (examiner)

Title and subtitle
Machine Condition Monitoring of Production Equipment

Abstract

This study investigates the possibility of implementing a machine monitoring system on IBAS2, a production machine responsible for aligning an optical lens with an image sensor. A machine-monitoring system could possibly reduce downtime, costs, and production recalls. After examining IBAS2, vibration analysis emerged as a promising monitoring approach. The research aimed to capture the natural vibrations exhibited by the machine during normal operation, serving as a baseline for understanding its functioning under normal conditions. The results obtained from this investigation demonstrate repetitive vibration patterns associated with specific machine components. Moreover, altering the velocity of a machine component leads to a distinct variation in the vibration pattern observed from the collected data. Furthermore, the results obtained from vibration measurements exhibit promising potential for detecting indications of machine wear. By leveraging accurate data that establish the machine's normal vibration patterns, we propose a future implementation of an AI model designed to detect deviations from the norm. This could lead to a vibration-focused machine monitoring system that predicts upcoming failures in IBAS2.

Keywords

Classification system and/or index terms (if any)

Supplementary bibliographical information

ISSN and key title
0280-5316

ISBN

Language
English

Number of pages
1-78

Recipient's notes

Security classification

http://www.control.lth.se/publications/