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# Motor Current Based Misalignment Diagnosis on Linear Axes with Short-Time Fourier Transform (STFT)

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**Abstract**

Machines and their components wear down over the course of time. A cause for increased wear can be misalignment issues that stay undetected and cause follow-up damages. Therefore, online monitoring of machines in the industry is of great importance. In this study, the axial misalignment occurring in different dimensions is determined. For this, a time frequency-based Short Time Fourier Transform (STFT) signal processing algorithm is used. The aim of the study is to diagnose faults without using sensors and external data collection systems, but rather by capturing motor current data from the servo motor of the machine.

## 1. Introduction

In recent years, the concept of maintenance has been more comprehensive, with the aim of reducing the incidence of breakdowns and extending the life cycle of industrial equipment. Common maintenance strategies are preventive, which are carried out periodically and condition-based or in a corrective manner, which means it is done after a fault has occurred and therefore this method contains unexpected faults, causing an increase in costs and changes in the production chain.

Hence, preventive maintenance is more effective than corrective maintenance, it can prevent most faults, yet unexpected faults can occur. Also, especially labor costs, inventory, and unnecessary replacement of equipment or components are costly [1].

Apart from these, predictive maintenance analyses the condition of the equipment, and a possible failure can be detected at an early stage. Predictive maintenance aims to predict the abnormality occurring in a machine element without causing catastrophic damages. It is usually conducted in the form of signal capture, signal analysis, and decision making, and usually in real-time. Common signal sources are vibration, temperature, pressure, acoustic emission, or electric current [2].

For this reason, acquisition and processing methods have been developed in order to increase the availability of the machines and to minimize the loss of money and time due to faults. Monitoring such signals or parameters to verify the operating status of a machine is called condition monitoring [1]. The most important of these, condition monitoring is frequently used in critical systems to avoid unexpected events, detect and identify failures, and protect against catastrophic breakdown.

Linear feed axes are one of those critical systems. Used wherever rotational motion is translated into linear motion, they ensure positional accuracy of workpieces and tools alike.

Their positional accuracy directly affects the load capacity, quality, and efficiency of the production processes. On this machine, part faults occur due to pitting, crack, corrosion, and wear problems [3-4]. As the size of the problems increases, the possibility of axis errors increases, and eventually large wear and distortion of the linear axis will occur. This causes faults to affect the other machine parts and loss of production quality [3-4].

In the literature, few works have been done on the diagnostics of linear axes. The most important resource for this study, Putz et al. have presented a new condition monitoring system for sensorless fault detection in dynamic linear axes and used motor current. They used the Choi-Williams distribution signal processing algorithm on the motor current of the investigated linear axis. An algorithm for fault detection was not used, and only a study on gear damage was carried out in this work. The performance of the different signal processing algorithms have not been tested [5].

Besides natural wear, misalignment and arising lateral forces have a large impact on feed axis failure. As a result of the misalignment of one machine with another machine, unpredictable radial forces occur in the bearings of both machines. Misaligned components are more prone to failure due to increased load on bearings and seals. Misalignment may result from many problems such as the assembly of unsuitable machine parts, asymmetrically applied loads, and improper seating of the machine part on the base part [6-7]. Therefore, the detection of misalignment on the industrial drive is very valuable for the robustness and reliability of the machine [8]. As a result, industrial and academic studies have been done to detect misalignment in various ways and amongst these are vibration, current signature, acoustic analysis temperature, flux, laser systems analysis, and so on.

STFT is a popular algorithm in time-based signal processing. In addition, frequency-based methods do not give good results due to the short sampling time and the waiting time of the table at the start and endpoints. Because of these problems, it is more appropriate to use a time-frequency-based algorithm[9-11].

When literature is reviewed on linear feed axis fault detection. These are studies based on vibration, dynamic loads, gyroscope, pressure, and linear potentiometer data. There is no motor current-based operation. All of these techniques fall under sensor-based diagnostics. A study is a sensorless approach. When its performance was compared with other studies, in most of the studies, axial misalignment at different levels, and the right side was not diagnosed. With this study, it is possible to detect axial misalignment at different levels [3, 12-13]. The biggest advantage of this system is that there is no need for sensors and an economical approach when many machines are used. For this reason, the paper presents a new Condition Monitoring System for sensorless fault diagnosis on linear feed axes with the motor current signal. The main goal of the study is real-time detection of the misalignment on the linear axes without using external sensors.

In this study, the axial misalignment of the table is determined by using the motor current data from the PLC. Since signals are complex, they are processed with time-frequency-based STFT.

