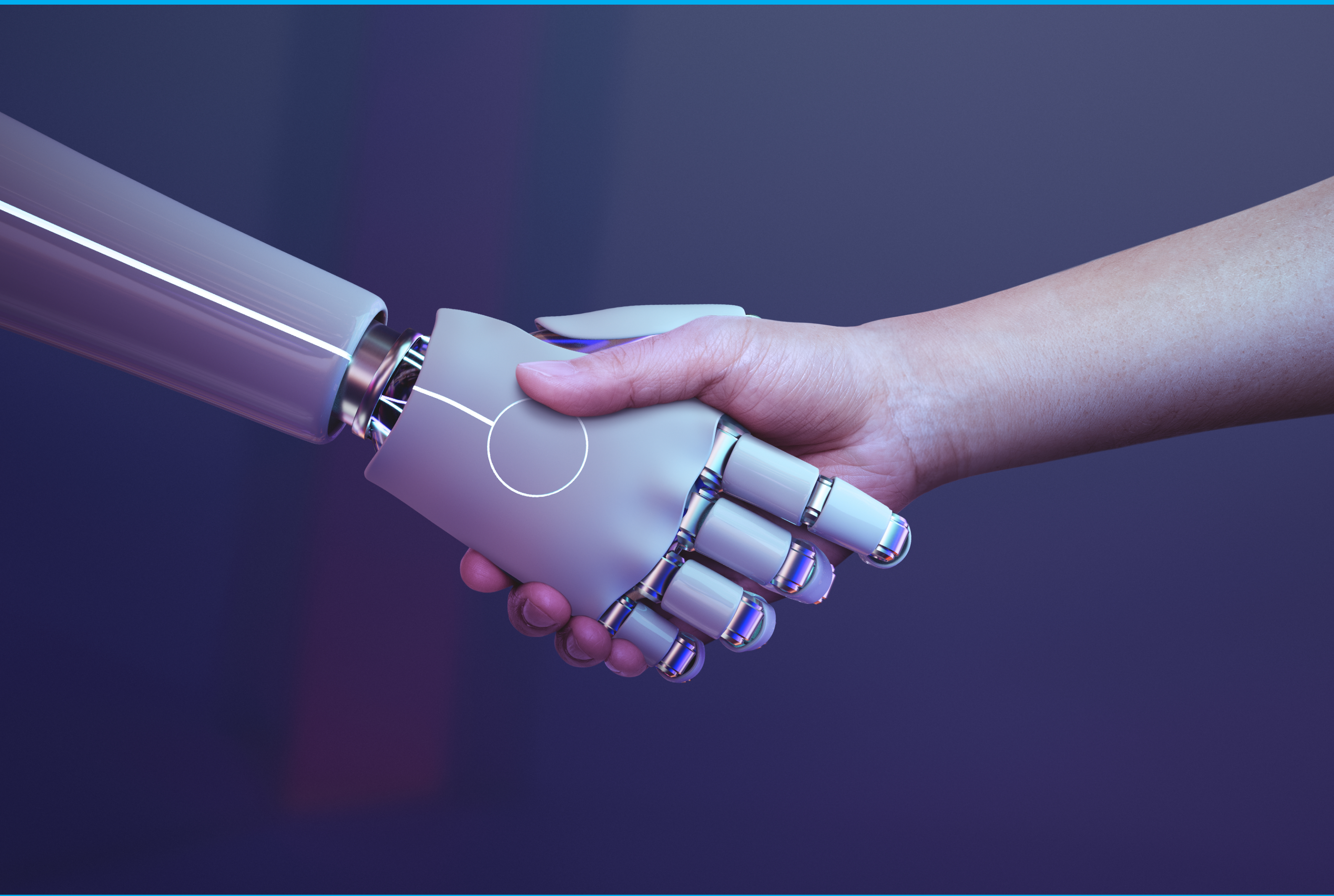
A Digital Twin for Condition Monitoring of an Industrial Chain Belt Conveyor System

Max Verdoes | April 2023



A Digital Twin for Condition Monitoring of an Industrial Chain Belt Conveyor System

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Summary

Chain belt conveyors play an increasingly important role in various industries. Research and development of conveyors has mainly focused on belts for bulk mass material transport, often neglecting chain belt conveyors. A chain belt consists of a continuous series of interconnected chain links. The chain belt conveyor system is driven by a gearmotor, which in turn moves a sprocket that is mounted on a fixed frame to guide the chain belt. The efficiency and reliability of chain belt conveyors are critical factors for optimizing transport and minimizing downtime for industrial processes. Therefore, methods and models for predictive maintenance regarding chain belt conveyors are of high interest to the industry. Currently, no models for predictive maintenance are available for chain belt conveyors, resulting in poor maintenance strategies and little understanding of the efficiency of the systems.

Research Question

The objective of this research is to create a versatile and robust model, suitable for implementation across various industrial chain belt conveyor systems. In this regard, the following research question is addressed:

"How to Develop a Digital Twin for Condition Monitoring an Industrial Gearmotor Driven Chain Belt Conveyor System?"

In order to answer this question, the goals, requirements and boundaries for the model should be investigated first. Subsequently, potential models for developing a chain belt conveyor digital twin, enabling condition monitoring, must be explored to identify suitable approaches.

