DOCTORAL THESIS

Fault Tolerant Control and Diagnosis Strategies for Cartesian Industrial Robot Motion Control Planning System

Siarhei Autsou

TALLINNA TEHNIKAÜLIKOOL
TALLINN UNIVERSITY OF TECHNOLOGY
TALLINN 2025

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14/2025

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SIARHEI AUTSOU

TALTECH PRESS

TALLINN UNIVERSITY OF TECHNOLOGY
School of Engineering
Department of Electrical Power Engineering and Mechatronics
This dissertation was accepted for the defence of the degree 12/02/2025

Supervisor:
Dr. Toomas Vaimann
Dept. of Electrical Power Engineering and Mechatronics
School of Engineering
Tallinn University of Technology
Tallinn, Estonia

Co-supervisor:
Prof. Anton Rassõlkin
Dept. of Electrical Power Engineering and Mechatronics
School of Engineering
Tallinn University of Technology
Tallinn, Estonia

Opponents:
Prof. Dr. Alberto Borboni
Dept. of Mechanical and Industrial Engineering
University of Brescia
Brescia, Italy

Dr. Levon Gevorkov
Power Systems Group
Catalonia Institute for Energy Research (IREC)
Barcelona, Spain

Defence of the thesis: 27/03/2025, Tallinn

Declaration:
Hereby I declare that this doctoral thesis, my original investigation and achievement, submitted for the doctoral degree at Tallinn University of Technology has not been submitted for doctoral or equivalent academic degree.

Siarhei Autsou

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ISSN 2585-6898 (publication)
ISBN 978-9916-80-265-6 (publication)
ISSN 2585-6901 (PDF)
ISBN 978-9916-80-266-3 (PDF)
DOI https://doi.org/10.23658/taltech.14/2025
Printed by Koopia Niini & Rauam

Autsou, S. (2025). *Fault Tolerant Control and Diagnosis Strategies for Cartesian Industrial Robot Motion Control Planning System* [TalTech Press]. https://doi.org/10.23658/taltech.14/2025

TALLINNA TEHNIKAÜLIKOOL
DOKTORITÖÖ
14/2025

Tõrketaluvusega juhtimis- ja diagnostikastrateegiad tööstusliku karteesianroboti liikumise planeerimise juhtimissüsteemi jaoks

SIARHEI AUTSOU

KIRJASTUS

Contents

List of Publications

The list of author's publications, based on which the thesis has been prepared:

I **Autsou, S.**; Kudelina, K.; Vaimann, T.; Rassõlkin, A.; Kallaste, A. Principles and Methods of Servomotor Control: Comparative Analysis and Applications. Appl. Sci. 2024, 14 (6), 2579. https://doi.org/10.3390/app14062579.

II **Autsou, S.**; Kudelina, K.; Vaimann, T.; Rassõlkin, A.; Kallaste, A. Condition Monitoring of a Cartesian Robot with a Mechanically Damaged Gear to Create a Fuzzy Logic Control and Diagnosis Algorithm. Appl. Sci. 2024, 14 (10), 4241. https://doi.org/10.3390/app14104241.

III **Autsou, S.**; Vaimann, T.; Rassõlkin, A.; Kudelina, K. Analysis of Possible Faults and Diagnostic Methods of the Cartesian Industrial Robot. Proc. Est. Acad. Sci., 71 (3), pp. 227–240, 2022, doi: 10.3176/proc.2022.3.04.

IV **Autsou, S.**; Kudelina K.; Vaimann T.; Rassõlkin A. The Usage of Fuzzy Logic for Detecting Mechanical Faults in Gearboxes of Robotic System. 2024 International Conference on Electrical Machines (ICEM), Torino, Italy, 2024, pp. 1–7, doi: 10.1109/ICEM60801.2024.10700425.

V **Autsou, S.**; Vaimann, T.; Rassõlkin, A.; Kudelina, K. Fault Diagnosis System of Cartesian Robot for Various Belt Tension. International Conference on Diagnostics in Electrical Engineering (Diagnostika), Pilsen, Czech Republic, 2022, pp. 1–4, doi: 10.1109/Diagnostika55131.2022.9905111.

VI **Autsou, S.**; Vaimann, T.; Rassõlkin, A.; Kudelina, K. Spectrum Analysis Additional Vibrations of Cartesian Robot by Different Control Modes. 18th Biennial Baltic Electronics Conference (BEC), Tallinn, Estonia, 2022, pp. 1–5, doi: 10.1109/BEC56180.2022.9935595.

VII **Autsou, S.**; Vaimann, T.; Rassõlkin, A.; Kudelina, K.; Asad, B. Influence of Different Tooth Belt Transmission Faults on the Work of a Cartesian Robot. 20th International Conference on Mechatronics - Mechatronika (ME), Pilsen, Czech Republic, 2022, pp. 1–5, doi: 10.1109/ME54704.2022.9982815.

Author’s Contribution to the Publications

Contribution to the papers in this thesis are:

I Siarhei Autsou is the primary author of this article. He developed a fuzzy logic control and diagnosis algorithm, based on the vibration signal occurring in conditions of gearbox mechanical damages. He also wrote the initial draft of the paper.

II Siarhei Autsou is the primary author of this article. He compiled a detailed review of existing and popular servo motor control methods and conducted a comparison of these methods. He also wrote the initial draft of the paper.

III Siarhei Autsou is the primary author of this article. He analysed the obtained results of the fuzzy logic algorithm for detecting the heating of the worm in the screw transmission. He also wrote the initial draft of the paper.

IV Siarhei Autsou is the primary author of this article. He compiled a review of transmission types used in robotics systems and provided a comparative description of existing methods for diagnosing mechanical damages. He also wrote the initial draft of the paper.

V Siarhei Autsou is the primary author of this article. He developed a mathematical model of the cartesian robot's gearbox and researched to determine the behavior of the transmission in the event of mechanical damage. He also wrote the initial draft of the paper.

VI Siarhei Autsou is the primary author of this article. He researched detecting damages to the tooth belt transmission of a cartesian robot by analyzing the spectrum of the vibration signal obtained experimentally. He also wrote the initial draft of the paper.

VII Siarhei Autsou is the primary author of this article. He conducted an experimental study to compare the influence of belt tension on the robot's transmission, aiming to determine the extent of the impact of damage on the transmission. He also wrote the initial draft of the paper.

Abbreviations

AL	Fuzzy logic variable of membership function indicating low amplitude
AM	Fuzzy logic variable of membership function indicating medium amplitude
AH	Fuzzy logic variable of membership function indicating high amplitude
FL	Fuzzy logic variable of membership function indicating low frequency
FH	Fuzzy logic variable of membership function indicating high frequency
F200	Fuzzy logic variable of membership function indicating frequency of 200 Hz
F250	Fuzzy logic variable of membership function indicating frequency of 250 Hz
F300	Fuzzy logic variable of membership function indicating frequency of 300 Hz
F350	Fuzzy logic variable of membership function indicating frequency of 350 Hz
F400	Fuzzy logic variable of membership function indicating frequency of 400 Hz
F450	Fuzzy logic variable of membership function indicating frequency of 450 Hz
Neg	Fuzzy logic variable of membership function indicating negative acceleration
Pos	Fuzzy logic variable of membership function indicating positive acceleration
SL	Fuzzy logic variable of membership function indicating low speed
SLL	Fuzzy logic variable of membership function indicating minimum speed (low low)
SM	Fuzzy logic variable of membership function indicating medium speed
SH	Fuzzy logic variable of membership function indicating high speed
TL	Fuzzy logic variable of membership function indicating low torque
TLL	Fuzzy logic variable of membership function indicating minimum torque (low low)
TM	Fuzzy logic variable of membership function indicating medium torque
TH	Fuzzy logic variable of membership function indicating high torque
ZeroNeg	Fuzzy logic variable of membership function indicating close to zero negative acceleration
ZeroPos	Fuzzy logic variable of membership function indicating close to zero positive acceleration

Symbols

a	Border of the triangle/trapezoid membership function in fuzzy logic algorithm
b	Border of the triangle/trapezoid function membership function in fuzzy logic algorithm
c	Center of the triangle / Maximum of the trapezoid / Middle of the gaussian membership function in fuzzy logic algorithm
d	Maximum of the trapezoid function membership function in fuzzy logic algorithm
g	Acceleration of free fall
l	Length of the of Z axis
k	Number of iteration
k_1	Coefficient representing weighting factors based on the specific system dynamics and design criteria
k_2	Coefficient representing weighting factors based on the specific system dynamics and design criteria
m_1	Weight of the Y and Z axes
m_2	Mass of the load
s	Current system state
s'	Next system state
x_2	Coordinate the mass center of the load in the initial position
x_1	Coordinate the mass center of the load in the final position
A_1	Unknown constant 1 to be determined through further analysis
A_2	Unknown constant 2 to be determined through further analysis
A_3	Unknown constant 3 to be determined through further analysis
F	Braking force acting on the robot axis
W	Strength of resistance of the robot axis
S	Bellman function
α	System impact
γ	Discount coefficient
σ	Width of the gaussian function
ω	Natural frequency of the load oscillation
A(s)	Impact sets in the current state
$P(s'\|s,\alpha)$	Transient possibility to the next state after impact
$R(s,\alpha)$	Optimal criteria after impact
V(s)	Optimal strategy in the current state
$V_k(s)$	Optimal strategy in the current state of k-iteration

1 Introduction

1.1 Motion Planning in Industrial Robotics Control System

Motion planning plays a significant role in robotics, it helps to determine a possible trajectory for a robot to move from the initial state to a desired location while avoiding obstacles and observing specific constraints [1], [2]. The motion planning control system in robotics is based on three key components [2]: an actuator (electric, pneumatic, or hydraulic) [3], [4], a control system configured according to the required parameters (such as performance, accuracy, and operation in unpredictable conditions) [1], [5], and a transmission that converts the actuator's force into mechanical movement [6]. The primary actuator in nowadays robotics system is the electric motor [1], [7].

Electric motors have a wide range of uses and allow for the creation of new technologies and the modernization of existing ones [8], [9]. Each type of electric motors finds its application in robotics, allowing for greater efficiency, productivity, conservation of material and energy resources, etc. However, achieving the necessary goals depends not only on the use of specific types of electric motor but also on the correct selection of their size and control methods, depending on the specified conditions. These factors such as speed range, torque, accuracy, environmental and mechanical conditions play a critical role in this decision [10], [11].

Additionally, unconventional motors designed for specific application (such as industrial robotics) may require a completely different control method in certain applications than the one they are adapted to. Electrical motor used in robotics and automation enable the expansion of the range of applications with a high degree of efficiency in transportation, manufacturing, assembly, and other areas [12]–[14]. Thus, selecting a control method for operation in different conditions in various industrial sectors is extremely acute and requires careful analysis. In addition, the impact of mechanical factors, such as unexpected vibrations, misalignments, possible joints damages, and transmissions issues, should also be considered when choosing a control method. These factors can significantly affect the robot's performance and lifespan.

1.2 Control Methods of Industrial Robots

The choice of control method for industrial robots is based on achieving desired parameters, such as control preciseness, system performance, energy consumption, etc. Additionally, the control system should be resilient to disturbances, easily integrated into a larger network, and adaptable to changing conditions [2], [5]. Various control methods are used to reach the desired performance parameters of mechanisms. However, maintaining system reliability and stability remains a central challenge. Robotic systems operating in industrial environments are often subjected to various mechanical loads and interferences, which lead to unintended vibrations, wear, and, ultimately, equipment failure. Consequently, the choice of control method should also consider the monitoring of the robotic system's condition and the early diagnosis of issues.

To ensure efficient robot operation under varying conditions, the main control methods are summarized in Table 1.1. This analysis highlights their applicability, benefits, and limitations.

Table 1.1. The main control methods in robotics with corresponding attributes.

Control method type	**Control algorithms**	**Benefits and limitations**
PID-control	• Classical PID-control [15]–[17]; • Autotuning PID-control [18], [19];	**Benefits:** • Simple to implement and tune; • Well-suited for linear systems and stable processes; • Widely used and applicable in most applications. **Limitations:** • Efficiency decreases with significant delays or rapidly changing conditions; • Requires careful parameter tuning for good results, especially in complex systems; • Sensitive to noise, which can cause instability.
Adaptive control	• Gain scheduling control [20], [21]; • Self-tuning regulators [22], [23]; • Adaptive fuzzy logic control [24], [25];	**Benefits:** • Ability to adjust to changing system parameters in real-time; • Improves control accuracy under uncertainty and variable conditions; • Applicable in systems where an accurate model cannot be created. **Limitations:** • Complex to implement and computationally intensive; • May not handle fast or sharp changes in parameters effectively; • Requires mechanisms for real-time parameter estimation.
Optimal control	• Pontryagin's maximum principle [26], [27]; • Bellman's dynamic programming [28], [29]; • Lagrange method [30];	**Benefits:** • Allows for minimizing or maximizing a target function; • Ensures efficient and economical trajectories and actions; • Useful for systems requiring high precision and cost minimization. **Limitations:** • High computational complexity, especially for multidimensional tasks; • May require an accurate mathematical model, which is not always available; • Limited adaptability since optimal solutions are designed for fixed conditions.

Control method type	Control algorithms	Benefits and limitations
Robust control	• Classic fuzzy logic control [31]; • Multi-model control [32]; • H∞ control [33];	**Benefits:** • Resilient to significant uncertainties and disturbances; • Ensures stability and predictability even when parameters change; • Effective in systems with substantial modelling errors. **Limitations:** • Complex tuning requiring specialized knowledge; • Potentially high computational cost during design; May lead to conservative solutions, reducing system efficiency.
Predictive control	• Predictive control with finite horizon [34]; • Predictive control with infinite horizon [35]; • Stochastic predictive control [36]	**Benefits:** • Considers the future behavior of the system, allowing for prediction and optimization; • Takes constraints into account, important for complex systems; • Provides precise control and good response to external disturbances. **Limitations:** • High computational requirements, especially for large prediction horizons; • Dependence on the accuracy of the mathematical model; Complex implementation for tasks with rapidly changing parameters.
Discrete control	• Finite state machine control [37]; • Timed finite state machine control [38];	**Benefits:** • Simple to implement for tasks that can be represented as a sequence of states; • High reliability and predictability in simple systems; • Easy-to-understand logic that simplifies debugging and testing. **Limitations:** • Limited flexibility and adaptability, unsuitable for complex or continuous processes; • Can become cumbersome as the number of states and logical conditions increases; Poor fit for tasks with high uncertainty or unpredictability.

The chosen control method must effectively mitigate the consequences of disturbances and also prevent their occurrence. However, vibrations in the moving parts of the robot (transmission), caused by mechanical damage, often go unnoticed and tend to be cumulative. This, in turn, leads to additional wear, repair, or failure of equipment. Identifying signs at an early stage can not only be detected but also their impact on the robotic system's structure can be minimized with the proper control method.

When considering the control methods described above in terms of improving the reliability and stability of a robotic system in the presence of undesirable disturbances, the following advantages stand out: optimal, predictive and robust control.

1.3 Optimal Control Systems

Control systems are rapidly evolving, transforming, and adapting to modern conditions, leading to an expansion of capabilities in controlling mechanisms. New control methods, such as piecewise-linear control, the use of artificial intelligence, or machine learning, enable achieving excellent control quality [9], [39]. However, alongside these new methods, traditional approaches maintain their popularity and are being redefined for new application areas, such as optimal control systems [40]–[42].

Optimal control systems are a combination of methods and algorithms designed to achieve the best (optimal) management results for a dynamic system. The main goal of optimal control systems is to maximize output parameters that determine the quality of control and minimize undesirable criteria affecting performance. Optimal control systems also consider most of the constraints imposed on the dynamic system. The key aspects of optimal control include [43]–[45]:

- Formalization of the problem;
- Definition of performance criteria;
- Constraints;
- Determination of optimal strategy;
- Adaptation to changes.

Building an optimal control system starts with defining the dynamic system to be controlled, the objective function, and the performance criterion for optimization. The dynamic system is a mathematical model describing the system's behavior over time. The objective function takes various forms depending on whether the minimization or maximization task is set.

Performance criteria are parameters that determine the quality of control. Choosing an appropriate criterion allows monitoring how well the control objective is achieved. Depending on the specific task and requirements of the dynamic system, the criterion could involve minimizing time, cost, resource consumption, or maximizing performance and profit.

When developing an optimal control system, it's essential to consider the constraints imposed on the dynamic system. Constraints include various physical parameters like speed or time, as well as technical parameters depending on the system's design, such as maximum load [44].

The next aspect in developing an optimal control system is finding the optimal control strategy to either maximize or minimize performance criteria. Various methods are used for determining the strategy, such as Pontryagin's maximum principle, Bellman's dynamic programming method, fuzzy logic-based algorithms, machine learning algorithms, etc [46]–[48].

In the case of unpredictable optimal control problems or working in stochastic environments, optimal control systems must be sufficiently adaptive and flexible. Achieving this result involves using various combinations of methods to react to changes promptly and maintain the optimal control strategy.

Based on the literature analysis, Bellman's dynamic programming method is suitable for optimizing the control of a robotic system under mechanical disturbances for the following reasons [49]–[51]:

1. Recursive approach to solving control problems.

By breaking the main task into smaller sub-tasks, Bellman's dynamic programming method increases its efficiency in decision-making under changing conditions. When subjected to vibrational disturbances, the Bellman approach recalculates the optimal solution at each step, allowing the control system to adapt to disturbances while maintaining operational stability.

2. Lack of strict conditions and applicability to uncertain systems.

Unlike other methods, such as the Lagrange method or Pontryagin's maximum principle, the Bellman approach is better suited for systems with numerous dynamic parameters. Vibration parameters, such as frequency and amplitude, as well as robotic system parameters like speed, torque, precision, and acceleration, can change unpredictably in the event of mechanical damage. The Bellman method ensures a more reliable response by recalculating the optimal trajectory compared to other methods that rely on a fixed optimal trajectory.

3. Adaptability to constraints and improved response efficiency.

Response time minimization is achieved through continuous searching for the optimal solution, which, in turn, contributes to the stability of the mechanical system. Taking constraints into account at each step, especially those related to variable disturbances, eliminates the need for complex modeling of the robotic system.

4. Compatibility with other algorithms.

Bellman's method can complement certain algorithms, introducing new dimensions to control strategy development. For instance, combining it with fuzzy logic algorithms can create a predictive diagnostic system, minimizing the impact of damage before its destructive effects begin.

1.4 Predictive and Robust Control Strategies

Predictive and robust control strategies are key components in the fields of industrial automation, robotics, and the aviation and automotive industries [52]. Predictive control aims to forecast equipment failure and identify potential faults to prevent breakdowns without adhering to a fixed schedule of maintenance tasks. In turn, robust control strategies address uncertainties, noise, and disturbances, as well as changes in environmental and operating conditions, ensuring stable operation of mechanisms under various circumstances [53]. These methods are crucial in systems where environmental conditions, processes, or external disturbances can be unpredictable [52], [54].

Together, predictive and robust control strategies can be broken down into key components [55], [56]:

- Condition monitoring and uncertainty modelling allow to collect data from sensors, measuring various process or mechanism parameters in real-time, allows for a thorough study of system dynamics and potential uncertainties. This leads to the development of a mathematical model describing system behavior under different conditions.

- Data analysis and controller design provide to identify patterns, anomalies, errors, and potential equipment failures. Controllers are then developed to maintain system stability and performance in the presence of deviations. These controllers use various algorithms, such as PID control, optimal control, fuzzy logic, and artificial intelligence.
- Predictive modelling and sensitivity analysis identify key stages and determine the possibility of equipment failure and the need for maintenance. At the same time, sensitivity analysis of control system performance to uncertainties is conducted to identify potential improvement opportunities.
- Preventive actions, simulation, and testing through analysis and prediction of failures reliable operation of control systems and mechanisms is ensured under different operating conditions.

In this context, predictive and robust control systems allow for reduced equipment downtime, which would otherwise be required for maintenance and adjustment to new operating conditions; cost savings due to high adaptability; and improved safety, quality, and efficiency by reducing the impact of uncertainties, noise, and disturbances on equipment.

Among the control methods presented above, fuzzy logic stands out for its adaptability, robustness, and ability to predict events. Fuzzy logic possesses several key features that make it particularly effective in handling mechanical damage in robotic systems [57]–[60]:

1. Adaptive approach to uncertainties.

Fuzzy logic enables the management of imprecise data, which is especially crucial for robotic systems affected by vibrational disturbances. The absence of a requirement for prior parameter tuning for each event scenario allows a fuzzy logic-based control system to adapt to changing conditions.

2. No requirement for a precise mathematical model.

This simplifies the process of designing, implementing, and configuring a fuzzy logic control system, enabling generalization across various scenarios without excessive detail.

3. Rule-based control for predictive capabilities.

The use of a rule base enables the creation of predictive control systems to assess future states, setting fuzzy logic apart from other algorithms. The use of empirical data and a set of rules ensures high response speed.

4. Integration with other control methods.

Fuzzy logic can complement other control strategies, broadening control horizons and achieving the required quality. The distribution of fuzzy sets to encompass various scenarios enables a shift from focusing solely on the system's current state to building a control strategy that adapts to changes.

5. Resistance to disturbances and adaptability to changes.

Fuzzy logic ensures robust control even in the presence of significant deviations in system operation. Furthermore, its lack of reliance on extensive calculations saves computational resources, enhancing system performance.

Thus, in terms of developing a robust and predictive control strategy, the fuzzy logic algorithm excels due to its adaptability, precision, and computational efficiency.

1.5 Hypotheses

The research field of the thesis in fault diagnosis and robust control strategies have taken a turn with the optimal control system integration. This integration way is assumed to increase the accuracy and performance of the robotic system and optimize the detection of mechanical faults to eliminate their consequences. Based on the vibrational analysis the thesis's purposes present how to update the mathematical model of the robot to achieve the desired performance characteristics under various conditions. Through current research, the following hypotheses are proposed:

- Vibrational analysis of a robot's moving parts, based on using accelerometers with special placement, will allow for precise determination of the frequency characteristics of specific mechanical damages.
- The data from the vibrational analysis can be used to develop optimal robot control strategies based on Bellman's dynamic programming and an algorithm based on fuzzy logic.
- Using optimal control based on Bellman's dynamic programming will reduce the control system's response time to disturbances caused by unwanted vibrations and increase the stability of the mechanical system.
- The fuzzy logic-based algorithm may be capable of predicting and diagnosing mechanical damages.
- The combination of vibrational analysis and the fuzzy logic algorithm can simplify the task of predicting repairs of robotic systems and enhancing the stability of control systems in the presence of mechanical damages.

1.6 Objectives of the Thesis

The main aim of the thesis is to design and develop an optimal control and diagnosis system for an industrial robot. The system provides detection and prediction of faults, also controls the robotic system behaviour using robust control strategies. The system should be adaptive, flexible, accurate and analyse data in real-time. At the same time, adaptive control and fault prediction diagnosis of the optimal control system are important. The research questions consider different fault types and optimal control strategies for interacting, predicting, and eliminating mechanical damages in robotic systems. In this case, the goals of this thesis are:

- Development of a scaled demonstrator with a data acquisition system for vibration analysis data collection.
- Design and modelling an optimal control system based on Bellman's dynamic programming method for eliminating oscillations.
- Development of a fuzzy logic algorithm for diagnosing mechanical faults in robotic system.
- Implement a fuzzy logic algorithm to control a robotic system under mechanical damage conditions.

1.7 Scientific Contributions

1.7.1 Scientific Novelty

- Vibration analysis method using strategically placed accelerometers to determine vibration characteristics (frequency and amplitude) for both normal and damaged transmission operation.

- Methodology of application of Bellman’s dynamic programming optimal regulator for eliminating undesirable oscillations in the robotic systems.
- Designing a novel adaptive and suitable application oriented on the fuzzy logic algorithm for diagnosing mechanical faults and controlling the robotic system under these conditions without using accurate mathematical models.
- An analysis of the control characteristics of optimal control system based on Bellman’s dynamic programming method and a novel application oriented on the fuzzy logic for eliminating consequences of mechanical damages.

1.7.2 Practical Novelty

- Development of a scaled demonstrator for vibration analysis data collection.
- Definition of the reference and faulty frequencies of the tooth belt transmission and screw transmission of the robot system.
- Modelling of the Bellman’s dynamic programming optimal control regulator for eliminating vibration based on vibrational spectrum.
- Modelling of the fuzzy logic diagnosis and control algorithm for detecting mechanical faults and control robotic system under these conditions.

1.8 Outline of the Thesis

The thesis is structured into five chapters are as follows.

Chapter 2 covers the review of related works. This chapter focuses on gearbox faults, types of control systems, and the description and analysis of Bellman’s dynamic programming method and fuzzy logic method.

Chapter 3 describes the design of the experimental part for getting vibration signals. This includes the description of the experimental test bench and its components, measurement setup, and laboratory test parameters. Also, this chapter covers the vibrational signal analysis by the fast Fourier transform method.

Chapter 4 focuses on designing the optimal control system. The first part of this chapter includes the mathematical description of cartesian robots like two-mass system and contains the mathematical derivation of the optimal controller. The second part of the chapter covers modelling process of the optimal regulator in two ways are eliminating and accelerating. The chapter analyzes and compares the modelling results of the obtained optimal controllers.

Chapter 5 contains details of designing the fuzzy logic algorithm for diagnosis of mechanical damages and control robot under these conditions. This algorithm is based on the analysis of vibrational signals. The chapter provides a detailed description of the algorithm’s derivation and output, as well as the results of its modeling using real data.

Chapter 6 presents the conclusion and future work of this research.

2 State of the Art in the Industrial Robots Motion Field

Robotic systems are widely used in modern manufacturing. These systems increase productivity while reducing the consumption of materials, energy, and human resources [61]. Robots help ensure human safety by handling hazardous materials and operating in unfavorable environments. However, despite their many advantages, robotic systems require maintenance, repair, and replacement in the event of wear or damage [62]. To extend the lifespan of a robotic system, properly selected actuators (primarily electric motors) are used. Control systems for robots are developed based on various algorithms to achieve the desired quality of operation. Predictive maintenance and diagnostic systems for moving mechanical parts of robots are being implemented and advanced to ensure high productivity and reduce maintenance costs [63], [64].

2.1 Electrical Machines in Robotics as Actuators

One of the extensive areas of implementing electric machines is robotics. Servo motors play a crucial role as actuators in robotics. This type of motor has found wide application in this field due to its advantages, namely [I]:

- ✓ Precise control over angular position, velocity, and acceleration, enabling high positional accuracy of robotic actuators [65], [66].
- ✓ Feedback in the form of potentiometers and encoders [67], [68]. These sensors, integrated into the servo motor’s design, provide real-time feedback on position and velocity, facilitating adjustments and corrections to deviations from desired parameters, thereby enhancing precision and stability [69], [70].
- ✓ Despite their small size, servo motor-drives can deliver high torque, making them indispensable in applications with limited installation space or requiring lifting heavy loads or applying significant force [71], [72].
- ✓ Servo motor-drives can be easily integrated into various control systems due to the versatility of control approaches. There are numerous methods for controlling servo motors, allowing for the development of various applications [73]–[75].

The conversion of electrical energy into mechanical energy is achieved with minimal losses when using servo motor-drives [76], [77].

Thus, servo motor-drives enhance the accuracy, versatility, and performance of mechanisms and applications. However, the motor control system also significantly influences operational characteristics [65], [78], [79]. The robot’s diagnostic and control system are equipped with an adequate number of sensors to monitor the mechanism’s behavior in real-time during work operations. However, these sensors only track parameters in the power and control systems of the machines [80]–[82]. This leads to the inability to prevent or predict the robot’s behavior in case of mechanical part failure. As a result, damages such as wear, heating, or breakdown of parts in the robot’s transmissions and connecting links go unnoticed and lead to serious consequences. Consequently, mechanisms lose their efficiency, working characteristics decrease, or they may completely fail.

Based on this literature review, discusses what faults in mechanical parts (e.g. gearboxes, reductors, couplings, joints, etc.) may occur during work operations and how a fuzzy logic-based control system can be used to create a predictive robust control system capable of operating under specified conditions.

2.2 Gearbox Analysis: Structure and Faults

Gearboxes play an important role in robotic systems. They consist of various transmission types, transfer force from the actuator to other parts of the robot, and coordinate the movement of these parts [83]. The correct choice of transmission types in gearbox affects the system's efficiency, maneuverability, precision, and lifecycle. Depending on the purpose, characteristics, and conditions, several types of transmissions are used in robotic systems [83]–[85], [II]:

1. Tooth transmission is used for working with high loads and minimal backlash. It is popular in small systems due to its compactness.
2. Belt transmission is used to transmit force in more complex and larger robotic systems. It is popular for its constant gear ratio, lightweight, and noiseless operation.
3. Chain transmission is used in large robotic systems where significant forces and loads need to be transmitted.
4. Screw or worm transmission is used in linear systems requiring precise positioning.

An example of a robot gearbox is shown in Figure 2.1.

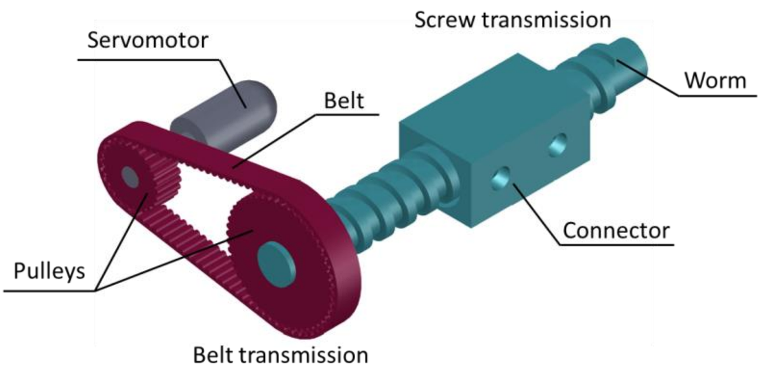


Figure 2.1. The example of the gearbox (previously published in article V).

Faults in the gearbox can significantly affect the performance, operational characteristics, durability, and energy efficiency of robotic systems. Gearbox failures develop gradually and don't instantly lead to system failure [86]. This process can extend over a long period, and even minor damage can result in serious consequences, disrupting system operation and eventually leading to complete failure. The most common gearbox damages include [II, III]:

✓ Wear and tear of wheels and pulleys.

All moving parts of the gearbox are subject to wear. Over time, gears and pulleys wear out due to constant friction, resulting in increased clearance between them and potentially reducing the system's accuracy and performance [87], [88].

✓ Misalignment of pulley centers.

Misaligned pulleys cause excessive friction, noise, and wear on gears and transmission belts. Improper pulley alignment can result from manufacturing defects, additional vibration, and mechanical stress [89].

✓ Lubrication and contamination issues.

Insufficient lubrication and contamination accelerate wear, increase friction, and lead to overheating and breakdown of transmission components. Lubrication is necessary to prevent metal-to-metal contact and reduce friction. Inadequate lubrication in the gearbox can lead to frequent repairs and downtime [90], [91].

- ✓ Overloading, vibrations, and impacts.

Subjecting the gearbox to loads beyond its design capacity, as well as shocks and vibrations, accelerates wear, deformation, and stress on transmission parts [92], [93]. Overloading, along with additional vibration, arises from excessive loads, sudden impacts, external forces, and mechanical imbalances [94].

Addressing gearbox issues requires a combination of servicing methods and the installation of modern monitoring and control systems to prevent frequent inspections and repairs. Reliable design solutions will ensure reliability and performance under various operating conditions.

2.3 Control Systems for Eliminating Vibrations

When addressing the task of mitigating and preventing damage in transmissions, five main types of control methods are distinguished based on system constraints and environmental conditions [95], [96]:

- Regulation;
- Optimal control with a finite or infinite forecasting horizon;
- Optimal control with constraints;
- Adaptive and robust control;
- Stochastic control.

Regulation mainly aims to minimize the error between the output signal of the dynamic system and the desired (specified) value [97]. Methods such as the least squares method or PID control are used for this purpose [98], [99].

Optimal control with a finite or infinite forecasting horizon is used to determine the control strategy based on the forecast of the system's state and future conditions [100], [101]. In the case of a finite horizon, the optimal control system aims to determine the control strategy over a fixed time interval [102]. In the case of an infinite horizon, the optimal control system determines the control strategy over an infinite time interval, considering the subsequent states of the system and the conditions of influence [103]. Dynamic programming algorithms like Bellman's equations are used to implement such control strategies.

Optimal control with constraints creates a control strategy for a dynamic system considering the presence of constraints to maximize or minimize performance criteria under specified conditions [46], [104]. Algorithms such as Pontryagin's maximum principle or quadratic programming are used to solve constrained control problems [46], [105].

Adaptive and robust control combines some algorithms, which can adjust to changing environmental conditions or control task requirements while maintaining the optimal control strategy [106]–[108]. Algorithms based on adaptive regulation, fuzzy logic, and machine learning are used to tune adaptive and robust control systems [109], [110].

Stochastic control systems are designed to operate in dynamic systems where random processes occur [111], [112]. These control systems consider the probability distribution and statistics of finding the optimal control strategy [113], [114]. To solve such problems, algorithms like the Kalman filter or Markov decision processes are typically used.

Each of these methods is applied in various fields depending on the task at hand and has its benefits and limitations. However, only three of them are often used in robotics and their comparison is presented in Table 2.1.

Table 2.1. Comparison of optimal control system types.

Control system type	Applicable algorithms	Benefits and limitations
Optimal control with a finite or infinite forecasting horizon	• Bellman's dynamic programming [47]; • Linear quadratic regulation [115]; • Model predictive control [116].	**Benefits:** • Forecasting. Ability to anticipate future changes and manage them. • Flexibility. Allows for determining optimal control strategy at any time interval. **Limitations:** • Mathematical complexity. Working with large time intervals requires significant computational resources. • Noise sensitivity. The presence of additional or unwanted noise that cannot be eliminated leads to the destabilization of the control system.
Optimal control with constraints	• Pontryagin's maximum principle [46]; • Constrained model predictive control [117].	**Benefits:** • Safety. Ensuring compliance with imposed constraints on the mechanism enhances control stability. • Adaptability. Allows for determining control strategy under any constraints. **Limitations:** • Implementation complexity. Calculation and application of complex algorithms are required to account for all constraints, which complicates the design of the control system. Probability of obtaining a suboptimal control strategy.
Adaptive and robust control	• Robust model predictive control [118]; • Adaptive neural network control [119]; • Fuzzy logic algorithm [48].	**Benefits:** • Forecasting. Working in variable conditions allows for predicting system states and adapting to changes without full reconfiguration of the control system. • Flexibility. The ability to adapt to any environmental conditions enhances real-time control efficiency.

Control system type	Applicable algorithms	Benefits and limitations
		Limitations: • Complexity of tuning. Parameter tuning and adaptation rules adjustment are required, which can be labour-intensive. Instability. Incorrect settings selection may lead to loss of control system stability.
Stochastic control	• Linear quadratic gaussian [120]; • Stochastic model predictive [121]; • Monte Carlo optimization [122].	**Benefits:** • Uncertainty management. Ability to account for random disturbances and occurrences of external forces to enhance control system stability. • Operation in a stochastic environment. Enables the construction of a control system for any environment with uncertain data. **Limitations:** • Computational complexity. Requires significant computational power for the design and operation of the control system. Sensitivity to precise mathematical models. An accurate mathematical model of the process or mechanism operating in a stochastic environment is required, which can be labor-intensive in real-world conditions.

Based on the literature review of control methods for robotic systems, two approaches stand out for the task of mitigating, preventing, and diagnosing transmission damage: optimal control with a finite or infinite forecasting horizon and adaptive and robust control. These methods possess the necessary qualities to build a control system based on analyzing vibrations that arise in the event of transmission damage.

Among the algorithms, Bellman's dynamic programming stands out due to its features, like forecasting, flexibility, and overcoming dynamic complexity [49]. This algorithm allows for optimizing control considering the current and future states of the system. This property is crucial for assessing system damage since the known vibration spectrum can be used to establish an optimality criterion that minimizes the consequences. Moreover, the ability to adapt the optimal control trajectory at each step guarantees optimal control. The algorithm is well-suited for both finite and infinite horizons, making it applicable for long-term use. By breaking the main task into smaller subtasks, Bellman's dynamic programming is particularly effective under conditions of mechanical damage to a robot, as it enables the division of the overall task into manageable parts. Such an approach reduces the influence of damage on the robot's performance by ensuring that the system can adapt dynamically to changing operational conditions while accounting for the future impact of the damage.

For controlling a robotic system with a damaged transmission, fuzzy logic stands out due to its properties, as functioning under uncertainty, adaptation to changes, and ease of setup and integration [57], [60]. Fuzzy logic is indispensable in situations where the mathematical model of a robotic system becomes unclear due to damage. This is critically important for control, as fuzzy rules can be configured to operate effectively under uncertainty. Furthermore, the vibration spectrum can be easily interpreted through linguistic variables, simplifying control and configuration. In cases of system degradation, such as worsening transmission damage, fuzzy logic easily adapts to changes, enhancing the reliability and robustness of the control system. Despite the complexity and multitasking nature of the system, the implementation and configuration of fuzzy logic remain relatively straightforward, and integration with other control methods is seamless.

Based on the above, Bellman's dynamic programming and fuzzy logic together create a synergistic control system combining adaptability, optimality, and robustness. Fuzzy logic mitigates noise sensitivity, while dynamic programming ensures global optimality. Furthermore, combining these two algorithms allows for assessing the current state of the mechanical system and calculating an optimal control strategy.

Unfortunately, the high computational demand of these algorithms complicates their integration into modern systems, which is why most studies lack precedents for exploring such a control system. Additionally, the insufficient development of diagnostic methods means that using vibration spectra as input data requires the development of new diagnostic approaches and evaluations. Therefore, it is essential to examine these two algorithms in more detail to assess their potential for building a control system for a robotic system operating with a damaged transmission.

2.4 Bellman's Dynamic Programming Method

Bellman's dynamic programming is a mathematical approach to solving optimal control problems, based on the principle of breaking down the problem into smaller fragments and finding the optimal solution for each of them [123], [124].

The main stages of dynamic programming are as follows [125], [126]:

1. Problem formulation.

The main task is broken down into fragments, for which optimality conditions are defined, and an optimal solution is found at each step. The most common example for such type of control is robot control with a specific sequence of actions.

2. Quality assessment.

For each step, an assessment of optimality is made. A quality function is created, which, considering various factors such as resource costs, desired outcomes, etc., evaluates the optimality of the solution.

3. Finding the optimal path.

Considering each step individually allows for determining the optimal control strategy for the overall problem solution.

4. Strategy preservation.

To reduce computational complexity, intermediate data is stored to avoid redundant calculations for simpler tasks.

5. Formation of a complete control strategy.

After determining the optimal solutions for all tasks, they are combined, and an overall control strategy is formed.

Two main expressions are used for forming optimal control according to Bellman's dynamic programming principle: the Bellman optimality equation (1) and the Bellman recurrence equation (2) [126]–[128].

$$V(s) = max_{a \in A(s)} \left\{ R(s,a) + \gamma \sum\nolimits_{s' \in S} P(s' \mid s,a) V(s') \right\}; \tag{2.1}$$

where, s – current system state; s' – next system state; α – system impact; V(s) – optimal strategy in the current state; A(s) – impact sets in the current state; R(s, α) – optimal criteria after impact; γ – discount coefficient; P(s' | s, α) – transient possibility to the next state after impact.

$$V_{k+1}(s) = max_{a \in A(s)} \left\{ R(s,a) + \gamma \sum\nolimits_{s' \in S} P(s' \mid s,a) V_k(s') \right\}; \tag{2.2}$$

where $V_k(s)$ – optimal strategy in the current state in k-iteration.

Bellman's dynamic programming algorithm is an excellent fit for addressing the problem of mitigating vibration effects. This is supported by the algorithm's distinct advantages.

By breaking down the problem into smaller functions, the control algorithm enables a detailed understanding of local dynamics, including nonlinear behavior. For example, in the case of a robotic manipulator subject to oscillations, dynamic programming optimizes the control input for each joint, minimizing vibration amplitude step by step [123], [124].

The quality criterion of this algorithm allows for considering various developmental scenarios and adapting the control system to specific needs. This approach not only mitigates the effects of damage and vibrations but also minimizes energy consumption and system wear. Thus, vibration suppression can simultaneously manage multiple parameters influencing production quality and safety [129].

To solve the problem of vibration suppression, it is essential to identify a trajectory and control strategy that avoids resonance frequencies and effectively reduces the impact of vibrations on the system. By analysing the system's response at each step, dynamic programming can create a global control strategy. In this way, the algorithm determines the sequence of actuator forces needed to compensate for disturbances [130].

It should also be noted that due to its step-by-step optimization, this algorithm is ideally suited for dynamically changing environments. Given that vibration characteristics can change in real time almost instantaneously, the adaptability of Bellman's dynamic programming ensures the stability of the control system [131].

2.5 Fuzzy Logic Algorithm

Given the diversity of methods, optimal control finds applications in aerospace engineering, for optimizing the movement and trajectory of ships and aircraft, and robotics, for developing controllers, autonomous vehicles, and controlling robotic manipulators. Fuzzy logic-based control systems enable the processing of imprecise data and categorizing them into belonging to a particular output, unlike binary logic, where the output parameter can only take on values of "0" or "1". Fuzzy logic is an excellent tool for creating control systems for mechanisms with nonlinear dynamics, complex relationships, and ambiguous or insufficient input parameters [110], [132], [133].

A fuzzy logic-based control system operates according to a specific algorithm.

Fuzzy logic replaces traditional binary sets with fuzzy sets, which allow elements to have partial membership in a set. Each fuzzy set is characterized by a membership function that assigns degrees of membership to elements in the universe of discourse [134], [135].

Fuzzy rules form the basis of the control logic in the fuzzy logic control system. These rules are expressed in the form of "if-then" statements, where linguistic variables (e.g., "low", "medium", "high") are used to represent inputs, outputs, and control actions. Fuzzy rules capture expert knowledge and heuristics about the system's behavior [136], [137].

Fuzzy inference involves applying fuzzy logic rules to determine the system's response to input conditions [138]. It consists of two main steps: fuzzification and inference. Fuzzification converts crisp input values into fuzzy sets using membership functions, while inference combines fuzzy rules to produce fuzzy output sets [139], [140]. Three main types of membership functions are used in this step. There are triangle (2.3), trapezoidal (2.4), and gaussian (2.5) membership functions.

$$triangle(x; a, b, c) = \begin{cases} 0, & x \leq a \\ \dfrac{x-a}{b-a}, & a \leq x \leq b \\ \dfrac{c-a}{c-b}, & b \leq x \leq c \\ 0, & c \leq x \end{cases}; \tag{2.3}$$

where, a, b – borders of the triangle function; c – the center of the triangle function.

$$trapezoid(x;a,b,c,d) = \begin{cases} 0, & x \leq a \\ \dfrac{x-a}{b-a}, & a \leq x \leq b \\ 1, & b \leq x \leq c\,; \\ \dfrac{c-a}{c-b}, & c \leq x \leq d \\ 0, & x \leq d \end{cases} \tag{2.4}$$

where, a, b – borders of the trapezoid function; c, d – the maximum of the trapezoid function.

$$gaussian(x;c,\sigma) = e^{-\frac{1}{2}\left(\frac{x-c}{\sigma}\right)^2}; \tag{2.5}$$

where, c – the middle of the gaussian function; σ – the width of the gaussian function.

Fuzzy aggregation combines the outputs of multiple fuzzy rules to generate a single fuzzy output set. This process can involve methods such as minimum, maximum, or weighted averaging to aggregate the contributions of individual rules [139].