## 2. Theoretical Background

### 2.1. Short Time Fourier Transform(STFT)

Sometimes, frequency-based feature selection can give wrong results. Because the time-dependent variation of the signal is not visible in this. For this, time-frequency-based techniques are used. It is also possible to detect when the problem occurs with time-based feature selection techniques. This is because the STFT is applied over the entire time frame, it must be calculated in the specific time frame. Its signal of certain sizes splits into windows. Applies the Fourier transform to each window. And it places them vertically according to time. The X-axis shows time, the y-axis shows frequency change with time, and the color change shows frequency amplitude value [14-15]. Fourier Transformation of windowed signal in STFT is done as in equation 1. The spectrogram is derived by equation 2.

$$F_x^{\gamma}(\tau, f) = \mathcal{F}\{x(t)\gamma^*(t-\tau)\} = \int_{-\infty}^{\infty} x(t)\gamma^*(t-\tau)e^{-j2\pi ft}dt \quad (1)$$

$$S_x^{\gamma}(\tau, f) = \left|F_x^{\gamma}(\tau, f)\right|^2 = \left|\int_{-\infty}^{\infty} x(t)\gamma^*(t-\tau)e^{-j2\pi ft}\,dt\right|^2 (2)$$

## 3. Experimental Setup

The experimental setup at WBK institute consists of a ball screw feed drive system. This experimental setup allows to carry out experiments, analyse the system, and introduce misalignment in the assembly. The experiment setup has the ball screw mechanism, fixed and loose bearings with their housings, the table, ball rails, guideways, the nut bracket, the coupling, and the servo motor with its controller. The assembly is installed on the machine Pillow Blocks. Beckhoff brand servo motor turns the screw drive. As a result of its rotation, the table attached to it moves linearly. With the Twincat PLC suite, the raw current data is captured and processed with the signal processing algorithm. The experimental setup is shown in figure 1. In addition, the working principle of the study is shown in figure 2. The table goes at a constant speed of 100mm/s. It pauses for a short time due to the communication delays of the PLC at the start and endpoints.

Each experiment was repeated twenty-one times while these data were taken. It was seen that the data obtained for each condition were similar. The screw drive of the table is bedded with two Pillow Blocks. The Pillow Block1 was fixed. However, this Pillow Block has 1 mm right axis misalignment caused by the assembly. This is a good example to show that it is possible to diagnose more than one axis misalignment. Misalignment problems are simulated by shifting the Pillow Block2 to the right and left. The technical drawing for the

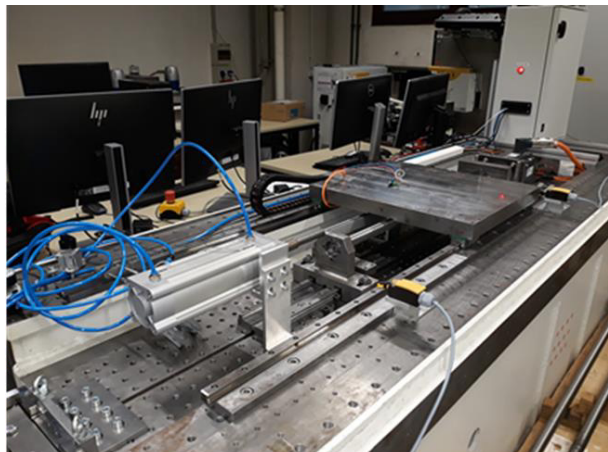detailed representation of the experimental set is shown in Figure 3.



Fig. 1. Experimental setup.



Fig. 2. Working principle of study.



Fig. 3. Technical drawing of the experimental setup.

## 4. Results

When we look at the results of the study. The current data received from the servo motor is shown in figure4. As shown in the figure, in the normal situation, 0.5 and 1 mm axis misalignments are not fully separable. Hence, further signal processing is required. As seen in the signal, there were small increases in amplitude value when there was axial misalignment. Experiments were carried out by taking stroke 100 mm and table speed 100 mm/s.