In order to achieve this, the following subquestions are considered:

1. What is the state-of-the-art of digital twins and condition monitoring in an industrial setting?
2. Is the currently available hardware sufficient for a digital twin and condition monitoring?
3. How are digital twins and condition monitoring defined in literature?
4. How can the subsystems of the digital twin be modelled?
5. How can data be leveraged to identify unknown parameters in the system?
6. How can the model be used to identify anomalies in the system?

Approach

The state-of-the-art of digital twins and condition monitoring related to chain belt conveyors were discussed. The research was conducted at SEW Eurodrive to address the questions at hand. SEW Eurodrive is considered representative for the industrial environment as it is a prominent player in the drive industry. Consequently, the research aimed to establish a benchmark and gain insights into the current status of the drive industry by analyzing company documents and collaborating with engineers.

Several issues were identified during the research. First of all, the availability of usable data is limited. Furthermore, the only sensor available for collecting data from the physical system is the gearmotor using the variable frequency drive (VFD). Additionally, more understanding is required regarding the necessary data and its potential applications. The model must be generalized, ensuring compatibility without necessitating modifications to the existing operational systems. Engineers lack insights into the system's parameters, often resorting to approximations of parameters during the design process. These approximations can be high compared to the actual values, which leads to over-dimensioning. Mapping these parameters could enable tracking of degradation over time. However, no current methods exist for predicting or mapping degradation or breakdowns. The performance and efficiency of the physical systems can not be compared as there is no method used as the industrial standard. Hardware limitations also restrict advancements, as the components are typically designed to "just" meet requirements in order to maintain a low price. Given the competitive industrial setting, clients prioritize cost and reliability.

The industrial environment is described, along with its inherent limitations and challenges. To optimize the application of digital twins for condition monitoring, the model should be widely applicable and the necessary parameters for the model should be readily available and universally employed. Analysing the currently used parameters, it has been indicated that a minimum of 7 parameters are required. All these parameters are collected by the gearmotor using the VFD. The torque is the main parameter of interest. SEW Eurodrive utilizes a proprietary motor model to compute the generated torque. The torque, speed and position set point and actual value are measured, as they provide insights for the comparison of the model and the physical system.

A literature review is conducted to provide a comprehensive understanding of predictive maintenance, digital twins and condition monitoring. Predictive maintenance is an approach to maintenance in which the condition of equipment or systems is continuously monitored to predict and prevent potential issues before they occur. Digital twins are a concept with various interpretations and in this research defined as followed; A digital twin is a virtual representation of a physical object or system that provides real-time and historical data on its performance, behavior and condition. It is a digital model that replicates the physical properties and processes of the system and can be used to simulate and analyze different scenarios and outcomes. Condition monitoring is the process of monitoring the health and performance of equipment and systems to detect potential issues or failures. Digital twins and condition monitoring serve as a tool for implementing PdM. These concepts are explained to show the potential of this research.

Furthermore, the literature review was performed to explore the possibilities for modelling the general system. Belt conveyors for bulk mass material transport are a highly re-

searched topic and are in line with chain belt conveyors. Distinctions are made for the two different systems, this determines what literature for belt conveyors is applicable for chain belt conveyors. The chain belt conveyor is a chain consisting of interconnected links, it is closed form and does not rely on friction to drive the belt. A sprocket with teeth interconnecting the belt is used, resulting in no slip. The chain belt is always under tension, as the natural drift time of the chain belt is less than the time it takes the electric motor to decelerate the chain belt. The methodologies and analysis of the belt conveyor are used as a guideline throughout this research. A new model for chain belt conveyors based on first principles was proposed. This model is based on the fundamental mechanical analysis of chain belt conveyors. A Coulomb's friction model of a sliding mass was proposed as this represents the sliding of the chain belt over the guiding rails. Phenomenons for industrial chain belt conveyors, such as stick-slip and the polygon effect were examined. Data collection limitations in an industrial setting led to the proposal of a transfer function to represent the electric motor. Using a transfer function minimizes the measured parameters per data set. The gear unit generates two main types of losses, mechanical losses (tooth friction) and churning losses. A rigid body model was proposed as this allows for minimal required specifications and is a widely applicable model. For future research a K-stiffness model was proposed, this requires more specifications of the chain belt conveyor.

The parameter estimation method *Recursive Least Squares* was proposed for system identification. Recursive least squares is a technique to estimate parameters of the physical system using collected data sets. The data is leveraged to identify the best fit of the model and the collected data from the physical system. This model-based approach is possible as the physical system of interest is known and leveraged for system identification. The parameters of the system can be compared, creating insights into the characteristics and losses of the system.

Multiple methods are proposed for anomaly detection. For the estimated parameters used for system identification, thresholds are used. If the estimated parameters are out of bounds, this can be an indication for possible occurring anomalies. The collected data sets are analysed using a *Fast Fourier Transform* (FFT). This allows to create insights into the frequencies that are present in the collected signals. If specifications of the physical system are known, ranges for frequencies of interest can be determined. The difference in amplitude of the frequencies can be an indicator of anomalies in the system. Order analysis is performed to show the produced frequencies at specific velocities. These methods are used for frequency analysis and are of great use to detect over-time changes in the physical system.