Defuzzification converts the fuzzy output set into a crisp control action or decision. This involves determining a single value or a set of values that best represents the fuzzy output set, typically using methods such as centroid defuzzification or weighted average [140].

Based on the fuzzy logic control algorithm, it can be said that this method is highly adaptable to any task. Moreover, fuzzy logic does not require the calculation of an exact mathematical model of the process or mechanism. Additionally, fuzzy logic mirrors human reasoning, making it relatively easy to apply to various conditions. Consequently, the fuzzy logic control algorithm finds its application in areas such as autonomous systems, enabling smooth and efficient control, industrial automation, allowing the control of many transient processes, and robotics, facilitating transportation and precise control of machines and robots [141], [142].

2.6 Chapter Summary

There are numerous methods for controlling robotic systems, each designed for specific purposes, as evidenced by the review presented in this chapter. Control systems are constantly evolving to achieve greater performance, precision, or to mitigate undesirable effects caused by external factors. Faced with new challenges, robotic control systems are modernized to enable prediction, data analysis, and stable operation under varying conditions.

Despite significant advancements in the development of control systems, certain gaps remain in the application of specific control algorithms across different domains. This is because many issues are not yet considered significant, or the algorithms have not been optimized for external conditions (such as mechanical damages, environmental contamination, etc.). Such algorithms include Bellman's dynamic programming and fuzzy logic. In the field of condition monitoring and diagnostics of the mechanical components of robotic systems, these algorithms have not been fully developed. Many approaches to building control systems are focused on machine learning rather than vibration analysis, leaving the potential of dynamic programming and fuzzy logic in this area untapped. These algorithms offer unique advantages and demonstrate their capabilities when additional parameters for evaluating vibrational signals are available. This enables the development of a control system capable of mitigating undesirable effects caused by damage to the mechanical components of robotic systems. It also provides the possibility of controlling the robot under these conditions and diagnosing damage at early stages, ensuring timely maintenance, reducing wear on other mechanical components, and predicting the behavior of the mechanism in uncertain conditions.

The limited use of fuzzy logic and Bellman's dynamic programming algorithms can be attributed to their high computational resource requirements and the complexity of adapting these algorithms to uncertain scenarios of mechanical failures. However, by studying potential damage in robot transmissions, it is possible to obtain the necessary data to significantly reduce the computational demands of these algorithms and facilitate their integration into existing control systems. Addressing this gap could lead to significant advancements in the reliability, performance, and safety of industrial robotic systems, motivating further research in this direction.

3 Condition Monitoring of Robots

Robots in industry play an important role in many industrial applications, ensuring safety in the workplace and various production conditions. Monitoring the condition and implementing reliable control strategies for robots has always been significant in the industry. The use of optimal control systems in areas of predictive maintenance and condition assessment is advancing in modern research [63], [64].

The application of reliable control strategies, specifically optimal control systems, in industrial applications is evolving towards predictive maintenance to increase productivity and reduce the number of scheduled and unscheduled repairs and maintenance. Periodic and unscheduled repairs lead to loss of time and resources due to equipment downtime and loss of production productivity. Therefore, more research is focused on identifying damages at an early stage to prevent downtimes and find new ways to ensure equipment maintenance [86], [95], [96].

This allows for the development of an algorithm for real-time damage detection data assessment. Combining condition monitoring and reliable control strategies enables the use of several types of analysis: vibration, thermal, acoustic, and performance. Each type of analysis is intended to detect specific faults [143]–[146].

Vibration analysis is based on measuring the vibration levels of robot components, such as transmissions, bearings, and joints. Accelerometers are used for this purpose, recording the necessary data. Increased vibration levels can indicate imbalance, misalignment, or wear of moving parts. This method is useful for detecting damage in moving parts that are subject to increased friction [145].

Thermal analysis is based on determining thermal signatures using infrared cameras. Overheating of the robot’s moving parts can indicate lubrication problems, friction, or stress on the robot’s body. This method is effective for detecting overheating of motors and joints [143].

Acoustic analysis involves analyzing high-frequency sounds emitted by materials under load or friction. Cracks, friction, or other anomalies and damages generate sounds. Acoustic sensors or sensitive microphones are used to capture sounds, allowing early detection of fatigue cracks and component wear [144].

Performance analysis is based on assessing the working parameters of the robot, such as speed, torque, or energy consumption. Robot sensors and software are used for real-time data analysis. However, deviations from working parameters can indicate both mechanical damages and system errors [146].

Based on a literature review of these methods, it can be stated that vibration analysis integrates well into the strategy of reliable control systems and condition monitoring. Thus, this type of analysis can be taken as the basis for diagnosing and managing robots under the influence of mechanical damages.

3.1 Scale Demonstrator

The scale demonstrator is built for experiments and getting vibration data from the robot. The demonstrator consists of the Hirata cartesian robot, vibration sensors, and a data acquisition system. The view of the scale demonstrator to collect data for different faults is presented in Figure 3.1.

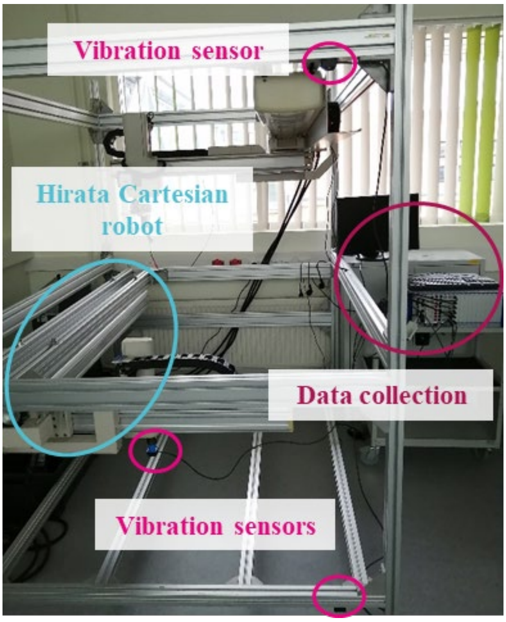


Figure 3.1. The view of the scale demonstrator with data collection system. (previously published in article IV)

The scale demonstrator was constructed to evaluate the impact of transmission damage on the structure of the Cartesian industrial robot. For this purpose, the operational characteristics of vibration were assessed under normal transmission conditions. Subsequently, damage was introduced, and experiments were conducted to evaluate the vibration performance of the robot with a damaged transmission.

These experiments are essential for obtaining data on vibration frequency and amplitude to understand the relationship between damage and its effects on the robot's vibrations during operation. By collecting sufficient data and analyzing it, a correlation between damage and vibrations can be established. Based on this data, a control system can be developed to enable the robotic system to operate under these conditions and to diagnose the damage effectively.

The data is collected from the robot in a healthy and faulty state using Data Acquisition System Dewetron and acceleration sensors. Data are collected in safe conditions to prevent extreme situations. For this purpose, the robot's parameters are set to certain limits. The specification of the robot and parameters for the experiment are presented in Table 3.1.

Table 3.1. Specification of the robot and parameters for the experiment.

Parameter		Value	
		Specification parameters	Experimental parameters
Number of axes		4	2
Motor power, W	X	400	400
	Y	200	200
	Z	100	—
	W	30	—
Max. speed, mm/s	X	1200	200
	Y	1200	200
	Z	1000	—
	W	1200°	—
Stroke, mm	X	1200	1000
	Y	700	700
	Z	200	—
	W	540°	—
Repeatability. mm	X	±0.02	
	Y		
	Z	±0.01	
	W	±0.02°	

Only two out of four axes were chosen for the experiment on collecting vibration signals. This was done because the Z and W axes have sufficiently rigid mounting, making capturing the required vibration characteristics impossible. Additionally, it is important to note that both axes represent a separate structure that can be easily replaced, which is why these axes are not considered valuable resources for obtaining the necessary data.

3.2 Components

The proposed data acquisition and control system for the experimental setup consists of the robot controller, teach pendant and three accelerometers (DIS-QG40N) united into one network. The control components allow to control of the robot in semi-automatic mode and help to avoid undesirable oscillations during the experiment. Teach pendant is used for setting needed parameters into the robot controller and implemented of the necessary robot operations. The technical specification for the accelerometers is given in Table 3.2.

Table 3.2. Technical specification for the accelerometer DIS-QG40N.

Parameter	Value
Measuring ways	3 axis (XYZ)
Measuring range	±4 g.
Output signal	0.5 – 4.5 V
Resolution	4 mg
Sensitivity error	± 2%
Output refresh rate	3 ms

The sensors were installed on the top and bottom of the test bench (presented in Figure 3.1), as well as on the robot’s gripping system. These positions allow for capturing the robot’s vibrations directly and eliminate unwanted oscillations from the test bench frame in the main signal. Consequently, the robot's vibration signal is fully filtered from extraneous interference, except for noise caused by the vibration of individual parts of the robot’s structure. However, since these vibrations are insignificant, they can be disregarded.

3.3 Artificial Faults

During the experiment, it was determined that the gearbox has its natural frequencies, which indicate its normal operation. Each transmission of the gearbox has distinct frequencies, but when combined, they provide an overall representation of the transmission's performance. However, to obtain the necessary data, it is essential to introduce damage to the gearbox structure. This will generate erroneous signals with additional amplitudes and frequencies, which will serve as the basis for developing the control system.

Under operating conditions, three types of mechanical faults can occur in the transmission of a cartesian robot: over-tension of the timing belt in the tooth belt transmission, heating of the worm in the screw transmission, and damage or excessive wear of the gears and pulleys in the transmissions. The experiment considered two types of failure: over-tension and heating. The third type was not considered, as the chance of this damage occurring in real conditions is quite low. Additionally, the transmission parts where this type of failure could occur are made of wear-resistant materials to avoid jamming.

Belt over-tension occurs when the centers of the pulleys are vertically misaligned relative to each other. This type of damage is shown in Figure 3.2.

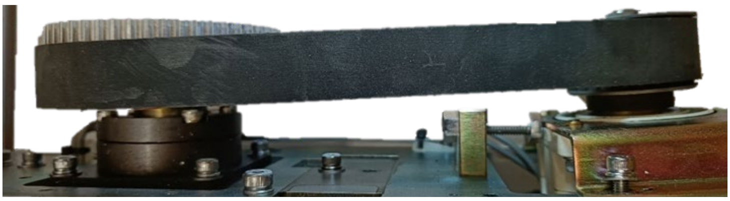


Figure 3.2. The example of the belt over-tension in the tooth belt transmission. (previously published in article II)

Over-tension creates additional force and load on the shaft of the robot's servomotor, which, in turn, leads to vibrations during transition points, when the direction of the robot's movement changes to the opposite.

Worm heating in the screw transmission occurs when there is insufficient lubrication or contamination. This type of damage is shown in Figure 3.3.

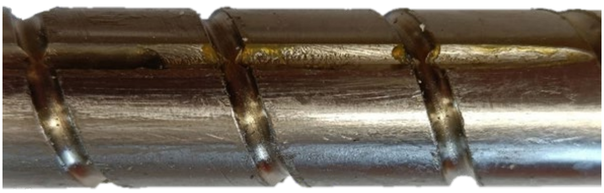


Figure 3.3. The example of the worm heating in the screw transmission. (previously published in article II)

Worm heating causes additional vibrations throughout the robot's workspace, reducing positioning accuracy and accelerating the wear of transmission components. This type of damage is also directly related to the parts of the transmission that are in constant contact. Due to additional wear, it can be assumed that the third type of damage is a consequence.

To obtain necessary data about the reference and faulty gearbox state the steps of the experiment for getting natural and artificial vibration data are presented in Figure 3.4.

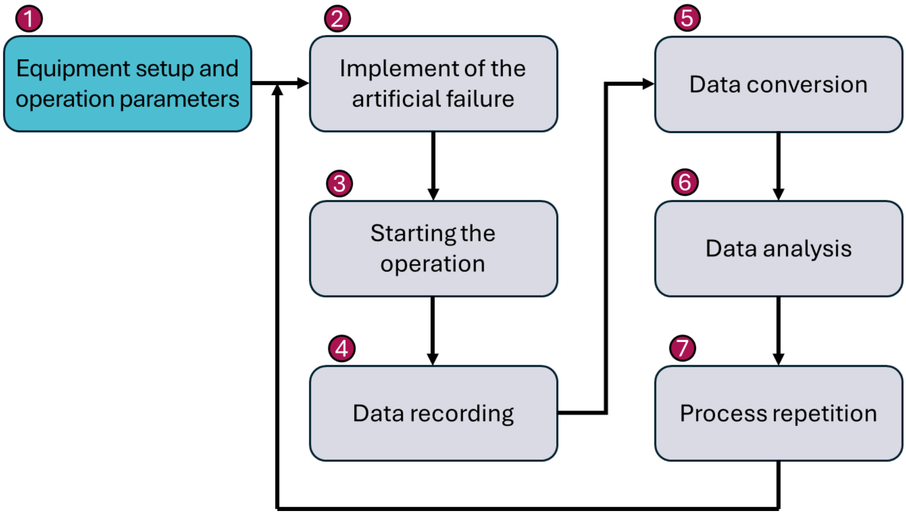


Figure 3.4. The flowchart of the experiment steps.

1. This step involves mounting sensors on the lab stand, connecting instruments to the data acquisition system, and setting the robot's operating parameters, such as speed, acceleration, the number of working axes, and movement paths.

2. At this stage, mechanical damage was introduced into the robot's transmission structure (first belt over-tension, then worm heating) separately for each axis of the robot.

3. Loading the robot's program in semi-automatic mode using the control panel, as well as monitoring control parameters and tracking the robot's movement trajectory.

4. Reading and recording data from vibration sensors along the three axes X, Y, and Z for the two robot axes, X and Y. The axes are considered separately to avoid "overlapping" of data.

5. Changing the data format to obtain an accurate representation of the processes occurring within the robot's structure and extracting the necessary parameters from the sensor's output signal.

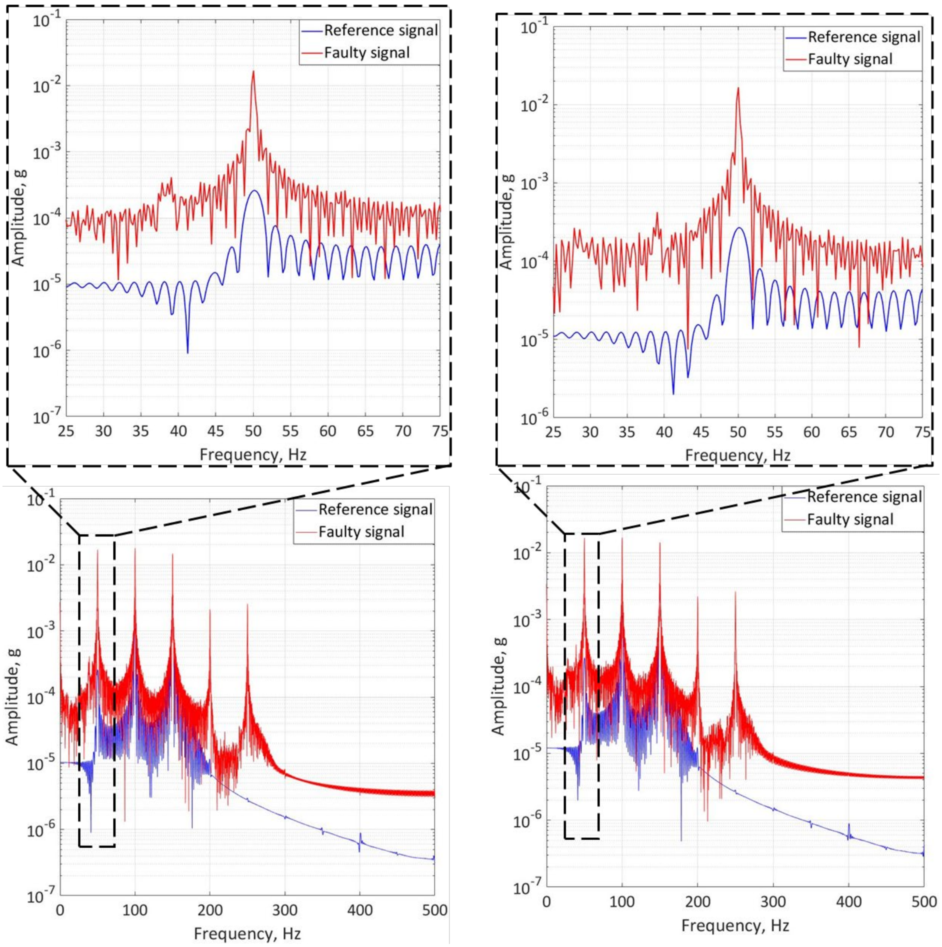
6. Extracting the frequency spectrum of the vibration signal using fast Fourier transform for further use in the development of diagnostic and control algorithms.

7. To get a full picture of the ongoing processes, the experiment was conducted multiple times for each of the robot's axes and under various conditions, specifically: healthy conditions (without additional noises and artificial failures), introducing an over-tension fault for the X and Y axes, and implementing a heating fault for the X and Y axes.

3.4 Measurement Analysis of Getting Data

Based on the experimental setup the vibration spectrums are obtained. During of the experiment, the reference signal (healthy state of the robot) and faulty signal (state of the robot under over-tension or heating faults) are received. The data analysis was carried out using the FFT method to determine the reference (natural) frequencies of the robot's transmission, as well as to isolate frequencies that are generated directly as a result of mechanical damage. To achieve more accurate results, the FFT window was selected with a range of 500 Hz. This was done because the mechanical components of the robot's transmission typically have vibrational frequencies in the low to mid-frequency ranges [147]–[149], and most mechanical damage is detected below this limit. Therefore, there is no point in considering a window with a higher frequency range.

The results of vibration signal analysis for timing belt over-tension of the tooth belt transmission by X and Y axes are presented in Figure 3.5.



(a) (b)

Figure 3.5. The spectra analysis of the output vibration signal by X-axis (a) and Y-axis (b) for the over-tension fault of tooth belt transmission. (previously published in article I)

The vibrational spectra in Figure 3.5 illustrate the frequency analysis of two distinct signals: a reference signal representing the healthy operation of a cartesian robot gearbox and a faulty signal that captures the effects of over-tension due to misaligned pulley axes. These graphs help to understand how the system's vibrational characteristics shift under faulty conditions, providing valuable insights into mechanical performance and fault diagnosis.

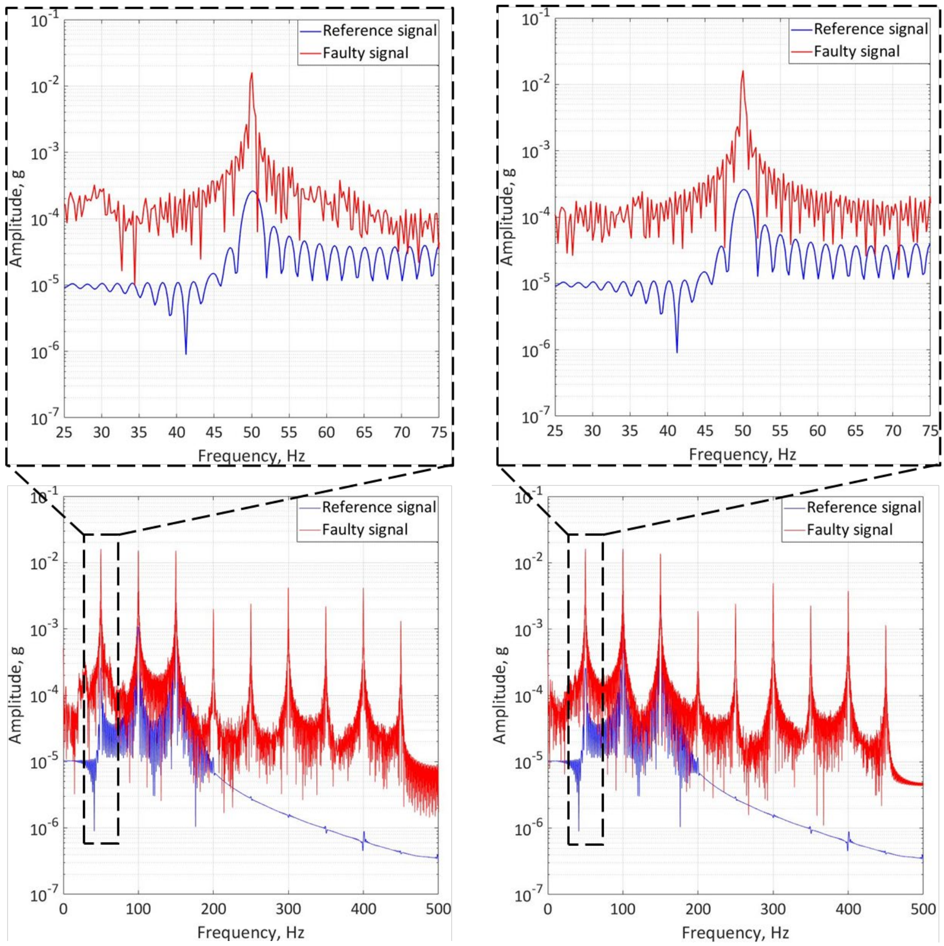
In both spectra, the reference signal (shown in blue) corresponds to the nominal or healthy state of the gearbox, where the belt tension is set according to factory specifications. This signal exhibits clear peaks at approximately 50 Hz, 100 Hz, and 150 Hz, representing the fundamental frequencies associated with the gearbox's normal operation. These frequencies are characteristic of the system when functioning under normal conditions, and the vibrational amplitudes at these points are relatively low, indicating a well-tuned, stable system. In contrast, the faulty signal (shown in red) shows the system's response under over-tension, a condition where the transmission belt is subject to excessive tension due to pulley misalignment.

Focusing on the vibrational spectrums by both axes, the reference signal shows dominant peaks in the expected frequency range. The system, in its healthy state, maintains low amplitudes at these critical frequencies, ensuring smooth operation. However, the faulty signal reveals a starkly different behavior. In addition to the fundamental peaks seen in the reference signal, the faulty spectrum introduces new peaks in higher frequency ranges, particularly 200 Hz and 250 Hz. This broadening of the frequency response, along with the substantial increase in amplitude, indicates that the over-tension causes increased mechanical stress and friction, leading to a more energetic vibrational response. The amplitude of these faulty peaks is significantly higher. This elevated response signals that the system is under abnormal strain, a direct consequence of the excessive tension in the transmission belt.

In both spectra, the faulty signal demonstrates a markedly different vibrational profile compared to the reference signal. The presence of these higher frequency components and their elevated amplitudes suggest that over-tension introduces significant resonances that were not present in the nominal state. These resonances likely stem from increased friction, belt tension, and mechanical misalignment, all of which contribute to the generation of excess vibrational energy. Moreover, the noise floor in the faulty signal appears to be elevated across the spectrum, particularly at lower frequencies, which may indicate additional vibrations from external sources, such as adjacent machinery or loose components within the system.

The over-tension fault's impact on the system is clear: the increased vibrational amplitude and the expansion of the frequency range up to 250 Hz signal that the system is experiencing abnormal mechanical stress. This stress could lead to faster degradation of the transmission components, such as the belt, pulleys, or even the gearbox itself, if not corrected promptly. By comparing these spectra, it becomes evident that a healthy system maintains a controlled vibrational response, while over-tension introduces significant irregularities that can be detected through spectral analysis. Thus, monitoring the vibrational spectrum of a transmission system is crucial for early fault detection, allowing for timely maintenance and avoiding potential mechanical failures.

The results of vibration signal analysis for worm heating of the screw transmission by X and Y axes are presented in Figure 3.6.



(a) (b)

Figure 3.6. The spectra analysis of the output vibration signal by X-axis (a) and Y-axis (b) for the heating fault of screw transmission. (previously published in article III)

In contrast, the second set of vibrational spectra examines the vibrational behavior of the cartesian robot gearbox under the influence of a worm heating fault in the screw transmission. The reference signal (blue) again represents the normal state of the system, with stable peaks at 50 Hz, 100 Hz, and 150 Hz, while the faulty signal (red) captures the effects of heating.

In the spectrums, the faulty signal due to the heating fault shows an increase in amplitude, particularly in the 200–450 Hz range. The heating of the screw transmission causes thermal expansion and deformation, which leads to increased friction and mechanical misalignment. These changes generate broader vibrational peaks across a wide frequency range, indicating that the heating fault excites multiple vibrational modes. The higher frequencies in this case are indicative of the system's struggle to maintain stability under thermal stress. The heating-induced vibrations are not confined to specific points in the system; instead, they have a stochastic nature, affecting multiple components simultaneously and leading to erratic behavior.

Unlike the over-tension fault, which manifests as a more predictable increase in vibrational amplitude at higher harmonics, the heating fault introduces randomized vibrational disturbances that are more challenging to mitigate. The broadening of the frequency range and the significant increase in amplitude suggest that overheating impacts the entire system, leading to increased wear on bearings, gears, and other mechanical parts.

3.5 Chapter Summary

This chapter covers a unique vibration analysis method using strategically placed accelerometers (shown in Figure 3.1) on the novel Cartesian scale demonstrator for mechanical fault testing, enabling precise identification of frequency and amplitude characteristics under both normal and damaged transmission conditions. Experiments involving artificial damage to the Cartesian robot's gearbox revealed key vibration signals and spectra, distinguishing normal operational frequencies from those indicating damage. These findings provide a foundation for creating advanced control strategies, including systems based on Bellman's dynamic programming to mitigate damage effects and fuzzy logic algorithms for effective damage diagnosis and operation under compromised conditions.

4 Optimal Control System for Compensation the Damage Impact

In the case of mechanical damage to the robot's transmission, which can lead to undesirable load oscillations, optimal control (Bellman dynamic programming) can offer effective solutions for several reasons [129]–[131]:

- Dynamic programming allows finding the optimal solution based on minimizing a cost function. The algorithm accounts for the system's dynamics and finds the optimal trajectory for the entire process, effectively preventing undesirable oscillations.
- The algorithm can account for random disturbances and uncertainties in the system, allowing for flexible real-time control adaptation to changing conditions.
- Optimal control relies on precise mathematical models of the system, enabling consideration of all physical parameters.
- Optimal control can minimize load oscillations and vibrations by finding optimal control actions at each step. This ensures smooth and steady control, even in the presence of damage.

To create an optimal control system for eliminating robot vibrations, it is necessary to define its mathematical model for the given case. In this context, we consider the elimination of load vibrations caused by mechanical damage to the robot's transmission. When damage occurs, and therefore, the resulting vibrations intensify the impact on the robot's load, leading to additional undesirable effects such as reduced positioning accuracy and increased dynamic load on the motors. To address this type of impact, the Cartesian robot axis should be represented as a two-mass system, and optimality criteria should be defined [123], [124].

Figure 4.1 presents the two-mass model for moving the load with a Cartesian robot along the Y-axis. The Z-axis in this model represents the load's attachment point, and only its weight is considered in creating the mathematical model.

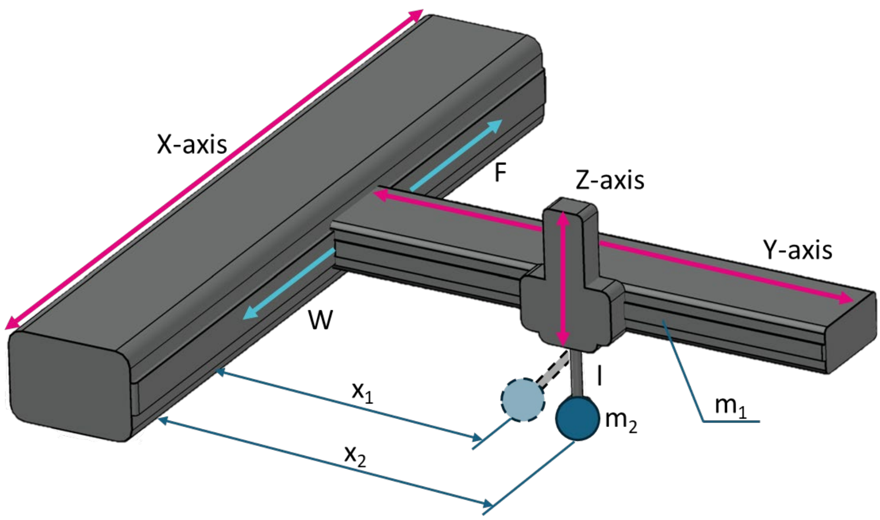


Figure 4.1. Two-mass model of the movement mechanism of Cartesian robot.

It is also important to note that the distance from the X-axis to the attachment point of the load can be neglected due to the rigid connection of the robot's axes to each other. In this regard, the system of differential equations describing the behavior of the two-mass system for moving the robot with the load will be as follows [49], [150]:

$$\begin{cases} m_1 \frac{d^2x_1}{dt^2} + m_2 x_2 \frac{g}{l} = F - W \\ m_2 \left(\frac{d^2x_2}{dt^2} - \frac{d^2x_1}{dt^2}\right) + m_2 x_2 \frac{g}{l} = 0 \end{cases}, \tag{4.1}$$

where m_1 is the weight of the Y and Z axes; m_2 is the mass of the load; x_1, x_2 are the coordinates of the mass centers of the load in initial and final positions, respectively; g is the acceleration of free fall; l is the length of the Z axis; F is the total traction or braking forces acting on the frame; W is the strength of resistance of the frame movement.

Consider that when the robot moves without changing speed during operation, even in the case of changing the direction of movement, the system of differential equations can be reduced to a single second-order equation:

$$\frac{d^2x}{dt^2} + \omega^2 x = \frac{F - W}{m_1} \tag{4.2}$$

where $\omega = \sqrt{\frac{g}{l}\left(1 + \frac{m_2}{m_1}\right)}$ is the natural frequency of the load oscillation.

The differential equation (4.22) can be transformed into a system of canonical equations by introducing the following notation $u = \frac{F-W}{m_1}, z_1 = x$:

$$\begin{cases} \dot{z}_1 = z_2 \\ \dot{z}_2 = (u - \omega^2 z_1) \end{cases}. \tag{4.3}$$

Two optimal criteria are obtained based on the mathematical model of the two-mass system. One of them is criteria based on the value load deviation from the vertical and dynamic component of the driving force, another one is criteria based on the value transition time and dynamic component of the driving force. These two criteria are the backbone of two optimal control models: the eliminating model and the accelerating model.

4.1 Eliminating Optimal Control Model

As an optimization criterion, the complex integral criterion is chosen. This criterion shows a relationship between the square of deviation load from the vertical and the square of the dynamic component of the driving force [49], [150]:

$$I = \int_0^T \left[k_1 x^2 + k_2 \left(\frac{F - W}{m_1}\right)^2\right] dt \tag{4.4}$$

where k_1, k_2 are the coefficients representing weighting factors based on the specific system dynamics and design criteria, which influence the importance of each term in the cost or performance index.

The coefficient k_1 is tied to the control force and how much penalty you assign to the mismatch between F and W, normalized by the mass m_1. A larger k_1 means you prioritize minimizing this force error.

The coefficient k_2 means it can prioritize reaching the desired performance (force balance) more quickly.

Considering the previous notations the criterion can be rewritten in the next form:

$$I = \int_0^T [k_1 z_1^2 + k_2 u^2] dt \tag{4.5}$$

The method of dynamic programming Bellman is used for minimizing the optimal criterion. The main functional equation is based on minimizing a specific functional that accounts for both the state variables and the control input. The Bellman functional equation is written as [49], [150]:

$$min\left[k_1 z_1^2 + k_2 u^2 + \frac{\partial S}{\partial z_1} z_2 + \frac{\partial S}{\partial z_2}(u - \omega^2 z_1)\right] = 0, \tag{4.6}$$

where S is the Bellman function, which represents the value function that we aim to minimize. The function S depends on the state variables z_1 and z_2, and its partial derivatives concerning these states play a key role in the control process.

The optimal control law u is obtained by the first differentiate equation (4.6) to u. It gives the necessary conditions for minimization. Setting this condition to zero leads to the following relationship:

$$2k_2 u + \frac{\partial S}{\partial z_2} = 0. \tag{4.7}$$

Solving for the control variable u, the optimal control law is calculated:

$$u = -\frac{1}{2k_2}\frac{\partial S}{\partial z_2}. \tag{4.8}$$

This equation (4.8) provides the control input u as a function of the state variables through the partial derivative of the Bellman function concerning z_2.

After substituting the expression for u back into the original Bellman equation (4.6) the following equation is got:

$$k_1 z_1^2 + \frac{\partial S}{\partial z_1} z_2 - \omega^2 z_1 \frac{\partial S}{\partial z_2} - \frac{1}{4k_2^2}\left(\frac{\partial S}{\partial z_2}\right)^2 = 0. \tag{4.9}$$

To solve the partial differential equation (4.9) the Bellman function S can be represented in a quadratic form, which is a standard approach for linear-quadratic control problems. In this case, the equation for the Bellman function is next:

$$S = A_1 z_1^2 + A_2 z_1 z_2 + A_3 z_2^2, \tag{4.10}$$

where A_1, A_2, and A_3 are unknown constants to be determined through further analysis. This quadratic form is typical in optimal control problems, where the value function is often a second-order polynomial in the state variables.

To find the constants need to take partial derivatives of S concerning z_1 and z_2:

$$\frac{\partial S}{\partial z_1} = 2A_1 z_1 + A_2 z_2, \tag{4.11}$$

$$\frac{\partial S}{\partial z_2} = 2A_3 z_2 + A_2 z_1, \tag{4.12}$$

These expressions can now be substituted into equation (4.9) to determine the values of the coefficients A_1, A_2, and A_3. The resulting system of equations will provide the specific solution for the Bellman function, and thereby, the optimal control strategy for the system.

$$\begin{gathered}\left(k_1 - \frac{A_3^2}{4k_2} - A_3\omega^2\right) z_1^2 + \left(A_3 - \frac{A_2^2}{k_2}\right) z_2^2 + \\ + \left(2A_1 - \frac{A_2 A_3}{k_2} - 2A_2\omega^2\right) z_1 z_2 = 0.\end{gathered} \tag{4.13}$$

The equation (4.13) will be true if the expressions in parentheses are equal to zero since the variables z_1 and z_2 cannot be zero. Therefore, the equation (4.13) can be rewritten as a system of algebraic expressions:

$$\begin{cases} k_1 - \dfrac{A_3^2}{4k_2} - A_3\omega^2 = 0, \\ A_3 - \dfrac{A_2^2}{k_2} = 0, \\ 2A_1 - \dfrac{A_2 A_3}{k_2} - 2A_2\omega^2 = 0. \end{cases} \tag{4.14}$$

This system of equations (4.14) typically results in two real solutions and two complex ones. However, only one real solution is selected because, in this scenario, the system's motion is smooth, and the maximum control effort remains small. The real solution ensures the physical feasibility and stability of the control system. After solving the system of nonlinear equations and finding the roots, we substitute the real root into the optimal control equation (4.8) derived earlier. The optimal control law can now be written as:

$$u = \frac{z_1(R - T)}{k_2}, \tag{4.14}$$

where

$$R = k_2\omega^2 - \sqrt{[k_2(k_1 + k_2\omega^4)]}, \tag{4.15}$$

$$T = \sqrt{2} z_2 \sqrt{k_2\left[\sqrt{[k_2(k_1 + k_2\omega^4)]} - k_2\omega^2\right]}. \tag{4.16}$$

Thus, by synthesizing the control law, the final expression for the optimal control is successfully derived with input u, a function of the state variables z_1, z_2, and the parameters k_1, k_2, ω. This function represents the control strategy that minimizes the cost function while maintaining system stability.

4.2 Accelerating Optimal Control Model

The algorithm for determining the optimal acceleration control model is similar to the previous model; however, the difference lies in the form of the integral optimality criterion, which, in turn, leads to a completely different form of the optimal controller. This criterion shows a relationship between the square of transition process time and the square of the dynamic component of the driving force [150], [151]:

$$I = \int_0^T \left[k_2 t^2 + k_1 \left(\frac{F - W}{m_1}\right)^2\right] dt \tag{4.17}$$

The criterion can be rewritten in the next form:

$$I = \int_0^T [k_2 z_2^2 + k_1 u^2] dt \tag{4.18}$$

The main Bellman's functional equation written as:

$$min\left[k_2 z_2^2 + k_1 u^2 + \frac{\partial S}{\partial z_1} z_2 + \frac{\partial S}{\partial z_2}(u - \omega^2 z_1)\right] = 0, \tag{4.19}$$

The optimal control law is calculated as:

$$u = -\frac{1}{2k_1}\frac{\partial S}{\partial z_2}. \tag{4.20}$$

After substituting the expression for *u* back into the original Bellman equation (4.19) the following equation is got:

$$k_2 z_2^2 + \frac{\partial S}{\partial z_1} z_2 - \omega^2 z_1 \frac{\partial S}{\partial z_2} - \frac{1}{4k_1^2}\left(\frac{\partial S}{\partial z_2}\right)^2 = 0. \tag{4.21}$$

To solve the partial differential equation (4.21) the Bellman function *S* can be represented in a quadratic form, which is a standard approach for linear-quadratic control problems. In this case, the equation for the Bellman function is next:

$$S = A_1 z_2^2 + A_2 z_1 z_2 + A_3 z_1^2, \tag{4.22}$$

To find the constants need to take partial derivatives of *S* concerning z_1 and z_2:

$$\frac{\partial S}{\partial z_1} = 2A_3 z_1 + A_2 z_2, \tag{4.23}$$

$$\frac{\partial S}{\partial z_2} = 2A_1 z_2 + A_2 z_1, \tag{4.24}$$

These expressions can now be substituted into equation (4.19) to determine the values of the coefficients A_1, A_2, and A_3. The resulting system of equations will provide the specific solution for the Bellman function, and thereby, the optimal control strategy for the system.

$$\left(k_2 - \frac{A_1^2}{k_1} + A_2\right) z_2^2 - \left(A_2\omega^2 + \frac{A_2^2}{4k_1}\right) z_1^2 + \\ + \left(2A_3 - \frac{A_1 A_2}{k_1} - 2A_1\omega^2\right) z_1 z_2 = 0. \quad (4.25)$$

The equation (4.25) will be true if the expressions in parentheses are equal to zero since the variables z_1 and z_2 cannot be zero. Therefore, the equation (4.25) can be rewritten as a system of algebraic expressions:

$$\begin{cases} k_2 - \frac{A_1^2}{k_1} + A_2 = 0, \\ A_2\omega^2 + \frac{A_2^2}{4k_1} = 0, \\ 2A_3 - \frac{A_1 A_2}{k_1} - 2A_1\omega^2 = 0. \end{cases} \quad (4.26)$$

This system of equations (4.26) typically results in two real solutions and two complex ones. However, only one real solution is selected because, in this scenario, the system's motion is smooth, and the maximum control effort remains small. The real solution ensures the physical feasibility and stability of the control system.

The optimal control law can now be written as:

$$u = 2\omega^2 z_1 - \frac{z_2\sqrt{k_1(k_2 - 4\omega^2 k_1)}}{k_1}. \quad (4.27)$$

Thus, by synthesizing the control law, the final expression for the optimal control is successfully derived with input u, a function of the state variables z_1, z_2, and the parameters k_1, k_2, ω. This function represents the control strategy that minimizes the cost function while maintaining system stability.

4.3 Modelling Results

To conduct simulations of eliminating and accelerating optimal control systems, it is necessary to recreate the optimal controller derived mathematically in the Simulink environment. The input parameters for this controller include acceleration and braking forces, and a vibration signal from the accelerometer is integrated into the controller to simulate real operating conditions of the optimal control system.

Thus, Figure 4.2 shows a model of the optimal control system for the Cartesian robot, designed to eliminate unwanted load (shown in Figure 4.1) oscillations caused by mechanical damage to the gearbox.

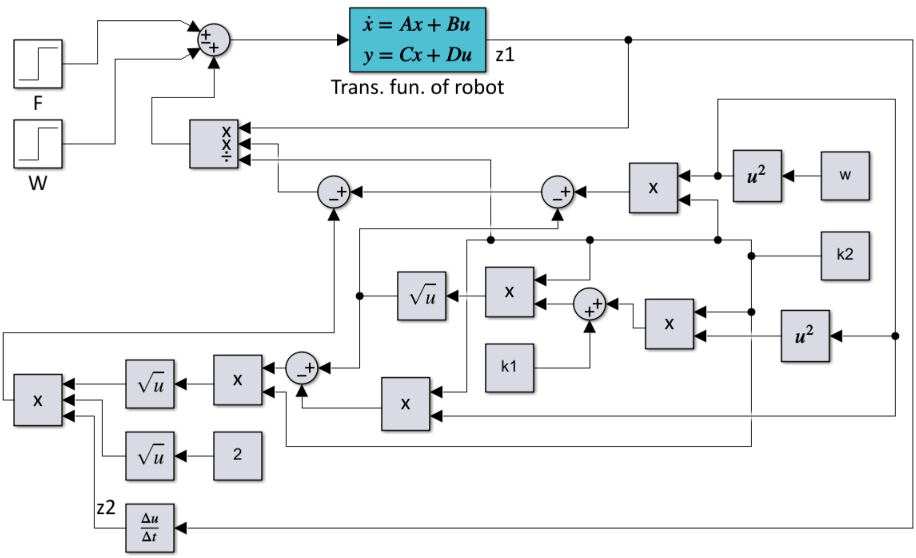


Figure 4.2. The optimal controller structural scheme for the Cartesian robot by eliminating modelling.

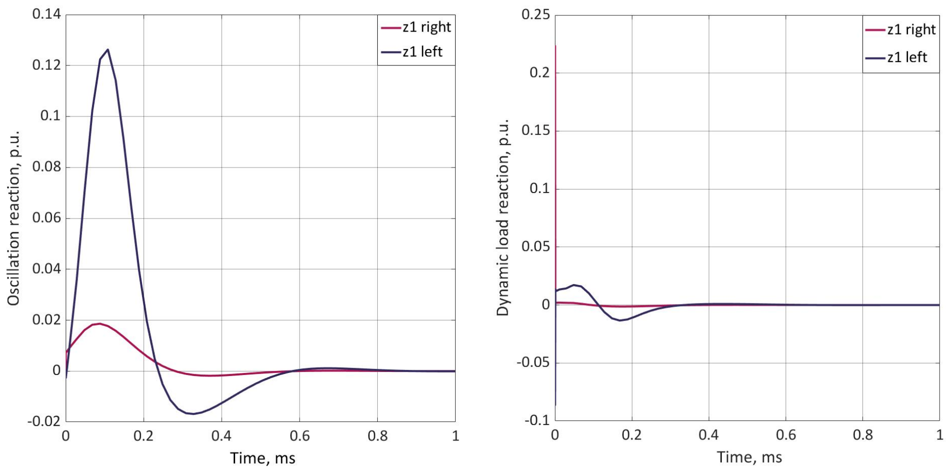
The optimal controller (gray blocks) shown in the diagram is designed to manage and mitigate the undesirable load oscillations in a Cartesian robot, particularly under conditions where mechanical damage may occur – damage that was illustrated by the vibrational spectra in previous analyses. This controller is structured to provide real-time feedback and adjustments to the robot's movements, ensuring stability and precision even in the presence of mechanical disturbances, such as the ones caused by over-tension or heating faults.

The main part of this scheme is the state-space representation of the robot (blue block), which models its dynamic behavior. The robot's transfer function – the block labeled with matrices A, B, C, and D – describes how the system responds to inputs and how the outputs are generated based on its internal state. This forms the foundation of the control system, as it encapsulates the essential characteristics of the robot's mechanical structure and dynamics.