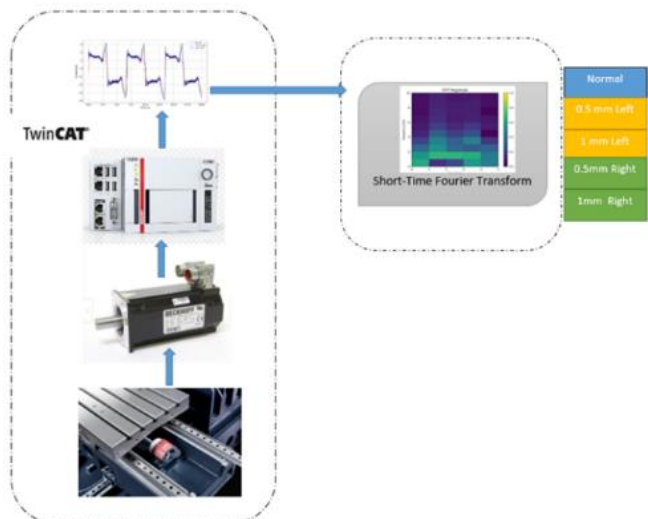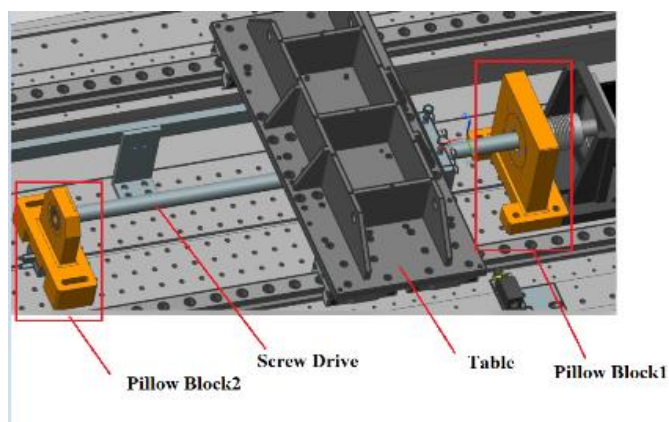Fig. 4. The current value of servomotor read from PLC

Current values processed with STFT are shown in Figures 5-7. The figure shows 5 seconds of operation. The time is depicted on the x-axis, the frequency change accordingly on the y-axis, and the frequency amplitude change is encoded in the heat map colors. The unit of Amplitude is Amper(A). As can be seen from the parameters, the frequency of the system is very low. The table waits briefly at the start and endpoints. Moving periodically from start to endpoint and is doing the cycle process. When these are evaluated, the frequency amplitude value increases during the table return. It is possible to find the axial misalignment on the machine by following these changes. Figure 5 normal state, Figures 6 and 7 are the results of 0.5mm and 1 mm left axis misalignment respectively. The color contrast in the region indicated by the red rectangle changes depending on the axial misalignment.
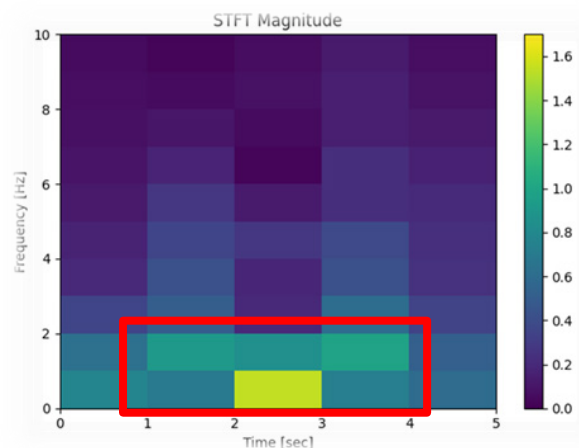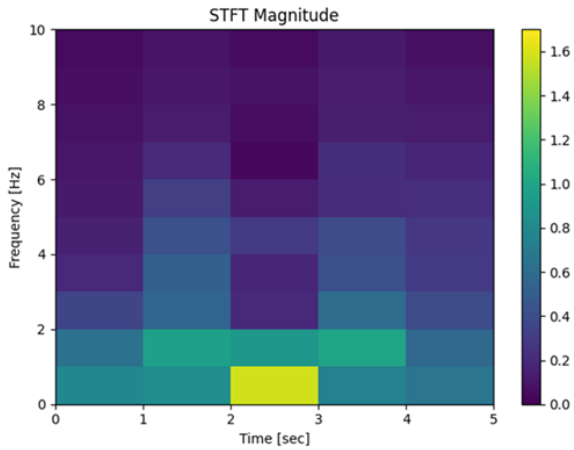