The residuals are the error between the predicted value of the model and the data collected from the physical system. A *statistical residual analysis* is performed to acquire information on the statistical nature of the residuals. By comparison and changes of the statistical features, valuable insights into the physical system can be obtained.

To indicate the performance of the physical system the *Transport Loss Factor* was proposed. This implies the factor of the mechanical work compared to the work to transport the payload. This allows for comparison of chain belt conveyors and other methods of transportation. This method for rating the performance of the chain belt conveyor is suggested to be used as the industry standard.

The method of *dynamic weighing* was proposed. This implies the measuring of the transported mass on the belt, only by using the torque from the data set collected from the physical system. The possibility of knowing the weight without needing any adjustments to physical systems can be very insightful. For example, to determine the correlation of degradation and the transported weight. An initialization method was proposed in the case study. Currently, dynamic weighing is only performed with dedicated sensors. Dynamic weighing can be applied to a wide range of chain belt conveyors without any adjustments using this model.

The model was created in Matlab Simulink. The dynamics of the model are based on the equation of motion used for belt conveyors. The position controller has been replicated to precisely imitate behaviour of the physical system. The data sets collected from the physical system are used as an input for the model. A transfer function for the generated torque is conducted via experiments using a flywheel model. The specifications of the gear unit are known by SEW Eurodrive and are separated in mechanical and speed dependent losses. The chain belt conveyor system is modelled as a rigid Coulomb's friction mass model. This is the first time this model is utilized for a chain belt conveyor.

The model was verified by performing multiple different input cases. These are ramps, stairs and trapezoidal speed profiles in positive and negative direction. The behaviour of the model is evaluated and subsequently demonstrating the model is valid. The validation has been performed by comparing the model to data generated by a chain belt conveyor. The behaviour of the position controller has been validated using collected data of operational chain belt conveyors. No data is available that is collected over a longer period of time to show degradation in the system. Five unique data sets are created using the same transported weight. Subsequently, these data sets are analysed using FFTs resulting in no significant discrepancies in amplitude. The initial conditions for parameter estimation are tested by showing the inputs and outputs based on different initial conditions.

A case study is performed at SEW Eurodrive, Rotterdam. Only straight chain belt conveyors are of interest. Furthermore, a white chain belt conveyor is selected for the case study. Data sets are manually created using weights on trays, that are transported by the chain belt conveyor. Empty trays and trays with 0 to a 100 kilograms in increments of 10 kilograms are examined during testing. This results in 11 different situations for the load case. Experiments have been performed for the system identification of the white chain belt conveyor. Thereafter, the dynamic weighing is tested. In the end, the model can accurately estimate the weight on the belt to minimum of 95%, which is the industry standard. An analysis of the frequencies of the physical system is performed to show the validation of the model and the used assumptions. This is only possible by collaboration with the chain belt manufacturer, as chain belt specifications are required. It is shown by using FFTs that the frequencies do not change with the currently used data sets and therefore, future research was proposed to examine over time changes of the chain belt conveyor. The statistical analysis of the residuals was performed, analysed and compared. The performance and efficiency of the system is expressed using the Transport Loss Factor and compared between different weights. The transport loss factor is in line with the expected factor for continuous transport.

Conclusion

The novelty presented by this research is a first principle model for a chain belt conveyor based on Coulomb's friction with the capability of system identification, anomaly detection, dynamic weighing and the performance comparison of chain belt conveyors. This model includes the actual position controller of the physical system and the electric motor is modelled using a transfer function determined by experiments. Data collected from chain belt conveyor systems can be leveraged using the model to gain insights into physical systems, instead of driving a black-box system. The data collected from the physical systems is fed as the input for the model, ensuring an optimal replication of the system's behaviour. The model requires data over longer periods of time for anomaly detection. The case study shows that the model is robust and accurate for the system identification and has a minimum of 95% accuracy for dynamic weighing. The model is created only using the data collected from the gearmotor using the VFD, which enables the development of a model with extensive adaptability, suitable for numerous chain belt conveyor systems within the industry, without the need for any adjustments to operational systems. This results in a generalized and robust model with wide-ranging applicability throughout the industry to gain insights into currently operational chain belt conveyors. Further research is suggested using data over longer periods of time to track and predict degradation and the build-up of anomalies in the system. Improvements to the modelling of the subsystems was suggested, for example the proposed K-stiffness model for the chain belt conveyor.

Preface

This thesis represents the final milestone in achieving my Master of Science degree in Mechanical Engineering at the Delft University of Technology. I would like to thank my supervisors from the university Andrea Coraddu and Henk Polinder. I sincerely appreciate the time and effort you have invested in assisting me throughout this process, as well as the valuable insights shared during our numerous meetings. Without your guidance and constructive feedback, my project would not have reached the same level of quality and refinement.

This research was conducted at SEW Eurodrive in Rotterdam. First, I want to thank all the staff that has always helped me with a smile with everything I asked for. A special thanks to my colleagues at the engineering department, it was a blast to work with you guys. All the experience and knowledge you shared with me combined with the the indefatigable discussions on engineering are something I will not forget. In want to thank my supervisor Stijn Weel in particular, I learned so much during my time at SEW Eurodrive. Your feedback was sometimes ruthless, but always honest and with the best intentions. Of course Peter, Allard, Thijs, Otto, Jan, Matthijs, Mathijs, Frank, Bram and Vincent, you guys helped me tremendously and I will never forget the passion you guys have for the industry.