The controller continuously monitors the difference between the desired and actual states of the robot using feedback loops. These feedback mechanisms are crucial for detecting deviations caused by external disturbances, such as those generated by vibrational faults. The system takes this error signal and feeds it back into the control algorithm to adjust the robot's actions dynamically. The gain blocks, represented by the components labeled k_1 and k_2, play a critical role in scaling the control actions based on the feedback. These gains are optimized to ensure that the corrections made by the controller are proportional to the error magnitude while preventing excessive or insufficient adjustments. Proper tuning of these gains is vital to minimizing oscillations without introducing instability into the system. The controller includes mechanisms for disturbance rejection, which are particularly important given the unpredictable nature of mechanical damages, such as those associated with over-tension and heating faults. The blocks that estimate disturbances assess external forces or vibrations acting on the robot, allowing the controller to distinguish between expected behavior and abnormal conditions that require corrective action.

This optimal controller can be integrated into the Cartesian robot’s control system by replacing or enhancing its existing motion control module. In a real-world setting, the controller would be implemented using a digital signal processor or a programmable logic controller capable of executing the real-time control algorithms required by the dynamic programming approach. The system would continuously receive feedback from position sensors, velocity sensors, and accelerometers, which measure the robot’s state and detect any anomalies caused by mechanical issues. All controller parameters would need to be carefully tuned during the commissioning phase to ensure optimal performance under varying load conditions and disturbances.

The responses of the control system on the undesirable oscillations and elimination of the dynamic load of the servomotor in conditions of mechanical damage are presented in Figure 4.3.



(a) (b)

Figure 4.3. The control system’s response to asymmetric load oscillations (a) and dynamic load (b) in conditions of mechanical damage in the robot's gearbox by eliminating modelling.

In the case of asymmetric load oscillations (a), the system’s reaction is characterized by an initial overshoot, with the right side (z_1 right) peaking at approximately 0.13 p.u. An overshoot of this magnitude indicates that the system’s control action is quite aggressive initially, likely to quickly counterbalance the load imbalance. However, excessive overshoot could lead to unnecessary stress on the robot’s components, so careful tuning of this parameter is essential.

As time progresses, the oscillations gradually decay, and the system moves towards stabilization. This is measured by the settling time, which in this case occurs 0.6 ms. This relatively fast settling time demonstrates that the control system is effective at damping the oscillations, reducing them to within a small margin around the steady-state value. The system exhibits good damping characteristics, as the oscillations diminish smoothly without escalating or persisting for too long, which would have indicated instability or poor control. The response is underdamped, meaning that oscillations are allowed initially but are progressively reduced, which is typically desirable for maintaining both stability and responsiveness in dynamic systems.

The oscillations in dynamic load are minimal, remaining close to zero throughout the response. This indicates that the control system efficiently manages load variations, maintaining the robot's stability with minimal deviation from the desired state. Notably, there is no significant overshoot or oscillation in this response, further demonstrating the control system's ability to smoothly adapt to changes in load without requiring aggressive corrections.

The smoothness and stability of the dynamic load response (b) are key indicators of the control system's robustness under varying load conditions. The system reacts promptly to these changes, with fluctuations settling almost immediately. The transient process here is extremely short, with the response stabilizing in less than 0.3 ms, which underscores the system's ability to provide rapid corrections and maintain control under dynamic loads.

As the system stabilizes, both the right and left sides converge toward values near zero, signifying a minimal steady-state error. This reflects the controller's ability to accurately bring the robot's components back to their intended positions, effectively compensating for the disturbances. The minimal steady-state error is monitored in both cases, in the asymmetric oscillations and dynamic load reactions.

Figure 4.4 presents the model of the optimal control system for the Cartesian robot during the accelerated transient process under conditions of undesirable oscillations resulting from gearbox mechanical damage.

Based on an accelerating regulator, the control system is also founded on the optimal control law derived using Bellman's dynamic programming method. The structure of this control system differs significantly from the previous one, with the main goal of this regulator being to accelerate the transient process of damping oscillations and reducing the dynamic load on the robot's servomotor as quickly as possible without additional oscillations. The main components of this system, as in the previous case, include the block for converting the transfer function of the Cartesian robot into state space, and the gains k_1 and k_2, which are responsible for the quality of the transient process.

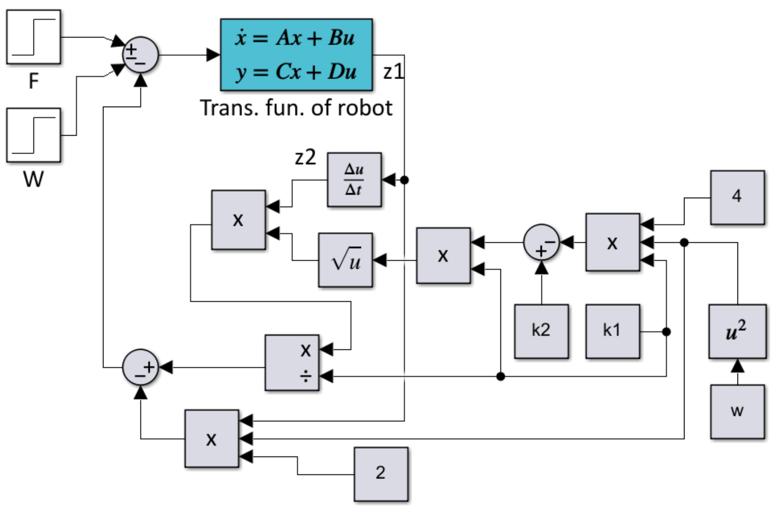
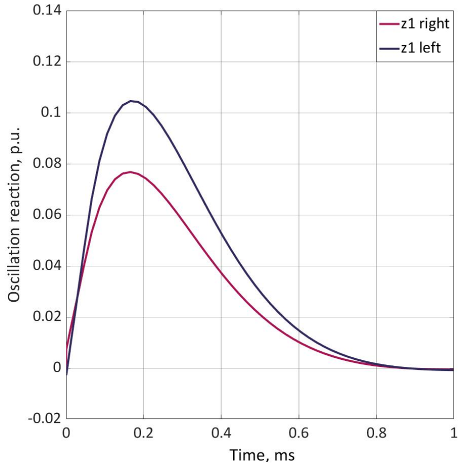
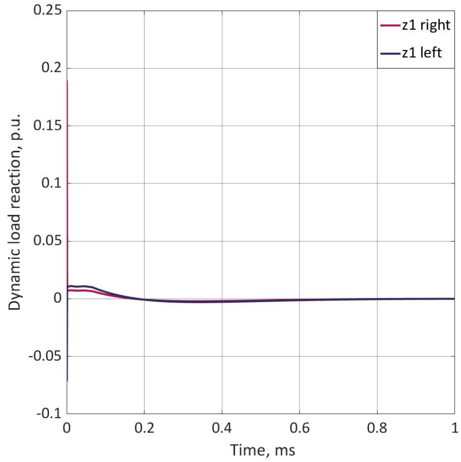


Figure 4.4. The optimal controller structural scheme for the Cartesian robot by accelerating modelling.



(a)



(b)

Figure 4.5. The control system's response to asymmetric load oscillations (a) and dynamic load (b) in conditions of mechanical damage in the robot's gearbox by eliminating modelling.

In the case of accelerating modelling the control system reaction to asymmetric oscillations (a) has also overshoot, but smaller than in eliminating modelling. The right side peak (z_1 right) reaches the amplitude of approximately 0.11 p.u., while the left side (z_1 left) lags slightly behind, peaking at a slightly lower value. This difference between the right and left sides highlights an imbalance in how the system reacts to the disturbance, which can be attributed to the nature of the mechanical damage.

The overshoot seen here reflects the control system's initial aggressive response to counteract the load imbalance and to restore equilibrium as quickly as possible. However, a higher overshoot may also indicate increased stress on the robot's mechanical components, potentially leading to additional wear and tear over time. After this initial peak, the oscillations begin to decay gradually, reflecting the system's damping mechanism, which works to reduce vibrational energy over time.

The system stabilizes in 0.8 ms, indicating its settling time – the period within which the oscillations have decreased to a minimal, steady-state level. The response demonstrates an underdamped characteristic, where oscillations occur but are controlled and gradually decrease without leading to instability.

In dynamic load response (b), the system displays a more controlled and less oscillatory reaction compared to the asymmetric load case. The dynamic load fluctuations are minimal and remain close to zero throughout the transient process, with no significant oscillations or overshoot observed.

The system's handling of dynamic load changes demonstrates smoothness and stability compared to eliminating modelling, as the oscillations settle rapidly with no major deviation from the steady-state value. The transient process in this case is 0.2 ms. It's less than the system stabilizing, underscoring the control system's ability to manage dynamic forces with minimal correction time. This level of performance suggests that the system is well-tuned to address dynamic loads efficiently, ensuring the robot remains stable and maintains operational precision even under varying external forces.

The steady-state error appears minimal, as both sides eventually converge towards zero, showing that the system effectively restores the robot to its intended operational state after compensating for the disturbance.

4.4 Chapter Summary

The chapter presents a unique methodology for applying Bellman's dynamic programming to design optimal regulators that effectively eliminate undesirable oscillations in robotic systems. By leveraging this approach, the response time of the control system to disturbances caused by unwanted vibrations is significantly reduced, and the mechanical system's stability is enhanced.

The chapter synthesizes and simulates two types of regulators, derived based on optimality equations for eliminating and accelerating modeling criteria. These regulators, using vibration signals obtained from prior experiments, demonstrate their ability to manage external disturbances effectively. Results confirm success in two critical areas: eliminating undesirable oscillations and reducing the dynamic load on the robot's servomotor. The transient response characteristics validate the stability of the system even under maximum disturbance, with rapid damping, absence of oscillatory behavior after the transient phase, and no static error.

An optimal and unique solution was achieved, showcasing the integration of the regulator into the robot's control system by replacing the existing module. Real-time feedback enables sensor signal tracking to adjust outputs dynamically. This approach provides a robust foundation for enhancing the performance and reliability of robotic systems under varying operational conditions.

5 Fuzzy Logic Diagnosis and Control Algorithm

Creating a fuzzy logic algorithm for fault diagnosis and robot control in error-prone conditions is based on analyzing vibration signal spectra in both normal and faulty states. The development process includes several key stages, each crucial for ensuring the accuracy and reliability of the system's operation:

1. The first step is identifying the parameters for fault diagnosis and proper robot control. Since fuzzy logic models human decision-making processes, key variables must be identified during experiments and system characteristic studies. These variables describe the parameters to be monitored (e.g., vibration amplitude and frequency) and form the basis for further calculations.

2. Membership functions play a critical role in fuzzy logic as they define the relationship between the input data (e.g., vibration signals) and the degree of their belonging to certain categories that describe the system's state (e.g., "movement speed", "presence of damage"). For each fuzzy variable, an appropriate membership function must be selected. Choosing the right shape of these functions (e.g., triangular, trapezoidal, Gaussian) allows for adequate modelling of the real system's behavior. These functions should accurately reflect the nature of the variable's changes related to the robot's condition.

3. A fuzzy rule base is created after defining the variables and membership functions. These rules consist of logical "if-then" operators that connect the input data with output decisions. For example, a rule might be: "If the vibration frequency exceeds a certain threshold and the amplitude is within a critical range, then the robot is likely to have suffered significant mechanical damage". The rule base serves as the logical backbone of the fuzzy logic algorithm and is used for fault diagnosis and adaptive control of the robot in fault conditions.

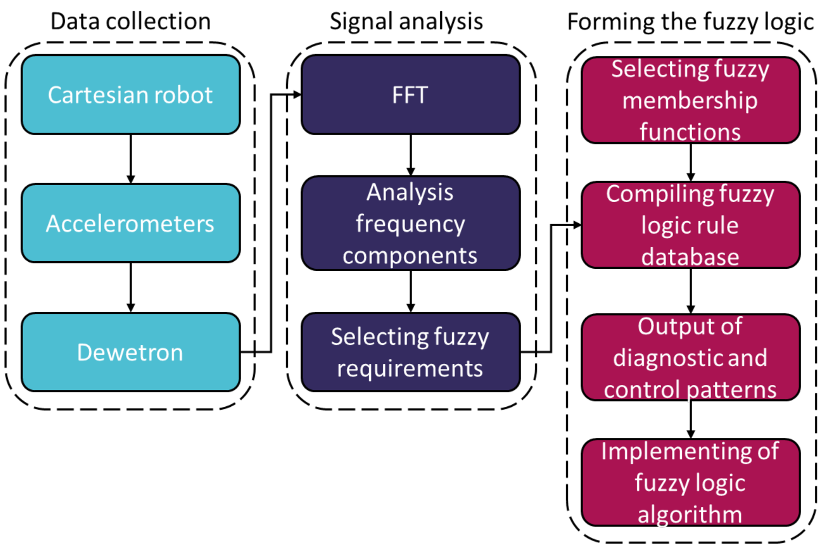


Figure 5.1. Overview of obtaining a fuzzy logic algorithm.

Thus, the process of creating a fuzzy logic algorithm for robot control and condition diagnosis consists of sequential stages: data collection, signal analysis, forming the fuzzy rule system (Figure 5.1.), as well as testing and tuning the system to ensure proper operation under real-world conditions. This approach allows effective robot management and early fault diagnosis, improving reliability and resistance to mechanical damage.

Implementing the fuzzy logic algorithm into the existing robot control system is carried out using the real input and output signals from the controller used in the control system. Therefore, the general operation of the fuzzy logic algorithm can be represented in the form shown in Figure 5.2.

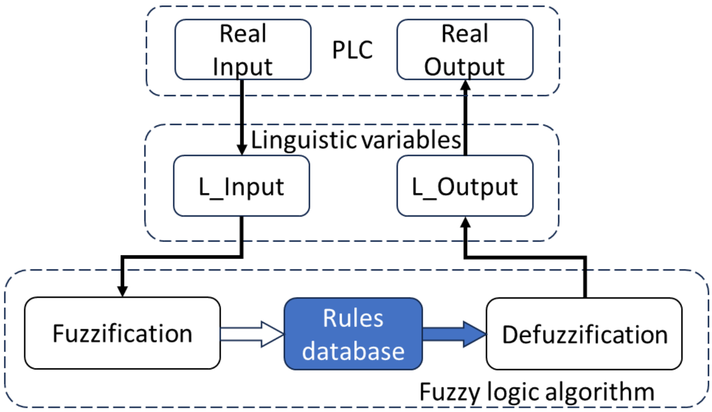


Figure 5.2. The general operation of the fuzzy logic algorithm.

5.1 Selecting Fuzzy Membership Functions

During experimental work, it was determined that the following parameters were accepted as input variables for the fuzzy logic: vibration frequency and amplitude, over-tension frequency, heating vibration frequency, and fault amplitude. The output variables of the fuzzy logic are the robot's speed, torque, acceleration, and the fault type degree. The scheme of the fuzzy logic algorithm processes is presented in Figure 5.3.

The presented diagram illustrates the integration of the robot control system under mechanical damage and the damage diagnosis system. The vibration frequency and amplitude parameters are directly used for the robot control system and influence the output parameters of the robot's drive speed, torque, and acceleration. The parameters of frequency over-tension, frequency heating, and fault amplitude are used to determine the presence of damage. Both control systems, based on the fuzzy logic algorithm, use data obtained during experiments to identify the robot's reference and faulty operating frequencies. The variables in the diagram are described by membership functions, with each variable having its function shape that best reflects its behavior in real-time operation.

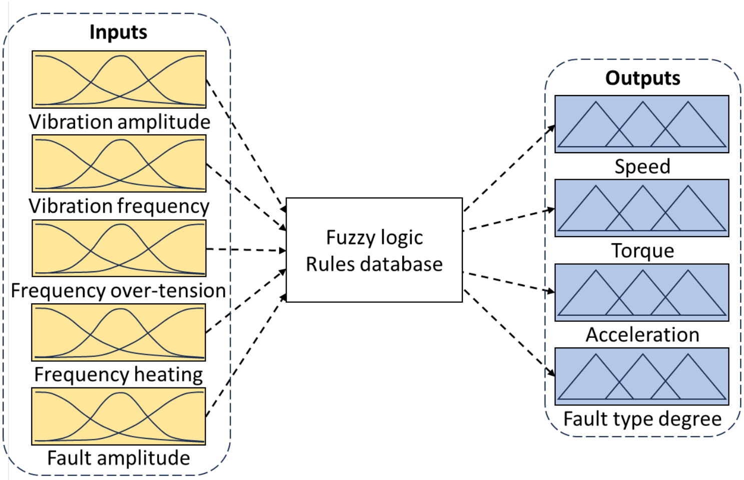


Figure 5.3. The scheme of the fuzzy logic algorithm processes. (previously published in article II)

Membership functions are described the control system parameters are illustrated in Figure 5.4.

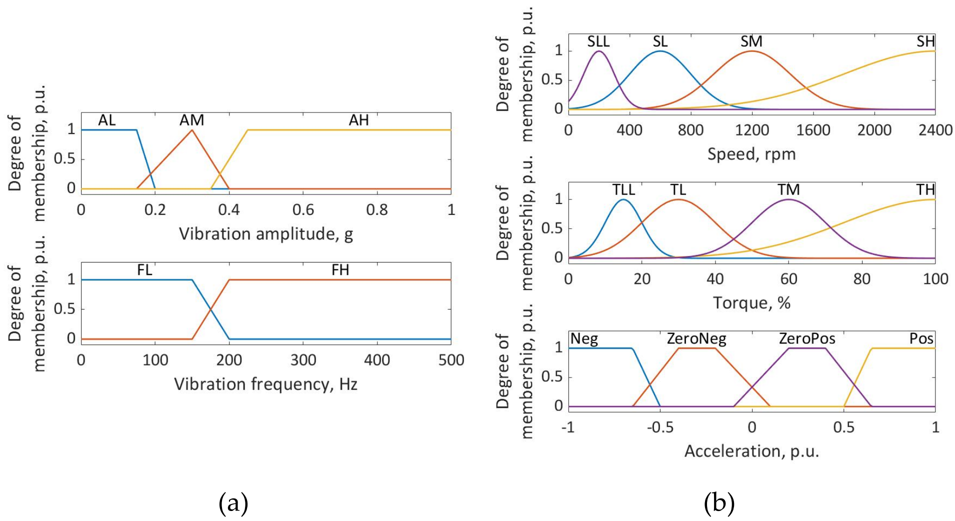


Figure 5.4. The control membership functions of input (a) and output (b) variables. (previously published in article I)

The vibration amplitude membership function includes three variables labeled as AL (Amplitude Low), AM (Amplitude Medium), and AH (Amplitude High).

AL corresponds to low amplitudes, where vibrations have minimal effect on the system’s components.

AM represents medium amplitude, which could indicate the maximum of nominal robot vibration and the beginning of potential issues, such as minor misalignments or early signs of wear.

AH covers high amplitudes, which usually signify severe mechanical damage or over-stress conditions, such as those caused by over-tensioning or worm screw transmission faults. The triangle shape in the AM zone reflects a smoother transition between low and high values, allowing for more sensitivity control when the amplitude is in a mid-range. This ensures the control system does not react too aggressively when the amplitude is neither low nor critically high, providing stability in response.

The vibration frequency membership function also has two variables: FL (Frequency Low) and FH (Frequency High).

FL covers low-frequency vibrations, which correspond to nominal operational conditions or vibrations caused by less critical disturbances, such as minor imbalances or misalignments.

FH corresponds to high-frequency vibrations, which may indicate severe issues like mechanical damage in the transmission system, as seen in the spectra of over-tension and heating faults. The change between FL and FH is more abrupt, reflecting that high-frequency vibrations tend to be more detrimental and require faster, more immediate control action. This sharper boundary helps the system respond quickly to prevent undesirable conditions.

The speed membership function has four variables: SLL (Speed Low Low), SL (Speed Low), SM (Super Medium), and SH (Super High).

SLL and SL indicate slow speeds, where the system is operating in low-performance conditions. In the event of mechanical damage (i.e., an increase in vibration amplitude and frequency), the robot’s speed is reduced to a minimum to avoid serious consequences.

SM reflects a medium speed, where the system runs optimally under normal conditions.

SH covers higher speed ranges, suggesting that the system can increase performance but at the risk of higher vibration and potential mechanical stress. Also, this variable symbolizes stable robot workability without any faults.

Thanks to the overlapping nature of the functions and the Gaussian function shape, the change occurs smoothly rather than abruptly.

The torque function is divided into four variables: TLL (Torque Low Low), TL (Torque Low), TM (Torque Medium), and TH (Torque High).

TLL and TL are associated with lower torque values. As the speed increases, the required torque decreases because less force is needed to maintain movement at higher speeds in normal conditions.

TM represents the optimal torque range for regular operation.

TH reflects high torque, which could be necessary in cases of mechanical damage at low speeds, the situation is different. The system must compensate by applying more torque to ensure smooth transmission and prevent further damage. This increased force helps overcome any additional resistance or friction caused by the fault, allowing the robot to maintain its performance even under compromised conditions.

The overlap between TL and TM, as well as TM and TH, allows the control system to apply precise adjustments to torque based on varying operational demands and vibration data. The Gaussian function shape helps to change torque between different regimes smoothly and decreases the vibration consequences.

The acceleration function has four key variables: Neg (Negative), ZeroNeg (Zero Negative), ZeroPos (Zero Positive), and Pos (Positive).

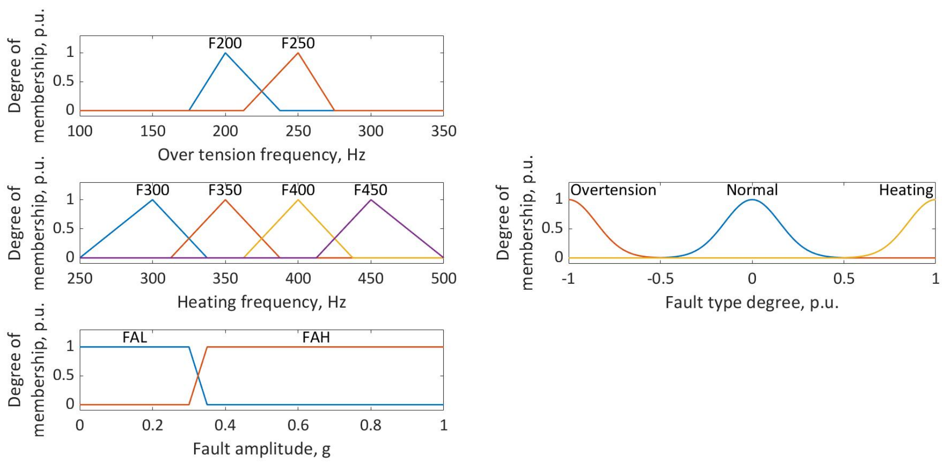
Neg represents deceleration, which is required to mitigate vibrations and prevent the system from further accelerating during critical conditions.

ZeroNeg and ZeroPos reflect states of minimal change, where the system remains in a steady operational mode.

Pos refers to positive acceleration, indicating an increase in velocity when the system is stable and can safely handle greater speeds.

The symmetrical layout of this membership function ensures balanced control when transitioning between increasing or decreasing accelerations. The trapezoidal forms of the function help to hold the torque on the necessary level until incoming changes are ended.

Membership functions are described the control system parameters are illustrated in Figure 5.4.



(a) (b)

Figure 5.5. The diagnosis membership functions of input (a) and output (b) variables. (previously published in article I)

Over-tension frequency covers two distinct frequency zones (F200, F250), representing levels of over-tension fault frequencies.

F200 and F250 correspond to over-tension frequencies (200 and 250 Hz), which may indicate belt tension issues. The triangle form of this function shows that transmission is not immediately damaging but requires attention.

Heating frequency covers four distinct frequency zones (F300, F350, F400, F450), representing levels of heating fault frequencies.

The occurrence of any of these frequencies (300, 350, 400, 450 Hz) will signal the onset of mechanical damage to the worm in the screw transmission, and attention should be given to this situation before it becomes critical. In this case, the triangular shape of the membership function is necessary for accurately tracking frequency peaks, as well as nearby values, which are presumed to indicate the beginning of the worm's heating process.

The fault amplitude function represents vibration amplitudes, with two regions: FAL (Fault amplitude low) and FAH (Fault amplitude high).

FAL corresponds to low-amplitude faults, where mechanical vibration levels are minor and do not pose an immediate threat to the system.

FAH covers high-amplitude faults, which could indicate severe mechanical problems, such as overloading, misalignments, or transmission defects. The sharp boundary between these two functions ensures that the system reacts quickly to critical amplitude changes, as they may indicate imminent mechanical failure.

5.2 Creating Fuzzy Logic Rules Database

The rule base of the fuzzy logic algorithm is founded on the ‘if...then’ principle, allowing for the selection of the best control method for the mechanism under different conditions. This same principle is applied in damage diagnosis, simplifying the process of defining conditions for the system.

The rules for the fuzzy logic algorithm are based not only on the chosen variables and their membership functions but also on the observation of the behavior of the controlled system. This means that the rules are developed during the experimental stage of collecting vibration data. Through these observations, it was determined that a reduction in vibration amplitude is directly proportional to a decrease in speed and inversely proportional to an increase in torque. Likewise, the robot's acceleration also affects the vibration amplitude.

In the context of diagnosing mechanical damage, the fuzzy logic rules are based on analyzing the spectra of vibration signals. By monitoring these spectral characteristics, the system can detect deviations that signal potential mechanical damage, allowing preventive actions to be taken before a critical failure occurs. This diagnostic capability enables the fuzzy logic system to respond in real-time, adjusting control parameters to mitigate the effects of emerging damage, such as reducing speed to lower vibration levels or increasing torque to compensate for mechanical stress. Thus, the algorithm enhances both operational safety and the longevity of the robot’s components by providing a proactive approach to damage management.

The fuzzy logic rules for controlling Cartesian robot under gearbox mechanical damages and diagnosis of them are presented in Table 5.1.

Table 5.1. Rules of fuzzy logic algorithm.

Number	**IF**	**THEN**
1	Vibration frequency is **FH** *AND* Frequency over-tension is **F200**	Fault type degree is **Overtension**
2	Vibration frequency is **FH** *AND* Frequency over-tension is **F250**	Fault type degree is **Overtension**
3	Vibration frequency is **FH** *AND* Frequency heating is **F300**	Fault type degree is **Heating**
4	Vibration frequency is **FH** *AND* Frequency heating is **F350**	Fault type degree is **Heating**
5	Vibration frequency is **FH** *AND* Frequency heating is **F400**	Fault type degree is **Heating**
6	Vibration frequency is **FH** *AND* Frequency heating is **F450**	Fault type degree is **Heating**
7	Vibration frequency is **FL** *AND* Frequency over-tension is *NOT* **F200** *AND* Frequency heating is *NOT* **F300**	Fault type degree is **Normal**
8	Vibration frequency is **FL** *AND* Frequency over-tension is *NOT* **F250** *AND* Frequency heating is *NOT* **F350**	Fault type degree is **Normal**

Table 5.1. Rules of fuzzy logic algorithm. (continued)

9	Vibration frequency is **FL** *AND* Frequency heating is *NOT* **F400**	Fault type degree is **Normal**
10	Vibration frequency is **FL** *AND* Frequency heating is *NOT* **F450**	Fault type degree is **Normal**
11	Vibration frequency is **FL** *AND* Fault amplitude **FAH**	Fault type degree is **Overtension**
12	Vibration frequency is **FL** *AND* Fault amplitude **FAH**	Fault type degree is **Heating**
13	Vibration frequency is **FH** *AND* Fault amplitude **FAL**	Fault type degree is **Overtension**
14	Vibration frequency is **FH** *AND* Fault amplitude **FAL**	Fault type degree is **Heating**
15	Vibration amplitude is **AL** *AND* Vibration frequency is **FL**	Speed is **SH** Torque is **TLL** Acceleration is **Positive**
16	Vibration amplitude is **AM** *AND* Vibration frequency is **FL**	Speed is **SH** Torque is **TLL** Acceleration is **ZeroPos**
17	Vibration amplitude is **AH** *AND* Vibration frequency is **FL**	Speed is **SL** Torque is **TL** Acceleration is **Neg**
18	Vibration amplitude is **AL** *AND* Vibration frequency is **FH**	Speed is **SM** Torque is **TH** Acceleration is **Positive**
19	Vibration amplitude is **AM** *AND* Vibration frequency is **FH**	Speed is **SM** Torque is **TH** Acceleration is **ZeroNeg**
20	Vibration amplitude is **AH** *AND* Vibration frequency is **FH**	Speed is **SLL** Torque is **TM** Acceleration is **ZeroPos**

5.3 Output of Diagnosis and Control Patterns

As a result of the simulation, behavior patterns of the robot’s control parameters (speed, torque, and acceleration), as well as the degree of diagnosis of mechanical damage, were obtained. The results of the control system simulation based on the fuzzy logic algorithm are presented in Figure 5.6.

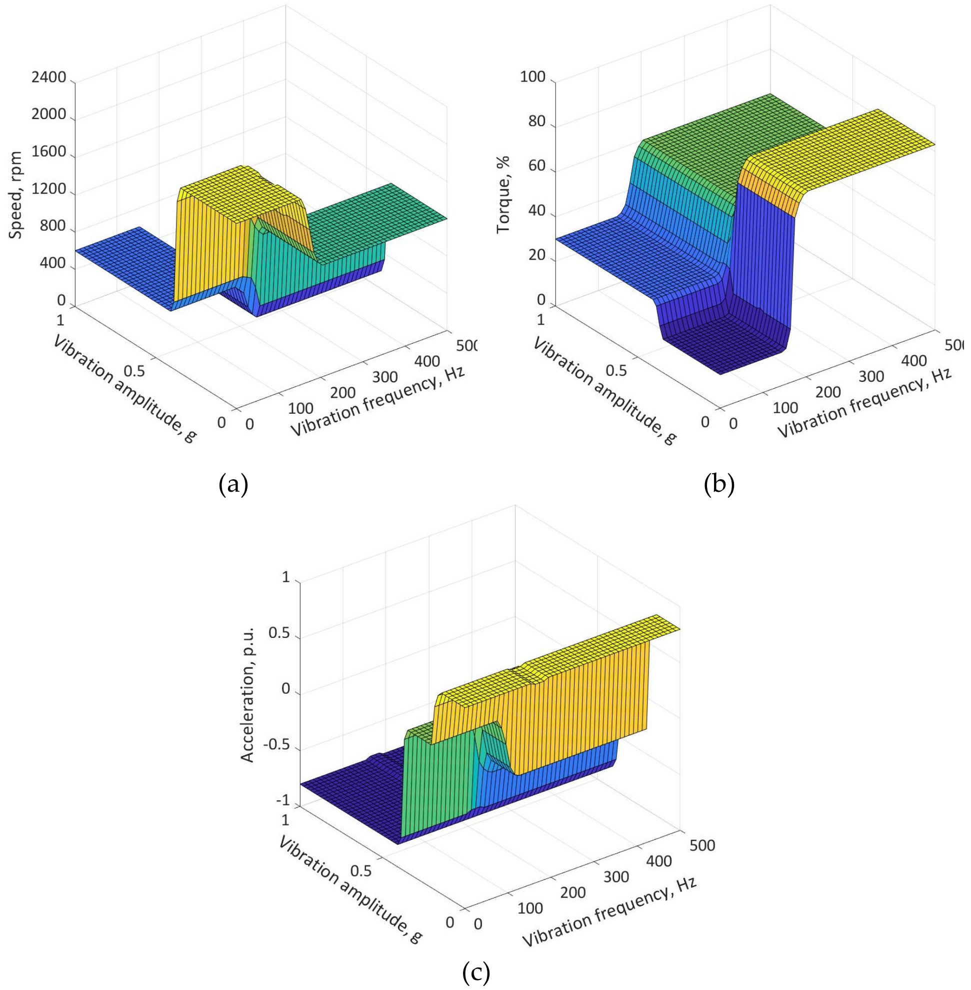


Figure 5.6. Results of modelling fuzzy logic algorithm for control parameters speed (a), torque (b), and acceleration (c). (previously published in article II)

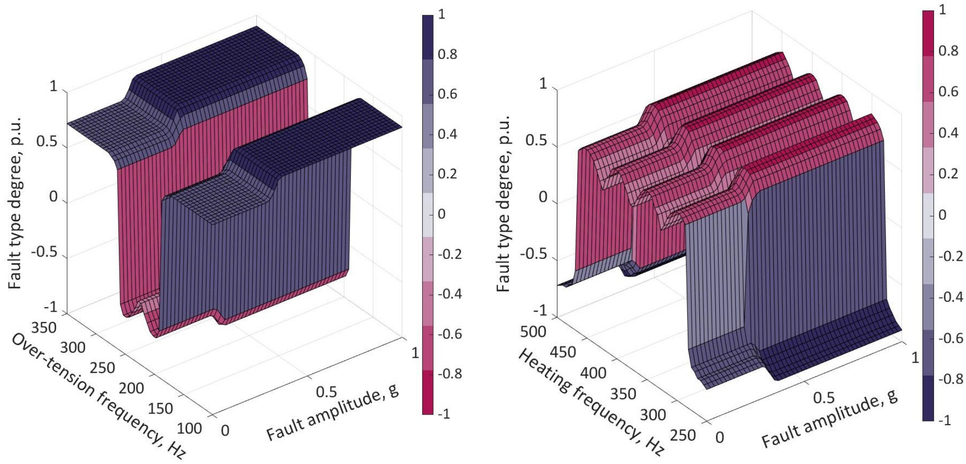
Figure 5.6 (a) presents the simulation pattern of the dependence of vibration amplitude and frequency on the robot's movement speed. The robot's speed increases significantly with a decrease in amplitude, reaching a limit in the range between 0.1 and 0.4g. As the vibration frequency rises, the speed drops to an average value at the same vibration amplitude levels. The movement speed decreases substantially when higher amplitudes and frequencies are reached, where mechanical damage in the robot's transmission is detected. The fuzzy logic algorithm responds to the increase in vibration levels by reducing the speed to compensate for the added stress and maintain the robot's movement stability. This highlights the system's adaptation to mechanical damage in the transmission.

Figure 5.6 (b) shows the simulation of torque. The relationship between torque and vibration amplitude and frequency is inverse to that of speed. As the speed increases, the torque decreases, but when mechanical damage occurs, particularly at higher frequencies and amplitudes, the torque rises to maintain proper operation. Torque increases when the amplitude exceeds 0.4g, ensuring that sufficient force is applied to the transmission to prevent further mechanical stress in the system. The higher torque values for greater vibration amplitudes and frequencies are due to the system adjusting to meet the increased demand for force caused by potential faults.

Figure 5.6 (c) describes the simulation of acceleration depending on the vibration amplitude and frequency. The fuzzy logic algorithm allows necessary adjustments during the occurrence of mechanical damage. At higher vibration levels, the acceleration decreases, which correlates with the need to adjust the robot's movements to mitigate the impact of mechanical damage. The fuzzy logic system increases acceleration at lower vibration amplitudes, ensuring that the robot responds quickly to disturbances and reduces the likelihood of malfunctions. The change in acceleration following this pattern reflects the system's adaptability to the impact of mechanical damage, allowing for a faster response to faults.

The fuzzy logic algorithm effectively adjusts the robot's control parameters in response to mechanical failures based on the degree of vibration amplitude and frequency. It reduces speed to compensate for mechanical damage, increases torque to ensure sufficient force is applied and regulates acceleration to maintain a quick response to vibration disruptions. These results indicate a reliable control system capable of maintaining performance despite faults, enhancing the robot's reliability and stability in dynamic operating conditions.

The results of the diagnosis system simulation based on the fuzzy logic algorithm are presented in Figure 5.7.



(a) (b)

Figure 5.7. Results of modelling fuzzy logic algorithm for fault type degree: over-tension (a) and heating (b).

Figure 5.7 (a) shows the relationship between the severity of belt over-tension failure in the robot's tooth belt transmission and the frequency, determined during the analysis of vibration signals, as well as the amplitude of vibrations. The system detects the presence of damage across the entire amplitude range when frequencies caused by over-tension occur. The model suggests that at higher vibration amplitudes, especially in the range of 0.4g and above, the system quickly identifies the severity of the fault, indicating a higher degree of failure. The failure severity decreases for lower amplitudes or frequencies, which suggests that the system is highly sensitive to increased fault levels under these conditions. The degree of the over-tension fault is set to –1 (indicating 100% detection of the failure in the transmission). This degree is determined using a membership function.

Figure 5.7 (b) displays the appearing degree of worm heating failure in screw transmission. This pattern shows a similar trend to the previous one. The failure severity sharply increases with higher vibration amplitudes (above 0.4g) and remains relatively constant in the presence of heating frequencies. This indicates that, as in the previous graph, the system's diagnostic sensitivity to vibration amplitude is high, allowing it to distinguish between different failure levels based on vibration frequency. In this case, the maximum degree of damage is 1 (indicating 100% detection of the fault in the transmission), and it is artificially set using a membership function, just like in the first case.

Both graphs demonstrate the diagnostic system's ability to identify faults based on vibration characteristics, focusing on amplitude and frequency. The fault severity increases significantly at high amplitudes, while frequency serves as an identifier. This highlights the system's effectiveness in detecting failures in the gearbox or mechanical components by analyzing vibration signatures, allowing it to respond appropriately to mechanical damage and ensure optimal performance under fault conditions.

5.4 Comparison and Combination of Both Algorithms

Since both methods are effective for achieving the set goals, a comparative analysis of both methods is warranted. Both optimal control and the fuzzy logic algorithm have their advantages and disadvantages, which should be considered when choosing a method.

Optimal control uses a mathematical model of the system to optimize performance and minimize undesirable oscillations and vibrations. This method ensures smooth and stable control by minimizing a cost function, and maintaining stability even in the presence of mechanical damage. Moreover, both proposed approaches for optimal control aim to address different consequences. The eliminating method focuses on reducing load oscillations, while the accelerating method is aimed at shortening regulation time and dynamic load, allowing for flexible control depending on the situation. It is important to note that this method requires an accurate mathematical model, which makes it sensitive to errors and noise. Additionally, implementing optimal control requires significant computational resources due to the iterative nature of the method.

Fuzzy logic, on the other hand, adapts to changing conditions and disturbances without needing an exact mathematical model, making this algorithm more flexible in uncertain environments. The presented method diagnoses faults and adjusts parameters based on vibration signal analysis, ensuring reliable operation in unpredictable conditions. Fuzzy logic is also easier to integrate into existing equipment due to its rule-based approach. However, the accuracy of control depends on the completeness and quality of the rule base and membership functions, and extensive experimental data is required to fine-tune these rules for effective use.

Thus, both methods have their strengths and weaknesses. The choice between them depends on the requirements for model accuracy, computational resources, and the specific application of the control system.

Combining these methods is proposed with fuzzy logic as the primary level for real-time diagnosis and control. The optimal control algorithm would be used only in cases requiring high precision and fast response and recovery from disturbances. Additionally, optimal control can be used for calculating adjustments for future impacts, thus predicting the behavior of the controlled system. In the case of damage, fuzzy logic would serve as the diagnostic tool, while optimal control would focus on compensating for the damage and optimizing performance.

5.5 Chapter Summary

This chapter proposes a new method for diagnosing mechanical damage in a robot's gearbox and controlling the mechanism under the influence of such damage. The method is based on a fuzzy logic algorithm and data from vibration signal analysis. Mechanical damage induces undesirable oscillations with specific amplitudes and frequencies, and this information was used to develop an algorithm for diagnosing these faults and controlling the robot under such conditions. As simulations demonstrate, the algorithm successfully achieves the set goals and shows a high degree of efficiency in assessing the damage. Furthermore, the control system, based on fuzzy logic, adjusts the robot's control parameters to the desired outcome, thereby minimizing the consequences of mechanical damage. The presented results are promising, and the control and diagnostic system can be successfully achieved using the proposed method. However, it is important to note that this algorithm requires testing with various complex combinations of faults to adjust the fuzzy rule base and improve the results respectively.

6 Conclusion and Future Work

This chapter concludes the results of the research based on the objectives. Besides, the future work is introduced to improve and continue the current research.

6.1 Conclusion

The main objectives of this research are threefold. The first is to develop a data collection system for assessing damage conditions in robotic systems. The second is to create an optimal control algorithm to suppress unwanted oscillations of the transported load caused by mechanical damage. The third, and most crucial, is to develop an algorithm for diagnosing and monitoring the robot's condition to ensure smooth operation and prevent mechanical damage.

The primary focus of the data collection system is the accuracy of the collected data, free from excessive noise and deviations. This was achieved through the proper placement of sensors on the experimental setup, accounting for potential noise. Experiments on data collection and analysis demonstrated that the use of spectral analysis, specifically the Fast Fourier Transform method, allows for the detection of damage at early stages. The resulting vibration spectra showed changes in the frequency characteristics of the robot's gearbox in both reference and damaged states. The analysis identified frequencies associated with two types of damage, namely, over-tension in the tooth belt transmission and worm heating in the screw transmission. This opens up opportunities for further research in predictive maintenance and the development of diagnostic and control algorithms. This will help reduce equipment downtime and increase the overall productivity of robotic systems.

The second part of the thesis focuses on the application of optimal control methods, particularly Bellman dynamic programming, to address the issue of eliminating unwanted oscillations. Using this method allows for the creation of an optimal control system to minimize costs and make the system adaptive and resistant to disturbances. A key feature of this strategy is the use of an accurate mathematical model of the robot in state space. This allows for the consideration of important physical parameters and provides predictions based on real dynamic characteristics. The robot's movement axis is modeled as a two-mass system, enabling adequate assessment of oscillation processes occurring due to mechanical damage.

The use of real data from accelerometers allows for highly accurate assessments of the model's state. The feedback and error control mechanisms in the model facilitate the prompt detection of deviations and corresponding adjustments in the robot's motion control. Analysis of the model's response to asymmetric oscillations shows a significant level of overshoot, indicating the system's aggressive response to external disturbances. The absence of oscillations in the transient process indicates good system stability. The quick settling time demonstrates the control system's high efficiency under dynamically changing load conditions. The proposed optimal control strategies will significantly improve the robot's positioning and reduce dynamic loads on the drives, which in turn will lower the likelihood of system failures in the event of mechanical damage.

The final important part of this thesis is the development of a fuzzy logic algorithm for fault diagnosis and robot control in conditions of increased likelihood of mechanical damage, based on the analysis of vibration signal spectra. The process of creating the algorithm consists of several stages.

First, linguistic variables are defined, which describe certain system parameters (e.g., vibration amplitude and frequency). These variables form the basis for further algorithm development. Second, the membership functions of the linguistic variables are constructed, allowing for the consideration of input parameters according to various criteria, such as vibration levels, frequencies of over-tension, or heating errors. Clear boundaries of these functions ensure the system's rapid response to critical changes. Third, fuzzy logic rules are established, playing a central role in robot control and diagnostics. These rules are formed based on experimental data obtained from observing the system's behavior. They allow the system to account for the relationship between changes in vibration frequency, amplitude, and the robot's parameters, such as speed, torque, and acceleration, and are used to develop a damage diagnosis algorithm.

Simulation modelling has shown that the fuzzy logic algorithm is capable of effectively responding to changes in vibration characteristics by adjusting the robot's control parameters. For example, when high-amplitude and high-frequency vibrations occur, the system reduces the robot's speed and increases torque to compensate for the additional load on the mechanical components. The system also adjusts the robot's acceleration to prevent further vibration growth and stabilize operation under damaged conditions.

The diagnostic system, based on fuzzy logic, allows real-time monitoring of vibration spectral characteristics and timely detection of deviations that signal possible mechanical damage. The algorithm responds to such damage by adjusting control parameters, which helps prevent critical failures and extends the lifespan of the robot's components. Vibration signals are used to determine the presence of damage, such as worm screw transmission overheating or belt tension issues, allowing the system to respond before the damage becomes critical.

Thus, the proposed fuzzy logic algorithm not only improves the reliability of the robot control system but also ensures early fault diagnosis. This contributes to increased system resilience to mechanical damage, extends the lifespan of its components, and minimizes the risk of failures.