Fig. 5. Normal state
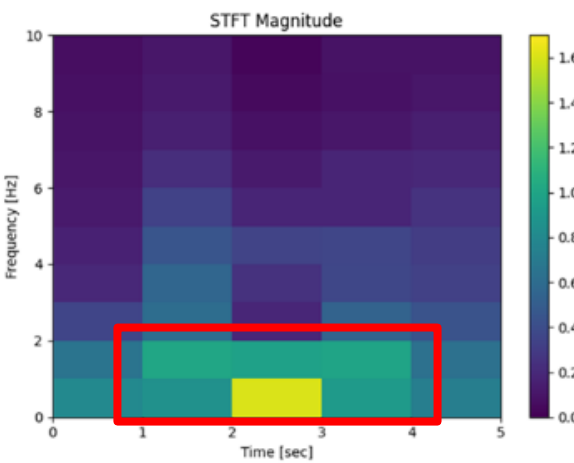
Fig. 6. 0.5mm left side misalignment
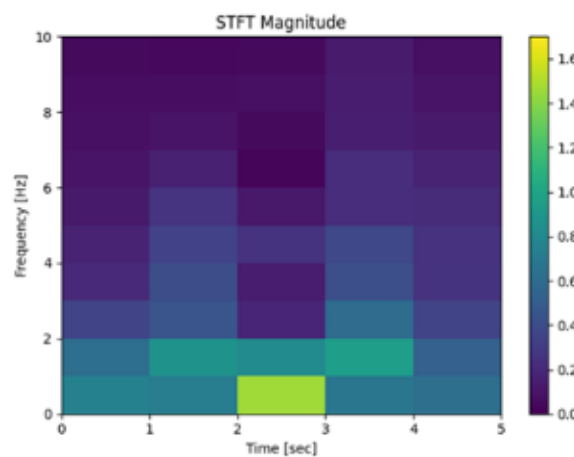


Fig. 7. 1mm left side misalignment



Fig. 8. 0.5mm right side misalignment

When we introduce axial misalignment to the right of the experimental setup, the amplitude value decreases. This is evident from the color contrast. Right axis misalignment results are given in Figures 8 and 9. The reason for this is the right axis misalignment in Pillow Block1 at the beginning of the experimental setup. When the axial misalignment is given to the right, this angle value is reduced and the amplitude decreases.

Normally, the amplitude should increase in the right axis misalignment. Since the angle value increases more in the axial misalignment to the left, it increases in amplitude.
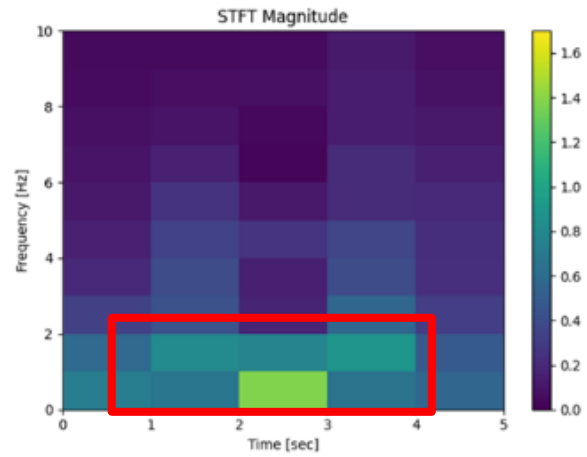


Fig. 9. 1mm right side misalignment

In order to understand the change more clearly, Figure 10 was made by taking the maximum magnitude values. Different axis misalignments and normal state are shown on the x-axis, and the maximum magnitude values in these cases are shown on the y-axis.
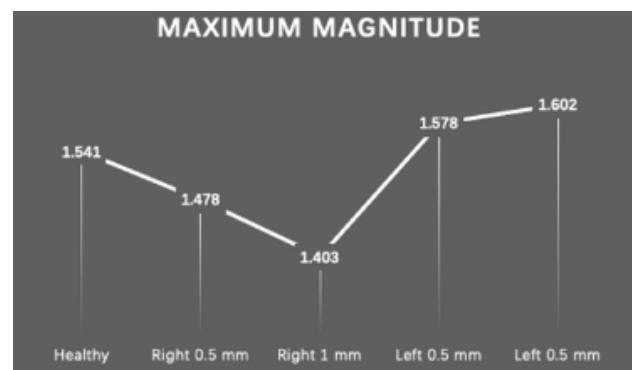


Fig.10 Maximum Magnitude for every situation

## 5. Conclusion

We showed that it is possible to detect axial misalignment in linear feeding axes by receiving the current data from the servo motor with the help of PLC and by signal processing. Also, there is no need for data collection systems and sensors for this process. We aspire to make sensorless condition monitoring more prominent and valuable by removing the need or expensive data capturing equipment. When the left and right axis misalignment values are increased, it is seen that the color contrast in the marked regions changes. When we give these pictures to machine learning and deep learning algorithms[16-18]. The results of the signal processing algorithm can be classified by machine learning and deep learning methods. Thus, it is possible to find these problems that occur in the machines automatically. It is also thought that this method can be used to find many mechanical problems. It will contribute to the spread of fault diagnosis in machinery in the industry.

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