To my supervisor from the country I visited in my gap year after high school, Gabriel Lodewijks. I remember sending you the first e-mail as a stranger, but after all the meetings we had I feel grateful for your supervision. By my roommates referred to as my "secret weapon" when we had our meetings. A act of kindness I will never forget and see as exemplary in my career to come. One day we will meet so I can see who was listening to me all those hours behind a screen. I can never thank you enough, your feedback has been invaluable and I enjoyed all the interactions we had.

At last, I want to thank my roommates and friends for all the energy they have given me. Throughout this project they were always there for me, supporting me no matter what. My families, mother and sisters, for the unconditional love and support throughout the years. It was never easy to explain what I was up to, but finally we reached the goal and I could not have done it without you guys. I am grateful for my loving girlfriend, Florine, that has helped and supported me so incredibly much, always with love and never backed down from any challenge. I can not think of a better team supporting me in doing everything I do in life.

Thank you all.

Max Verdoes
Delft, April 2023

Abbreviations

Abbreviation	Definition
AC	Alternating Current
AI	Artificial Intelligence
CM	Condition monitoring
DC	Direct Current
DT	Digital twins
FDD	Fault Detection and Diagnosis
FFT	Fast Fourier transform
I4.0	Industry 4.0
IG	Industrial Gear units
IoT	Internet of Things
ML	Machine Learning
OEM	Original Equipment Manufacturer
PdM	Predictive Maintenance
R&D	Research and Development
RLS	Recursive least squares
RMS	Root Mean Square
RUL	Remaining Useful Life
SEW	Süddeutsche Elektromotorenwerke
TLF	Transport loss factor
USD	United States Dollar
VFD	Variable Frequency Drive

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Chapter 1

Introduction

1.1. Research Context

In 2022, the global industrial electric motor market was estimated to be worth approximately 21 billion US dollars, with a predicted annual growth rate of 3.12% leading to a valuation of 25.3 billion in 2028 [1]. This market is highly competitive, with numerous players in the industrial electric motor industry. Electric motors are often used in combination with gear units, coupled they are known as gearmotors. These gearmotors are crucial to a variety of industries and systems, such as belt conveyors, production lines, elevators and cranes.

To create a competitive advantage and remain relevant in the industry, new technologies must be developed. Industry 4.0 and servitization are currently representing two of the most prominent trends in the industry. Servitization involves transitioning from a product-oriented to a service-oriented business model, which includes providing support, service and expertise in addition to products. This approach generates increased revenue by providing additional services to customers. Industry 4.0 refers to the automation and utilization of smart technology to modernize traditional production processes [2]. These two trends are complementary, with servitization being focused on enhancing customer value and Industry 4.0 adding value to the production process [3].

Within the context of Industry 4.0 and digital transformation, various terms such as Predictive Maintenance (PdM), big data, Internet of Things (IoT), Fault Detection and Diagnosis (FDD), Condition Monitoring (CM), Digital Twins (DT) and Remaining Useful Life (RUL) have become prevalent. However, adoption of these techniques in the industry has been slow and challenging. In academic research, there has been significant emphasis on PdM, a technique that involves predicting breakdowns or defects in systems that deteriorate over time by monitoring the system's condition. PdM encompasses several precise meanings, including prognostics, fault detection and diagnosis and condition monitoring. To achieve accurate results of electric gearmotor health, newer techniques such as Artificial Intelligence (AI) and Machine Learning (ML) are utilized to correlate multiple parameters with complex models. Examples of these parameters include vibrations, temperature and auditory analysis. The working of these AI models can be complex, require sufficient data and are difficult to comprehend.

The primary objective of PdM is to optimize production facilities by minimizing downtime and maintenance costs while maximizing production. Unplanned downtime is one of the primary causes of lost productivity in the manufacturing sector, resulting in delays, dissatisfied customers and loss of income. It is estimated that unforeseen downtime costs industrial manufacturers approximately 50 billion US dollars annually [4]. Although electric gearmotors are not directly responsible for this downtime, they play a crucial role in manufacturing systems and therefore are of great interest. The US Department of Energy, Energy Efficiency & Renewable Energy analysis indicates that PdM can reduce maintenance costs by 25% to 30% [5, 6]. Given that maintenance accounts for 15% to 70% of overall production costs, this can lead to significant savings [5, 6]. The figures are promising, yet the adoption of PdM technology outside of academia is slow. A survey of 256 companies by PwC shows that 63% of companies still use visual or basic instrument inspections [7]. Other surveys conducted by Siemens indicate that 93% of the 230 interviewed companies consider their maintenance systems to be inefficient [8]. While there is a growing willingness to adopt PdM, a gap remains between academic knowledge and implementation by industries.

Numerous factors contribute to the limited adoption of PdM in industry. Wickern et al. [9] highlights financial and organizational obstacles. Tiddens et al. [10] identifies the unavailability of high-quality data, the inadequate understanding of PdM's value and the literature's focus on technical aspects as contributing factors. Other components include poor commitment from top management [11], organizational culture issues [12] and data security concerns [13].