6.2 Future Work

The proposed control systems can be validated through laboratory tests on a real object, as well as experiments involving the introduction of additional faults or their combinations. This will help assess the flexibility and accuracy of the proposed models, improve their performance, and identify potential limitations of the algorithms.

For optimal control systems, testing should be conducted under various operating conditions of the robot, including variable loads and increased positioning demands. This will help identify weak points in the model's behavior and improve the optimal control strategy.

The fuzzy logic-based control algorithm also requires additional experiments with various vibration signals to ensure its robustness against larger disturbances. Introducing other faults will expand the database of linguistic variables and fuzzy rules, potentially increasing the accuracy of fault detection with a greater number of diagnostic criteria. Additionally, integrating the fuzzy logic algorithm with machine learning systems should be considered to enhance the system's ability to detect faults at earlier stages.

Thus, future research will focus on expanding diagnostic capabilities and improving the robustness of mechanisms against mechanical damage, which will ultimately significantly increase the reliability and efficiency of robotic systems in industrial environments. Combining both methods is proposed with fuzzy logic as the primary level for real-time diagnosis and control. The optimal control algorithm would be used only in cases requiring high precision and fast response and recovery from disturbances. Additionally, optimal control can be used for calculating adjustments for future impacts, thus predicting the behavior of the controlled system. In the case of damage, fuzzy logic would serve as the diagnostic tool, while optimal control would focus on compensating for the damage and optimizing performance.

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Acknowledgements

First, I would like to express my gratitude to my colleagues and fellow PhD students, who made my academic journey both engaging and enriching.

I extend my heartfelt thanks to my supervisors for their invaluable expertise and guidance throughout this journey.

I am deeply grateful to the opponents and members of my doctoral committee for their insightful feedback and constructive criticism, which have significantly contributed to my work.

I also thank my family and friends for their unwavering support throughout this entire journey.

Finally, a special thanks to the most important person in my life, whose support and inspiration have been my constant source of strength.

Abstract

Fault Tolerant Control and Diagnosis Strategies for Cartesian Industrial Robot Motion Control Planning System

The main objective of this research is to develop a multi-level approach to enhancing the reliability and efficiency of unconventional machines and applications, including robotic systems. The basis for developing this approach is mechanical damage in the transmissions of robotic systems and unstable operating loads characteristic of industrial environments. The primary goals are to improve control, diagnostics, and failure prediction to minimize downtime, increase productivity, and prevent critical system failures. These tasks are becoming increasingly relevant due to the growing use of robotic systems across various industries.

The research sets out three key objectives. The first involves developing a data collection system to monitor the mechanical condition of the robot, particularly when mechanical damage occurs or there is a risk of it. To achieve this, an experimental lab setup with sensors was developed to collect data on the robot's vibrations and oscillations during its operations. Using spectral analysis, specifically Fast Fourier Transform, it was possible to identify mechanical issues such as belt over-tension in a tooth belt transmission and worm heating in the screw transmission. The results of vibration signal analysis indicate significant differences in the frequency spectra of the robot in its reference condition versus when damage is present. This, in turn, allows for early identification of damage and prevention of further degradation. This approach provides the foundation for predictive maintenance and minimizes maintenance costs.

The second objective of the research is to develop an optimal control system capable of suppressing unwanted load oscillations caused by mechanical damage to the gearbox. To achieve this, Bellman dynamic programming is applied, allowing for the creation of an adaptive control system that minimizes time costs and enhances the system's robustness against stochastic disturbances. A two-mass system model of the robot was adopted to evaluate the oscillatory processes with sufficient accuracy and optimize the control system to minimize oscillations. As shown through modelling, the proposed strategy demonstrates high accuracy and stability under disturbances. This approach reduces the dynamic load on the robot's drives, which mitigates the impact of mechanical damage on the overall structure, thereby extending the system's operational life.

The final part of the study focuses on the development of a fault detection and control algorithm for the robot in the presence of damage, based on fuzzy logic. The fuzzy logic algorithm is designed to process vibration signal analysis and make control decisions. To ensure the algorithm's accuracy, appropriate linguistic variables and their membership functions were selected, along with a base of fuzzy rules. These components were chosen based on experimental data from vibration collection. The fuzzy logic algorithm links changes in vibration characteristics with the condition of the robot's transmissions, enabling control under mechanical damage conditions without severe consequences. Simultaneously, real-time gearbox diagnostics are conducted to assess the state of the mechanical system. Modelling results show that the system responds effectively to changes in vibrations by adjusting the robot's parameters to stabilize its operation and prevent further structural damage. This approach allows the robotic system to adapt to changes, maintaining operability even under conditions of mechanical failure.

The research results demonstrate the significant potential of the proposed solutions for improving the performance and reliability of robotic systems in real-world industrial processes. It is expected that the proposed control and diagnostic algorithms will not only allow timely responses to mechanical damage but also prevent such issues, reducing the likelihood of critical failures and extending equipment life. Thus, this research represents an important step forward in the field of control and diagnostics for robotic systems operating under the increased probability of mechanical damage. The proposed methods and algorithms provide substantial improvements in both control accuracy and fault diagnosis, ultimately contributing to enhanced overall reliability and efficiency of robotic systems in industrial environments.

Lühikokkuvõte

Tõrketaluvusega juhtimis- ja diagnostikastrateegiad tööstusliku karteesianroboti liikumise planeerimise juhtimissüsteemi jaoks

Selle uurimistöö peamine eesmärk on välja töötada mitmetasandiline lähenemine, et suurendada ebatraditsiooniliste masinate ja rakenduste, sealhulgas robotisüsteemide, töökindlust ja tõhusust. Selle aluseks on robotisüsteemide ülekannete mehaanilised kahjustused ja ebastabiilsed töökoormused, mis on iseloomulikud tööstuskeskkondadele. Peamised eesmärgid on täiustada juhtimist, diagnostikat ja rikete prognoosimist, et minimeerida seisakuid, suurendada tootlikkust ja ennetada kriitilisi süsteemirikkeid. Need ülesanded muutuvad üha olulisemaks seoses robotisüsteemide kasvava kasutamisega erinevates tööstusharudes.

Uuringus seatakse kolm põhieesmärki. Esimene eesmärk on välja töötada andmekogumissüsteem roboti mehaanilise seisundi jälgimiseks, eriti kui esineb mehaanilisi kahjustusi või on nende oht. Selle saavutamiseks töötati välja eksperimentaalne laboriseade koos anduritega, et koguda andmeid roboti vibratsioonide ja võnkumiste kohta tööprotsessi käigus. Spektraalanalüüsi, täpsemalt kiire Fourier' teisenduse abil, tuvastati mehaanilisi probleeme, nagu rihmülekande liigpinge ja kruviülekande kuumenemine. Vibratsioonisignaali analüüsi tulemused näitasid olulisi erinevusi roboti sagedusspektrites kahjustuste korral ning normaaltalitluse puhul. See võimaldab kahjustusi varakult tuvastada ja rikke edasist süvenemist ennetada. Selline lähenemine loob aluse ennustavale hooldusele ning vähendab hoolduskulusid.

Uuringu teine eesmärk on välja töötada optimaalne juhtimissüsteem, mis suudab summutada soovimatud koormusvõnkumised, mis on põhjustatud käigukasti mehaanilistest kahjustustest. Selle saavutamiseks rakendatakse Bellmani dünaamilist programmeerimist, mis võimaldab luua adaptiivse juhtimissüsteemi, omakorda minimeerides ajakulu ja suurendades süsteemi vastupidavust stohhastilistele häiretele. Roboti kahe massi süsteemi mudelit kasutati võnkeprotsesside täpseks hindamiseks ning juhtimissüsteemi optimeerimiseks, et vähendada võnkumisi. Modelleerimise tulemusena näitas pakutud strateegia häirete korral suurt täpsust ja stabiilsust. See lähenemine vähendab roboti ajamitele mõjuvaid dünaamilisi koormusi, leevendades mehaaniliste kahjustuste mõju kogu struktuurile ja pikendades süsteemi tööiga.

Uuringu viimane osa keskendub tõrgete korral töötava roboti rikete tuvastamise ja juhtimise algoritmi väljatöötamisele, kasutades hägusloogikat. Hägusloogika algoritm on loodud töötlema vibratsioonisignaali analüüsi ja tegema juhtimisotsuseid. Algoritmi täpsuse tagamiseks valiti sobivad muutujad ja nende kuuluvusfunktsioonid ning hägusreeglite baas. Need komponendid valiti vibratsioonide kogumise eksperimentaalsete andmete põhjal. Hägusloogika algoritm seob vibratsioonitunnuste muutused roboti ülekannete seisundiga, võimaldades juhtimist mehaaniliste kahjustuste korral ilma tõsiste tagajärgedeta. Samal ajal viiakse läbi käigukasti reaalajas diagnostika mehaanilise süsteemi seisundi hindamiseks. Modelleerimise tulemused näitavad, et süsteem reageerib vibratsioonide muutustele tõhusalt, kohandades roboti parameetreid tööprotsessi stabiliseerimiseks ja edasiste kahjustuste ennetamiseks. Selline lähenemine võimaldab robotisüsteemil kohaneda muutustega, säilitades töövõime isegi mehaaniliste rikete tingimustes.

Uuringu tulemused näitavad pakutud lahenduste märkimisväärset potentsiaali robotisüsteemide jõudluse ja töökindluse parandamisel reaalses tööstusprotsessis. Eeldatakse, et väljapakutud juhtimis- ja diagnostikaalgoritmid võimaldavad mitte ainult õigeaegset reageerimist mehaanilistele kahjustustele, vaid ka nende ennetamist, vähendades kriitiliste rikete tõenäosust ja pikendades seadmete eluiga. Seega tähistab see uuring olulist sammu edasi robotisüsteemide juhtimise ja diagnostika valdkonnas, kus suureneb mehaaniliste kahjustuste tõenäosus. Pakutud meetodid ja algoritmid tagavad olulise täiustuse nii juhtimistäpsuses kui ka rikete diagnoosimises, aidates lõpuks kaasa robotisüsteemide töökindluse ja efektiivsuse parandamisele tööstuskeskkonnas.

Author’s Publications

Publication I

Autsou, S.; Kudelina, K.; Vaimann, T.; Rassõlkin, A.; Kallaste, A. Principles and Methods of Servomotor Control: Comparative Analysis and Applications. Appl. Sci. 2024, 14 (6), 2579. https://doi.org/10.3390/app14062579.

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Review

Principles and Methods of Servomotor Control: Comparative Analysis and Applications

Siarhei Autsou *, Karolina Kudelina, Toomas Vaimann, Anton Rassõlkin and Ants Kallaste

Department of Electrical Power Engineering and Mechatronics, Tallinn University of Technology, 19086 Tallinn, Estonia; karolina.kudelina@taltech.ee (K.K.); toomas.vaimann@taltech.ee (T.V.); anton.rassolkin@taltech.ee (A.R.); ants.kallaste@taltech.ee (A.K.)

* Correspondence: siarhei.autsou@taltech.ee

Abstract: Servomotors have found widespread application in many areas, such as manufacturing, robotics, automation, and others. Thus, the control of servomotors is divided into various principles and methods, leading to a high diversity of control systems. This article provides an overview of types of servomotors and their basic principles and control methods. Principles such as digital signal processing, feedback control principle, field-oriented control, and integration with Industry 4.0 are discussed. Based on these control principles, the article presents popular control methods: PWM control, current control, two-loop control, fuzzy-logic control, and programmable control. The article concludes with a comparison of the presented methods on several criteria, and as an example, it includes the results of modeling a servomotor using the fuzzy-logic control method.

Keywords: current control; machine vector control; fuzzy control; programmable control; pulse-width modulation; servomotors; two-term control

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Citation: Autsou, S.; Kudelina, K.; Vaimann, T.; Rassõlkin, A.; Kallaste, A. Principles and Methods of Servomotor Control: Comparative Analysis and Applications. *Appl. Sci.* **2024**, *14*, 2579. https://doi.org/10.3390/app14062579

Academic Editor: Javier Poza

Received: 29 February 2024
Revised: 15 March 2024
Accepted: 18 March 2024
Published: 19 March 2024

1. Introduction

Modern production cannot do without electric motors, which are used in various fields. Various types of electric motors are employed for diverse purposes, allowing for increased productivity, energy efficiency, and cost-effectiveness in any manufacturing process [1–4]. Thanks to motors, the possibilities of production are constantly expanding, enabling the use of more complex and advanced mechanisms, and creating new development opportunities. One way of advancing production is the use of robotic systems, where servomotors are directly employed [5–7].

Servomotors in robots are used to enhance the precision or smoothness of a mechanism's operation, depending on the task it performs. Therefore, the control of drives must have a similar nature, enabling the achievement of the required goals. However, the more complex the drive control method, the more intricate the control system will be, leading to additional costs but at the same time enhancing production characteristics [7–10].

The control of servomotors has not only changed in recent years but continues to evolve, revolutionizing various industries, particularly robotics and automation. Initially, these motors were controlled using analog methods, but with the advancement of digital technologies, control has become more precise and versatile [11–14].

Various technologies for servomotor control are currently employed, including digital signal processing systems, feedback systems, field-oriented control, and control systems integrated with Industry 4.0. All these types of servomotor control are used to achieve different results, each having its own merits and drawbacks, which are discussed in these works [15–21].

This work is a general overview of the topic of servomotors, their devices and principles of operation, popular methods of control, and ways to expand existing and new control systems. It is worth noting that motor control is constantly evolving, allowing for the exploration of new control methods, such as the transition from analog to digital systems, from open-loop systems to feedback systems, and so on. The development of control systems enables the improvement of the efficiency, precision, and adaptability of motors in various industries, leading to the conclusion that new technologies will have more complex yet integrable solutions.

The second chapter of this article provides a description of the structure and operating principles of servomotors and discusses the main objectives of their use. The third and fourth chapters introduce the control principles mentioned above and outline some methods of controlling servomotors that are suitable for a specific type of control. The fifth chapter is a comparison of the presented types of control. The chapter does not provide experimental data but rather offers a comparative characterization based on previously conducted research.

2. Servomotors: Structure, Operating Method, Types, Main Characteristics

2.1. Structure and Operating Method

A servomotor is a type of electromotor, the shaft of which can be controlled with high accuracy. A shaft of a servomotor can rotate at the required angle or with constant rotational speed. Servomotors have become widespread in robotics for these properties [22,23].

A servomotor consists of a DTC motor, gearbox with shaft, and controller with necessary sensors (encoder, position sensor, etc.). A draft of the construction of a servomotor is presented in Figure 1.

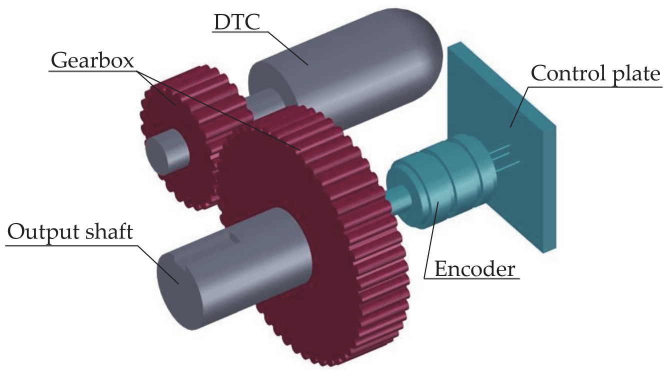


Figure 1. The draft of the servomotor.

The gearbox in servomotors is used to reduce speed and increase torque on the output shaft. A potentiometer or encoder is used to track the rotation angle or speed of the shaft, thus creating a closed-loop control system with feedback [23–25].

A popular method of controlling a servomotor is pulse-width modulation (PWM). This method is based on determining the angle of rotation or speed of the output shaft based on the pulse length at a given frequency. The use of PWM for controlling servomotors is based on the following principles [26–28]:

1. PWM generates pulses of varying width (duration) with different periods.

$$D = \frac{T_{ON}}{T_{period}} \times 100, \tag{1}$$

where D—pulse duration, T_{ON}—the ON time of the signal, and T_{period}—the total period of one PWM cycle.

$$f = \frac{1}{T_{period}}, \tag{2}$$

where f—PWM frequency.

2. To control the speed of the servomotor, the width of the pulses is changed, allowing the regulation of the power supplied to the motor.

$$PW = D(PW_{max} - PW_{min}) + PW_{min}, \tag{3}$$

where PW—pulse width and PW_{max} and PW_{min}—the maximum and minimum pulse width supported by the servomotor.

3. Control of the position of the servomotor is possible using feedback. To adjust the position, the voltage applied to the motor, after the PWM signal is converted, is compared to the desired voltage, resulting in a control signal.

$$\alpha = D(\alpha_{max} - \alpha_{min}) + \alpha_{min}, \tag{4}$$

where α—angular position of the servomotor and α_{max} and α_{min}—the maximum and minimum angles of the servomotor.

4. PWM is also used to regulate a smooth trajectory of movement from one point to another for the servomotor.
5. In addition to PWM, PID controllers and microcontrollers are applied to enhance the efficiency of regulation and control.

This method has gained popularity due to its simplicity of implementation and low cost. PWM also provides high efficiency in speed and positioning control, making it applicable in applications requiring a high response to control input and precise control. Examples of such applications may include non-dynamic systems such as fans, pumps, or conveyors [29,30]. However, to achieve the best results, other principles of controlling servomotors are applied, which will be discussed below.

2.2. Servomotor Types

Currently, servomotors are divided into several types based on six different criteria: the type of motor used, the type of current, the type of construction, the function performed, the signal processing method, and the type of gearbox.

Based on the type of motor used and the type of current, servomotors are classified as synchronous or asynchronous, and using alternating or direct current, respectively. Considering that asynchronous motors are more powerful, this type of servomotor is produced only for alternating current. Synchronous motors have lower power but provide greater accuracy; in conjunction with direct current, they allow for achieving smaller motor dimensions and using this type of servomotor for autonomous mechanisms [31–35].

In terms of construction, servomotors are divided into brush motors, coreless motors, and brushless motors. Unlike brush motors, brushless models have a wider range of rotation speeds, allowing them to be used in processes requiring high-speed movement. However, controlling a brushless motor requires the presence of a PLC, regardless of the tasks it performs [33,36–38].

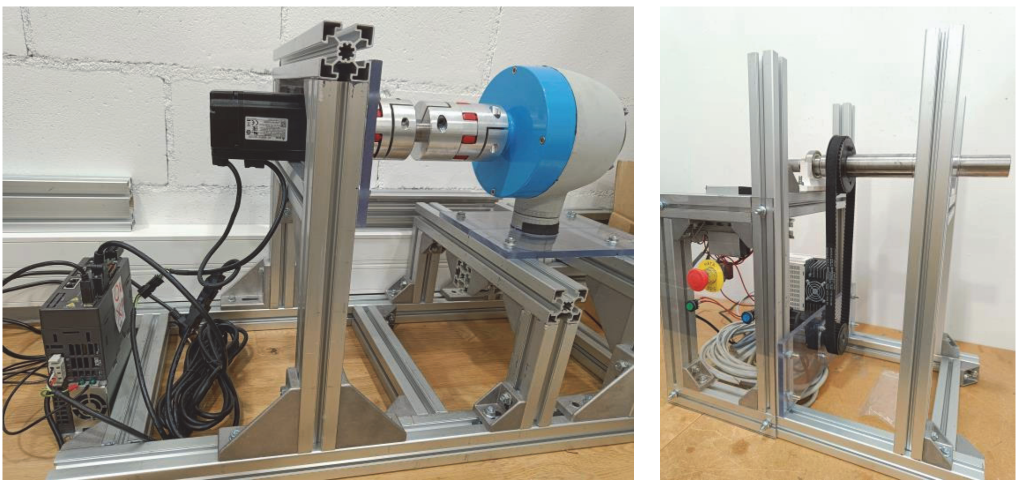
According to the function performed, servomotors are divided into two groups: maintaining a specified rotation angle or rotational speed. Based on the names, the first group of servomotors is used to bring mechanisms to the required position, such as locks, dampers, cranes, etc. The second group of servomotors is used to move objects in the working area and is employed in manipulators, various CNC machines, etc. Depending on the function performed, the main control parameter in the servomotor will differ: the motor's rotation range or moment of inertia for the first or second group of motors, respectively [15,17,39–42].

In terms of signal processing, servomotors are divided into analog and digital motors. The main difference between these groups is the control principle. Analog motors use microchips, while digital ones use microprocessors. Due to technological advancements, digital servomotors have replaced analog ones due to their increased response speed to the control signal. Consequently, these servomotors have increased positioning accuracy and the ability to maintain a constant torque [43–46].

For example, in Figure 2, a servomotor used in a Hirata Cartesian robot (Hirata Corporation, Kumamoto, Japan) is depicted. It is a synchronous alternating current motor with the function of maintaining a constant rotational speed, as it is used to move the robot axis along the working area [47,48].

Figure 2. The servomotor used in a Hirata Cartesian robot.

Motors with the function of maintaining a constant rotational speed are also used in laboratory setups of a digital twin of a wind generator [49], as well as in diagnosing damage to bearings [50,51] depicted in Figure 3a,b. Motor control is carried out using a frequency converter, allowing the selection of an appropriate motor control mode, adjustment of controller settings for different operating conditions, calibration of control to eliminate malfunctions, and more.



(**a**) (**b**)

Figure 3. Using servomotors in various test benches: (**a**) as the digital twin of a wind generator; (**b**) in diagnosis of bearing faults.

For example, in bearing fault diagnosis setup, discrete motor control is used to maintain a constant rotational speed. The use of a potentiometer to set an analog speed signal is not appropriate because there is a high probability of additional disturbances that would affect the rotational speed of the output shaft. For the digital twin setup of a wind generator, modeling methods are used, since, to maintain a constant rotational speed, the input speed signal is converted from a database stored in the cloud.

2.3. Servomotor Characteristics

The main technical characteristics of servomotors are as follows [18,52–57]:

- Torque (shaft force).
- Operating voltage.
- Rotational speed.
- Maximum rotational angle.
- Dimensions and weight.
- The torque indicates the rate of acceleration of the output shaft and its ability to overcome the resistance to the rotation of the load. The ability to realize the full potential of the servomotor is directly proportional to the torque.
- The rotation speed of the servomotor indicates the time it takes for the output shaft to turn by 60°. For example, a rotation speed of 0.07 s means that the servomotor shaft will turn by 60° in 0.07 s. The working voltage of the servomotor power supply affects both the rotation speed and the torque.
- The maximum rotation angle indicates the angle to which the output shaft of the servomotor can turn. In modern production, servomotors with continuous rotation are used, meaning that the maximum rotation angle is 360°. However, in some mechanisms, motors with smaller rotation angles, such as 120°, 180°, 270°, etc., are used.
- The dimensions of the servomotor affect the choice of the motor used to produce the mechanical structures in which they will be installed. This parameter is important for devices where speed, lightness, and compactness are crucial, such as drone models.
- Of the technical characteristics mentioned above, only three directly influence the control of servomotors: torque, rotation speed, and rotation angle. Depending on the selected control mode, the control parameter of the servomotor will differ.

For example, the main technical characteristics of the servomotor mentioned above are presented in Table 1.

Table 1. The main technical characteristics of the Hirata Cartesian robot servomotor [47,58].

Characteristic	Value
Torque	2.4 Nm
Input (operating) voltage	116 V AC
Rotational speed	3000 r/min
Output power	0.75 kW

3. Basic Principles of Servomotor Control

As mentioned above, four main principles exist for controlling servomotors: digital signal processing, feedback control, field-oriented control, and integration with Industry 4.0.

3.1. Digital Signal Processing in Servomotors

Digital signal processing has allowed for the optimization of servomotor control, expanding boundaries in control methods and opening up new possibilities. Digital signal processing enables the limitations of analog control systems to be bypassed, thus laying a new foundation for more effective servomotor management. Based on [59–62], it is possible to identify the key aspects in the construction of this principle and draw conclusions about its advantages and disadvantages.

Key points in digital signal processing for servomotor control include:

1. Precision control. Digital signal processing allows the use of advanced control algorithms that enhance control accuracy. This is achieved as digital controllers can receive, process, and respond to changes in input signals in real time, skipping many stages in tuning the control action.
2. Adaptive control. Since servomotors operate in dynamic environments with changes in load and the occurrence of various errors, the principle of digital signal processing helps integrate adaptive control for servomotors. This type of control neutralizes

disturbing influences in real time and adjusts control depending on new conditions, thus improving the performance and efficiency of servomotors.

3. Noise filtering. In real production environments, servomotors are subject to interference and noise from other devices, production line structures, additional loads, etc. The principle of digital signal processing allows the identification and neutralization of noise to maintain the accuracy of the control signal at the required level.
4. Network interaction and communication. The communication of servomotors within a unified system is facilitated by the principle of digital signal processing. Coordinating actions, adjusting control, and other networking capabilities enable synchronized control of servomotors in complex manufacturing processes, such as robotic technological lines.

However, along with the merits of digital signal processing, there are some drawbacks to this principle:

1. Computational power. Implementing digital signal processing algorithms requires significant computational resources. To ensure real-time signal processing, it is necessary to accurately calculate the processing time and controller signal responses to fully realize the potential of the entire control system.
2. Integration with existing control systems. Integrating control based on digital signal processing with other systems may pose challenges due to compatibility issues and the need for proper design of the control interface.

3.2. Feedback Control Principle in Servomotors

Feedback control systems are closed-loop control systems that compare the actual output signal with the desired one. Based on the difference between these values, they adjust the control settings, thereby changing the system's behavior to minimize the deviation of the output signal. In the case of servomotors, feedback control systems provide a specified value for the position, speed, or any other output parameter of the motor. Based on [63–67], it is possible to identify the key aspects in the construction of this principle and draw conclusions about its advantages and disadvantages.

A feedback control system consists of the following components:

- Sensor. In the case of servomotors, encoders or potentiometers are mainly used to continuously track the speed or position of the motor's output shaft.
- Controller. This is the part responsible for processing feedback signals and generating control actions through an integrated controller to the motor. Most control systems use a PID controller for its speed and minimization of output error.
- Desired output signal. This is the target value that the motor control system aims to achieve. Any parameter can be taken as the desired value, forming the basis for the control system.

The working principle of a feedback control system is quite simple and operates on a clear algorithm. The sensor continuously monitors the output value in real time and sends data to the controller. The error is then calculated by comparing the signals, and a control action is output. Using the controller and its components, a control signal is generated to minimize the deviation and increase the stability of the control system.

Advantages of feedback systems include:

1. Accuracy. Continuous control of the output value allows feedback systems to achieve high levels of maintaining the desired output signal.
2. Dynamic response. Feedback control systems provide a quick response to changes in load, disturbances, or noise, allowing servomotors to be used in changing conditions.
3. Reduction in static error. The controllers used in these systems minimize static error and reduce the transient process time.
4. Stability. The closed-loop control increases the overall stability of the control system.

3.3. Vector Control Principle in Servomotors

Vector control is a control method that allows the optimization of the control of alternating current (AC) motors and synchronous motors with permanent magnets. This control method uses an approach where the torque and current flux of the motor are separately considered. The main idea is to transform the three-phase current and voltage into a rotating coordinate system, aligning the magnetic flux with the rotor's magnetic field. This enables independent control of the torque, leading to better dynamic response of the control system, reduced additional noise, and increased efficiency. Based on [68–72], it is possible to identify the key aspects in the construction of this principle and draw conclusions about its advantages and disadvantages.

The main components of the field-oriented control system are:

- Coordinate transformation. Vector control relies on transforming currents into a coordinate system using Park and Clarke transformations, simplifying the control task and optimizing the motor's operation.
- Current control. Precise control of currents is crucial. Independent torque control allows for minimizing losses and improving efficiency.
- Use of PI controllers. Using controllers of this type helps reduce control errors, enhance responsiveness, and provide continuous support for the desired motor performance.

The key advantages of the vector control principle include:

1. Improved dynamic response. Fast and accurate motor control enables instant dynamic response.
2. Reduction of torque disturbances. This significantly reduces torque fluctuations, ensuring smooth motor operation.
3. Increased efficiency. Optimization of motor currents and minimization of losses lead to improved overall motor efficiency.
4. Increased power density. The design of more compact and lightweight servomotors with higher power can be achieved, making them suitable for use in limited spaces.

3.4. Integration with Industry 4.0 Principle in Servomotors

Industry 4.0 enables the use of smart technologies that alter the behavior of mechanisms in the industry, with servomotors being one of the key elements in smart technologies due to their provision of precision and efficiency. Thanks to integration with Industry 4.0, new opportunities have emerged in predictive management and seamless communication of production processes and mechanisms. Based on [16,73–77], it is possible to identify the key aspects in the construction of this principle and draw conclusions about its advantages and disadvantages.

The main points of integration with Industry 4.0 are:

1. Internet of Things (IoT) connectivity. Servomotors connected to Industry 4.0 are part of a unified Internet of Things network. This connection allows real-time monitoring of motor conditions, collecting a wealth of data such as operational parameters, temperature, vibration, etc.
2. Data analysis and predictive maintenance. Modern methods of data analysis allow the collection of data streams from servomotors into a unified database. This systematic organization of data enables the prediction of motor behavior and planning maintenance and repairs, thus avoiding unjustified equipment downtime.
3. Remote monitoring and control. Servomotors connected to Industry 4.0 can be remotely controlled. This is beneficial in large-scale manufacturing where engines are distributed over a large area, requiring remote control and monitoring of engine conditions for timely management adjustments without on-site intervention. Remote monitoring reduces delays and increases overall production efficiency.
4. Standardization. The use of specific standards, such as Open Platform Communications Unfired Architecture (OPC UA), facilitates the integration of servomotors into a unified network with other production components.

5. Adaptive control. Integration with Industry 4.0 allows the development and use of flexible servomotor control systems. Control systems can adapt promptly to changing conditions and respond to disturbances, thereby reducing setup time and downtime.
6. Energy efficiency. By connecting servomotors to a unified network using Industry 4.0 protocols, it is possible to reduce the energy consumption of production and optimize processes to use a more logical distribution of energy resources.

4. Control Methods of Servomotors

According to the principles of servomotor control outlined above, the basic common control methods are distinguished: PWM control, current control, two-loop control, fuzzy-logic control, and programmable control. PWM control has been described earlier in the article; it should be noted that this type of control is based on the principle of digital signal processing, allowing control of the position, speed, and trajectory of the output shaft of the servomotor.

4.1. Current Control

Current control, also known as torque control, is based on changing the current in the windings of the servomotor. This method allows precise regulation of the torque on the motor shaft because the current magnitude is proportional to the torque. Current control, which provides high accuracy in torque control, is suitable for applications where load control is required, as well as the need for overload protection. Examples of such applications include systems where maintaining stable control is important, such as industrial robots and autonomous motion systems [78,79].

The basis of current control is the principle of feedback and regulation. Feedback on the current is applied to the servomotor, the current is measured in the windings, and the value is sent to the controller for comparison with the set value (Equation (5)). When the measured value deviates from the set value, the regulator generates a control signal for the power amplifier. The power amplifier, in turn, adjusts the voltage on the motor windings to bring the current value to the desired level [80,81].

$$e = I_s - I_m, \tag{5}$$

where e—deviation error, and I_s and I_m—the set and measured value of the current.

The regulator in this type of control method consists of three parts and their combinations: proportional, integral, and differential.

The proportional component uses the following equation for increasing performance:

$$P = eK_p, \tag{6}$$

where P—proportional control signal, and K_p—proportional coefficient.

The integral component uses the following equation for error elimination:

$$I = K_i \int e dt, \tag{7}$$

where I—integral control signal, and K_i—integral coefficient.

The differential component uses the following equation for reducing the amount of overshoot:

$$D = K_d \frac{de}{dt}, \tag{8}$$

where D—differential control signal, and K_d—differential coefficient.

The main advantages of this method include the following [82,83]:

1. High precision in regulating torque.
2. Quick response to changes. Current control allows easy adaptation to external changes.
3. Energy savings. Efficient energy use is due to the adaptive properties of current control.

4. Impact on positioning accuracy. Strict control of torque allows controlling the position of the shaft in the final position.

The main drawbacks of the method, which differ from other methods and negatively affect further development, are the requirements for the accurate measurement of torque and flux parameters and sensitivity to changes in motor parameters, namely inductance and resistance [82,83].

4.2. Two-Loop Control

Two-loop control connects feedback loops, typically consisting of positional and velocity loops. This method enhances the efficiency of motor control by ensuring precision in positioning and speed. Two-loop control allows a balance between system dynamics and control accuracy to be maintained, so the application of this control method is common in medical devices and automatic manufacturing lines.

The positional loop is designed to control the position of the servomotor's output shaft and sets the direction of its movement to a specified point. A control signal for the electric motor is created by comparing the current position with the set position using a potentiometer. The control signal is generated to minimize positioning errors [42,84].

The velocity loop aims to stabilize the rotational speed of the servomotor's output shaft. The feedback from the velocity loop measures the current rotational speed and compares it with the desired speed, calculated based on the positioning error from the positional control loop [42,84].

The mathematical apparatus of the two-loop control is dame such as current control. The difference between these two apparatuses is the amount of regulators used for each loop.

The advantages of two-loop control include the following [84–86]:

1. Precision in positioning.
2. Stability of the speed control system.
3. Dynamic response. Interaction between both loops allows the servomotor control system to respond promptly to changes.
4. Integration with other methods. A two-loop control-based system easily integrates with control systems based on other methods, such as field-oriented control.

The main drawback of two-loop control is the requirement for the precise tuning of the regulator coefficients in both loops. Achieving optimal control and stable system operation demands more complex mathematical calculations. However, the mathematical calculations required are much less than that of more advanced methods, such as FOC and fuzzy logic [84–86].

4.3. Field-Oriented Control

Field-oriented control (FOC), based on the vector control principle, is a method of controlling current and voltage in a servomotor, considering the direction of the magnetic field rotation. FOC supports system control dynamics and efficiency, which is suitable for high-performance systems and mechanisms with high precision. Examples of applications may include CNC machines and laser cutting machines [72].

The field-oriented control method involves transforming the magnetic field into a rotating coordinate system known as the "d-q" system. The d-axis is aligned with the magnetic flux, while the q-axis is perpendicular to the d-axis. This transformation aligns the magnetic flux inside the motor along one axis, and the variable current is aligned along the other axis, which is the torque axis. Therefore, control is carried out based on the variable current [71,87].

The mathematical equation for Park transformation is:

$$\begin{bmatrix} i_\alpha \\ i_\beta \end{bmatrix} = \begin{bmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix} \begin{bmatrix} i_d \\ i_q \end{bmatrix}, \tag{9}$$

where i_α and i_β—stator currents in fixed axes, i_d and i_q—stator currents in rotated axes, and θ—magnetic flux rotation angle.

The mathematical equation for Clark transformation is:

$$\begin{bmatrix} i_d \\ i_q \end{bmatrix} = \begin{bmatrix} \cos(\theta) & \sin(\theta) \\ -\sin(\theta) & \cos(\theta) \end{bmatrix} \begin{bmatrix} i_\alpha \\ i_\beta \end{bmatrix}, \tag{10}$$

The feedback system measures the magnetic flux and then, using Park and Clarke transformations, converts them from the stator coordinate system to the rotating d-q coordinate system. The use of a PI controller in a field-oriented control system allows maintaining the specified flux for each axis. The Clarke transformation is used to create d-q coordinates, and the inverse Park transformation is used to transform the currents back into the stator coordinate system [71,87,88].

The equations for motor voltage and torque are as follows:

$$T_e = \frac{3}{2} p\left(\psi i_q + (\psi_m - \psi) i_d\right), \tag{11}$$

$$V_e = R_s i_s + L_s \frac{di_s}{dt} + e_s, \tag{12}$$

where V_s—stator voltage, R_s—stator resistance, L_s—stator inductance, i_s—stator current, p—number of pole pairs, ψ—rotor flux, ψ_m—maximum rotor flux, T_e—electromagnetic torque, e_s—back EMF.

Advantages of the field-oriented control method [71,87,88]:

1. Precision control. This method allows for increased precision in controlling both the torque and speed of the servomotor.
2. Low noise and vibration levels. FOC reduces mechanical and electrical noise in the operation of the servomotor.
3. High energy efficiency. The method reduces losses and allows for increased energy utilization efficiency.

The development of FOC faces two of its most significant drawbacks: complexity of implementation and sensitivity to motor parameters. The more complex the mechanism control system, the more difficult the algorithm implementation and the more precise the behavior model should be. In turn, changes in motor parameters lead to the revision of the entire control algorithm [71,87,88].

4.4. Fuzzy-Logic Control

The use of fuzzy logic in servomotor control allows for optimizing and adapting the motor control system to changing input conditions. Fuzzy-logic control primarily provides flexibility and adaptability in conditions of fuzzy tasks and a lack of complete data. Accordingly, fuzzy logic finds its application in applications with variable loads, mechanisms operating in a changing environment, and robotic systems. Fuzzy logic-based control is built on the following stages [89–91]:

1. Identification of input conditions: In the case of a servomotor, the input variables are typically the position or speed of the output shaft.
2. Definition of fuzzy rules: Creating fuzzy sets with different degrees of membership for each input variable and establishing rules that link the conditions into a unified system.
3. Fuzzy logical inference: Applying the defined rules to each input value.
4. Aggregation: Combining the applied rules to determine the control action.
5. Defuzzification: Converting the overall control action rule into a specific value that is then applied to the servomotor.

Although fuzzy logic does not require an exact mathematical model, tuning this method is quite labor-intensive. The development of the method is also influenced by the difficulty of predicting its behavior under different conditions and achieving optimal performance without loss of computational efficiency [89,92].

Considering that for fuzzy logic there is no need to use special and accurate mathematical models, the structure of the algorithm can be illustrated as in Figure 4.

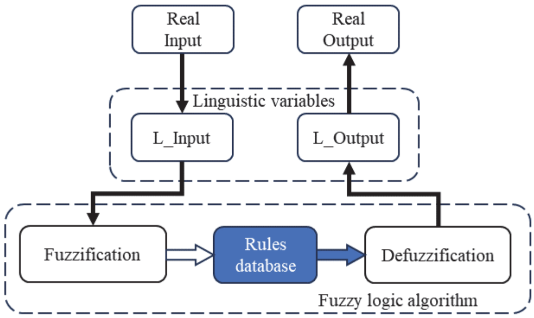


Figure 4. The fuzzy logic algorithm structure.

Unlike binary logic, where variables are divided based on the values of true or false, fuzzy logic determines the degree of membership of a variable to 0 or 1. The use of this type of control allows for adapting the control system to operate in changing conditions, even under the influence of various stochastic disturbances such as changes in load, detection of mechanical errors, etc. Fuzzy logic control is effective in situations where predicting the behavior of the mathematical model of the system is challenging, and there is no possibility of its precise determination [89,92].

Such systems include digital twins, which, when working with real-world objects, have a significant degree of uncertainty. Therefore, the adaptability of a control system based on fuzzy logic is an ideal solution for managing a digital twin and can also serve as a tool for creating a multitasking control system.

4.5. Programmable Control

Programmable control of a servomotor is based on the use of specialized software and external controllers to manage the speed, positioning, and torque of the motor. This method is associated with the principle of integration with Industry 4.0. Programmable control, depending on the task, provides adaptive control and tuning, allowing integration with other control systems. Accordingly, this method of servo motor control finds its application in automated production control systems and robotics [93–95].

By using an external controller, programmable control allows a range of desired positions to be defined through corresponding commands and supports various motion variations, such as smooth start and stop, acceleration profiles, maintaining constant speed or torque, and so on [81,96].

The use of feedback in the programmable control system is essential, and the feedback can be either incremental or absolute. Measuring the position or rotational speed of the servomotor's output shaft allows for a clearer response to errors that may occur during positioning and a smooth response for their elimination. The flexibility of control is also supported using different coordinate systems (including relative or external) [97–99].

Interaction with other devices in the control system through the software method is ensured by using various protocols, such as EtherCAT, Modbus, etc. Additionally, the software method allows the creation of Supervisory Control and Data Acquisition (SCADA) systems for interaction between machines and humans. The use of different programming languages, as well as proprietary servomotor libraries, allows optimizing costs for control and integration of the motor into existing control systems [100–104].

Programmable control, based on its features, has such drawbacks as programming complexity and implementation due to the presence of many disparate control systems, and depending on computational power, there may be a loss of real-time performance. It is also worth noting that this method is the only one among all those analyzed in this paper that requires constant debugging and maintenance of all involved systems.

Programmable control is illustrated using the example of a digital twin of a wind turbine, presented at the beginning of the article. This method is ideal for integrating multiple different interfaces into a unified system and enables the quick analysis of input data from various sources, making it a versatile approach to software methods.

4.6. Other Modern Methods

In addition to the methods of servomotor control discussed above, there are new methods emerging that have not yet gained widespread use in industrial, robotics, and other fields, and therefore are not considered in comparison with the presented methods. However, it is worth noting that modern servo motor control methods are a very promising direction in the development of control systems. Such methods include Model Predictive Control (MPC), Neural Network Control (NNC), piecewise linear control, and others.

MPC is a control method where the use of an accurate mathematical model of a mechanism or process can create a behavior model and determine performance criteria in advance [105]. This control finds its application in areas where control of systems with delays or variable characteristics is necessary, such as chemical production and long-acting robotic systems [106,107]. However, even though MPC allows optimization of system performance based on the desired criteria, the computational power of this method remains a significant downside that limits its proliferation. Creating a complex mathematical model, as well as computing the optimal solution at each time step, is a challenging task for most mechanisms and productions [21,108].

NNC is a control method that uses neural networks and principles of artificial intelligence to approximate nonlinear control functions and the mathematical model of the process. This type of servo motor control is used in systems where it is impossible or difficult to create an accurate mathematical model, such as multi-level autonomous control systems [109,110]. This method resonates with fuzzy logic-based control methods and possesses similar positive qualities such as flexibility, adaptability of control, and the ability to react quickly to external influences [111]. However, unlike fuzzy logic, training a neural network requires a huge amount of data and resources, as well as a significant amount of time, which is an obstacle in the real world where fast decision-making based on unexplored data is required.

Piecewise linear control of servo motors is a control method that allows the motor control curve to be divided into separate linear segments to achieve control points with sufficiently high precision [112]. This method is characterized by its simplicity of implementation and discretization of control space, with each control segment having its own characteristics. This method is an optimal solution where the use of complex algorithms is too costly and the number of computational resources is significantly limited [113,114]. However, this method is quite a specific solution and has many limitations when applied to solving complex and dynamic tasks [115].

5. Comparison of Servomotor Control Methods

Comparison of servomotor control methods may vary to some extent for each technical solution; therefore, this work proposes a general comparison based on several parameters: speed, accuracy, adaptability, energy efficiency, popularity, ease of implementation, and material resource costs. These are general indicators that can be used to assess the effectiveness of the presented control methods and choose the most suitable one for a specific case.

Each characteristic plays a key role in building a control system and is evaluated on a five-point scale:

- Speed is necessary to evaluate the responsiveness of the control system to incoming disturbances and changes in input parameters (1—low speed, 5—high speed).

- Accuracy is the primary parameter for systems based on positioning (1—low accuracy, 5—high accuracy).
- Adaptability is responsible for the degree of adaptability of the control system to changing conditions (1—low flexibility, 5—high flexibility).
- Energy efficiency indicates the amount and quality of consumed energy (1—increased energy consumption, 5—low energy consumption).
- Popularity not only indicates the degree of method dissemination in the industry but also access to reliable information on creating a control system based on a particular method (1—low popularity, 5—high popularity).
- Ease of implementation is important for assessing the complexity of developing and maintaining the created control system (1—easily implemented, 5—difficult to implement).
- Material resource costs influence the economic factor of developing a control system, its costliness, and payback period, considering efficiency and performance aspects (1—high costs, 5—low costs).