As a result, research has begun to address the issue of delayed PdM adoption and further study into PdM models. In addition, research methodologies that adhere to real-world conditions instead of laboratory experiments are utilized, which are the basis for many scientific articles. The crucial aspect is to recognize existing PdM approaches and comprehend how they can be effectively implemented in an industrial setting. To address this scientific gap, this research proposes a solution on how predictive maintenance can be sustainably implemented in the industrial manufacturing sector.

1.2. Research Field

This research is performed at SEW-EURODRIVE B.V. (from now on addressed as SEW Eurodrive), being a division of SEW-EURODRIVE GmbH & Co KG. It is a business with subsidiaries in 52 countries all around the world and the headquarter is located in Bruchsal Germany. The headquarter in Bruchsal is the main production facility and houses the main research and development (R&D) department. SEW Eurodrive produces many products like gear units, electric motors, gearmotors, automated guided vehicles (AGVs), inverter technology and more. An example of the product line can be seen below in figure 1.1. With approximately 19.000 employees worldwide, of which 600 work in the R&D and more than 3.1 billion in sales revenue in 2021, SEW Eurodrive is considered one of the global market leaders [14]. Being a market leader requires assertiveness and therefore, SEW Eurodrive is constantly innovating to differentiate itself from its competitors and to exceed customer demands.

SEW Eurodrive operates in a highly competitive sector where differentiation and innovation are critical to maintaining a competitive edge. To achieve this, SEW Eurodrive offers clients quality, service and expertise. As a result, the company has built a loyal client base that values a partner who provides complete engineering, maintenance and service solutions in addition to products. Approximately 80% of SEW Eurodrive's clientele comprises original equipment manufacturers (OEMs), who construct machinery incorporating SEW components. For example, car assembly lines and airport baggage handling equipment. SEW Eurodrive has an opportunity to assist these OEM clients in transitioning to

Figure 1.1: Product Line SEW Eurodrive [15]

servitization. The company has been developing products and accumulating knowledge in preparation for the Industry 4.0 trend. Collaboration with clients is required to adopt these technologies into their facilities. Despite financial incentives driving its popularity, adoption of Industry 4.0 technologies among end-users remains low [7, 8].

Chain belt conveyor systems are thoroughly used throughout the industry and the prevention of breakdowns is of importance. Therefore, industrial PdM solutions are of high interest. The general system studied in this research consists of the electric motor, gear unit, position controller and the driven chain belt conveyor system, presented in Figure 1.2. The only data collected from the physical system is obtained using the variable frequency drive (VFD) that drives electric motor.

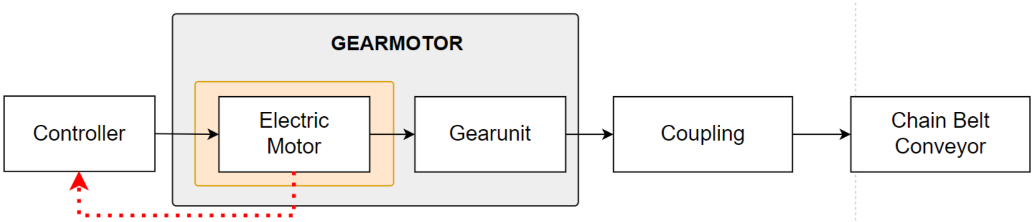


Figure 1.2: General system of interest

To create an overview of the components in the general system an input-output diagram is presented. In Figure 1.3, the red arrows represent the inputs and the green arrows the outputs of the subsystems. As implicated, the simplification shows the output of the previous subsystem is the input for the next subsystem. The three main causes for failure are established with SEW Eurodrive engineering experts. The first failure is a bearing failure, which mostly can be detected as a build-up of noise. The second failure is a blockage in the system, causing obstructed movement thus failing of the system. The third failure is a gear failure in the gear unit. In an industrial setting SEW Eurodrive only provides the gearmotors and has no responsibility over the installed physical system. The way the driven systems are installed and setup are not controlled or supervised by SEW Eurodrive. However, by leveraging the collected data from the physical system in combination with models based on the physical system, insights into the physical system can be gained.

The general description of a chain belt conveyor is as follows: A frame with a guiding rails supports a chain belt conveyor. The chain belt conveyor consists of a series of con-

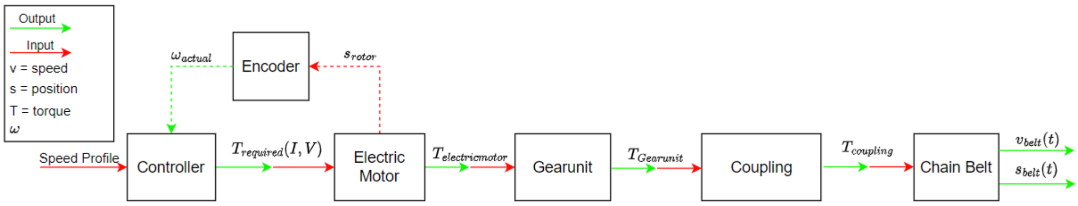


Figure 1.3: Input-Output diagram of general system

nected chain-links. The cross section of the chain belt conveyor system is shown in Figure 1.4 and is closed form. The red belt moving the mass towards the driving sprocket, the blue belt is the returning belt and the contact areas are shown in green, as shown in Figure 1.5. The chain belt conveyor creates a linear movement, driven by a rotational movement of the gearmotor.

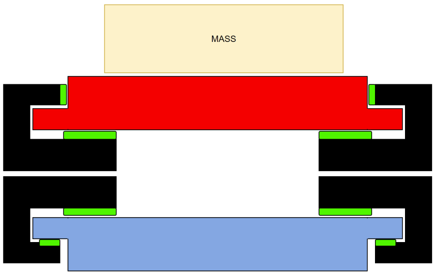


Figure 1.4: The cross section of the system

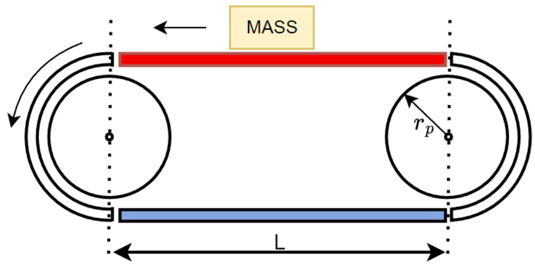


Figure 1.5: Side view of the system

SEW Eurodrive has developed software called DriveRadar, which is an umbrella term for all services related to digitization, condition monitoring and predictive maintenance. DriveRadar is developed to meet the needs of clients and is increasingly popular over the last years. The implementation is not easy for SEW Eurodrive and ways to improve the adoption are explored. The lack of development can be explained by a main factor, which is investment costs for the client. To be competitive in the market the price of the hardware has to be suppressed, allowing no room for additional sensors. Therefore, it is of interest to find ways to utilize data that is currently collected by the clients operational systems. Gearmotors are driven by a VFD, that can be used as the "sensor" of the physical system. The requirement for extra sensors is undesired, as it results in additional investment costs. These conditions results in a project that is scalable for many clients without any changes to their operational systems. This results in the following question: *How much information from the physical system can be extracted with the currently available data collected from SEW Eurodrive clients and what value can be provided?*

1.3. Research Problem

The industry has expressed a desire for digital twin models to enable condition monitoring of industrial chain belt conveyor systems. Currently, there is no industry standard digital twin available for industrial chain belt conveyor systems. The methodologies and theories that do exist are primarily applicable in non-industrial settings and used for different applications hindering adoption. The scientific and practical challenges associated with this problem statement are addressed in the following sections.

1.3.1. Scientific Problem Statement

The amount of scientific research focused on bridging the gap between academic and industrial digital twin models is limited, indicating the differences in the interest of academia and the industry. Disparities exist between digital twin models in literature and those that are applicable in industrial settings. This can be attributed to the differences in the availability of data and knowledge. The literature presents a variety of techniques to solve problems more efficiently, faster or more accurately. Often, minor improvements are proposed to existing setups and the results and improvements are demonstrated through simulations with a set of assumptions.

In contrast, the industry typically has less available information and operates within a financially competitive environment. Here, many parameters are unknown and must be estimated based on expertise. Creating a digital twin to assess the performance of the system, using system identification, creates insights into different aspects and allows for the comparison of operational systems.

1.3.2. Practical Problem Statement

The implementation of PdM has been limited so far, despite the potential benefits of lower maintenance costs and increased productivity. This is due to various factors such as financing, management, expertise, culture and quality of data. These factors play significant roles in determining PdM adoption in the industry. This knowledge gap presents an opportunity for SEW Eurodrive to assist clients in implementing a digital twin model for condition monitoring. However, a model for a chain belt conveyor is currently not present. In the industry, data is primarily collected from gearmotors using the VFD and no other sensors are present in the operational physical systems. Additional sensors would require additional investment costs, making them undesired. As a result, the gearmotor currently operates as driving a black-box system.

The fundamental question of interest is how to model the chain belt conveyor system and how much information can be extracted from the system. Engineers can respond more effectively if they have access to a wider range of information on the operational system. This enables them to gain a more comprehensive understanding of the situation and allows them to respond accordingly. Furthermore, the information gathered from the system can be utilized to evaluate the performance of the system, and subsequently, provide insights into aspects such as energy consumption. Energy usage has become a crucial aspect since the consumption and cost of electricity has increased globally. A model to create insights for chain belt conveyors is a big step towards predictive maintenance. This is in line with the goal to optimize the production facilities, all while minimizing the energy consumption.

1.4. Research Objective

The objective of this research is "The Development of a Digital Twin for Condition Monitoring of an Industrial Gearmotor Driven Chain Belt Conveyor System". In collaboration with SEW Eurodrive a model is developed for chain belt conveyors in their production facility in Rotterdam. The general concept of a digital twin for condition monitoring is shown in Figure 1.6. The main feature of the digital twin is a model that is personalised by the real-time data updating the model to real-time conditions. By creating a digital twin the behaviour of the system can be inferred.