A visual comparison of characteristics is provided in Figure 5.

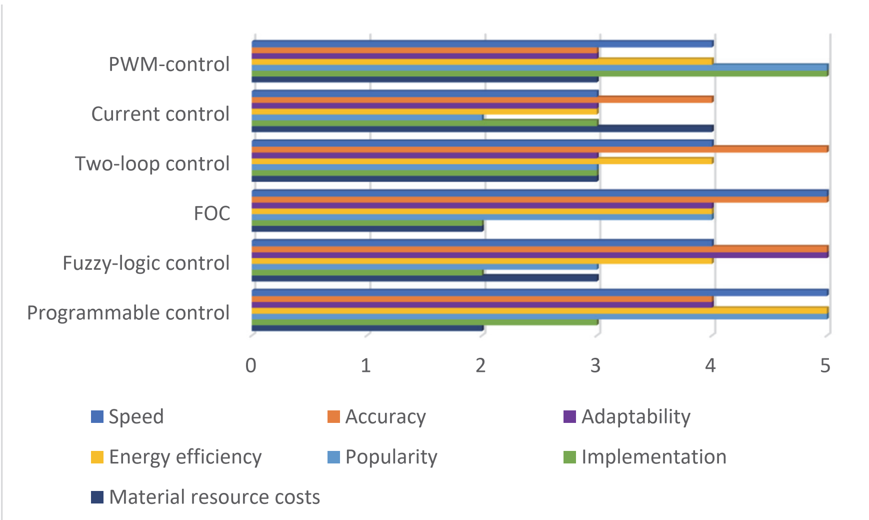


Figure 5. Comparison of the main characteristics of servomotor control methods.

As seen from the comparison, the most popular and energy-efficient method today is the programmable control of servomotors. However, the simplest to implement is PWM control, and in terms of adaptive control, fuzzy logic algorithm is considered. In terms of accuracy, three control methods stand out: two-loop control, FOC, and fuzzy logic control. In summary, when choosing a method for servomotor control, it is advisable to consider the initial characteristics of the desired control, i.e., to select control parameters that bear greater responsibility for performing specific operations.

In the control of the Hirata Cartesian robot's servomotor operations, direct control based on fuzzy logic algorithm is used. This is because the algorithm is not only used for motor control but also for diagnosing mechanical damage in the robot's transmissions. Therefore, important characteristics for servomotor control include accuracy, adaptability, and control speed. Additionally, the adaptability of fuzzy logic, coupled with high precision, allows its utilization in configuring digital twins for modeling various conditions and behavioral variations. Fuzzy logic facilitates the development of a control system along multiple directions, enabling the digital twin to emulate human logic based on external factors. This human-like decision-making ability is crucial in scenarios where rigid rule-based systems may fall short, providing a more nuanced and realistic approach.

6. Fuzzy Logic Control of the Hirata Cartesian Robot Servomotor

The speed and torque control of Hirata Cartesian robot servomotor is based on the frequency and amplitude of the vibration signal that occurs because of mechanical damage in the robot's transmissions. This correlation is based on several reasons, namely the detection of damage in the transmissions and the robot's operation under conditions of damaged transmission.

Control based on fuzzy logic operates by defining linguistic variables and constructing a fuzzy set of data. Therefore, the fuzzy logic algorithm does not require the determination of an exact mathematical model of the robot for servomotor control.

Fuzzy sets for linguistic input variables related to the amplitude and frequency of vibrations are illustrated in Figure 6.

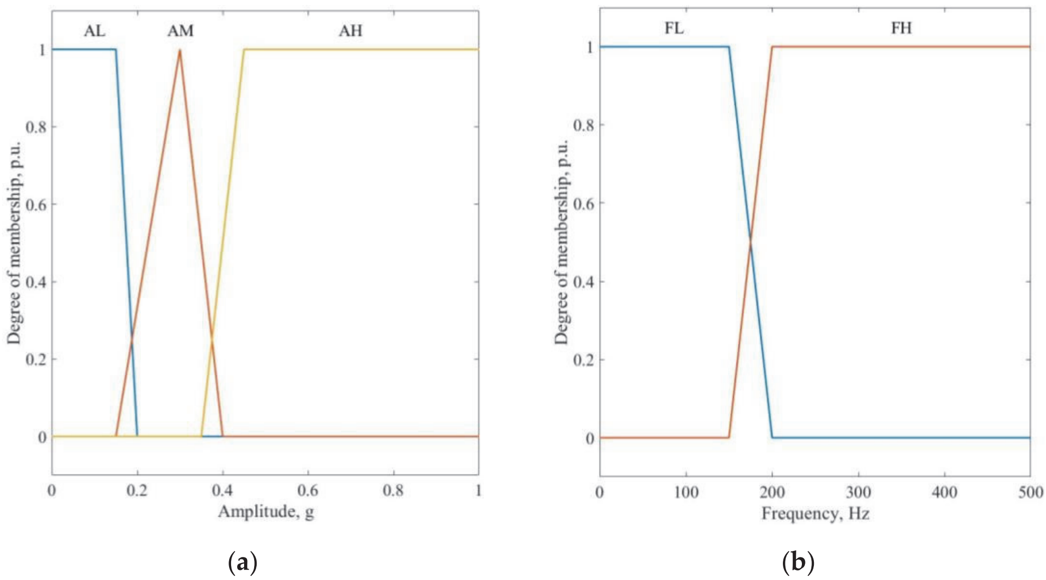


Figure 6. Fuzzy sets for linguistic input variables: (**a**) vibration amplitude, where AL—low amplitude, AM—medium amplitude, AH—high amplitude; (**b**) vibration frequency, where FL—low frequency, FH—high frequency.

The shape of the membership function is chosen to align with the logic of the robot's operation under specified conditions. For instance, the nominal vibration of the robot during work operations is 0.3 g for the nominal motor rotation speed at which the maximum speed of the robot's working element is achieved. Therefore, for the fuzzy set of amplitude, trapezoidal and triangular functions are chosen, while only trapezoidal functions are selected for frequency. Gaussian functions are chosen for the output parameters of the speed and torque of the servomotor to ensure smoother regulation of these parameters.

Fuzzy sets for linguistic output variables related to the speed and torque of the servomotor are presented in Figure 7.

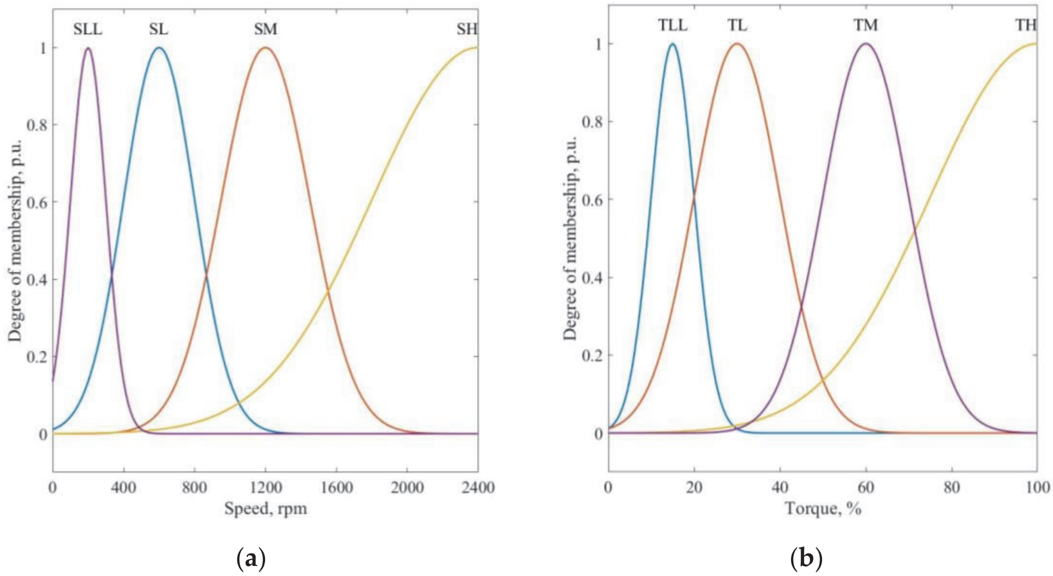


Figure 7. Fuzzy sets for linguistic output variables: (**a**) servomotor speed, where SLL—minimum speed, SL—low speed, SM—medium speed, SH—high speed; (**b**) servomotor torque, where TLL—minimum torque, TL—low torque, TM—medium torque, TH—high torque.

As a result, based on the presented fuzzy sets and the derived fuzzy rule base, patterns for the speed and torque of the servomotor can be obtained. The simulation results are illustrated in Figure 8.

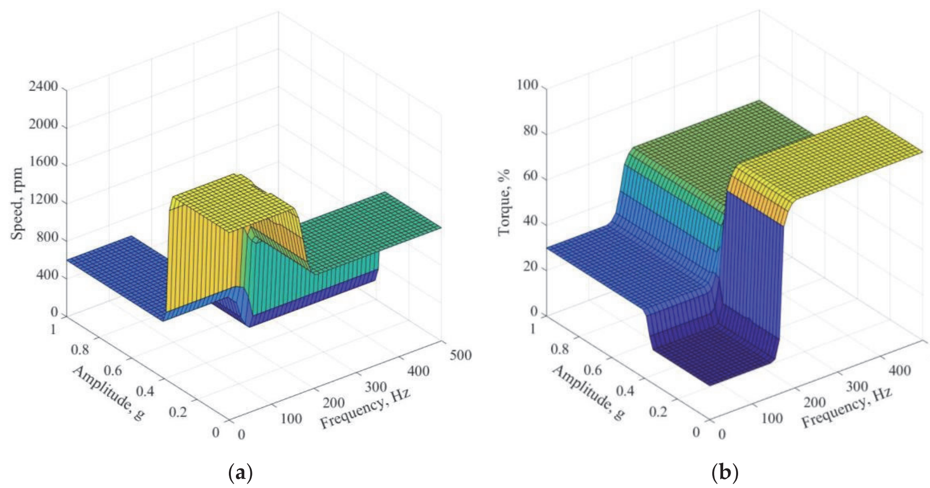


Figure 8. Patterns for the speed (**a**) and torque (**b**) of the servomotor.

As seen from the simulation results, the speed parameter is inversely proportional to the torque of the servomotor. This is implemented to overcome the consequences of mechanical damage to the robot's transmission. When a fault is detected, the robot's movement speed decreases, and the torque increases to mitigate the impact of undesirable consequences on other parts of the robot. This also helps reduce the influence on its fundamental characteristics, such as positioning accuracy, performance, and energy efficiency.

7. Conclusions

In this work, the structures, implementation, types, and basic principles and methods of servomotor control are described while highlighting its benefits, limitations, and application possibilities. PWM control, utilizing digital signal processing, proves effective in controlling position, speed, and trajectory. Current control, or torque control, stands out for its high precision in regulating torque, quick response to changes, energy savings, and impact on positioning accuracy.

Two-loop control, integrating positional and velocity loops, enhances motor control efficiency, offering precision in positioning, stability in speed control, dynamic response, and integration with other methods. Field-oriented control (FOC), based on the vector control principle, ensures precision control, low noise and vibration levels, and high energy efficiency through the transformation of the magnetic field.

Fuzzy-logic control, relying on fuzzy sets and logical inference, enables adaptive motor control in changing conditions, making it ideal for uncertain systems like digital twins. Finally, programmable control, associated with Industry 4.0, utilizes specialized software and external controllers, offering high flexibility, efficiency, easy integration, and interaction with various protocols and SCADA systems.

The comparison of servomotor control methods presented in this work provides a comprehensive overview of various parameters crucial for assessing the effectiveness of different control techniques. The parameters of speed, accuracy, adaptability, energy efficiency, popularity, ease of implementation, and material resource costs serve as valuable indicators in making informed decisions about the choice of a control method based on specific requirements.

The analysis reveals that programmable control stands out as the most popular and energy-efficient method, while PWM control is the simplest to implement. For adaptive control, the fuzzy logic algorithm is considered, and for accuracy, two-loop control, FOC, and fuzzy-logic control are highlighted.

Each method has its niche and strengths, and the choice depends on the specific requirements of the application. The adaptability of fuzzy-logic control and the efficiency of programmable control make them particularly versatile, addressing challenges in uncertain environments. As technology advances, the selection of a servomotor control method should align with the evolving demands of precision, adaptability, and efficiency in diverse industrial applications.

Author Contributions: Conceptualization, S.A.; methodology, S.A.; validation, A.R., T.V. and K.K.; formal analysis, S.A.; investigation, S.A.; resources, S.A.; data curation, S.A., A.R. and A.K.; writing—original draft preparation, S.A.; writing—review and editing, A.R., A.K. and K.K.; visualization, S.A.; supervision, A.R. and T.V. All authors have read and agreed to the published version of the manuscript.

Funding: The research leading to these results received funding from the PSG453, 2020–2024, "Digital twin for propulsion drive of autonomous electric vehicle".

Data Availability Statement: Dataset available on request from the authors.

Conflicts of Interest: The authors declare no conflicts of interest.

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Publication II

Autsou, S.; Kudelina, K.; Vaimann, T.; Rassõlkin, A.; Kallaste, A. Condition Monitoring of a Cartesian Robot with a Mechanically Damaged Gear to Create a Fuzzy Logic Control and Diagnosis Algorithm. Appl. Sci. 2024, 14 (10), 4241. https://doi.org/ 10.3390/app14104241.

applied sciences

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Article

Condition Monitoring of a Cartesian Robot with a Mechanically Damaged Gear to Create a Fuzzy Logic Control and Diagnosis Algorithm

Siarhei Autsou *, Karolina Kudelina, Toomas Vaimann, Anton Rassõlkin and Ants Kallaste

Department of Electrical Power Engineering and Mechatronics, Tallinn University of Technology, 19086 Tallinn, Estonia; karolina.kudelina@taltech.ee (K.K.); toomas.vaimann@taltech.ee (T.V.); anton.rassolkin@taltech.ee (A.R.); ants.kallaste@taltech.ee (A.K.)

* Correspondence: siarhei.autsou@taltech.ee

Abstract: The detection of faults during an operational process constitutes a crucial objective within the framework of developing a control system to monitor the structure of industrial mechanisms. Even minor faults can give rise to significant consequences that require swift resolution. This research investigates the impact of overtension in the tooth belt transmission and heating of the screw transmission worm on the vibration signals in a robotic system. Utilizing FFT techniques, distinct frequency characteristics associated with different faults were identified. Overtension in the tooth belt transmission caused localized oscillations, addressed by adjusting the acceleration and deceleration speeds. Heating of the screw transmission worm led to widespread disturbances affecting servo stress and positioning accuracy. A fuzzy logic algorithm based on spectral analysis was proposed for adaptive control, considering the vibration's frequency and amplitude. The simulation results demonstrated effective damage mitigation, reducing wear on the mechanical parts. The diagnostic approach, relying on limited data, emphasized the feasibility of identifying transmission damage, thereby minimizing maintenance costs. This research contributes a comprehensive and adaptive solution for robotic system diagnostics and control, with the proposed fuzzy logic algorithm showing promise for efficient signal processing and machine learning applications.

Keywords: condition monitoring; gears; fast Fourier transforms; fault diagnosis; fuzzy control; robot control; robot motion; process monitoring; vibration measurement

Citation: Autsou, S.; Kudelina, K.; Vaimann, T.; Rassõlkin, A.; Kallaste, A. Condition Monitoring of a Cartesian Robot with a Mechanically Damaged Gear to Create a Fuzzy Logic Control and Diagnosis Algorithm. *Appl. Sci.* **2024**, *14*, 4241. https://doi.org/10.3390/app14104241

Academic Editor: Javier Poza

Received: 11 April 2024
Revised: 8 May 2024
Accepted: 15 May 2024
Published: 16 May 2024

1. Introduction

Industrial robots are a cornerstone of modern automated manufacturing, spanning various industries. Their extensive and diverse applications, such as assembly lines, transportation, and complex and costly processes, underscore their indispensable role in contemporary society [1,2]. However, the precise and uninterrupted operation of these mechanisms depends on the seamless functioning of all their systems, including power components, control systems, and mechanical connections. Disruptions to any of these parts can lead to production failures and the loss of material and energy resources [3,4].

Typically, diagnostic systems embedded in robot controllers are oriented toward monitoring the condition of the power components and control systems of the robot. While such systems allow for monitoring the operation of the robot's main units and detecting malfunctions, they often overlook smaller mechanical connections, such as gearboxes, hinges, and other elements. The inability to track the behavior of mechanical connections makes these robot parts the most challenging for fault detection, potentially resulting in serious consequences, including complete robot failure [1,3].

The diagnosis of faults in robots uses many methods [3,5,6]:

1. Mathematical methods (fast and short-time Fourier transform, continuous wavelet transforms) [7,8];

2. Modeling methods (fuzzy logic, machine learning, and other artificial intelligence methods) [8,9];
3. Condition monitoring methods (control currents, temperature of mechanical parts, noise control, etc.) [10,11].

Therefore, for diagnostics, each of the methods presented has its own scope of application and is used to achieve various goals [1,6,7]. The mathematical methods are a powerful tool for evaluating and analyzing data, thereby identifying anomalies in the behavior of the mechanism. The modeling methods offer predictive and control capabilities, assessing discrepancies in the data obtained [11,12]. The condition monitoring methods enable real-time data acquisition, constantly evaluating possible deviations from normal operation, thereby allowing problems to be detected before a failure occurs.

The application of fuzzy logic-based diagnostic and control methods is of particular interest in the context of identifying faults in the mechanical parts of the robot. This approach avoids the use of precise mathematical models and ensures operation even if the integrity of the input data is compromised, in conditions in which other methods are least effective. The fuzzy logic algorithm processes information in such a way as to create a reliable system for diagnosing, controlling, and rectifying faults in challenging operating conditions [13,14].

The use of fuzzy logic principles allows for the adequate and adaptive adjustment of the robot's operating characteristics, taking into account uncertainties. This enables the maintenance of operational reliability, timely detection of damage, and determination of preventive measures for preserving structures and for their maintenance. Integrating such a system based on fuzzy logic is a way to enhance the stability and reliability of mechanisms, reduce equipment downtime, and improve performance in changing conditions [15,16].

This article is organized as follows: Section 2 of this article is a description of a Cartesian robot and its diagnosis system with a controller. The main faults detected by the controller are shown. Section 3 illustrates the gearbox structure of the Cartesian robot and includes the benefits and limitations of each part. Based on this information, the main gearbox faults are described. Section 4 describes the methodology used for generating the results of this article. Section 5 presents the specification of the test bench, the diagnosis results, and their description. Based on these results, the fuzzy logic algorithm was built. This section also shows the fuzzy logic algorithm modeling results for control parameters and fault type diagnosis.

2. Cartesian Robot Description

The Cartesian robot is a commonly found industrial robot in production [17]. This type of robot is used for any task, like moving details in the technological lines, working with dangerous materials, and accurate processes. Cartesian robots have different structures for any purpose [18]. The sketches of the main types of it are presented in Figure 1.

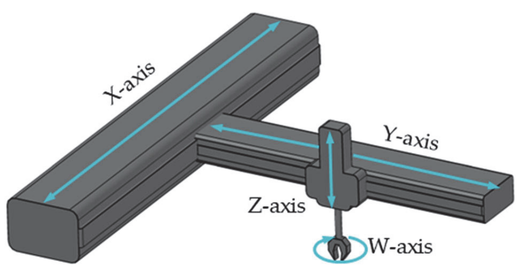


Figure 1. The sketch of Cartesian robots with fourorthogonal axes.

As seen from the figure, Cartesian robots have a few degrees of freedom. This means that the diagnosis system should have a special base of rules for each axis.

2.1. Hirata Cartesian Robot

The Hirata Cartesian robot (HCR), described in this research, is a Cartesian robot consisting of four axes set up perpendicular to each other. This robot was designed to work with special attachments and devices, for the implementation of different operations in which humans cannot participate [19,20]. A view of the HCR is presented in Figure 2.

Figure 2. The view of HCR.

2.2. Diagnosis System of the HCR

The diagnosis system of the HCR consists of the controller, the teach pendant, and various sensors, such as overload and origin sensors, limited switches, and encoders [19,21]. The view of the controller and teach pendant of the HCR are presented in Figure 3a,b.

(**a**) (**b**)

Figure 3. The view of the controller (**a**) and teach pendant (**b**) of the HCR.

Before starting work, the auto-calibration (A-cal) of the HCR should be executed. The A-cal mode is a regime for automatically returning the robot axes to their original positions and checking whether any faults are connected to the control and power systems of the robot. In this mode, the state information is executed [19,21].

The main faults are detected in the power and control systems of the robot. The list of the main faults is presented in Table 1. When a fault occurs in the controller or servo drive of the robot during the work process, a message about failure appears on the teach pendant [19,21].

Table 1. The list of main faults of the HCR.

Error Code	Description
Pos. error XXXX	Positioning cannot be completed.
Emergency stop	The emergency stop is activated.
A-cal error	A-cal cannot be completed normally.
Overrun XXXX	Overrun has occurred.
Positioning error	Positioning cannot be performed.
Overspeed	The speed is too high.
Driver error	An error has occurred in the servo amplifier/driver.
Enc error XXXX	The encoder has a broken wire.

The message "XXXX" shows the status of each axis of the robot. For example, the message "0101" means the faults occurred at the Y and W axes of the HCR.

The diagnosis system of the HCR may detect faults only in the control or power system of the robot. However, in the mechanical parts of the robot, such as gearboxes and joints, detection does not exist. The diagnosis system of the robot generates warnings and stops the mechanism only after fault consequences occur. This means that the mechanical parts of the robot are the weakest places; the robot is subject to the devastating consequences of even the slightest damage in case of failures occurring here [19,21].

3. HCR Gearbox

The gearbox of the HCR consists of two types of transmissions: tooth belt transmission (TBT) and screw transmission (ST). The TBT provides constant resolution for each axis with high accuracy, and the ST provides smooth movement of the robot. The sketch of the gearbox is presented in Figure 4.

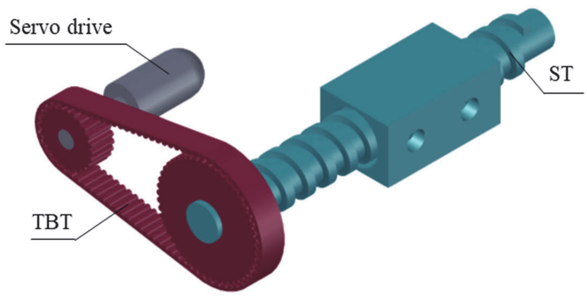


Figure 4. The sketch of the gearbox of the HCR.

Each of the gearbox parts has benefits and limitations that influence the Cartesian robot's work.

3.1. Tooth Belt Transmission

The benefits of the tooth belt transmission are a constant gear ratio, no need for lubrication, quiet work, and lack of undesirable vibrations. Consequently, the TBT has a large torque-carrying capacity, transmits mechanical power with constant speed, and lacks slippage between pulleys and timing belts. The limits of the TBT are associated with its benefits. The work of the TBT is provided by the tension of the timing belt. In this case, the tension adds resistance to torque and additional load to the motor shaft. Also, one of the conditions for normal working of the TBT is pulley alignment [22,23]. The real view of the tooth belt transmission of the gearbox is presented in Figure 5.

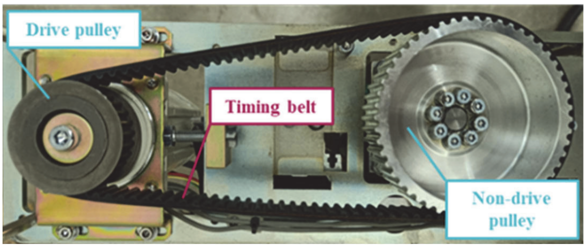


Figure 5. View of the tooth belt transmission.

3.2. Screw Transmission

Just like the tooth belt transmission, the screw transmission has a number of similar benefits, such as quiet and smooth motion, lack of undesirable vibrations, and simple design. Also, the ST has a high load-carrying capacity, self-deceleration property due to high inertia, and compact construction, which minimizes the needed length of the work area. The limits of the ST are low efficiency and additional wearing during the mechanism's operation. In this case, expensive antifriction materials and lubrication must be used to avoid constant repairing of the transmission [24]. The real view of the screw transmission of the gearbox is presented in Figure 6.

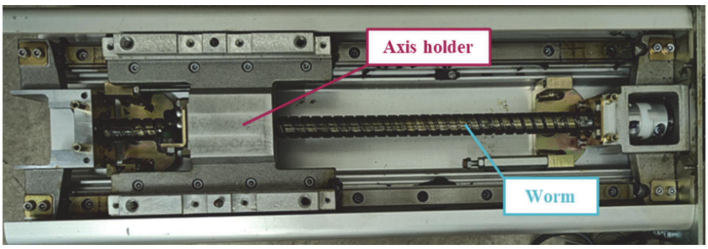


Figure 6. View of the screw transmission.

Based on the listed properties, the gearbox provides control of the HCR without significant noises, additional vibrations, and other disturbances. Also, this combination of transmissions leads to the following control characteristics of the robot as presented in Table 2 [20].

Table 2. Axis characteristics of the HCR.

Axis	Max Speed, mm/s	Stroke, mm	Max Payload, kg	Repeatability
X	1200	1200	5	±0.02
Y		800		
Z	1000	200		±0.01
W	1200°	540		±0.03°

The construction of the robot provides a good combination of speed and accuracy. In this case, the robot can work with various conditions and different processes, such as 3D-printing, movement processes, or working with dangerous materials and environments.

3.3. Gearbox Faults

The faults that occur during the working of the HCR have different characteristics and lead to various consequences. Any smaller deviations from nominal work have a possibility to cause serious damage to the robot and production. Besides the listed benefits and limitations, the gearbox has a few failures, such as heating, overtension of the timing belt, and jamming or teeth cracks [3].

Overtension of the timing belt occurs due to the misalignment of the transmission pulleys. In the case of misalignment by the vertical axis, high tension and skewing of the belt occur, leading to an additional load on the servo drives and resistance torque on the servo drive shaft. On the other hand, misalignment by the horizontal axis leads to low tension of the timing belt; however, in this case, the belt may fly off the pulley, and the robot will stop without any damage. Low tension works like a damper in the case of the HCR gearbox [18,25]. An example of displaced pulleys and, consequently, overtension of the belt is presented in Figure 7.

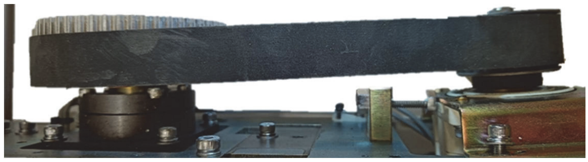


Figure 7. Example of the overtensioned timing belt of the gearbox.

The gearbox heats up under the following circumstances: when there is no lubricant, in conditions of high pollution, and if the gearbox part is under voltage. This failure leads to additional vibrations in the whole work area of the gearbox. As a result, the accuracy of the robot is reduced, and the wear of the gearbox material (tooth wheels, worm, screw mechanism, etc.) is increased. This failure is the second most common error that occurs in this type of gearbox. Usually, this mechanical damage refers to the parts of the transmission that are subject to continuous contact [24,26]. An example of the effect of heating on the screw worm of the gearbox is presented in Figure 8.

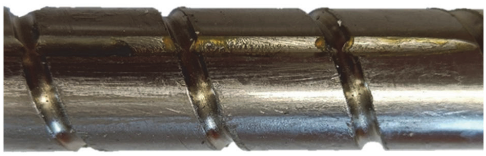


Figure 8. Example of the effect of heating on the screw worm of the gearbox.

Jamming or teeth cracks occur in two ways. The first part of this fault is fatigue of the metal, and the second part is unbalanced parts of the gearbox or loss of structural rigidity. Jamming of the gearbox leads to intermittent vibrations or a full stop of the robot. Teeth cracks provide cycle vibrations and deviations from the nominal accuracy and positioning of the robot [26,27]. An example of a broken pulley, in case of the appearance of a foreign body, is presented in Figure 9.

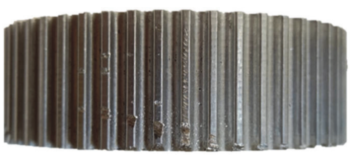


Figure 9. Example of pulley teeth cracks of the gearbox.

4. Diagnosis and Control Methods

Every fault that arises during robot operations possesses a distinct spectrum, which can be monitored through a few different methods. This study employed two specific methods. The initial approach involved utilizing the fast Fourier transform, enabling the assessment of various vibrations present in the output signal. The second method employed a fuzzy logic algorithm, thereby enabling the development of a control system that permits the robot to continue functioning under faulty conditions.

4.1. Fast Fourier Transform Diagnosis Method

The fast Fourier transform (FFT) is a sophisticated algorithmic technique widely employed in various fields of science, engineering, and mathematics. This transformation allows for the analysis of complex signals and the extraction of information about their frequency components [28,29].

The FFT technique finds applications in diverse fields, including signal processing, telecommunications, image processing, audio analysis, scientific computing, and many more. It allows researchers, engineers, and analysts to quickly analyze and manipulate signals in the frequency domain, enabling tasks such as filtering, spectral analysis, correlation, convolution, and data compression. Its efficiency has made it an indispensable tool in digital signal processing, providing the capability to handle real-time data streams and process vast amounts of information with minimal computational overhead [30,31].

The fast Fourier transform method is a groundbreaking algorithm that has transformed the landscape of digital signal processing and numerous related fields by providing an efficient means to compute the discrete Fourier transform. Its ability to drastically reduce the computational complexity of this operation has made it a cornerstone in modern scientific and engineering applications, allowing for the exploration and extraction of valuable insights from complex datasets in the frequency domain [32,33].

4.2. Fuzzy Logic Control Method

The fuzzy logic control method is an advanced computational approach used to make decisions and draw conclusions in situations in which the boundaries between different states or conditions are not well defined. Rooted in the principles of fuzzy logic, this method is particularly effective when dealing with complex and uncertain systems in which traditional binary logic might fall short [34].

Unlike classical logic, which relies on crisp definitions of true or false, fuzzy logic allows for degrees of truth to be expressed. It accommodates the inherent imprecision and uncertainty present in many real-world scenarios, making it well suited for diagnostic applications across various fields such as engineering, medicine, finance, and more [35,36]. The working scheme for fuzzy logic is illustrated in Figure 10.

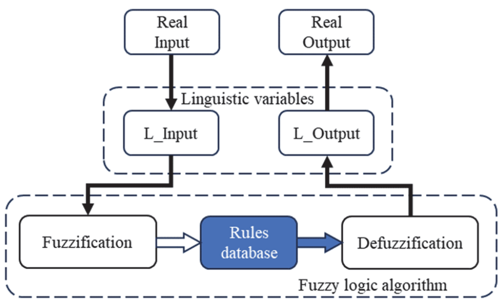


Figure 10. General scheme of the fuzzy logic algorithm.

The fuzzy logic algorithm operates through several key stages:

1. Identification of linguistic variables: Initial parameters are established to construct descriptions for input and output variables. For example, the variable “speed” is defined with specific values, such as “slow” or “fast”.
2. Establishment of fuzzy sets: Each linguistic variable and its corresponding value are defined by a fuzzy set, characterized by a membership function. These functions, which can take various forms like triangular or Gaussian, enable the flexibility of fuzzy logic, eliminating the need for precise mathematical models.

3. Fuzzification: Input variables are matched with their respective membership functions to generate a fuzzy output, determining the degree of membership of the input variable within a specific fuzzy set.
4. Formulation of fuzzy rule base: Fuzzy rules are defined that dictate the algorithm's actions based on combinations of input variables. These rules, based on linguistic variables and sets, employ logical operations like AND/OR to organize them into relevant categories.
5. Defuzzification: The inverse process of fuzzification, converting the degree of membership of the output parameter based on fuzzy rules into a numerical value. This numerical value guides subsequent control actions.

The fuzzy logic control method excels in scenarios in which uncertainty and imprecision are prevalent, such as medical diagnosis, fault detection in complex systems, risk assessment, and decision-making in dynamic environments.

5. Experimental Part

5.1. Experimental Test Bench

A test bench was built for conducting experiments. The view of the test bench is presented in Figure 11.

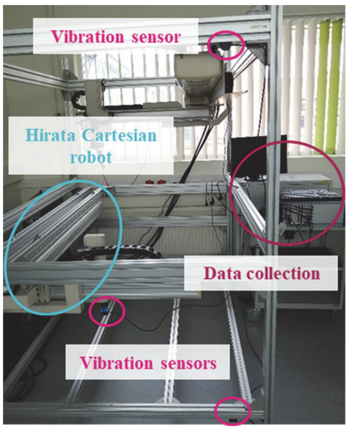


Figure 11. View of the experimental test bench.

The test bench consists of the Hirata Cartesian robot, the data collection system based on Dewetron, and three vibration sensors installed on the grab system of the robot and the top and bottom of the test bench.

The main sensor for measuring robot vibrations is installed on the Z-axis, directly on the gripping system. This placement allows the tracking of vibrations along both axes of the robot. The sensors placed above and below the laboratory stand structure are intended for measuring the stand's vibrations to eliminate additional noise from the main signal. This approach helps mitigate the influence of the stand's vibrations on the magnitude of the main sensor's signal. Accelerometers of the DIS QG40N-series (DIS Sensors, Soest, Netherlands) were used for the experiment. The technical specifications of the sensor are presented in Table 3.

Gearbox faults were sequentially introduced into the robot's structure. To obtain the necessary data, artificial faults were separately created in the gearbox, namely, overtension of the tooth belt transmission and heating of the screw transmission. For overtension of the belt, a displacement of the transmission pulleys was performed, as this type of damage is the most common. For heating the worm, lubrication was removed, simulating the case of contamination/drying of lubrication in the transmission.

Table 3. Technical specification of DIS QG40N.

Characteristic	Value
Measuring ways	3 axes (XYZ)
Measuring range	±4 g
Output signal	0.5–4.5 V
Resolution	4 mg
Sensitivity error	±2%
Output refresh rate	3 ms

During the experiment, several conditions were established: a minimum rotation speed of the robot's servo motor was set (200 rpm/s) to avoid unwanted damage. Measurements were conducted along two axes of the robot, X and Y, the robot movements were linear to track changes in the reference and faulty signals.

The experiment consisted of the following steps:

1. Data acquisition, collection of all data from vibration sensors by unfaulty (reference) and faulty signals. The vibrational signal, captured by accelerometers, was converted into an electrical signal, and proceeded into Dewetron inputs for processing, visualization, and storage.
2. Data processing, transformation of output vibration signals into spectra to obtain vibration amplitude analysis. Following data collection, Fourier transform analysis was performed to analyze the acquired data. Also, to eliminate unwanted noise by comparing signals from the accelerometers, Matlab (9.10.0.1602886, R2021a) filters were used.
3. Compilation of fuzzy logic rules library based on the spectra. Based on spectral analysis, data collection was conducted, and a rule base for the fuzzy logic algorithm was developed. This formed the foundation for the diagnostic and control system.
4. Development of a fuzzy logic control system.

5.2. Diganosis Results

During the experiment, vibration signals were acquired as the output. To analyze the frequency characteristics of these signals, the FFT technique was employed. The resulting spectra from this analysis of the tooth belt transmission due to overtension, captured along two axes, are presented in Figure 12a,b.

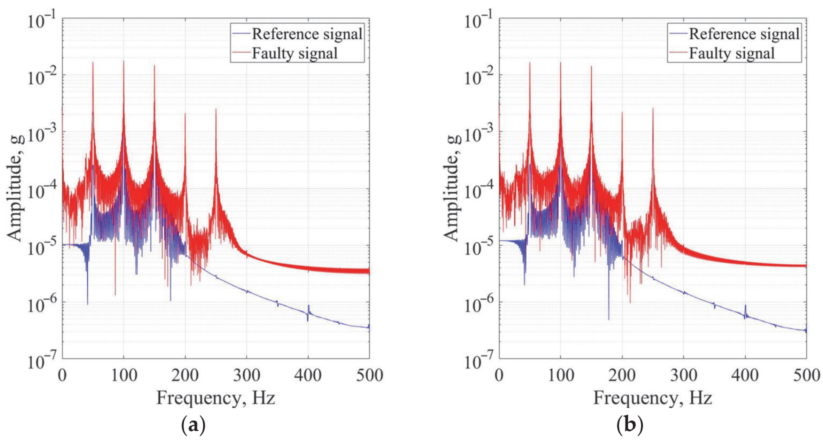


Figure 12. The spectral analysis of the output vibration signal by X-axis (**a**) and Y-axis (**b**) for the overtension fault of tooth belt transmission.

The graphs depict two signal types: a reference signal representing the transmission belt's normal tension (as per factory settings) and a faulty signal indicating overtension caused by a shift in the pulley axes' center. As seen from the reference signal, the nominal frequencies of the HCR gearbox were at the level 50, 100, and 150 Hz.

The additional noises that manifest between the main frequencies are oscillations of other robot parts that cannot be rigidly fixed, such as cable lines and protective metal structures. The nominal amplitude of the robot structure oscillations should not exceed 0.3 g. Considering the low noise amplitude, the presence of various frequency ranges, and the appearance of additional frequencies when the robot breaks down, which can be used to determine the type of damage, noise can be disregarded for the optimization and simplification of algorithm operations.

The belt overtension in the tooth belt transmission results in frequent oscillations occurring at the transition points within the robot's operational area. Transition points refer to instances in which the robot changes direction during its movement. Consequently, the tension of the belt affects the robot's performance only at specific locations within its operational space. Furthermore, the spectrum analysis highlights that the frequencies of vibration of the belt overtension are at the level of 200–250 Hz.

The resulting spectral analysis of the screw transmission, captured along two axes, in the case of the heating fault, is presented in Figure 13a,b.

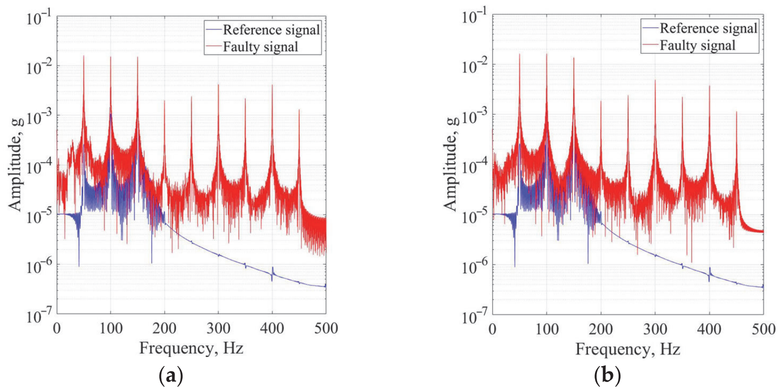


Figure 13. The spectral analysis of the output vibration signal by X-axis (**a**) and Y-axis (**b**) for the heating fault of screw transmission.

In contrast to the negative consequences of overtension in the belt, damage to the torque transmission worm can result in significant disturbances throughout the entire path of the robot's movement, affecting not only specific points.

These vibrations can lead to increased stress on the robot's servos, reduced positioning accuracy, and significant wear on other components of the mechanism. Furthermore, an analysis of the vibration spectrum indicated that these vibrations were not cyclic but rather stochastic, making their elimination and reduction of their impact more challenging. One proposed method to mitigate the effects of errors in the robot's design is to increase the torque in the servo drive to prevent potential gear jamming. Also, the frequency vibration diapason is wider than that in the case of the overtension fault and is equal to 200–450 Hz.

Based on subsequent comparisons of the frequency spectra, it is possible to develop a fuzzy logic algorithm that will determine the extent of damage in the transmission and propose corresponding speed and torque patterns for the robot control system.

5.3. Fuzzy Logic Algorithm Results

Based on the information obtained from the spectral analysis, it is possible to create a fuzzy logic algorithm for the diagnosis and control of the robot. Depending on the amplitude and vibration frequency, it is necessary to control the speed, torque, and acceleration of the moving parts of the robot. Diagnosis according to the fuzzy logic algorithm should be based on the frequency spectrum of the vibrational signal and the presence of vibration amplitude, i.e., the presence of low-frequency signals with a high fault amplitude, as well as high-frequency signals with low or high fault amplitudes. This will indicate transmission damage, and depending on the frequency range, the type of failure will be determined. The scheme of the fuzzy logic algorithm process is presented in Figure 14.

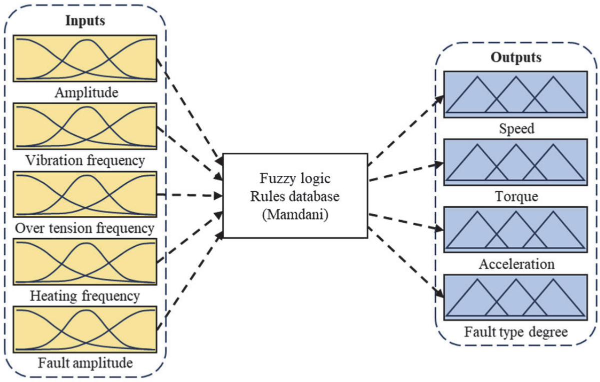


Figure 14. The scheme of the fuzzy logic algorithm process.

The membership functions of input and output variables that determine the fuzzy logic algorithm to control robot servomotors are presented in Figure 15a,b.

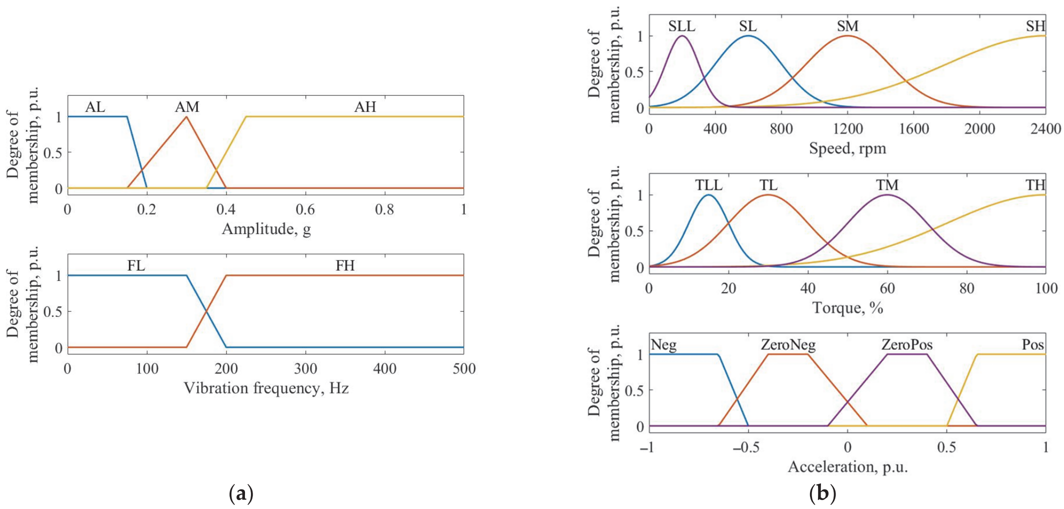
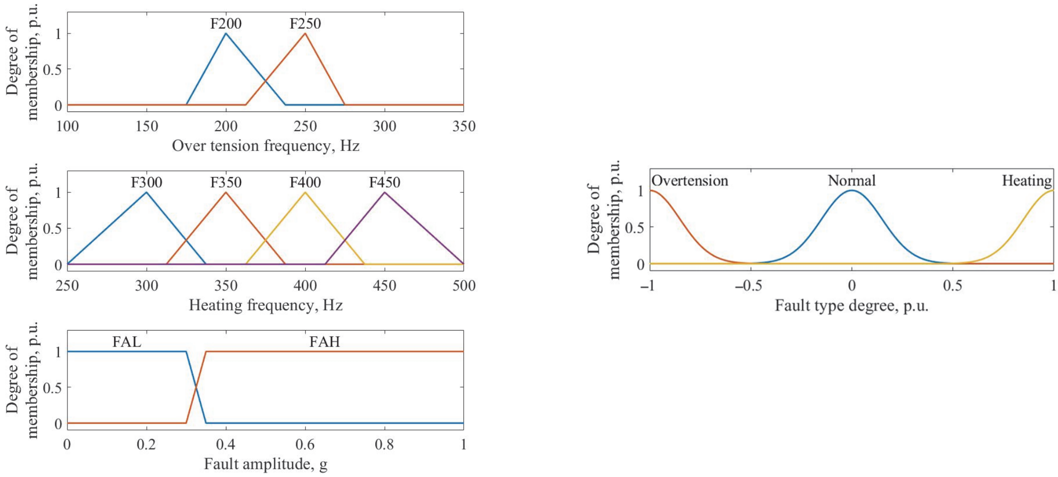


Figure 15. The control membership functions of input (**a**) and output (**b**) variables.

As seen in Figure 15, each membership function describes the linguistic variable. For the inputs, the variables were AL, FL—low amplitude and frequency of vibrations; AM—medium amplitude; AH, FH—high amplitude and frequency. For the outputs, the variables were SLL, TLL—minimum speed and torque of the servomotor; SL, TL—low speed and torque; SM, TM—medium speed and torque; SH, TH—high speed and torque; Pos, Neg—racing and braking of the robot, respectively; ZeroPos, ZeroNeg—weak acceleration and deceleration of the robot. The form of the membership functions was chosen in such a way that the input variables corresponded to the data based on the spectral analysis. The output variables were designed to ensure the smooth control of speed and torque, as well as maintain the required degree of acceleration or deceleration of the robot.

The membership functions of input and output variables that determine the fuzzy logic diagnosis algorithm for mechanical faults in the robot transmission are presented in Figure 16a,b.

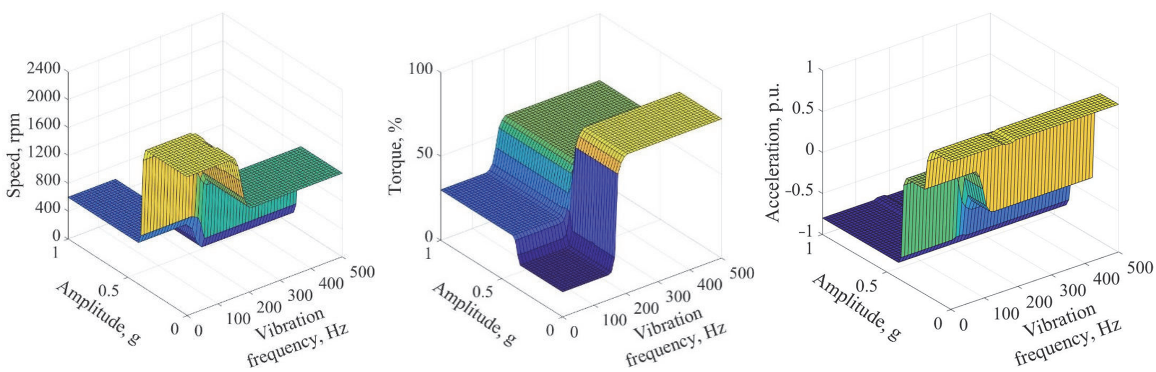


(**a**) (**b**)

Figure 16. The diagnosis membership functions of input (**a**) and output (**b**) variables.

As seen in Figure 16, for the inputs, the variables were F200, F250, F300, F350, F400, and F450—the vibration frequencies for 200, 250, 300, 350, 400, and 450 Hz, respectively; FAL—low fault amplitude of the vibration, FAH—high fault amplitude of the vibration. For the output, the variable fault types and their magnitudes were chosen in such a way that it was possible to identify mechanical damage in the transmission. Thus, the normal state of the transmission was equal to 0; the presence of belt overtension was equal to −1; and the presence of worm heating was equal to 1.

The modeling results of the control parameters (speed, torque, and acceleration) are illustrated in Figure 17a–c.



(**a**) (**b**) (**c**)

Figure 17. Results of modeling fuzzy logic algorithm for control parameters speed (**a**), torque (**b**), and acceleration (**c**).

As seen from the simulation results, with an increase in the amplitude and frequency of vibrations, the robot's speed decreased while the torque increased. This occurred to reduce the impact of vibrations on the robot's structure and prevent undesirable consequences and further breakdowns. The reduction in speed leads to a decrease in inertia, thereby reducing the amplitude of vibrations, while increasing the torque helps overcome the current impact of damage and diminishes its influence on the transmission. Regarding acceleration, the situation is different. Acceleration depends more on the amplitude of the vibrations than on their frequency, so with an increase in amplitude, the acceleration decreases. This results in the damping of vibrations, stabilizing the entire system.

The rule base of the fuzzy logic algorithm was structured in such a way that the control system's output parameters contributed to reducing the impact of damage on the transmission while ensuring the mechanical system's functionality. This ensures minimal wear on mechanical parts and, in turn, does not interrupt the execution of operational tasks, allowing the completion of the work cycle. Moreover, this control method is easily adjustable, making the entire system much more flexible and adaptive.

The modeling results for the diagnosis are illustrated in Figure 18a,b.

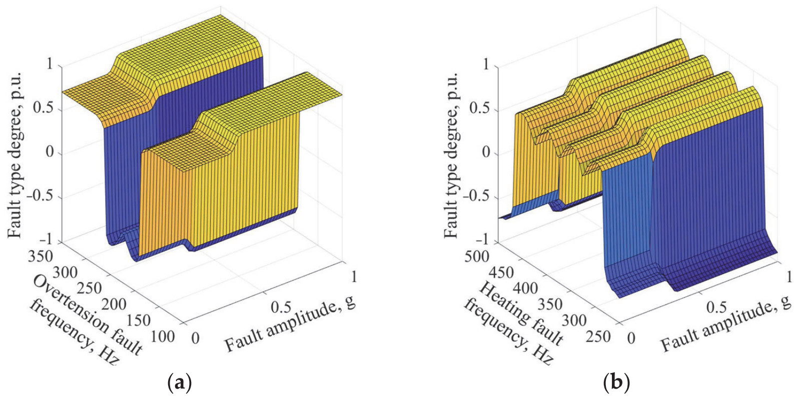


Figure 18. The control membership functions of input (**a**) and output (**b**) variables.

The diagnostic modeling results indicate the likelihood of damage in the transmission. Thus, the closer the output parameter is to the corresponding value for the presence of the corresponding frequency in the vibrational spectrum of the signal (-1 for overtension fault and 1 for worm heating fault), the more likely the presence of damage. By comparing the diagnostic patterns of damage with real signals, it is possible to identify the presence of damage even with a limited amount of data, relying solely on the frequency and amplitude of vibrations. It is important to note that values from the vibration sensor's input signal should be considered within specific frequency ranges. Therefore, in the presence of the necessary frequencies in the signal spectrum, the onset of damage can be identified even with the slightest amplitude. This diagnostic approach significantly reduces the frequency of repairs, meaning equipment maintenance will occur as needed, reducing overall maintenance costs.

Similar to the control system, this diagnostic system is easily adaptable to various types of damage, making it a versatile solution for signal processing and machine learning.

6. Conclusions

In conclusion, tests on the developed test bench prove the effectiveness of the methodology for diagnosing and controlling mechanical faults in robotic systems. The data collection, processing, and fuzzy logic algorithms to identify and address common issues like belt tension and gear heating in robot transmissions are used.

Analysis of the vibration signals from the experiments gave insights into different fault frequencies. By spotting distinct patterns through spectral analysis, a strong fuzzy logic algorithm for diagnosing and fixing faults accurately based on vibration frequency and amplitude was developed.

The fuzzy logic algorithm effectively adjusts robot parameters like speed, torque, and acceleration to mitigate the impact of faults on the transmission system. This ensures smooth operation while reducing wear on mechanical parts and preventing breakdowns.

The diagnostic modeling results highlight the reliability of the approach in identifying damage in the transmission system, even with limited data. This reduces the need for frequent repairs and lowers maintenance costs.

Overall, our findings emphasize the potential of fuzzy logic-based systems for enhancing the reliability of robots in dynamic industrial environments. The flexible methodology offers real-time fault detection and management, improving operational efficiency and reducing downtime in automated manufacturing processes.

For future work, we plan to explore other types of mechanical damage, upgrade our fuzzy logic rule database, and validate our algorithm for controlling and diagnosing faults. We will also investigate the use of fuzzy logic in machine learning and predictive maintenance. Additionally, our research can aid in setting up digital twins of transmission systems, robots, and other connected elements.

Author Contributions: Conceptualization, S.A.; methodology, S.A.; validation, A.R., T.V. and K.K.; formal analysis, S.A.; investigation, S.A.; resources, S.A.; data curation, S.A., T.V. and A.K.; writing—original draft preparation, S.A.; writing—review and editing, K.K.; visualization, S.A.; super-vision, A.R. and T.V. All authors have read and agreed to the published version of the manuscript.

Funding: The research leading to these results received funding from PSG453, 2020–2024, "Digital twin for propulsion drive of autonomous electric vehicle".

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy.

Conflicts of Interest: The authors declare no conflicts of interest.

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Publication III

Autsou, S.; Vaimann, T.; Rassõlkin, A.; Kudelina, K. Analysis of Possible Faults and Diagnostic Methods of the Cartesian Industrial Robot. Proc. Est. Acad. Sci., 71 (3), pp. 227–240, 2022, doi: 10.3176/proc.2022.3.04.

Proceedings of the Estonian Academy of Sciences,
2022, **71**, 3, 227–240
https://doi.org/10.3176/proc.2022.3.04
Available online at www.eap.ee/proceedings

DIAGNOSIS OF MECHANICAL FAULTS IN ROBOTICS

Analysis of possible faults and diagnostic methods of the Cartesian industrial robot

Siarhei Autsou*, Anton Rassõlkin, Toomas Vaimann and Karolina Kudelina

Department of Electrical Power Engineering and Mechatronics, Tallinn University of Technology, Ehitajate tee 5, 19086 Tallinn, Estonia

Received 24 November 2021, accepted 10 January 2022, available online 9 August 2022

Abstract. The paper discusses problems that occur in robotic arm control. The specific problems arise due to the wear of various types of gears (in the presented case, belt gear and worm gear). It is important to note that such errors need to be diagnosed in time, and the way of their elimination has to be determined, which should be resource-intensive and cost-effective. This article describes the basic types of robotic manipulators (robotic arm, telpher and Cartesian), presenting a review and study of the possibilities of errors in the movement of a robot, adjustment of a mechanical system, and determination of a strategy for solving the emerging problems. A comparison between various types of gear faults is also provided. Different ways of diagnosing faults are discussed, based on the advantages and disadvantages of the methods. The main objective of this study is to provide a complete overview of the mechanical areas where disturbances occur, their diagnosing, and methods of their elimination.

Keywords: electrical drives, mechatronics system control, robotic control, diagnosis.

1. INTRODUCTION

Industrial development and energy crisis are two aspects linked to the development of modern manufacturing. Increasing industrial power leads to the design and construction of more complicated mechanisms and increased consumption of energy resources.

Nowadays, no manufacturing is complete without the implementation of machines and special mechanisms. The use of robots, manipulators, and other autonomous devices ensures greater productivity for enterprises and reduces the risk of defective products. Smooth and accurate movements of robotic manipulators lead to the desired result with minimal loss of material and energy resources [1,2].

However, like any other system, robotic manipulators are subject to wear, namely the parts in which the force is transmitted from the motor that controls the movement of the robot to various mechanical parts using different gears [2,3]. Several types of transmissions are utilized for this purpose, each of which is used under certain conditions, to perform specific tasks. The wear of mechanical assemblies leads to the appearance of nonlinearities in the operation of robotic manipulators, reducing their technical capabilities [4]. As a consequence, there is a violation of the technological process, defective products, and numerous increased resource costs [5].

Diagnostics of the overall performance of industrial robots is the main task for the standard operation of mechanisms. Diagnostics should be carried out for different systems [1,6,7]:

- control system;
- power electronics;
- motors;
- mechanical system.

Diagnosis of the control system and power electronics involves diagnostic sensors used to obtain feedback from a robot and for more effective control mechanisms. This

* Corresponding author, siaaut@taltech.ee

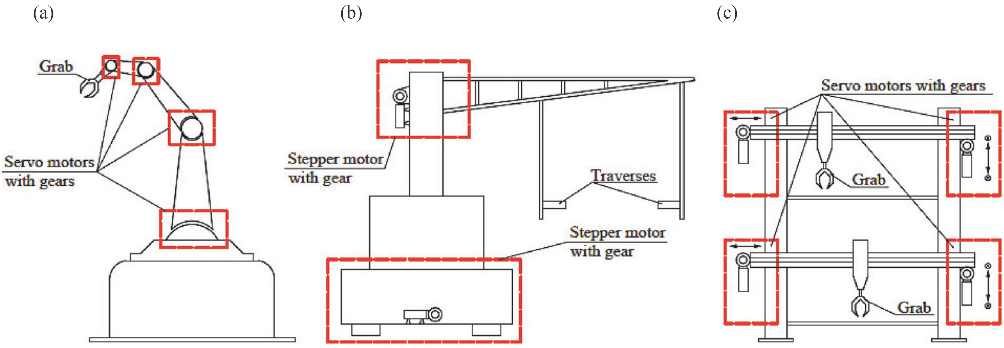

Fig. 1. Sketches of industrial robotic manipulators: (a) robotic arm manipulator, (b) telpher manipulator, (c) Cartesian robotic manipulator. Mechanical gear joints are areas marked by red lines.

type of diagnosis of the control system also includes checking of control algorithms and programs during the operation of an industrial robot [1,6,7].

The main research questions of this article are:

- definition of the character of gear faults;
- overview of diagnostic methods;
- showing the influence of the faults of different mechanical parts on each other.

This review is organized as follows. Section 2 describes industrial robots, motor types used to move parts of a robot, and how to transmit force to other parts of the robot. Section 3 specifies the types of gears that transmit force from the motor to other parts of the mechanisms. For every type of gear, the advantages and disadvantages are given, and problem areas are indicated. A comparison of gears based on common properties is also provided. Section 4 summarizes the types of diagnostic and monitoring methods related to transmission problems. The Hirata Cartesian robot is used as an example for comparing each type of diagnostic method.

Diagnosis of the motor and mechanical components as well as mapping of the most probable damage minimize the risks associated with malfunctioning of mechanisms and prevent serious damage. Moreover, diagnostics of different types of gears allows to understand how to eliminate emerging problems with minimal cost, which is an essential criterion in the context of globally developing production and caring for the environment [1,6,7]. This article is a general overview of gears used for industrial robots and the related faults. The basic types of industrial robots presented in this article, which have the same transmission as the Hirata Cartesian robot, will be the main subject of future research.

2. ROBOTS AND MOTORS

Industrial robots cover an essential segment of industry [1], they are used to perform work that poses a threat to human life and health [8,9]. Any industrial robot consists of mechanical parts to perform specific functions, such as moving weights or the structure of the robot, or grabbing details or parts of another mechanism. Each part is represented by a specific gear, specifically suited for the particular type of operation [1,10].

For a more detailed consideration of transmission types, an example of some of the main robotic manipulators is presented in Fig. 1 [8]. The robotic arm manipulator (Fig. 1a) is designed to move small details during the technological process and assemble other mechanisms. The telpher manipulator (Fig. 1b) is an industrial manipulator designed for operation with special attachments and devices as well as for moving heavy cargo along the technological line. The Cartesian robot (Fig. 1c) is designed for operation in technological processes of assembling and installing, usually applied in electronics manufacturing and conveyor systems [11,12].

As can be seen from the literature, servo drives and stepper motor drives are the most commonly used propulsion devices that satisfy high-performance requirements and allow the robot to move smoothly with precise accuracy. Both motor types have their advantages and disadvantages, and a comparative analysis from the point of view of the dedicated application (robotic manipulator) is presented in Table 1 [13–16].

As seen from the comparison, the servo motor is the best drive element in terms of backlash presence, the range of power used, and wear. However, its control

Table 1. Comparison of servo and stepper motors for a robotic manipulator

Criteria	Servo motor	Stepper motor
Requirements for the motor in terms of power and the type of gearbox	not needed	needed
Accuracy	high accuracy	high accuracy
Backlash/slippage	absent	present
Wear	low degree of wear	medium degree of wear
Immediate detection of failure	present	present
Need for additional sensors	needed for normal operation	needed to simply improve normal operation
Complexity of the control system	complex	not complex
Fixing of the motor shaft	needed	not needed
Cost	high price	low price

system is more complex than that of the stepper motor, and there is no holding torque. Therefore, several transmission types are used for servos, mainly the worm gear and the screw gear [16–19].

The areas marked by red lines in Fig. 1 indicate mechanical gears. The main task is to transmit force from the motor drive shaft to other parts of the robotic manipulator, allowing independent control for its different parts.

As shown in Table 1, each motor type should use additional sensors for higher operation accuracy. The number of faults occurring during the motor's operation is increasing, which means that diagnosis of the robot's operation should be performed on the mechanical and electrical systems. Therefore, diagnosis is further performed on control systems, power electronics, and the mechanical parts.

Faults occurring in the control system and power electronics lead to increased product failure, breaking the correct regime of operation, but do not allow the parts of the robot to be destroyed through protecting the systems.

Damage to the mechanical system causes more negative consequences because minor changes in smaller mechanical parts lead to the nonlinear character of the robot's operation. The situation leads to an increased consumption of energy resources and possible destruction of critical mechanical parts of the robot, which will require renovation and increase the consumption of material resources.

3. FAULTS IN THE TYPES OF GEARS

3.1. Gear train

A gear train is a mechanism that has gears to transmit force directly. It usually consists of two toothed wheels, one of which is called a cogwheel with fewer teeth, the other with more teeth is called a wheel [2,3,20]. A sketch of a gear train is presented in Fig. 2. The problem areas of the gear train (the possibility of jamming and overheating) are highlighted in red.

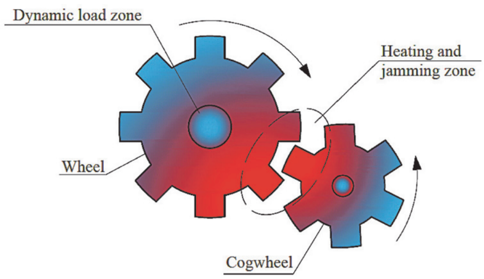

Fig. 2. Faults of the gear train.

The main advantages of the gear train are high efficiency, compactness, and high rotational speed, which allows it to be used at high power [21–23]. On the other hand, the disadvantages of the gear train which reduce the scope of its application are noise, increased dynamic load, frequent need for lubrication to avoid tooth jamming and abrasion, transmission rigidity [21–23]. Gear drives are mainly used for two purposes [24]: force transmission between parallel shafts and conversion of translational motion into rotary motion and vice versa. Therefore, those types of gears are used in cases where translational and rectilinear movement of a load or a high-power motor is used, e.g. moving the structure of a robotic manipulator along a technological line [25].

3.2. Belt gear

The belt gear is a mechanism that consists of at least two pulleys, with a belt stretched between them. The belt gears can be with or without teeth, depending on the load being transferred [2,3,20]. A sketch of the belt gear is presented in Fig. 3. The main failures that potentially affect belt gear performance are slippage and overheating.

The advantages of belt gears are closely linked to their disadvantages, e.g. belt slippage causes transmission

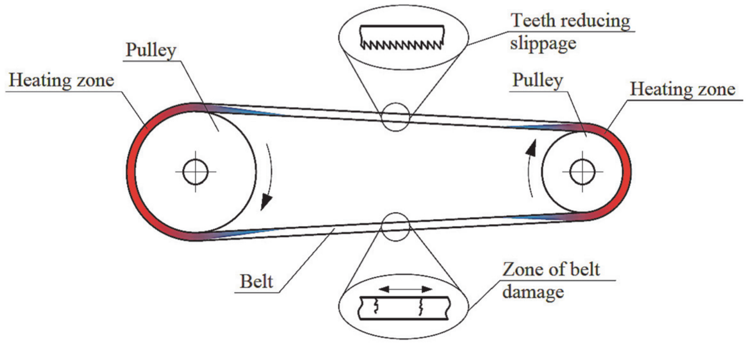

Fig. 3. Faults of the belt gear.

disruption and relieves shaft overload. Belt tension makes the transmission operation quiet and smooth, but it leads to additional heating. Some additional advantages include low cost and minimal damage to the structure in the event of some belt failures [21,26,27]. Usually, the belt gear is used to transmit force from the motor shaft to those parts of the mechanism that are in continuous motion and employed for variable small and medium loads. However, the belt gear is also used to transmit tractive effort over long distances, e.g. conveyor-type machines [28,29].

3.3. Worm gear

A sketch of the worm gear is presented in Fig. 4. Possible failures of the worm gear are jamming, overheating, and increased friction.

The worm gear is a mechanism that has a helical pair with teeth usually located orthogonally to each other. In the worm gear, the teeth of the worm slide over the teeth of the wheel, which leads to certain restrictions on its operation [2,3,20].

The advantages of the worm gear are smooth and quiet operation, compactness, and high kinematic accuracy, as well as the possibility of self-braking due to friction [21,30,31]. The disadvantages of the worm gear are associated with the friction of the teeth against each other, namely heating and low efficiency, the need to use antifriction materials, and jamming of the gear [21,30,31]. The significant performance characteristic of the worm gear is its assembly accuracy, which helps to reduce the chances of some imperfections and increases the service life [20]. Worm gears are used for direct force transmission, similar to the gear train, e.g. in industrial manipulators [32,33].

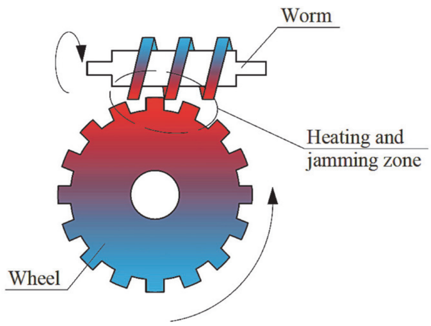

Fig. 4. Faults of the worm gear.

3.4. Chain gear

The chain gear is a mechanism that combines the gear train and the belt gear. Instead of cogwheels and wheels, sprockets are used, and instead of a belt, a chain is used that meshes with the sprockets [2,3,34]. A sketch of the chain gear is presented in Fig 5. The problem areas are related to abrasion and wear.

Since the chain gear is a combination of the gear train and the belt gear, its advantages are similar to those of such types of transmissions, such as high efficiency, the possibility of short-term overloads, the ability to transmit force over long distances, and no tension due to the chain engagement [21,35–37]. The disadvantages are similar to these of the gear train – the need for lubrication, noise, and additional dynamic load. The disadvantage of the chain transmission is the wear and tear of the chain joints [21,35,37]. Consequently, due to its design, the chain gear can be used where using a gear train is not possible

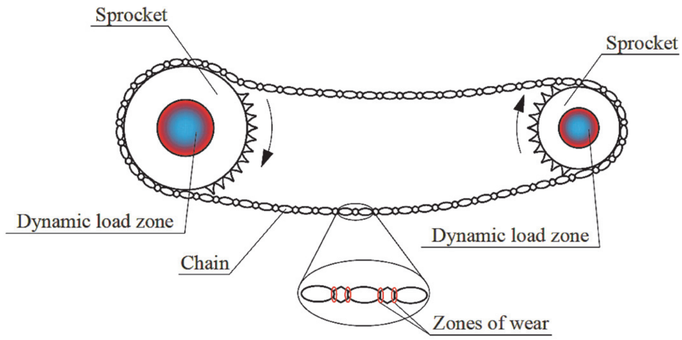

Fig. 5. Faults of the chain gear.

and the belt gear is not suitable for such operation [2,38,39].

3.5. Analysis of a gear type based on the application of the industrial robotic manipulator

Based on the above, each type of force transmission from the motor to other parts of the robot is used for performing specific tasks. It is necessary to consider separately each of the types for each system, and the expediency of using that particular transmission for the assigned task. When developing mechanisms, several criteria can be distinguished by which transmissions can be compared and according to which a suitable transmission can be chosen: compactness, power/area of application, degree of wear, and the possibility of transmitting force over long distances. A comparative analysis based on the authors' evaluation is presented in Fig. 6, where "5" is the highest and "1" the lowest proximity to the criterion.

As illustrated by the comparative diagram (Fig. 6), each of the presented gears has several advantages over the others in specific criteria, which allows one to select the gear best suited for particular operating conditions. However, the degree of wear of each gear is relatively high. This is due to the constant friction of the gear parts against each other, tension, and heating. Therefore, during the operation of the mechanism, errors caused by the degree of gear wear may occur. To prevent more damage to the mechanism, it is necessary to diagnose the parts that are subject to wear over time.

4. BEARING FAULTS

A bearing is a fundamental part of any gear or motor. A bigger part of the dynamic load is directly transferred to the bearing during the operating time of the motor. This means that many faults occur for different reasons, such as overload, friction, current on the shaft of the motor, damage due to improper lubrication, etc. [40]. As seen in Fig. 7, the following types of bearing damage occur most frequently [41]:

- material wear,
- cracks due to the wrong emplacement,
- friction due to insufficient lubrication,
- damage due to shaft current.

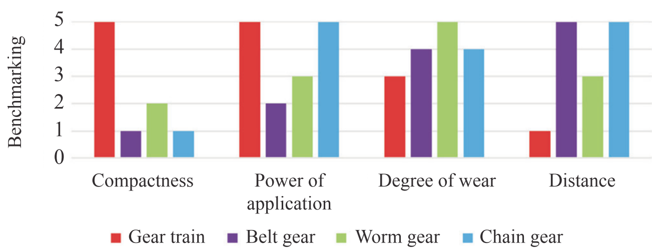

Fig. 6. Comparative analysis of gear types for industrial robotic manipulators.

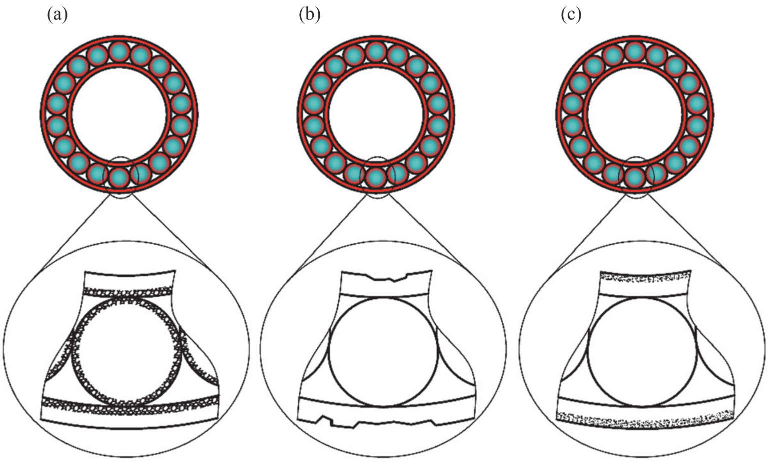

Fig. 7. Damage types of bearings: (a) material wear and friction due to insufficient lubrication, (b) crack due to the wrong emplacement, (c) pitting due to shaft current. The highlighted zones indicate the zones of increased friction.

Wear in the bearing usually occurs due to cyclic operation of the mechanism and when the motor is operating at different high speeds [42]. Overload occurs during the motor's operation in a stressed situation for the bearing, for example, as a result of additional tension or friction damage on the bearing surfaces. This damage causes unwanted vibration and increases the dynamic load on the motor shaft [43].

Wrong emplacement leads to an unequal load on the bearing and, as a result, an additional dynamic load on different areas. In this case, the bearing should be properly installed [44]. Before the installation it is required to check the shaft of the motor and the mounting surface of the bearing. If it is not done, it should be ensured that the bearing is mounted properly as its damage can lead to the destruction of the motor shaft or the different mechanisms connected with the shaft [43].

The latter type of fault can be caused by current in the motor. In this case, frosting or pitting take place on the surface of the bearing. As a result, the motor operation has nonlinear character [43]. No type of damage can be found without special devices, but this minor damage leads to bad faults in the operation of the mechanism. In this case, every damage should be diagnosed and steps should be taken to repair it [45].

5. METHODS OF DIAGNOSIS

It is essential to predict damage before starting work on an industrial robot. The performance, accuracy, and energy efficiency depend on the overall condition of the device. Even a minor deviation from the standard operation of one part of the mechanisms over time can have serious consequences [6,46]. Damage to transmissions is of difficult nature. There are spalls of a cogwheel, overfriction of gear parts, overheating and failure of the wheels, and breakage of the belt or chain, caused by tension or over-wear of the elements [7,40].

Various types of fault prediction and diagnostic methods are used to obtain information about the damage. Several types of diagnostics are used in practice, mainly [40,47]:

- Fast Fourier Transform (FFT),
- Short-Time Fourier Transform (STFT),
- Continuous Wavelet Transform (CWT),
- Advanced Diagnostic Techniques (ADT).

5.1. Fast Fourier Transform

The FFT is used to transform the input signal into different types of spectral analysis. This transformation provides information about the "degree of presence" of this or that frequency in the spectrum of the signal [48]. The FFT is used for stationary signals that do not change their spectral parts during that time. The pros and cons of the FFT analysis are schematically shown in Fig. 8.

The FFT analysis has several advantages. Firstly, it allows to reduce the number of calculations needed for the analysis of the input signal. Secondly, the FFT provides a prediction of the result, obtaining the result of the spectral analysis of the entire time axis. Thirdly, it also has a

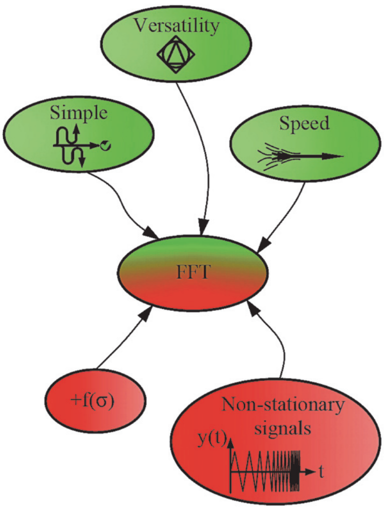

Fig. 8. Advantages and disadvantages of FFT.

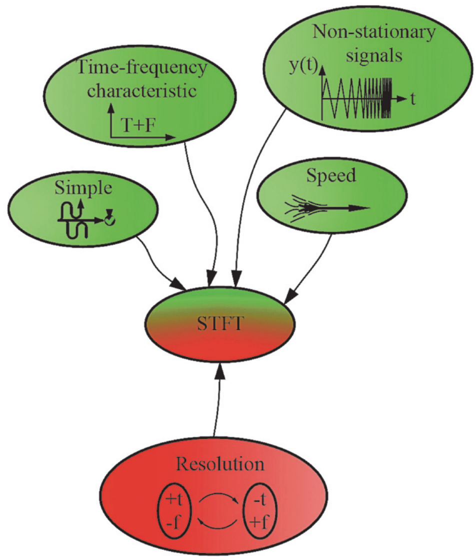

Fig. 9. Advantages and disadvantages of STFT.

simple structure without additional equations for the stationary signal [49,50].

At the same time, the following disadvantages need to be discussed. In the case of the FFT, it is impossible to analyze non-stationary signals as these signals have a complex structure with a different set of frequencies, which allows additional spectra to occur in the spectral analysis of the FFT. Furthermore, it is necessary to use a window weighting function f(σ) for the waveform to compensate for spectral dissipation, reducing the loss of information [51–54].

5.2. Short-Time Fourier Transform

The STFT can be used for non-stationary signals, and in this case the STFT is a function of two variables – time and frequency [55]. Non-stationary signals have a few frequencies for problem analysis, but the STFT takes a small amount of time, providing thus a good basis for the signal analysis. The pros and cons of the STFT analysis are schematically shown in Fig 9.

Unlike the FFT, the frequency-time characteristic is obtained. Unfortunately, the STFT has a significant disadvantage, which is related to the Heisenberg's principle [56,57]. This principle is based on two characteristics (momentum and position) of a point in an area that cannot be found with the same accuracy. If the STFT is used, a signal will disperse along one axis, narrowly localized along the other axis, and vice versa [58]. So, if a wide window is taken to localize a signal, poor resolution in time will be obtained, and in the other case, if a narrow window is taken, the uncertainty in frequency will increase [49,50]. Based on the above, to find a better solution to this problem, other diagnostic methods for damage should be used.

5.3. Continuous Wavelet Transform

The CWT is an alternative to the STFT because the CWT enables to solve problems with poor resolutions in time and frequency [59]. Usually, the CWT is used for signals that have a short-time high frequency and fewer long-term frequency components [60]. The principle of the CWT is similar to the STFT but it has two crucial differences [61–63]:

- CWT does not use the Fourier Transform for weighted signals;
- CWT width changes for each part of the signal, allowing a better spectral analysis.

The main benefits and drawbacks of the Wavelet Transform are shown in Fig. 10.

In practice, many signals have the same structure that allows the use of the CWT for a spectral analysis [64]. It means that by using the CWT, good resolution in time and poor resolution in frequency are obtained for a high-frequency area, and vice versa for an area with lower frequency [49,50]. In this case, the CWT has a few disadvantages such as an increased number of calculations

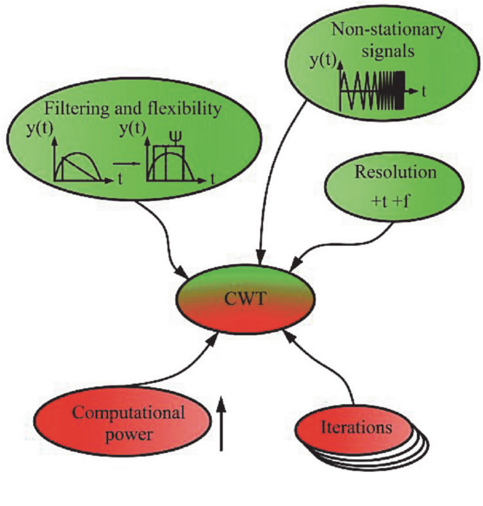

Fig. 10. Advantages and disadvantages of CWT.

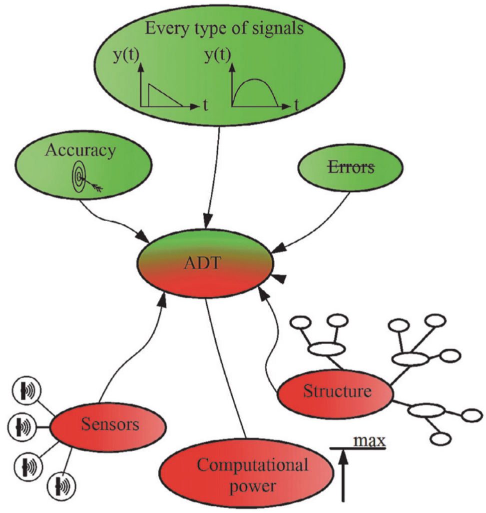

Fig. 11. Advantages and disadvantages of ADT.

for signal diagnosis, and as a consequence, necessary computational power is also increasing. Continuous Wavelet Transform is used in different fields: acoustics, medicine, industrial attachments, etc. Thanks to the CWT, various anomalies in the operation of different mechanisms can be detected [65].

5.4. Advanced Diagnostic Techniques

Advanced Diagnostic Techniques are modern methods that use artificial intelligence for faults diagnostics. These methods can include such algorithms as fuzzy logic (FL), machine learning (ML), and other methods to find slight deviations from the normal condition in mechanical and electrical parts of the robotic manipulator [66–69].

Fuzzy logic is used for the diagnosis of faults in gears or bearings. Fuzzy logic methods allow to adapt each control system to different failures [70–72] and to send a report about minor deviations from the normal operation of a mechanism [73–76]. At the same time, machine learning methods allow us to teach a control system that defines deviations and faults, the malfunctions of which lead to possible damage of the mechanism [77,78]. After a few tests the ML is able to find different types of faults without human control and perform operations for minimizing the consequences [79–81].

The main benefits and drawbacks of the above-mentioned techniques are shown in Fig. 11.

These methods have a complicated structure and many calculations but they have good accuracy and a low probability of errors. Moreover, the advanced techniques can be used for different signals, but additional sensors should be installed [82–86].

6. COMPARISON OF DIAGNOSTIC METHODS BY THE EXAMPLE OF THE HIRATA CARTESIAN ROBOT

Each of the above methods can be applied to different conditions. It depends on the type of output signals, the construction of the robot, the type of operation, etc. To compare the diagnostic methods, the Hirata Cartesian robot is taken as an example. This robot consists of three orthogonal axes that are connected with different gears (belt gear and worm gear highlighted in Fig. 12). The driving force is transmitted by the belt gear, the worm gear, and the gear train to move different parts of the robot. It means that any fault that can occur during the robot's operation leads to different types of disturbances, such as unwanted vibrations, increased friction, wear of the parts of the robot, and other disturbances. One can conclude that different types of signals are emitted in the case of damaged gears or disturbances of operating sensors [87]. The main aspects of the diagnostics of the Hirata Cartesian robot are presented in Table 2.

The comparison of the diagnostic methods is based on the advantages and disadvantages of the presented methods and is recommendatory in nature, based on the opinion of the authors.

(a) (b)

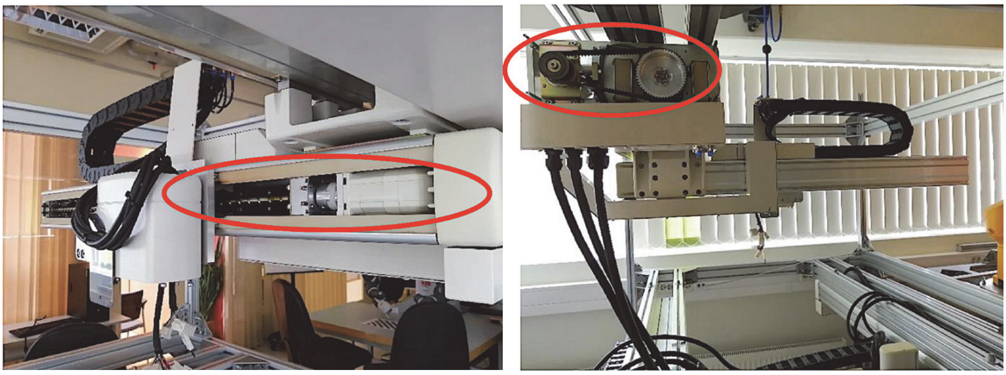

Fig. 12. Hirata Cartesian robot: (a) view with the worm gear, (b) view with the belt gear.

Table 2. Aspects of diagnostics

Aspect	Value
Model of the robot	CRWQ-H2010APHT-11.5-7-2LL-B
Diagnosis of the transmission	Toothed belt transmission
Parameters of the transmission:	
- diameter of the driving pulley;	75 mm
- diameter of the driven pulley;	150 mm
- length of the belt;	500 mm
- distance between centers.	200 mm
Working conditions	Soft, dust-free area, motors without load

Each of the above types of diagnostic methods can be used for finding and describing faults that can occur during the operation of the robot. Nevertheless, the CWT and ADT methods can work and perform the spectral analysis of signals without noise and do not depend on the type of signals. At present, the FFT and the STFT have a simple structure, and these methods do not need additional sensors and computational power.

Taking the above into account, it can be concluded that each type of diagnostic method can mark different types of damage and faults during the robot's operation, depending on the aims that are set. The FFT and STFT methods can be used for fast and straightforward marking when we have stationary signals or signals with a small amount of noise. The CWT and ADT methods can be used for more complicated faults, where we should mark different types of signals without any errors.

When examining Hirata Cartesian robots and which damage and faults can occur during operation, better methods for diagnosing faults in the control system of the robot and in the complex mechanical parts would be the CWT and the ADT. As the structure of the robot includes a few types of gears (belt gear and worm gear) and a few ways to move each part of the robot, which leads to stochastic disturbances, the simple and fast FFT or STFT will not solve the task of diagnosing damage and faults in this case, but could be used for diagnosing simple mechanical faults such as damage to the tooth of the belt or pulleys.

For modeling artificial damage to a mechanical part of the robot, the timing belt gear was chosen as an object. This transmission has second-order aperiodic transfer function:

$$W(s) = \frac{s}{G_2 s^2 + G_1 s + G}, \tag{1}$$

$$G_2 = \frac{r_{n2}^2}{u^2}(\rho A r_{02} \alpha_2 + q_m b), \tag{2}$$

$$G_1 = \frac{r_{n1}}{Pu(1.1 * 10^3 - 3.2 * 10^2 \pi r_{n1})}, \tag{3}$$

$$G = bF_y, \tag{4}$$

where r_{02} is the outer diameter of the driven pulley; r_{nl}, r_{n2} denote the inner radius of the driving and driven

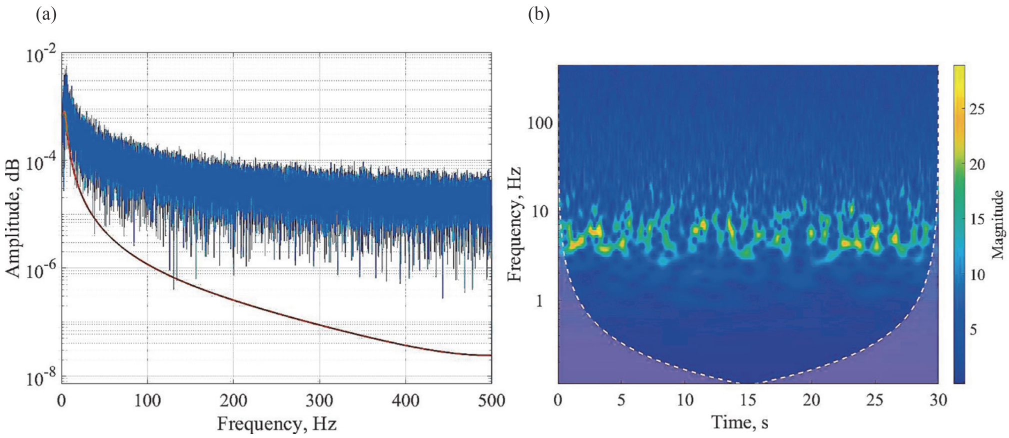

Fig. 13. Spectral analysis of the damaged toothed pulley of the belt gear in the Hirata Cartesian robot: (a) FFT method, (b) CWT method.

pulleys, respectively; ρ is the density of the belt, A represents the section of the belt; F_y denotes the beginning tension of the belt (table value); b is the width of the belt; q_m refers to the mass of 1 meter of the belt with a width of 1 mm (table value); α_2 is the angle of the belt girth at the driven pulley.

This transfer function was transformed into state-space, the response of the timing belt transmission to the pulley damage and the spectral analysis of this damage is shown in Fig. 13a,b.

The first graph is a spectral analysis of the output signal of the toothed belt gear by the FFT method presented in Fig. 13a. The graph shows the normal operation of belt transmission (red line) and the fully noisy output signal which occurred after disturbances (blue line). These disturbances occur during a transient process, for example, in the case of pulley or bearing damage or displacement of center pulleys. Figure 13b shows the diagnosis by the CWT method. The CWT method is a more presentable method than the FFT. In this case, additional information is provided about the faults. Based on these methods, it can be suggested which types of faults could occur in toothed belt transmission. This suggestion is based on the information about the character of faults. Each fault has a specific harmonic with definite frequency.