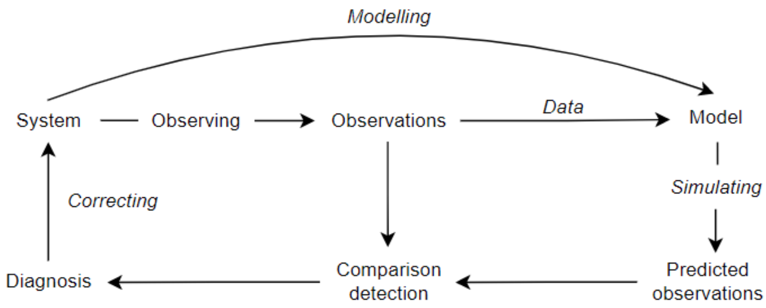


Figure 1.6: The general overview of the comparison of the model and the physical system

The physical system is known and this information can be exploited to model the physical system. The objective of the digital twin is to leverage the proposed model on the acquired data of the operational system for system identification, anomaly detection, dynamic weighing and a performance indication of the physical system for predictive maintenance. The model must function utilizing data from physical systems in their current state, without the need for adjustments. This approach eliminates the need for physical system modifications and results in a scalable model that can be broadly implemented throughout the industry without any prerequisites. The research question has been defined based on the gaps found in the literature research.

1.5. Research Questions

The following research question is presented:

"How to Develop a Digital Twin for Condition Monitoring of an Industrial Gearmotor Driven Chain Belt Conveyor System?"

To answer the main question the following sub-questions are formulated:

1. What is the state-of-the-art of digital twins and condition monitoring in an industrial setting?
2. Is the currently available hardware sufficient for a digital twin and condition monitoring?
3. How are digital twins and condition monitoring defined in literature?
4. How can the subsystems of the digital twin be modelled?
5. How can data be leveraged to identify unknown parameters in the system?
6. How can the model be used to identify anomalies in the system?

1.6. Research Scope

A broad understanding of digital twins and condition monitoring is required for the main parts of the research. By analyzing the state-of-the-art of digital twins and condition monitoring in the drive industry, a benchmark of the current industrial situation is established. The possibilities with currently available equipment and data are explored. A global understanding of digital twins and condition monitoring is given to understand the concept. The modelling for the subsystems of the chain belt conveyor is elaborated for an industrial setting. It is elaborated how the model and the data can be fit using parameter estimation for system identification. Subsequently, how the model can detect anomalies in the physical system. And finally, the method for the performance indication of the operational system is proposed. The primary goal of the model is leveraging data to identify unknown parameters of the physical system (system identification), anomaly detection and a performance indication. This is performed by only utilizing the data collected from the gearmotor using the VFD. It is of interest to explore to what extent the parameters of the physical system can be identified or add value. For the industry, it is of interest to establish the border of the minimal required information of the physical system for the model to function and to what extent the subsystems can be modelled. The model has to be generalized, resulting in a scalable model which can be implemented in many currently operational systems.

From the previous sections can be concluded that, the information required to develop a digital twin for condition monitoring in an industrial setting for a gearmotor driven chain belt conveyor, will be the main goal of the research. The digital twin has to operate in an industrial setting, which implies in manufacturing and production facilities. The model will be using data solely collected from the gearmotor using the VFD, there are no other sensors to collect data or information from the physical system. The following assumptions are made:

1. The drive equipment is always functioning properly
2. The chain belt is always under tension
3. A sprocket with teeth interconnecting the belt is used, resulting in no slip
4. The chain belt conveyor is driven according to the closed form principle
5. The friction of the chain belt is uniform for entire contact friction surface
6. The stop time is larger than the drift time for the deceleration cycle

To summarize the scope of this research project the following main points are presented:

1. The model has to be designed for an industrial setting (scalable and robust)
2. The model uses data collected only from the gearmotor using the VFD
3. Explore to what detail the subsystems can be modelled
4. Explore what is the minimal required input for the model
5. How to detect anomaly in the physical system
6. How can the performance of the physical system be assessed
7. The model is developed by incorporating the presented underlying assumptions for industrial chain belt conveyors

1.7. Research Outline

The previously mentioned sub-questions will be the leading structure of the research project. First, an overview of the current state of the industry is given to establish a baseline in Chapter 2. The currently available hardware and collected data is presented. Furthermore, the potential use and possibilities it provides are discussed. Thereafter, in Chapter 3 the following aspects are presented. A description of digital twins and condition monitoring is given to create a better understanding of the concept. Additionally, the modelling of the subsystems of the digital twin, the requirements and implications are explored. Furthermore, the methods to identify the unknown parameters and its requirements are shown. Subsequently, the possibilities for anomaly detection are presented. Thereafter, a conceptual model is shown in the Methodology 4. Following that, the models is verified and validated in Chapter 5. Afterwards, a case study is performed to show the performance of the model in Chapter 6. Finally, in Chapter 7 the conclusion, limitations and recommendations are discussed.

Chapter 2

State-Of-The-Art of the Drive Industry

To get a broader understanding of the project it is critical to comprehend the current situation in the industrial setting. To establish the benchmark, the current status of SEW Eurodrive and literature is analysed. Within this chapter, a comprehensive analysis and summary of the industry's state-of-the-art will be conducted, drawing upon insights from domain experts and SEW Eurodrive's expertise. The baseline is established for the gap concerning the digital twin and condition monitoring in the industry. The following subquestion is answered in this section: *"What is the state-of-the-art of digital twins and condition monitoring in an industrial setting?"*. Thereafter, the subquestion answered is: *"Is the currently available hardware sufficient for a digital twin and condition monitoring?"*

2.1. State-Of-The-Art at SEW Eurodrive

The state-of-the-art is determined by collaborating with SEW Eurodrive engineers and by examining reports from the company. A summary of the findings is provided below, along with important issues that have been discovered. It is critical to note that, while SEW Eurodrive will be utilized as a resource, the assumption is made that their current state represents the overall state of the industry and other companies addressing the same challenges.