From a diagnostic point of view, the main problems of the robot and its own transmission are related to non-constant load, shift operation mode, and placement difficulty of additional sensors. In addition, working conditions must be considered. For example, if the robot is working in a dirty room, slippage of the belt may occur. In this case, it is difficult to isolate additional noise presented in the output signal.

CONCLUSIONS

Industrial robots have a complex mechanical structure, the joints of the robot parts, represented by transmissions that transmit force from the motor to other parts of the robot, are subject to various types of damage, such as friction, heating, wear, and others. The main aim of this research is to make an analysis of the transmission faults and diagnostic methods, to provide a comparison of transmission advantages of industrial robots and to suggest different diagnostic methods for improving the efficient operation of the mechanisms. The methods presented in this article for diagnosing the damage and identifying faults allow timely detection of a malfunction in the robot's operation, thereby preventing considerable damage. The article shows the possibility of using different diagnostic methods for the Hirata Cartesian robot, based on the opinion of the authors.

For future work, models of all the gears that are part of the robot will be developed and the necessary experiments will be carried out. The Hirata Cartesian robot has many mechanical parts represented by transmissions, which makes it possible to simulate various damage cases and understand which diagnostic method is the best for each transmission. The research is aimed at diagnostics, selecting the best control mode, and developing a control system that provides the required level of robotic control.

AUTHOR CONTRIBUTIONS

Conceptualization – S. Autsou, A. Rassõlkin; methodology – S. Autsou; validation – A. Rassõlkin, T. Vaimann, K. Kudelina; formal analysis – S. Autsou; investigation – S. Autsou; resources – S. Autsou; data curation – S. Autsou, A. Rassõlkin, K. Kudelina; writing: original draft preparation – S. Autsou; writing: review and editing – A. Rassõlkin, T. Vaimann, K. Kudelina; visualization – S. Autsou; supervision – A. Rassõlkin, T. Vaimann.

ACKNOWLEDGEMENTS

The research leading to these results received funding from the EEA/Norway Grants 2014–2021 "Industrial Internet methods for electrical energy conversion systems monitoring and diagnostics". The publication costs of this article were partially covered by the Estonian Academy of Sciences.

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Tööstuslike kartesiaanrobotite võimalike rikete ja tuvastusmeetodite analüüs

Siarhei Autsou, Anton Rassõlkin, Toomas Vaimann ja Karolina Kudelina

Käesolev artikkel kirjeldab probleeme, mis kerkivad esile seoses roboti manipulaatori juhtimisega. Nimetatud mured tekivad eri tüüpi ülekannete kulumisest (esitletud juhtudel rihm- ja tiguülekanne), nagu ka artiklis on kirjeldatud. Oluline on märkida, et sellised kõrvalekalded normaaltalitluselt on tähtis aegsasti tuvastada ning leida ka sobivad võimalused nende kõrvaldamiseks, arvestades ressursi- ja kulutõhusust. Artikkel kirjeldab eri tüüpi roboteid (manipulaator, telfer, kartesiaanrobot), millele tuginedes antakse ülevaade võimalikest esinevatest riketest, mehhaanilise süsteemi kohandamisest ning tulenevalt sellest ka probleemide lahendamise strateegiatest. Lisaks esitatakse eri tüüpi ülekannete rikete omavaheline võrdlus ning kirjeldatakse rikete tuvastamise meetodeid tuginedes nende eelistele ja puudustele. Uurimuse peamine eesmärk on esitada täielik ülevaade mehhaanika valdkondadest, kus nimetatud kõrvalekalded robotite puhul esinevad, ja näidata võimalikke rikketuvastuse meetodeid ning võimalusi rikete kõrvaldamiseks.

Publication IV

Autsou, S.; Kudelina K.; Vaimann T.; Rassõlkin A. The Usage of Fuzzy Logic for Detecting Mechanical Faults in Gearboxes of Robotic System. 2024 International Conference on Electrical Machines (ICEM), Torino, Italy, 2024, pp. 1–7, doi: 10.1109/ICEM60801.2024.10700425.

The Usage of Fuzzy Logic for Detecting Mechanical Faults in Gearboxes of Robotic System

Siarhei Autsou
Department of Electrical Power Engineering and Mechatronics
Tallinn University of Technology
Tallinn, Estonia
siarhei.autsou@taltech.ee

Karolina Kudelina
Department of Electrical Power Engineering and Mechatronics
Tallinn University of Technology
Tallinn, Estonia
karolina.kudelina@taltech.ee

Toomas Vaimann
Department of Electrical Power Engineering and Mechatronics
Tallinn University of Technology
Tallinn, Estonia
toomas.vaimann@taltech.ee

Anton Rassõlkin
Department of Electrical Power Engineering and Mechatronics
Tallinn University of Technology
Tallinn, Estonia
anton.rassolkin@taltech.ee

***Abstract*—Using machine learning or artificial intelligence enhances the quality of control and the degree of diagnostics of mechanical system states. However, in cases of insufficient data, these methods cannot fully realize their potential. In such instances, fuzzy logic algorithms can serve as a complete alternative to these methods. Fuzzy logic does not require the calculation of a precise mathematical model. In case of unexpected faults, some data can be lost, or additional noise appears, which can lead to destabilization of the control system. Working with fuzzy sets and linguistic variables allows the construction of a high-level control and diagnostic system. This article explores the possibility of using a fuzzy logic algorithm to create a diagnostic system for mechanical damage based on a Cartesian robot and underscores the importance of this method in addressing such issues. The article provides a description of the method and its working principles, along with conclusions and results of damage detection in the robot.**

Keywords—Gears, Fault diagnosis, Fuzzy logic, Robot control, Vibration measurement

I. Introduction

The development of artificial intelligence [1] and machine learning leads [2], [3] to the emergence of new technologies, control systems, and diagnostic methods [4]. The development of these technologies has significantly impacted the diagnosis of mechanical faults across various industrial sectors [5].

Diagnosing mechanical damage and managing mechanisms under these conditions are crucial for ensuring the reliability and performance of robotic systems [4]. Methods such as vibration or acoustic analysis [6], [7] are employed to detect faults like gear wear [8], bearing damage [9], pulley misalignment [10], and more. It's important to notice, that diagnosing these kinds of faults in the gearbox of the mechanisms, is of significant meaning. Even smaller deviations in the structure of the transmission can lead to seriously consequences.

Integrating artificial intelligence and machine learning into these methods enhances diagnostic efficiency by enabling the analysis of large amounts of data [11]. However, achieving the desired results requires collecting extensive datasets and performing thorough processing and analysis, as well as developing precise mathematical models to improve accuracy and efficiency [12]. Due to this requirement, there are challenges in defining the data, and assessing the damage in mechanical systems becomes logistically complex without data loss. Consequently, machine learning faces difficulties in solving problems with insufficient data, which hinders making accurate decisions and predictions [13].

In these cases, the fuzzy logic algorithm stands out with its uniqueness. Operating based on fuzzy rules and sets, fuzzy logic allows for solving numerous problems and tasks in the field of uncertain and fuzzy data [14]. Research on fault management and diagnostics based on fuzzy logic principles has provided a powerful set of tools for solving complex and non-standard problems that do not fit within the confines of traditional precise mathematical models [15], [16]. The fundamental principle of fuzzy logic enables the transfer of human observations directly into control without prior preparation and tuning of mechanism behavior models [16], [17].

If, in real conditions, a certain volume of data may be lost or not obtained, for control and diagnostic algorithms based on fuzzy logic, this is not a problem. The ability to operate with fuzzy sets suggests new possibilities, solution paths, and perspectives for modeling real conditions. The fuzzy logic method easily adapts to the most unpredictable scenarios and non-standard conditions [18], [19].

The main idea of the fuzzy logic algorithm lies in the use of fuzzy "if-then" rules, expressing decision-making logic based on input data. This construction allows for building a broad control system and ensuring optimal performance in various scenarios. Based on a set of rules, fuzzy logic also allows for identifying and analyzing faults in mechanisms based on fuzzy data [20], [21].

Despite modern robotic systems having their diagnostic system, which evaluates the robot's condition in control and power circuits, it does not account for possible faults in the mechanical part of the robot, which can lead to significant consequences [22]. Mechanical breakdowns occur due to prolonged exposure to negative factors on parts of the robot, resulting in undesirable deviations in performance and efficiency, such as the occurrence of unwanted vibrations leading to a loss of precision in robot positioning [23]. The main aim of the work is to show fuzzy logic-based control and

The research leading to these results received funding from the PSG453, 2020-2024, "Digital twin for propulsion drive of autonomous electric vehicle".

2024 International Conference on Electrical Machines (ICEM) | 979-8-3503-7060-7/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICEM60801.2024.10700425

the diagnostic algorithm will identify the fault and reduce the risks of performance loss, smoothing the consequences of damage. Analysis of the vibrational signal spectrum allows for assessing the robot's condition and identifying the necessary fuzzy logic rules to create a control and diagnostic algorithm for mechanical damage.

In the second chapter of the article, the most common mechanical damages in robotic system transmissions are discussed, along with the consequences of these damages. The third chapter briefly describes the principles of fuzzy logic and introduces the advantages of this method. The fourth chapter presents experimental results on the development and implementation of a fuzzy logic algorithm for detecting mechanical damages based on the Hirata cartesian robot.

II. Gearbox Faults

The subject of the study is the transmission of the Hirata cartesian robot, which consists of two parts: a tooth belt transmission and a screw transmission. Each of these types of transmission has its advantages and disadvantages, which contribute to the robot's operation [24], [25].

The tooth belt transmission has advantages in maintaining a constant rotational speed and transmission ratio. In the cartesian robot, the transmission is reduced, allowing a decrease in the speed of the robot's working element and an increase in torque, thereby improving the smoothness of operation. The disadvantage of the transmission is the need for belt tensioning and the alignment of transmission pulleys [26], [27].

The screw transmission has high precision, high inertia, and smooth operation. These advantages help reduce the risks of unwanted vibrations and ensure smooth movement of the robot's working element. Disadvantages of the transmission include wear of its parts, the possibility of gear engagement, and excessive heating in the absence of sufficient lubrication [28], [29].

Based on the gearbox benefits and limitations of the Hirata cartesian robot can be concluded two main types of mechanical faults are belt over tension of the tooth belt transmission and heating of the screw transmission. The consequences of these faults are presented in Fig. 1 and Fig. 2.

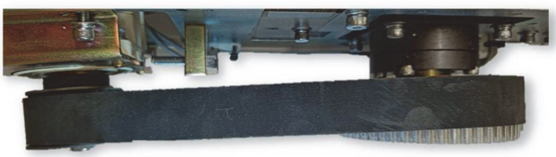

Fig. 1. Example of the bel over tension of the tooth belt transmission.

Belt over tension occurs in case of displacement of pulleys along the vertical axis relative to each other. Usually, this mechanical fault appears under the influence of the wrong setting way of the transmission, entry of a foreign body inside of the gearbox, or wearing of the pulley material [30].

This fault leads to additional vibrations at the transient points of the robot. These points are points where the movement direction of the robot is changed. In this case, the whole construction of the robot undergoes high loads because the amplitude of the vibration is high [31].

Fig. 2. Example of the heated worm of the screw transmission.

Heating occurs in no lubrication case or lubricant contamination. This fault appears in cases of prolonged operation under high loads and a contaminated environment, leading to the drying out and/or contamination of the lubricant inside the transmission. Also, contamination of the lubricant can lead to jamming of the transmission. As a result, there is significant wear on transmission parts and, consequently, loads increase on the robot's structure. At the same time, unwanted low-amplitude vibrations occur, which degrade the operational characteristics of the mechanism [32], [33].

III. Fuzzy Logic Algorithm

Fuzzy logic is a method of processing data based on the degree of membership of an input variable to a set of fuzzy sets. This method allows working with uncertain or incomplete data, enabling the identification of necessary control actions. Fuzzy logic is used in various fields, such as pattern recognition, control of complex systems, etc., making it an acknowledged universal method for control and diagnostics. The block scheme of the fuzzy logic algorithm is presented in Fig. 3.

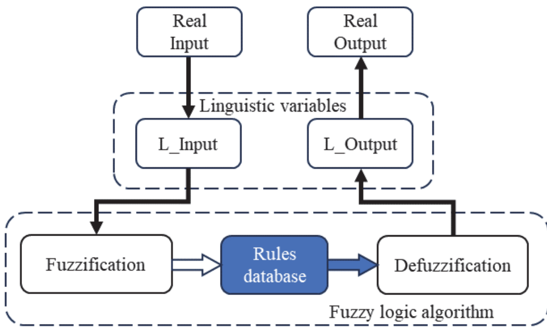

Fig. 3. Description of the control principle of fuzzy logic.

The fuzzy logic algorithm comprises several stages:

1. Definition of linguistic variables: Determining parameters based on which descriptions of input and output variables will be constructed. Examples of linguistic variables include "temperature" or "speed." Then, values for linguistic variables are defined; for instance, for the variable "temperature," values might be "cold" and "hot," while for the variable "speed," values could be defined as "slow" and "fast."

2. Definition of fuzzy sets: Each linguistic variable and its value are defined by a fuzzy set, which, in turn, is described by a membership function. The membership function can take various forms and types, such as triangular, trapezoidal, Gaussian, etc. The advantage of fuzzy logic lies in the presence of fuzzy sets, allowing the avoidance of finding an exact mathematical model for the mechanism or process.

3. Fuzzification: Matching the input variable and the membership function to obtain a fuzzy output, i.e., determining the degree of membership of the input variable to a specific fuzzy set.

4. Description of the fuzzy rule base: Formulation of fuzzy rules, which determine the algorithm's actions based on the combination of input variables. Rules are established based on linguistic variables and sets. The combination of input and output values is also based on the logic of AND/OR, enabling the grouping of fuzzy logic rules into various necessary categories.

5. Defuzzification: The reverse process of fuzzification, allowing for obtaining the degree of membership of the output parameter based on the fuzzy rule base and converting it into a numerical value used subsequently for creating control actions.

IV. Experimental Results

To obtain data suitable for building a control and diagnostic system based on the principles of fuzzy logic, a series of experiments were conducted to capture the vibrational signals of the robot during its operational tasks. The test bench for conducting these experiments is shown in Fig. 4.

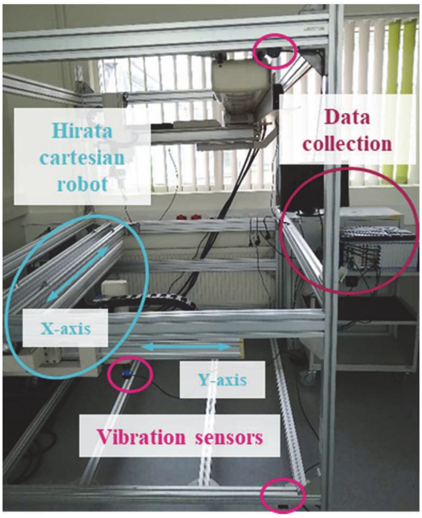

Fig. 4. Experimental test bench.

The laboratory setup consists of a Cartesian robot, a data acquisition system, and three vibration sensors installed on top, and bottom of the frame, and on the robot's working tool. These sensors measure the amplitude of the robot's vibrations along three axes. Reference and error signals were measured along the X and Y axes of the robot; measurements along the Z-axis were not conducted due to the robot's construction, which has rigid mounting along this axis, resulting in negligible vibrational oscillations. The signals from the vibration sensors are transmitted to the data acquisition system provided by Dewetron. Subsequently, the collected data undergoes further processing and analysis using the fast Fourier transform (FFT).

The vibration signals are measured by accelerometers of DIS QG40N-series with the next characteristics: three ways of measurement by X, Y, Z axes; measurement range is ±4g; output refresh rate is 3ms; resolution is 4 mg; output signal 0.5 – 4.5 V. These characteristics allow to get enough data for creating fuzzy logic algorithm.

A. Diagnosis Results

Experimental data were obtained in two directions. The first direction involved determining the belt over tension in the tooth belt transmission, while the second direction focused on identifying the worm heating in the screw transmission. Both errors were artificially induced: in the first case, the pulleys were misaligned relative to the horizontal axis, and in the second case, part of the lubricant was removed from the transmission worm gear to simulate the effects of heating.

Considering that during the robot's operation, its inherent oscillation amplitude can reach 0.3 g, it is important to also determine the frequency of these oscillations. Each part of the robot's transmission has its frequency of oscillations and based on the obtained information about the amplitude and frequency, the presence of mechanical damage can be determined. Therefore, spectral analysis of signals from vibration sensors is conducted to identify any faults. The spectral analysis is also presented on a logarithmic scale to filter out unwanted noise and to detect changes in signals, as the data range is sufficiently large.

The diagnostic results for belt over tension are presented in [26], [31], [34]. The results of spectral analysis for worm heating along the X and Y axes are presented in Fig. 5 and Fig. 6.

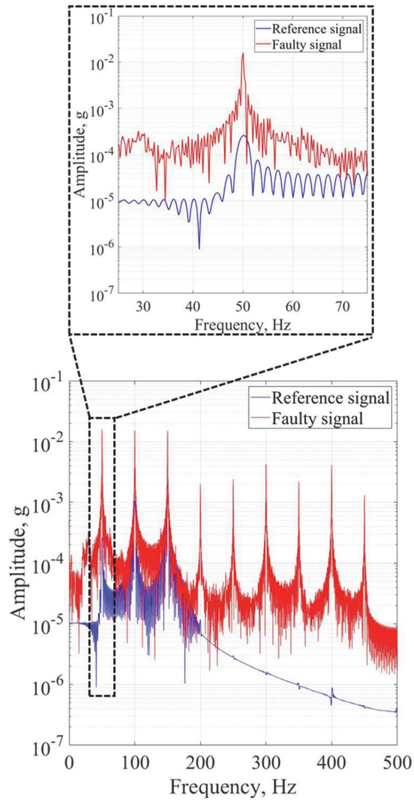

Fig. 5. Signal spectrum analysis of vibration sensor by X-axis.

As seen from the figure two types of signals are presented: the reference signal and the faulty signal. Upon close comparison of the signals, it is evident that the faulty signal contains a significant number of unwanted frequencies and amplitudes. Extra stochastic noise has been filtered out with the help of two other vibration sensors, that are mounted on the top and bottom of the test bench, to eliminate its influence on the assessment of mechanical damage presence.

Based on the experimental results, it can be assumed that the primary frequencies of the transmission fall within the range of 50-150 Hz. This implies that the presence of other frequencies is a clear indication of mechanical damage. Worm heating in the screw transmission, in the absence of an adequate amount of lubrication, leads to the emergence of additional frequencies within the range of 200-450 Hz, which is traced in the spectral analysis.

To assess transmission damage, it is also essential to monitor the amplitude of vibrations, ensuring it does not exceed the nominal value. That is, if there is a high amplitude of oscillation within the frequency range of 50-150 Hz, it may also indicate the presence of damage.

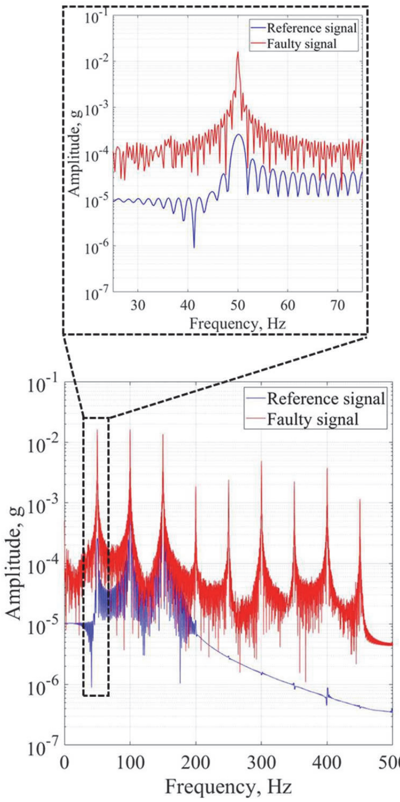

Fig. 6. Signal spectrum analysis of vibration sensor by Y-axis.

The spectral analysis along the Y-axis has a similar appearance to that along the X-axis, confirming the validity of the assumption that the occurrence of additional frequencies in the range of 200-450 Hz is indicative of overheating of the worm gear transmission in the absence or contamination of lubrication.

These conclusions form the basis for developing a fuzzy logic algorithm to predict the occurrence of mechanical damage in robot transmissions. It is important to note that to construct a fuzzy logic algorithm, it is necessary to determine the discrepancies in frequencies and vibration amplitudes. In this context, the method used to analyze the vibration signal is not crucial for building the fuzzy rule base.

B. Fuzzy logic algorithm results

The main aim of the developing the fuzzy logic algorithm is to create the control and diagnosis system, that will allow continue and finish the robot work operations in the conditions of the mechanical gearbox faults. For this purpose, reference and faulty frequencies of the gearbox and amplitude of the vibrations are determined, and based on it create fuzzy sets and rules for control system. Based on the above information linguistic variables, fuzzy sets, and fuzzy rule base can be determined. For linguistic variables input vibration amplitude, vibration frequency, and diapason of vibration frequency are chosen. For linguistic variables output speed, torque, acceleration, and fault type are chosen.

This method allows don't use big number of the data or exact mathematical model. In this case, the control and diagnosis system will be more adaptive and will copy the human logic which leads to a fairly quick and easy setup of the algorithm.

However, this work will consider modeling results related to diagnosis and determining of mechanical fault type in the gearbox. In this case, the scheme of the fuzzy logic algorithm is presented in Fig. 7.

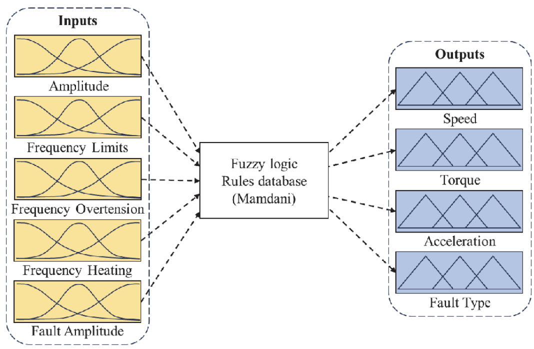

Fig. 7. Fuzzy logic algorithm designer scheme.

Input variables “Amplitude” and “Frequency Limits” are used to control the speed, torque, and acceleration of robot servomotors. Input variables “Frequency Overtension”, “Frequency Heating”, and “Fault Amplitude” are used for the diagnosis of faults in the gearbox. The fuzzy sets for variables “Frequency Heating”, “Fault Amplitude” and “Fault Type” are presented in Fig. 8, Fig. 9, and Fig. 10.

The values of the input variables for the membership functions were selected to correspond to the nominal operating conditions of the robot. Specifically, during the experiment, it was established that the reference transmission frequencies of the robot are 50, 100, and 150 Hz. Therefore, other frequencies that arise during operation indicate the presence of damage.

It is also important to note that the robot's vibration amplitude should not exceed 0.3g. However, if low vibration is observed at high frequency, there is already a probability of damage occurring. Thus, the membership functions form a set of rules that define the algorithm for diagnosing damage.

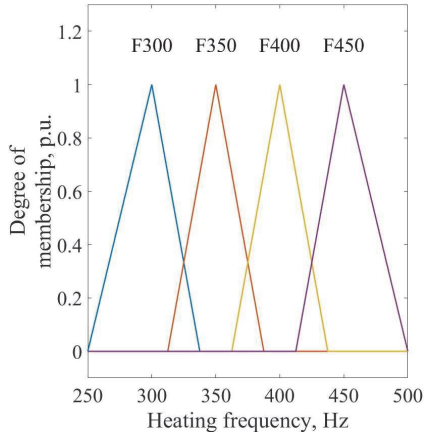

Fig. 8. Frequency heating fuzzy set.

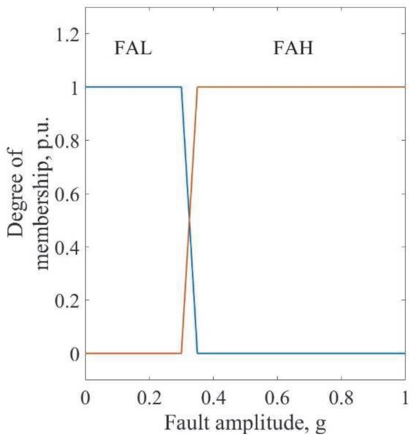

Fig. 9. Fault amplitude fuzzy set.

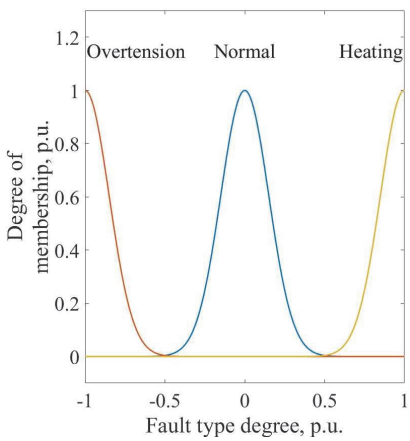

Fig. 10. Fault type degree fuzzy set.

As seen from Figures for inputs, variables are F200, F250, F300, F350, F400, and F450 – respectively vibration frequency for 200, 250, 300, 350, 400, and 450 Hz; FAL – low fault amplitude of the vibration, FAH - high fault amplitude of the vibration. For output, variables are "Overtension", "Heating", and "Normal" – fault detection degree.

Based on the fuzzy rule base the degree of presence heating in the gearbox can be displayed. The result is presented in Fig. 11.

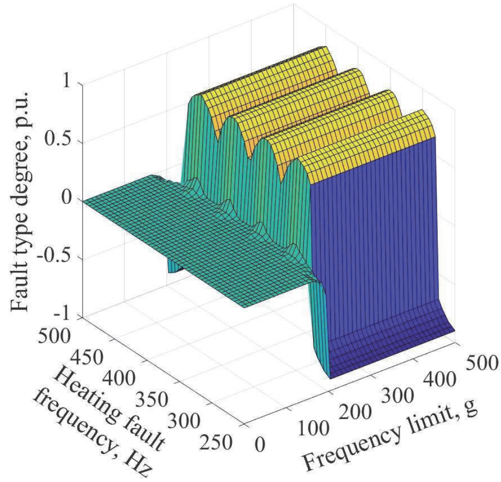

Fig. 11. The degree of presence heating based on gearbox vibration frequency.

For ease of assessment, the degree of detection of over-tension and heating faults was taken as -1 and 1 respectively. In the same vein, the degree of absence of failures is equated to 0. The closer the output value is to the corresponding magnitude, the higher the probability of the presence or absence of transmission damage. As evident from the results of modeling using the fuzzy logic algorithm, when assessing the degree of transmission damage based on the frequency spectrum of the vibration signal, it is possible to identify the presence of damage in the transmission.

As seen in Fig. 11, the probability of damage detection occurs after 200 Hz across the entire frequency spectrum. However, it is worth noting that evaluating the presence of damage solely based on frequencies is not precise, as it is also necessary to consider the amplitude of the vibrations. Therefore, in assessing the presence of heating fault frequency in the screw transmission worm and vibration amplitudes, the degree of damage presence will be significantly supplemented. The result of modeling the fuzzy logic algorithm for detecting heating damages in the robot's transmission based on the frequency and amplitude of the vibration signal is presented in Fig. 12.

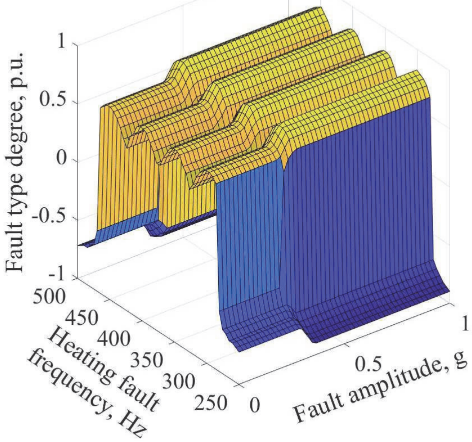

Fig. 12. The degree of presence heating based on gearbox vibration amplitude and frequency.

Including vibration amplitude in the assessment of damage allows for supplementing the result in such a way that even with the smaller amplitude of vibrations in the frequency spectrum of the heating fault, the algorithm will indicate the potential presence of damage in the transmission. Thus, the fuzzy logic algorithm enables the detection of damage in the robot's transmission and helps eliminate the consequences of their impact on the entire mechanism.

CONCLUSION

Based on the information provided, the conclusion can be drawn that the analysis and diagnosis of mechanical faults in the gearbox are being conducted using a combination of frequency spectrum analysis and fuzzy logic algorithm. The primary frequencies of the transmission are expected to fall within the range of 50-150 Hz, and the presence of other frequencies may indicate mechanical damage. Additional frequencies in the range of 200-450 Hz, attributed to worm heating in the screw transmission, are observed when there is insufficient lubrication. Also, because of frequency evaluation in the spectrum, it is possible to determine the presence of other mechanical damages in the transmission without obtaining a large volume of data, making the presented method a universal way to detect faults.

To assess transmission damage, both frequency and amplitude of vibrations are considered. The analysis involves linguistic variables such as vibration amplitude, vibration frequency, diapason of vibration frequency, output speed, torque, acceleration, and fault type. The use of linguistic variables allows for avoiding the use of a precise mathematical model for the control and diagnosis of the transmission. Thus, in the presence of new damages or deviations from the normal operation of the transmission, new variables can be introduced by observing its performance, and describing such behavior. Therefore, a diagnostic system based on the fuzzy logic algorithm can be easily upgraded without the need for additional resources.

The results indicate that the algorithm can identify the presence of damage in the transmission based on the frequency spectrum of the vibration signal. However, it is highlighted that evaluating damage solely based on frequencies may lack precision, necessitating consideration of vibration amplitudes as well. The inclusion of vibration amplitude in the assessment allows for a more comprehensive analysis, even detecting potential damage with smaller amplitudes in the frequency spectrum associated with heating faults. It is also worth noting that the closer the output signal is to the specified value of the evaluation degree (in this work, 1), the higher the degree of damage. Thus, the diagnostic system based on the fuzzy logic algorithm not only detects the presence of faults in the transmission but also allows for a qualitative assessment of the damage.

In summary, the fuzzy logic algorithm proves to be a valuable tool for diagnosing and determining mechanical fault types in the gearbox. The approach considers both frequency and amplitude factors, contributing to a more accurate assessment of transmission damage and aiding in mitigating the consequences on the overall mechanism. For future work, efforts will continue to enhance the fuzzy logic algorithm not only for diagnosing faults but also for controlling the transmission under damaged conditions. Additional mechanical damages and the conditions of their occurrence will be considered to supplement the algorithm. Also, the validation of the algorithm for real object will consider.

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V. Biographies

Siarhei Autsou was born in Novogrudok, Belarus, in 1992. He earned his BSc and MSc degrees in automation manufacturing processes in 2014 and 2015, respectively, from Belarusian State Technological University at the Department of Automation of Production Processes and Electrical Engineering. In 2017 and 2019, he completed two internships at Tallinn University of Technology in Tallinn, Estonia, at the Department of Electrical Power Engineering and Mechatronics. Currently, he is a PhD student and Junior Researcher and an early-stage researcher in the Department of Electrical Power Engineering and Mechatronics at Tallinn University of Technology. His primary research interests include the development and diagnosis of control systems, project engineering, PLC programming, and automation of production.

Karolina Kudelina was born in Narva, Estonia in 1997. She received BSc and MSc degrees in electrical engineering in 2015 and 2018 respectively. In 2019, during MSc study, she did the internship in University of Extremadura (Badajoz, Spain) at Department of Electrical, Electronic and Control Engineering. She is currently a PhD student and Junior Researcher in Department of Electrical Power Engineering and Mechatronics in Tallinn University of Technology. Since 2021, she is a chair of IEEE Estonia Women in Engineering. Her main research interest is condition monitoring methods for electrical machines and drive systems.

Toomas Vaimann (S'11-M'14-SM'20) was born in Pärnu, Estonia, in 1984 and received his BSc, MSc and PhD degrees in electrical engineering from Tallinn University of Technology, Estonia, in 2007, 2009 and 2014 respectively. He is currently a research professor in Tallinn University of Technology, Department of Electrical Engineering. Internationally, he has been a postdoctoral researcher at the Department of Electrical Engineering and Automation, Aalto University, Espoo, Finland, and worked as a visiting professor at the Faculty of Control Systems and Robotics, ITMO University, St. Petersburg, Russia. His main research interest is the diagnostics of electrical machines.

Anton Rassõlkin (S'12-M'16-SM'20) was born in Tallinn, Estonia, in 1985. He received the BSc, MSc, and PhD degrees in electric drives and power electronics from Tallinn University of Technology (Estonia) in 2008, 2010, and 2014, respectively. In 2010 he received a Dipl.-Ing. degree in automatic from the University of Applied Science Giessen-Friedberg (Germany). Presently, he holds the position of professor in Mechatronics at the Department of Electrical Power Engineering and Mechatronics, Tallinn University of Technology. His main research interests are mechatronics and electrical drives, particularly for electric transportation, as well as autonomous vehicles.

Publication V

Autsou, S.; Vaimann, T.; Rassõlkin, A.; Kudelina, K. Fault Diagnosis System of Cartesian Robot for Various Belt Tension. International Conference on Diagnostics in Electrical Engineering (Diagnostika), Pilsen, Czech Republic, 2022, pp. 1–4, doi: 10.1109/Diagnostika55131.2022.9905111.

Fault Diagnosis System of Cartesian Robot for Various Belt Tension

Siarhei Autsou
Department of Electrical Power Engineering and Mechatronics
Tallinn University of Technology
Tallinn, Estonia
siaaut@ttu.ee

Toomas Vaimann
Department of Electrical Power Engineering and Mechatronics
Tallinn University of Technology
Tallinn, Estonia
toomas.vaimann@taltech.ee

Anton Rassõlkin
Department of Electrical Power Engineering and Mechatronics
Tallinn University of Technology
Tallinn, Estonia
anton.rassolkin@taltech.ee

Karolina Kudelina
Department of Electrical Power Engineering and Mechatronics
Tallinn University of Technology
Tallinn, Estonia
karolina.kudelina@taltech.ee

2022 International Conference on Diagnostics in Electrical Engineering (Diagnostika) | 978-1-6654-8082-6/22/$31.00 ©2022 IEEE | DOI: 10.1109/Diagnostika55131.2022.9905111

Abstract — **Cartesian robots framework is a complex mechanical structure that consists of gearboxes, joints, and moving parts. The main problem with this structure is the impossibility to monitor any faults in mechanical parts that have occurred during work operations. An example of such a system, the Hirata cartesian robot, is described in the paper. The fault diagnosis system and main gearbox of the cartesian robot are researched. This article shows the significance of fault diagnosis in mechanical parts of industrial robots based on a mathematical model and real experimental results. Belt tension is the main fault considered in the article. For analysis of additional vibrations, fast Fourier transform and continuous wavelet transform are used. Based on spectrum analysis results, conclusions are described of the possible consequences of the presented fault.**

Keywords— fault diagnosis, robot motion, manipulators, gears, industrial robots

I. Introduction

Industrial robots (IRs) work with different devices and are used for many technological processes, such as galvanic processes, working with dangerous materials and others. Such systems must have perfect accuracy and smooth motions for achieving great work results. IRs are produced with sensors for detection failures in control, power, motion, and other subsystems [1], [2]. However, complex mechanical transmissions generally do not allow installing sensors or connecting them to joints, which are usually the weakest part of any mechanical system. Small damages occur in joints and influence the whole IR system [3], [4].

Fault diagnosis is a progressive way of improving the quality, workability, and safety of other mechanisms and devices [1], [5], [6]. Fault detection has proved efficient in different systems such as power systems, control systems, and mechanical and grab parts [7]–[9]. Each fault has a special track and nature. Based on this information, we can trace other damages until their origin and eliminate them [5], [8].

The failures in IRs mechanical parts are described in different works [10]–[13]. There are pulley tooth cracks, bearings faults, any rotation faults, etc. [10], [14], [15]. Failure diagnosis is implemented by different methods, such as random intuitive fuzzy decision [11], digital twin [12], or artificial intelligent methods [13].

Hirata cartesian robot (CR) is considered a case study in this research. This kind of IR has a complex structure consisting of axes connecting through gearboxes to each other, as shown in Fig.1. The Hirata CR has gearboxes, consisting of two transmissions: tooth belt transmission and worm transmission. Based on the above, the fault detection system in the mechanical parts of this CR should be improved, as the existing diagnostic system in the CR does not allow the diagnosis of emerging faults with desired precision.

This paper's main contribution is to develop a mathematical model of gearbox and analyze additional vibration signals in case of occurring faults. The description of these transmissions is presented in the paper. In the first chapter, a description of Hirata CR and the fault detection system of Hirata CR are presented. Also, the diagnosis algorithm of the robot is described. The second chapter of the paper describes a mathematical model of the gearbox based on previous research. The experimental part and its results are declared in the third chapter.

II. Hirata Cartesian Robot

Hirata CR is used for work with special attachments, such as electric, pneumatic and magnate grabs. This robot consists of three orthogonal axes and four joints (two linear and two rotation). The sketch of Hirata CR is presented in Fig. 1. The figure shows that CR consists of three linear axes and one rotating axis. Gearboxes are set along each axis and consist of the worm gear and tooth belt gear. Grab is connected to the Z and W axes for vertical and rotational movement.

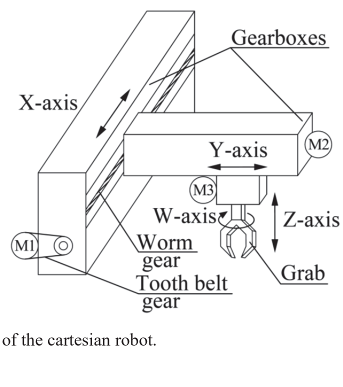

Fig. 1. Sketch of the cartesian robot.

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Hirata CR has a few important benefits, which are:

- constant resolution for each axis;
- ability to move across set positions with high accuracy;
- robust structure and smooth moving.

These benefits lead to getting perfect results in positioning and speed of motion. The main axis parameters of Hirata CR are presented in Table 1 [16], [17]. Also, it should be noted that the cartesian robot has a payload of about 5 kg.

TABLE I. HIRATA CARTESIAN ROBOT PARAMETERS

Axis	Maximal speed (1/sec)	Stroke (mm)	Position error (mm)	Motor power (W)
X	1200	1500	±0.02	400
Y		700		200
Z	1000	200	±0.01	100
W	1200°	540°	±0.03 °	30

Failures, which the diagnosis system of Hirata CR can detect, can be separated into two types. The first type of failure, such as overrun, overload, and encoder error, leads to an emergency stop. The second type of failure, such as positioning and measurement errors, leads to the CR's non-linear work. These errors are detected by comparing two signals: the reference signal, which is set in the controller, and the real-time output signal [17], [18].

The flow-chart of the diagnosis algorithm of Hirata CR is presented in Fig. 2. The diagnosis system of the robot is collected data for analysis first of all. After collection and analysis, filtering and screening of noise occur. Next, faults are identified and assigned a specific code. This code is derived from displaying of teaching pedant.

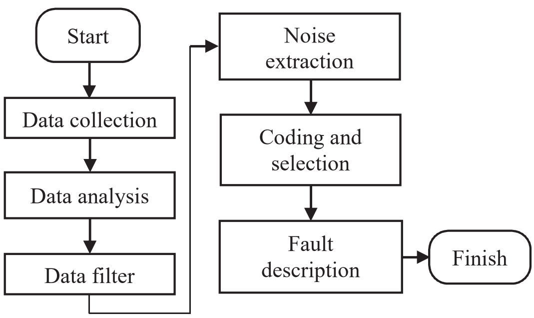


Fig. 2. Flow-shart diagnosis algorithm of the cartesian robot.

In this detection process, power and control faults can be detected. Yet, the faults occur in mechanical parts of the Hirata CR, such as in bearings, gearboxes and others, which cannot be detected using the existing diagnostic system. This research is aimed to improve this weak spot of the diagnostic system of Hirata CR and show the influence of small faults on gearbox operations.

III. DESCRIPTION AND MATHEMATICAL MODEL OF GEARBOX

A. Description of Main Gearbox

Hirata CR has three gearboxes. In this research, the main gearbox on X-axis is described. This transmission consists of two types of gear: tooth belt gear and worm gear. The first type is used for constant gear ratio, and the second one is used for quiet and smooth grab motion of Hirata CR.

The sketch of the main gearbox is presented in Fig. 3.

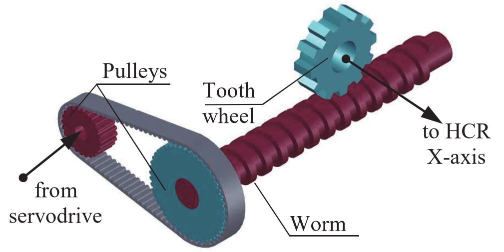


Fig. 3. Sketch the cartesian robot's main gearbox, where red elements are drive end parts, and blue elements are non-drive end parts.

The parameters of the gearbox, which are used for calculating the mathematical model and describing the transmission, are presented in Table 2 [16].

TABLE II. GEARBOX PARAMETERS

Gear type / Name of parameter	Tooth belt gear part	Worm gear part
Gear ratio	2	0,5
Length (mm)	525	1500
Diameter of drive end element (mm)	30	20
Diameter of non-drive end element (mm)	60	40
Lifetime (km)	51840	

B. Mathematical Model of Gearbox

The mathematical model of the gearbox is presented as a consistent transfer function of tooth belt gear and worm gear. The common transfer function of the gearbox is as follows:

$$W_g(s) = W_{tb}(s) * W_{wg}(s) \tag{1}$$

where the tooth belt gear transfer function is based on [19], [20]:

$$W_{tb}(s) = \frac{s}{As^2+Bs+C} \tag{2}$$

and the worm gear transfer function is based on [21]–[23]:

$$W_{wg}(s) = \frac{D(s-\omega_0 R_1)}{s^2+Es+F} \tag{3}$$

In the previous equations, variables are defined as:

$$A = \frac{r_{n2}^2}{u^2}(\rho K r_{02}\alpha_2 + q_m b) \tag{4}$$

where r_{02}, r_{n2} – outer and inner radiuses of the and non-drive end pulley respectively, u – gear ratio, ρ – density of the belt, K – section area of the belt, α_2 – the angle of belt girth, b – width of the belt, q_m – the mass of 1 m of the belt with width 1 mm (table value).

$$B = \frac{r_{n1}}{Pu(1.1*10^3-3.2*10^2\pi r_{n1})} \tag{5}$$

where P – the power of servomotor, r_{01}, r_{n1} – inner radiuses of the drive end pulley, respectively.

$$C = bF_y \quad (6)$$

where F_y – initial tension of the belt (table value).

$$D = 2T_s R_1(\omega_{max} - \omega_0) \quad (7)$$

$$E = -2\omega_0 R_1 \quad (8)$$

$$F = \omega_0^2 R_1^2 + (\omega_0 R_1 - \omega_{max} R_1)^2 \quad (9)$$

where T_s – maximal worm gear force, ω_0, ω_{max} – nominal and maximal angular speed of worm, R_1 – worm radius.

C. Gearbox Failures

In the gearbox of the CR, the following failures can occur [24]–[27]: overheating of gearbox in connection parts; an overload of gearbox in drive-end parts; jamming of gearbox in worm part.

Overheating is justified by continuous transmission operation under high loads, such as high moving speed and short distances of moving [24], [26]. Overload is substantiated by the additional load on the gearbox parts, such as high tension of the belt and the additional load on grabs of the IR [24], [26]. Jamming is probable in no lubrication case of worm gear part, which results in additional friction of metal parts between each other [27]. Overload faults are one of the most dangerous failures for the CR. These damages lead to serious consequences for the gearbox and CR as a whole. Overload leads to expensive repair of the whole CR or different mechanism elements. In this research, the level of belt tension of the toothed belt and gear part is considered. Low belt tension leads to a damper effect, but the slippage possibility is increased at the same time. High tension leads to added accuracy, but at the same time, additional load to gearbox elements occurs.

IV. Analysis of Additional Vibrations

Analysis of additional vibrations has a significant meaning. Small undesirable oscillations lead to metal fatigue, interference and wrong results. Modelling the gearbox system can reduce the possibility of vibrations occurrence, faults and overload. The main aim of modelling is to predict, based on results, when and where failures can occur. Results of the gearbox modelling are presented in Fig. 4.

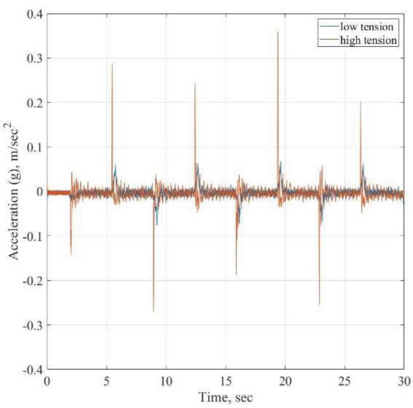


Fig. 4. Results of gearbox modelling with additional vibration, where the blue line – low belt tension (reference signal), the red line – high belt tension (real-time output signal with over tension of the belt).

As seen from the modelling results, gearbox operation has constant vibration. When the direction of rotation is changed in the gearbox, additional vibration occurs. In the case of high tension, overload with additional vibration is upper, then in the case with low belt tension.

For analysis of these signals, a fast Fourier transform is used. This analysis showed a difference between the gearbox's amplitude and frequency of additional vibration. Results of the analysis are presented in Fig. 5.

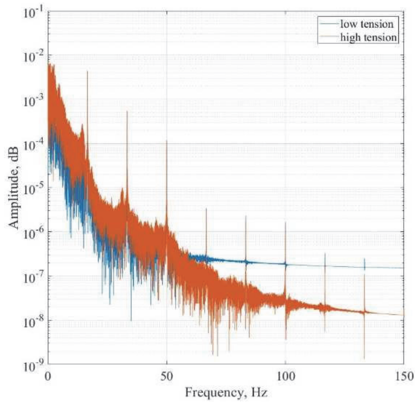
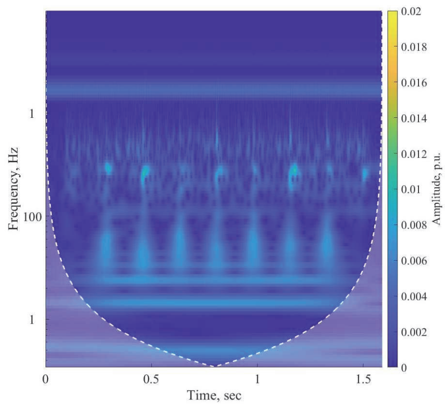
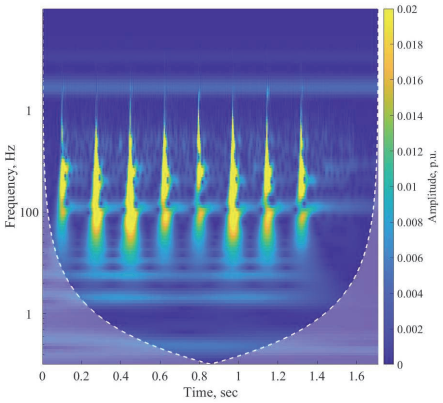


Fig. 5. Spectrum analysis of gearbox by fast Fourier transform, where the blue line – low belt tension (reference signal), the red line – high belt tension (real-time output signal with over tension of the belt).

As seen from spectral analysis, in the case of high belt tension frequency, amplitude and duration of the vibration are higher than with low belt tension. This means – that continuous work under these conditions will lead to serious consequences, such as overloading the drive system or jamming of the gearbox. For transient processes localization and synchronous analysis of time and frequency, continuous wavelet transform is used. Results of the analysis are presented in Fig. 6 (a, b).



(a)



(b)

Fig. 6. Spectral analysis of gearbox using continuous wavelet transform, where (a) - low belt tension(reference signal), (b) high belt tension (real-time output signal with over tension of the belt).

As seen from the results, the Hirata CR has significant vibrations during transient processes. Transient processes have occurred at points in which the movement direction of the robot is changed. In this case, it can be concluded that these points are weak places in the gearbox.

V. Conclusion

Even a small fault influences CR subsystems. Additional vibrations occur in joints, gearboxes and other mechanical parts, leading to considerable consequences. This can accelerate metal fatigue, the additional load on the motor, heating of joints and others. This research shows the significance of failures diagnosis in mechanical parts of Hirata CR. Modelling of the gearbox with different belt tension is shown. Results of modelling show significant vibrations during transient processes of the Hirata CR. In the case of high belt tension, the drive system has additional load, mechanical parts have additional oscillations, and the weakest place in the Hirata CR can be defined.

The fast Fourier transform and continuous wavelet transform are used to analyse output signals. The first method is used for getting fast results of spectrum analysis of output signal. The second method is used for transient processes localization. The results of modelling can be used to teach the existing system. For future work, other condition monitoring methods can be used to monitor other failures which may occur during industrial robot operations.

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Publication VI

Autsou, S.; Vaimann, T.; Rassõlkin, A.; Kudelina, K. Spectrum Analysis Additional Vibrations of Cartesian Robot by Different Control Modes. 18th Biennial Baltic Electronics Conference (BEC), Tallinn, Estonia, 2022, pp. 1–5, doi: 10.1109/BEC56180.2022.9935595.

Spectrum Analysis Additional Vibrations of Cartesian Robot by Different Control Modes

Siarhei Autsou
Department of Electrical Power Engineering and Mechatronics
Tallinn University of Technology
Tallinn, Estonia
siaaut@ttu.ee

Toomas Vaimann
Department of Electrical Power Engineering and Mechatronics
Tallinn University of Technology
Tallinn, Estonia
toomas.vaimann@taltech.ee

Anton Rassõlkin
Department of Electrical Power Engineering and Mechatronics
Tallinn University of Technology
Tallinn, Estonia
anton.rassolkin@taltech.ee

Karolina Kudelina
Department of Electrical Power Engineering and Mechatronics
Tallinn University of Technology
Tallinn, Estonia
karolina.kudelina@taltech.ee

2022 18th Biennial Baltic Electronics Conference (BEC) | 978-1-6654-6295-2/22/$31.00 ©2022 IEEE | DOI: 10.1109/BEC56180.2022.9935595

***Abstract* — Cartesian robot is a complex industrial robot, which is designed to work in hard and dangerous human conditions. This kind of robot has some control modes that help transform it for different tasks, such as movement details, 3D-printing, accuracy cutting processes, and others. Hirata cartesian robot is chosen for research in the paper. Additional vibrations occur in the industrial robot leading to unstable work. Usually, vibrations are occurred in mechanical parts of the industrial robot, like gearboxes, and joints. The problem with these parts is the impossibility to install any sensors for state monitoring oscillations. In this case, need to predict any mechanical faults or eliminate undesirable vibrations during the robot operations. This article considers belt over tension, as the origin of additional vibrations. Two types of control modes, manual and semiautomatic modes, are described in the paper. Also, fast Fourier transform and continuous wavelet transform are used for the analysis output signal. The first method is used for rapid damage assessment. The second method is used for the determination of the localization of damages. Experimental results, based on Hirata cartesian robot, are presented in the article.**

Keywords— continuous wavelet transform, gears, fast Fourier transform, fault diagnosis, motion control, robot control, robot motion.

I. Introduction

Modern industry seeks to eliminate expenses and increase energy efficiency [1]–[3]. Industrial robots (IRs) are one of the ways to achieve this aim [4]–[6]. IRs can be separate into different types, such as a cartesian robot, robot-arm, manipulators, and other, for making various works [7]. There are movement details between technological lines in the manufactory process, operations with dangerous materials, and accurate assembly operations [7], [8]. IRs have a suitable control mode for each operation. Control modes subdivide into manual, semiautomatic, and automatic. The name of the modes shows a difference in the degree of human involvement in robot control [7], [9].

Automatic robot control is a common control mode for IR. In this mode, the robot moves according to the given program and will after finishing the work program. Semiautomatic robot control is called also like “from button to position”. The operator pushes the button on the remote control and the mechanism will start to make an operation. The IR will stop at the endpoint. Manual robot control is used to check the control system, set the robot's parameters, and prepare for operations. All modes let to organize continuous production[7]–[12].

However, robots can’t work endlessly. IRs need maintenance, periodic repair, or replacement. These actions are related to the wear of mechanical parts of the mechanism. Suitable control mode and diagnosis mechanical parts help to continuous work of the IRs until finish the work process [13], [14].

Hirata cartesian robot (CR) is a research object in this article. This robot has good development potential. This CR has three control modes and a good diagnosis system. However, a lot of joints in the CR lead to the formation of weak places in the robot. In this case, need to choose the control mode of the robot and make different diagnosis procedures for improving the workability of the Hirata CR [15], [16].

The paper's main contribution is making an analysis of additional vibration that occur in the joints of Hirata CR by different control modes. The article's first chapter presents the description of these joints and control modes. Also, the reasons for vibrations in joints of Hirata CR are considered in the second chapter. The third chapter of the article shows experimental results and analysis of output signals by two diagnosis methods. Fast Fourier transform and continuous wavelet transform are used in the paper. The reason for choosing these methods is described in the article.

II. Description of the Research Object

A. Hirata Cartesain Robot

Hirata CR has a complex structure and consists of one to four orthogonal axes. These axes are connected by gearboxes. Each gearbox of the robot consists of two gears: tooth belt gear and screw belt gear. The sketch and main parameters of Hirata CR are presented in Fig. 1 and Table 1 [15].

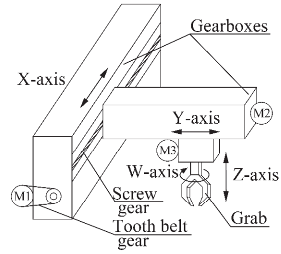


Fig. 1. Sketch of the Hirata cartesian robot.

TABLE I. MAIN PARAMETERS OF THE HIRATA CARTESIAN ROBOT

Axis	Maximal speed (mm/sec)	Compounded speed (mm/sec)	Motor power (kW)	Error (mm)	Maximal payload (kg)
X	1200	1697	0.4	±0.02	5
Y			0.2		
Z	1000	—	0.1/0.03*	±0.01	
W	1200°	—		±0.03°	

* The mode of motor power for the W-axis is 0.03kW.

Fig. 1 shows that each previous drive is used for moving the attached axis. The combination of tooth belt and screw gears are used for linear movement by X and Y axes. The same gear combination is used for linear movement by Z-axis and synchronous rotation movement by the W-axis.

As seen in Table 1, X and Y axes can move synchronously. This means other procedures can be allowed after stopping these axes[15], [16].

The Hirata CR has three main control modes [16], [17]:

- teach mode;

- check mode;

- auto/online mode.

The robot work by teach pendant in teaches and check modes. The first method is a kind of manual mode of work. In this mode, Hirata CR moves when the corresponding axis button is pressed. Speed in this case is minimal (not more than 100 mm/sec). The second method is semiautomatic. The robot moves from the initial to a final position which sending by addresses in the teach pendant. In this method speed (until 1000 mm/sec), acceleration, deceleration, and other settings can be changed [16], [17].

Auto/online mode differs by way of control. The program of movements is set by DO/DI signals in the auto mode. Online mode allows to connect CR with computer and write programs for robot movement. Like in check mode, different movement settings can be changed in the auto/online mode. The check mode is used for research in this paper [16], [17].

B. Description of Gearbox

The gearbox structure depends on the benefits and drawbacks of each part. The tooth belt gear provides a constant ratio value and speed limit from the motor. The screw gear provides smooth axis movement and additional braking due to saving inertia [15]. The sketch and main parameters of the gearbox is presented in Fig. 12 and Table 2.

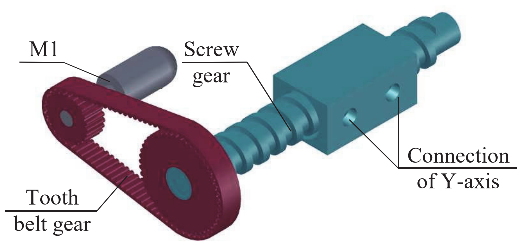


Fig. 2. Sketch of the gearbox.

TABLE II. MAIN PARAMETERS OF THE GEARBOX

Name of parameter	Tooth belt gear	Screw gear
Gear ratio	2	0.5
Length, mm	525	1000
Diameter, mm - drive end element	50	30
- non-drive end element	100	—
Width, mm	25	20

III. GEARBOX FAULTS

Undesirable vibrations occur due to faults and errors. Faults depend on some factors such as metal fatigue, lubricant existence, and load on the gearbox.

The main faults that occur in the gearbox are [18]–[21]:

- over/low tension of the timing belt;

- heating parts of the gearbox;

- jamming parts of the gearbox;

- pulleys and screw tooth cracks.

Over tension in the tooth belt gear lead to additional load for the drive system and undesirable resistance torque on the shaft. This fault influences the lifetime of the transmission. Positioning CR accuracy is reduced under over tension of the belt. The tension of the belt affects the gear ratio and makes it non-constant. In this case, CR has variable speed which oscillations of grab are induced [22], [23].

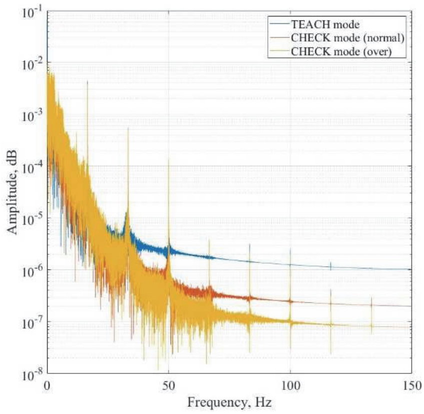
Heating takes place due to additional friction between the drive end and non-drive end elements of the gearbox. Friction occurs in no lubricant case or when transmission parts of the gear work under significant load. Heating influences gearbox integrity and the lifetime of transmission elements. In this case, additional vibration of the robot occurs due to an imbalance of gearbox parts caused by heating [21], [24].

Jamming and tooth cracks occur in case of metal fatigue of the transmission parts. These faults induce of emergency stop usually. However, the CR has significant vibrations and noises before an emergency stop. A crack's fault can be diagnosed in case of constant condition monitoring of the robot [23]–[25].

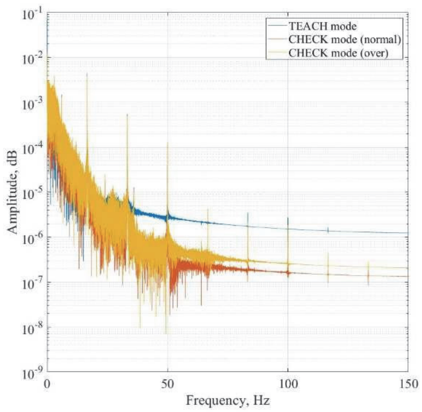
IV. EXPERIMENTAL RESULTS

Fast Fourier transform and continuous wavelet transform are used to analyze the additional vibration of the robot. The degree of belt tension is used for research.

Teach and check control modes of the Hirata CR are chosen for the experiment. The results of the spectrum analysis output signal are presented in Fig. 3 (a,b).



(a)



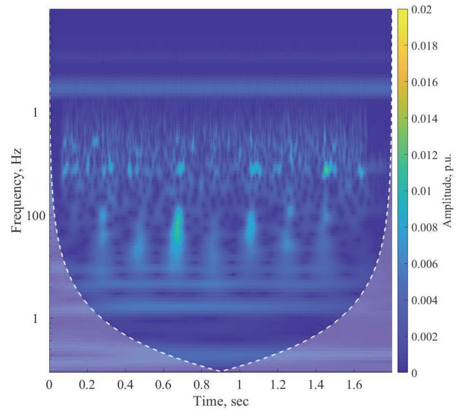
(b)

Fig. 3. Spectrum analysis of additional vibrations by different control modes, where (a) spectrum analysis by X-axis, (b) spectrum analysis by Y-axis; blue line – teach mode, red line – check mode with normal tension of the belt, yellow line – check mode with over tension of the belt.

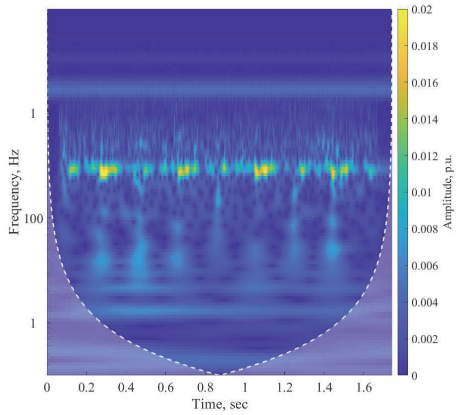
The figures show significant oscillations in check mode. It is because in teach mode movement speed is low (for the experiment speed was 100 mm/sec), but in the check, mode robot has a wide range of speed (acceleration until 700 mm/sec). Also, as seen from the results, the biggest vibrations occur on X-axis. The over tension also influences additional vibrations and load of the robot drive system. During the experiment it was found, that over belt tension leads to the stuck robot in the teach mode.

Fast Fourier transform (FFT) is used for getting fast spectrum analysis results and finding oscillations in the output signals. This method is a good diagnosis instrument to get a complete picture of the system states. However, FFT has a significant limit. The limit is discreteness. The output signal is measured in the current time moments. A part of information about the signal is lost in this case and, like a conclusion, the results may be significant distortions [13], [23], [25].

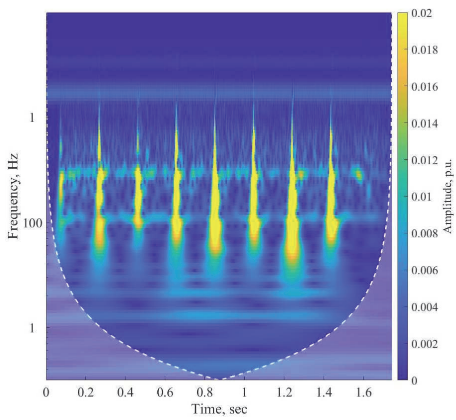
For the more visual influence of additional vibration by both axes CWT is used in the experiment. Results of spectrum analysis output signal by X and Y axes are presented in Fig. 4,5 (a,b,c) respectively.



(a)

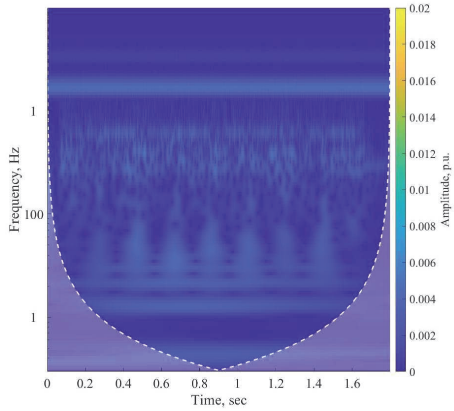


(b)

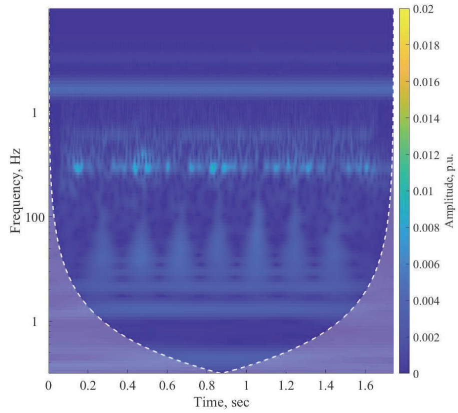


(c)

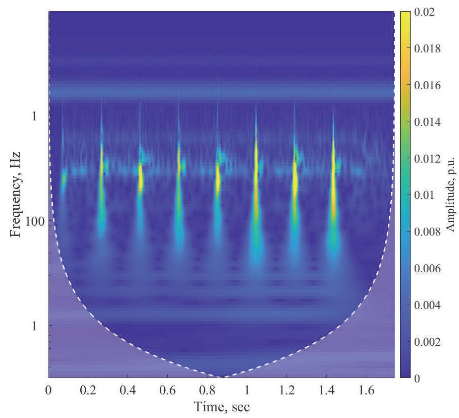
Fig. 4. Spectrum analysis of additional vibrations by X-axis, where (a) by teach mode, (b) check mode with normal tension of the belt; (c) check mode with over tension of the belt.



(a)



(b)



(c)

Fig. 5. Spectrum analysis of additional vibrations by Y-axis, where (a) by teach mode, (b) check mode with normal tension of the belt; (c) check mode with over tension of the belt.

Continuous wavelet transform (CWT) is used for synchronous analysis time and frequency of output signal. CWT can localize a transient process and select the necessary frequencies. CWT allows separating the output signal on parts. This method helps to study each part of the signal separately [23], [25], [26].

The results show a significant difference between control modes. The transient processes of the robot are displayed in the figures. However, in over belt tension case, additional vibration occurs during transient prosses. Smaller vibrations, which are displayed in the results, are standard work vibrations. These signals occur as the result of robot work.

Transient processes in the Hirata CR are moments when the movement direction of the robot is changed. As seen from the results in these moments CR has significant vibrations and therefore additional load on the drive systems. In the case of teach mode and check mode with normal belt tension, these vibrations are not so significant.

V. Conclusion

Research and diagnosis of additional vibrations by different control modes of the IRs are significant tasks. Right control mode and diagnosis of fault help to extend the lifetime of the mechanism in case of occurring faults. As seen from the results smaller faults have a significant influence on all CR.

The main types of faults and control modes of the Hirata CR are described in the article. Based on this information we can develop a common control system for controlling robots in fault-occurring cases. In this research over/low tension faults are described. Hirata CR hasn't been any undesirable vibrations in case of low belt tension, but the robot had significant vibrations and load on the drive system in the over belt tension case (with extremely belt tension robot has been emergency stop during the experiment). Also, the article shows the difference between control modes of the Hirata CR. Teach mode and check mode are taken in comparison.

Teach mode has a small movement speed. In this case, additional vibrations are difficult to determine, regardless of the faults. However, check mode has the biggest range of movement speed and undesirable vibrations are visible.

Significant vibrations are occurred during transient process in the HCR in case of over tension of the belt into the gearbox. In the HCR 0.04 - 0.03g (0.006 - 0.008 p.u.) is usual vibration, but in case of over tension HCR has 0.4g (0.02 p.u.) value of vibrations. This can lead to unbalancing structure of the robot, eliminating accuracy and additional load to the mechanical parts.

This article is directed toward the diagnosis of faults by different control modes. Data, which get during this research, will help to eliminate a lot of undesirable situations. Faults can be detected online without special software and expensive sensors installing. The main idea of using this data is setting additional algorithms for diagnosis mechanical faults into existing diagnosis system of the robots. In the future work will research other faults and mechanical parts of the Hirata CR.

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Publication VII

Autsou, S.; Vaimann, T.; Rassõlkin, A.; Kudelina, K.; Asad, B. Influence of Different Tooth Belt Transmission Faults on the Work of a Cartesian Robot. 20th International Conference on Mechatronics - Mechatronika (ME), Pilsen, Czech Republic, 2022, pp. 1–5, doi: 10.1109/ME54704.2022.9982815.

Influence of Different Tooth Belt Transmission Faults on the Work of a Cartesian Robot

Siarhei Autsou
Department of Electrical Power Engineering and Mechatronics
Tallinn University of Technology
Tallinn, Estonia
siaaut@ttu.ee

Toomas Vaimann
Department of Electrical Power Engineering and Mechatronics
Tallinn University of Technology
Tallinn, Estonia
toomas.vaimann@taltech.ee

Anton Rassõlkin
Department of Electrical Power Engineering and Mechatronics
Tallinn University of Technology
Tallinn, Estonia
anton.rassolkin@taltech.ee

Karolina Kudelina
Department of Electrical Power Engineering and Mechatronics
Tallinn University of Technology
Tallinn, Estonia
karolina.kudelina@taltech.ee

Bilal Asad
Department of Electrical Power Engineering and Mechatronics
Tallinn University of Technology
Tallinn, Estonia
bilal.asad@taltech.ee

2022 20th International Conference on Mechatronics - Mechatronika (ME) | 978-1-6654-1040-3/22/$31.00 ©2022 IEEE | DOI: 10.1109/ME54704.2022.9982815

Abstract— **Faults, which occur during the work of industrial robots, have different natures and characteristics. They emerge due to the continued hard work of the control system and mechanical parts. Diagnosis of each fault type is an important task because preliminary faults detection precludes expensive equipment replacement. In this paper, the significance of timely break detection is highlighted. Also, the possibility of fault elimination is displayed. Transmission failures and diagnosis methods, which can be used for fault elimination, are presented. In this report, a description of the Hirata cartesian robot, its diagnosis system, and the parameters of the robot are declared. This article presents experiments with belt tension of tooth belt transmission installed in the Hirata cartesian robot.**

Keywords— continuous wavelet transforms, fast Fourier transforms, fault diagnosis, gears, robots, vibration measurement.

I. Introduction

Modern world tends to reduce the undesirable influence of different faults and deviations from normal work of mechanisms [1]. A good way for avoiding unexpected breaks is to detect early damages in the mechanism. However, modern diagnosis systems do not have any instruments for the prediction of potential damages [2]. These systems can only stop technological processes after the occurrence of some significant damage. In this case, the research can be described in two ways: avoidance of dangerous situations and development of a diagnosis system, which would help to improve the safety of the technological process.

Diagnosis systems of the robots are a good tool to avoid expensive replacement of mechanisms, but usually, it cannot eliminate the possibility of faults [3]. In this case, the system, which will help to predict a probable fault, should be designed. Faults in the early stage are hardly detectable, but over by time, specific harmonics components indicating damage will occur [3], [4].

By revising industrial robots, a large percentage of a cartesian robot is used in by different manufacturers [5]. That type of robot is usually used for moving particulars between technological lines and construction processes with high accuracy. Sometimes, cartesian robots are used for work with dangerous materials. In this case, a better way to solve the abovementioned problems is to predict faults likely to occur during the technological process [6].

The research leading to these results received funding from the PSG453, 2020-2023, “Digital twin for propulsion drive of autonomous electric vehicle”.

According to [5], [6], faults in industrial robots can occur in power, control, and mechanical systems. Faults in the power system usually damage the motor, amplifier, frequency converter, and others. Robots have protection like power fuses that protect robots from different voltage fluctuations in the network. Usually, these faults occur very spontaneously and it is impossible to predict them. Also, power fuses are cheap and can be easily replaced. In this case, a diagnosis system does not need to include these types of faults [7]. Faults in the control system have a different character. These faults include any errors that occur during the technological process of the robot, for example, sensor errors, overload, overrunning, etc. It is hard to detect these faults, but in many cases, the control system already has a detection system for these failures that can notify users about it with special software of robots. In this case, diagnosis systems already exist and help to eliminate this type of fault as well as solve it [8]. Faults in the mechanical system influence other systems of robots. These types of failures can lead to overload or overstrain of the robot and break all mechanisms. Mechanical system faults can occur in any mechanical part of the robot, like the gearbox, bearing, and joint. But these types of faults are easy to be traced by the output signal of the system. It is possible to use any condition monitoring sensor, for example, a vibrometer, a thermometer, and others. Based on the data from additional sensors, there are more changes in predictions [9].

This research work presents the possibility of diagnosing mechanical system faults. The first chapter of this article is a review of the cartesian robot and its diagnosis system. This review contains the advantages and disadvantages of the diagnosis system in the case of the cartesian robot and the ways to improve it. In the first chapter, the main errors in power and control systems, which monitor the Hirata robot detection system, are given. Types of transmission faults and control are highlighted in the second chapter of this article. This chapter describes the nature of faults and reviews detection methods. The experimental part with Hirata cartesian robot is presented in the third chapter of this article. A description of the experiment and real data is given.

II. Review of the Cartesian Robot

Hirata cartesian robot (HCR) is used for this research. This kind of robot is a standard type of cartesian robot. Its construction can include from one to four axes. The view of HCR is presented in Fig. 1.

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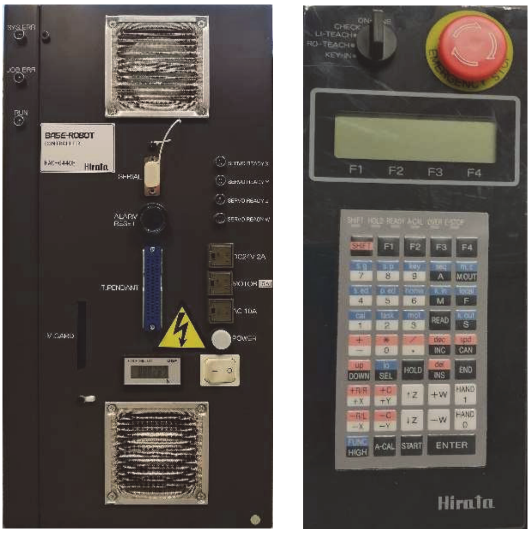
Fig. 1. View of the Hirata cartesian robot.

The robot consists of three orthogonal axes and four servo drives. This structure leads to making linear and rotational movements of the robot axes. It rotates the grab around the axis with the help of two types of gear: belt gear and worm gear. Set of HCR contains a controller and teach pendant for the control system. Also, this robot can connect to a PC by RS-232 with different software, for example, LabView [10], [11]. The views of the controller and teach pendant are presented in Fig. 2.



(a) (b)

Fig. 2. View of Hirata controller (a) and teach pendant (b).

The robot has a few types of sensors, such as overload, origin, limited switches, and encoders. Origin sensors and limited switches are installed at the initial and final positions of each robot axis for controlling stroke. Encoders and overload sensors are installed on each servo drive for speed control [11]. This combination of the sensors helps diagnose any faults in the power and control systems of the robot. The basic parameters of the HCR are presented in Table 1.

TABLE I. MAIN PARAMETERS OF HCR

Axis	X	Y	Z	W
Motor power, W	400	200	100	30
Max. speed, mm/sec	1200	1200	100	1200 º
Max. payload, kg	5			
Repeatability	±0.02		±0.01	±0.03º

The controller of HCR has a good diagnosis system for power and control systems. However, to monitor additional faults, which occur during the movement of the robot, like failures in the transmission, it is necessary to install additional sensors. The detection system of the controller can monitor only basic and significant parameters [10], [12]. The list of these parameters is presented in Table 2.

TABLE II. DIAGNOSIS PARAMETER OF HCR

Error message	Description
Position error XXXX *	Positioning cannot be completed
Emergency stop	Emergency Stop is activated
Overrun XXXX *	Overrun has occurred
Servo error XXXX *	Servo error has occurred
Over speed	Speed is too high
Positioning error	Positioning cannot be performed
Start motion error	Motor does not rotate
Driver error	Error has occurred in the servo amplifier/driver
Encoder error XXXX *	Encoder signal is not inputted

* Abbreviation "XXXX" is the description of the axis where an error has occurred. For example, "enc. error 1 0 0 0" means the encoder signal is not inputted from X-axis [12].

One of the ways to improve the diagnosis system is to use additional mathematical algorithms. These algorithms are based on the comparison of the reference output signal (reference signal is output signal with low tension of the timing belt) with the real output signal (for example, vibration) and finding deviations during the work. Methods that can be used are fast Fourier transform (FFT) and continuous wavelet transform (CWT).

III. TRANSMISSION FAULTS AND DIAGNOSIS METHODS

A. *Faults of Gearbox*

In the HCR, there are two types of gears: tooth belt transmission (TBT) and worm transmission (WT). Each of these types of transmissions has benefits and limitations based on the construction of the gear [11].

The first type of transmission is worm transmission. Each axis in the robot has this type of transmission. WT is often used because of its benefits like high accuracy, high inertia, and smooth motion. However, this type of gear has several limitations, which can lead to serious consequences, such as high additional friction, higher heat generation, and the possibility of jamming after wearing the material gear [13], [14]. The sketch of WT is presented in Fig. 3.

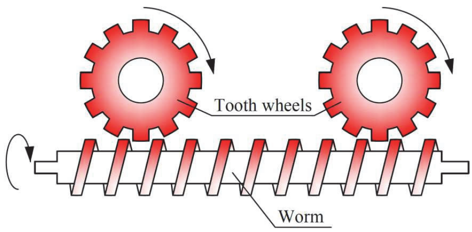


Fig. 3. Sketch of worm transmission.

The second type of transmission is tooth belt transmission. The tooth belt gear is used to connect servo drives with WT. As a benefit, the tooth belt allows achieving constant gear ratio and angular speed. Also, the smooth and quiet work of this gear helps to avoid additional undesirable vibration. In case of transmission breakage, it will not lead to expensive construction damages. However, limitations of the tooth belt gear include some restrictions: mandatory centering of pulleys, necessary tension of the belt, and overheating at high rotation speed [15]–[17]. The sketch of TBT is presented in Fig. 4.

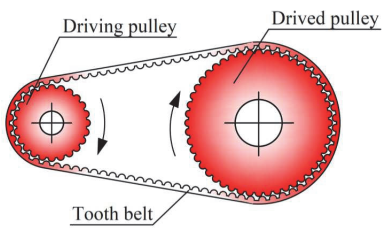


Fig. 4. Sketch of tooth belt transmission.

The red fields in the pictures are failure areas, where additional faults are occurring. In the case of WT, faults are area jamming, heating, and additional friction, in the case of TBT, faults are heating, over tension, and break of belt [13], [16].

B. *Diagnosis Methods*

For the research of gear faults diagnosis, FFT and CWT are used. For diagnostic purposes, FFT makes diagnosis of an output signal without numerous calculations and complex structures of the method [18], [19]. However, FFT has some significant limitations, such as the impossibility of evaluation of non-stationary signals and the need to use additional weight functions for getting the whole spectrum of the output signal. Also, sometimes results of FFT analysis cannot give a full picture of the output signal with different faults. In this case, the CWT method can be used [20]–[22].

CWT method can be used for getting additional information about the output signal [18], [23]. The benefits of this method are the possibility to monitor different types of signals. Besides, it is possible to get a good result by time or frequency in case of low/high-frequency signals or get an additional filter function for eliminating undesirable noises. Currently, CWT has two serious limitations: many iterations during the calculations process and, consequently, the usage of additional computational power for calculating the spectrum of output signal [20]–[22].

IV. Experimental Part

The experiment with HCR consists of two parts:

1. Measuring vibrations with the high tension of the belt in the TBT
2. Measuring vibrations with low tension of belt in the TBT

The sensing elements for the experiment were vibrations sensors of the model QG40N with an accuracy of 0.15 g. For output data acquisition, the DEWETRON system is used. The sensor is installed on the grab of the robot.

Output signals from the vibration sensor set on the grab of HCR are presented in Fig. 5. Noticeable deviations on the graph are points of change in robot positions. Another noise is the work of belt transmission with high or low tension of the belt.

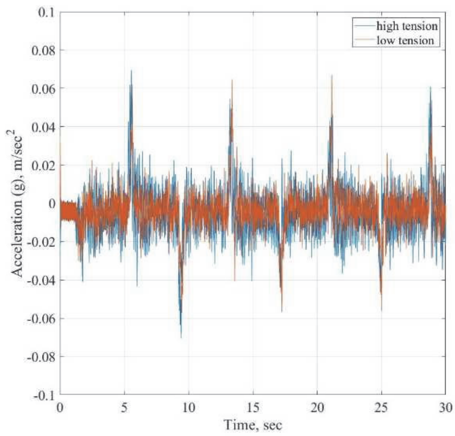


Fig. 5. Acceleration output signal from vibration sensor: blue line – high tension of the belt, red line – low tension of the belt.

The results of spectrum analysis by FFT are presented in Fig. 6.

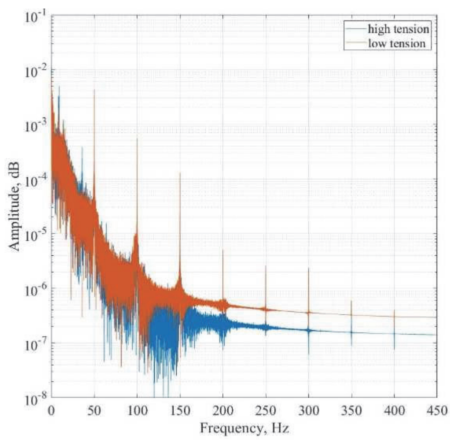
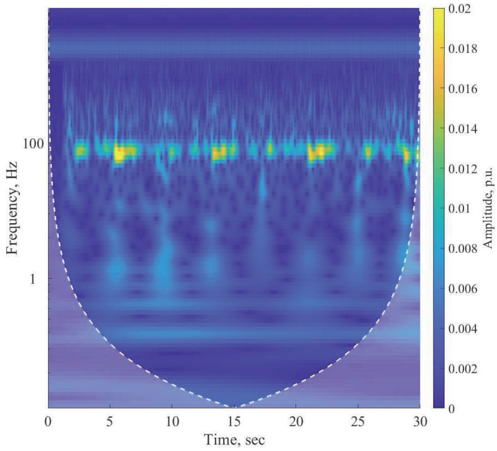
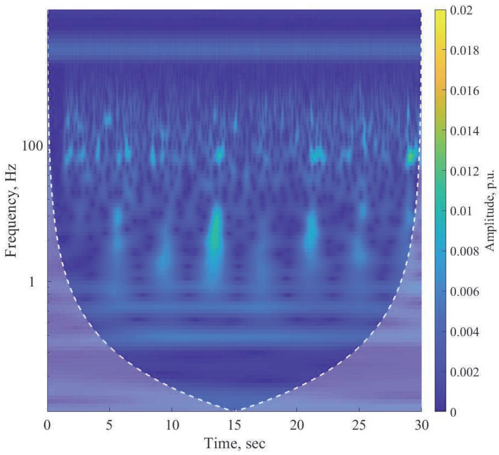


Fig. 6. Spectrum analysis of output signal from vibration sensor by FFT method: blue line – high tension of the belt, red line – low tension of the belt.

As seen from the results presented in Fig. 6, in both cases the HCR vibrations are in direction of position changes. Also, in both graphs, we can see vibrations during moving robots between positions. In the first case (blue line), vibrations have a larger amplitude than in the second case (red line). Based on these results, we can say that high tension of the belt leads to more additional vibrations. For more visual results and information, the CWT method is used. The results of the analysis output signal by continuous wavelet transform method are presented in Fig. 7 (a, b).



(a)



(b)

Fig. 7. Spectrum analysis of output signal from vibration sensor by CWT method, (a) – with the high tension of the belt, (b) – with low tension of the belt.

As seen from the results, additional vibration in the grab of HCR occurs in case of the high tension of the belt. This result shows better in CWT spectrum analysis. As seen from Fig. 7, in the first case, the grab of HCR has almost constant additional vibration than in the case of low belt tension. Also, it should be considered that the robot moves along the X and Y axes, and the vibration of worm transmissions by the X and Y axes follows.

As seen from the results in the reference signal (output signal with low tension of the timing belt) maximum of vibration is 0.012p.u. (~0.06g), but in the high-tension belt vibrations reach up to 0.02 p.u. (~0.1g). The maximum vibration for normal work of the HCR is 0.3g with the maximal speed of the robot. The speed of movement of the robot during the experiment was taken at the level of 200 mm/sec. In this case it is possible to estimate, that the vibrations at maximal speed would be around 1.8g. This vibration can lead to the expensive repair of the robot or its own mechanical parts. The results of the experiment may include the program of the controller of the HCR to compare output vibration signals for pulley imbalance in the TBT, which leads to over tension of the timing belt.

V. Conclusion

This research shows the influence of belt tension on the operation of HCR. Belt tension leads to additional vibrations during the work of the robot. As seen from the results, low tension of the belt in TBT allows a reduction of vibration on all mechanisms. It means that the belt, in this case, works like a damper. However, the experiment shows one more result about the accuracy of the robot. High tension of the belt in TBT leads to the higher positioning accuracy of the robot than low tension. The depends on additional factors, such as the length of TBT, working condition of worm transmission, and calibration of sensors.

By increasing the tension of the belt, the load on the drive system is also growing. In this case, the robot cannot operate, due to the need of making automatic calibration. Moreover, the additional load on the motors does not allow it.

In future work, an experiment with worm transmission will be made for checking the influence of WT damages on the cartesian robot. Also, other condition monitoring methods will be considered for signal analysis.

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Curriculum vitae

Personal data

Name:	Siarhei Autsou
Date of birth:	17.08.1992
Place of birth:	Novogrudok, Belarus
Citizenship:	Belarus

Contact data

E-mail:	siarhei.autsou@taltech.ee

Education

2021–2025	Electrical Power Engineering and Mechatronics, Tallinn University of Technology, PhD
2014–2015	Automation of Production Processes and Electrical Engineering, Belarussian State Technological University, MSc
2009–2014	Automation of Production Processes and Electrical Engineering, Belarussian State Technological University, BSc
1998–2009	Minsk, High school

Language competence

English	Fluent
Russian	Native
Estonian	Beginner

Professional employment

2022– till date	Tallinn University of Technology, School of Engineering, Department of Electrical Power Engineering and Mechatronics, Early Stage Researcher (1,00)
2018– 2021	Belarusian State Technological University, Department of Automation of Production Processes and Electrical Engineering, Assistant (1,00)
2015– 2016	Belarus, Minsk, “BelGiproTopGaz” and “BelNIITopProect”, Electrical design engineer (0,50)

Field of Research

- Electrical engineering
- Automation
- Fault diagnosis
- Fuzzy logic

Projects

- VNF22028 “Guidelines for Next Generation Buildings as Future Scalable Management of MicroGrids” (18.01.2022−17.01.2024); Principal Investigator: Toomas Vaimann; Tallinn University of Technology, School of Engineering, Department of Electrical Power Engineering and Mechatronics (partner); Financier: NordFosk.

Elulookirjeldus

Isikuandmed

Nimi:	Siarhei Autsou
Sünniaeg:	17.08.1992
Sünnikoht:	Novogrudok, Valgevene
Kodakondsus:	Valgevene

Kontaktandmed

E-post:	siarhei.autsou@taltech.ee

Hariduskäik

2021–2025	Elektroenergeetika ja mehhatroonika, Tallinna Tehnikaülikool, doktoriõpe
2014–2015	Tootmisprotsesside automatiseerimine ja elektrotehnika, Valgevene Riiklik Tehnikaülikool, magistirõpe
2009–2014	Tootmisprotsesside automatiseerimine ja elektrotehnika, Valgevene Riiklik Tehnikaülikool, bakalauresõpe
1998–2009	Minsk, Keskkool

Keelteoskus

Inglise	Kõrgtase
Vene	Emakeel
Eesti	Algtase

Teenistuskäik

2022– …	Tallinna Tehnikaülikool, Elektroenergeetika ja mehhatroonika instituut, Doktorant – nooremteadur (1,00)
2018– 2021	Valgevene Riiklik Tehnikaülikool, Tootmisprotsesside automatiseerimise ja elektrotehnika instituut, Assistent (1,00)
2015– 2016	Valgevene, Minsk, “BelGiproTopGaz” ja “BelNIITopProect”, Elektrikonstruktor (0,50)

Uurimisvaldkond

- Elektrotehnika
- Automatiseerimine
- Rikkediagnostika
- Häguslooogika

Projektid

- VNF22028 “Juhised mikrovõrkude halduseks järgmise põlvkonna hoonete näitel” (18.01.2022−17.01.2024); Vastutav täitja: Toomas Vaimann; Tallinna Tehnikaülikool, Inseneriteaduskond, Elektroenergeetika ja mehhatroonika instituut (partner); Finantseerija: NordForsk.

ISSN 2585-6901 (PDF)
ISBN 978-9916-80-266-3 (PDF)