SEW Eurodrive captures all Smart Factory components under the term "DriveRadar" [16]. The notion of the term *Smart Factory* refers to the final objective of manufacturing digitization, in which machines continually communicate data that can be utilized to self-optimize equipment or to handle issues across systems [17]. The goal is minimizing downtime and therefore improving productivity and efficiency which results in increased revenue. DriveRadar uses the collected data and allows for visuals and predictions to be created, which gives insights into the systems. In collaboration with engineers, which are experts in the field of interest, further actions can be considered. Currently, this software is the main project that is working towards Industry 4.0, therefore new projects such as a digital twin for condition monitoring is of high interest.

Predictive maintenance (PdM) is the goal of DriveRadar, a short introduction is provided for more context. A more elaborate description of PdM is provided in Section 3.1. Predictive maintenance is an approach to maintenance in which the condition of equipment or systems is continuously monitored to predict and prevent potential issues before they occur. Predictive Maintenance can be divided into 5 parts, starting with the collection of data to the final prediction. To get a better understanding of the predictive maintenance process, these sections are shown in Figure 2.1. The collection of data is performed with the SmartDataCollector. This implies the action of collecting data and converting it into readable files and belongs to the capturing phase. The pre-processing phase is of interest as it defines what data to collect and what are the optimal parameters to measure.

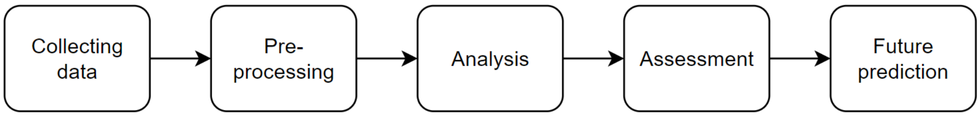


Figure 2.1: The flow of data for predictive maintenance

Besides DriveRadar, other software used by SEW Eurodrive is "Workbench" [18]. The primary objective of the Workbench software is to assist in the selection of hardware and equipment, it allows to plan and configure single or multiple systems in parallel. All SEW products are collected in a database and by providing the specifications and requirements of the physical system a mathematical model is used to calculate a result. This software is based on mathematical models, therefore it is considered as a model based engineering program. For the unknown parameters, like frictions or efficiencies, look-up tables are used with an estimated value. By using workbench the required components for a system can be determined based on the mathematical models. Workbench is based on first principles models where all the parameters are known. In practice this is not the case.

DriveRadar remains in its developmental stage, requiring substantial research and development efforts. SEW Eurodrive encounters challenges in implementing models and algorithms in industrial environments. Most clients and projects are unique, which results in distinctive requirements for the model. For example, a client can only need a gearmotor, while other clients need a full PdM solution from SEW Eurodrive. Working conditions in the industry are often dynamic and the use-case of a chain belt conveyor can vary significantly from day to day. The dynamic nature of the working conditions in the industry creates a challenging environment to develop a generalized model, that can be applied in a broad spectrum of situations. Factors such as temperature, degradation, speed and type of product can affect the optimal working conditions of the system and therefore require a flexible approach. To accommodate these variables, the model should be dynamic, adaptable and scalable. Furthermore, since parameters are not always known, companies like SEW Eurodrive have expressed interest in exploring models for system identification. By mapping the parameters over a longer period of time, predictions of the degradation can be performed. By creating a digital representation of the physical system, valuable insights can be acquired. Information such as overtime trends of degradation of the chain belt conveyor can be established. These insights can be of great value to SEW Eurodrive's customers, representing a significant step towards implementing predictive maintenance.

DriveRadar is an overarching term that encompasses software applications designed for intelligent and scalable services in Smart Factories, aimed at enhancing productivity. DriveRadar is currently in active development, the goal is to minimize unexpected breakdowns and operational disruptions by PdM strategies. Currently, the main focus of DriveRadar is research and development for industrial gear units (IG). These gear units are prevalent across a diverse range of industries and capable of delivering up to 5200 kNm [15]. The growing interest of clients in DriveRadar software indicates its potential value. The many factors that influence the possibilities for PdM, such as working environments and available equipment. Industrial clients consider a cost estimate for their maintenance strategies. If the investment costs of PdM applications are more than the potential payback within a certain amount of time, these PdM solutions are not appealing. A model that can be widely applied to currently operational physical system, without the need for adjustments, is proposed.

2.1.1. Data Availability Industry

The industrial environment entails limitations associated with the equipment. The main restriction is the availability of memory to collect data sets. The equipment to collect data sets meets a standard and is not designed for future applications like a digital twin. When collecting data sets, the parameters are selected manually. A data set of parameters over a period of time is referred to as a "scope". A scope can accommodate a maximum of 10 channels, each comprising 2048 samples. The sample time refers to the interval between each sample and is correlated to the total scope time. If a scope contains only 5 channels, the total scope time is double compared to scoping 10 channels. Similarly, if the sample time is halved, the total scope time is also reduced by half. As the sample time and scoped channels significantly affect the model's capabilities, these limitations in equipment must be considered.

Section 4.2 provides a more detailed explanation of the collected data for the digital twin. The parameters of interest primarily consist of a set point (target value) and the actual value (current value). These parameters can be expressed in either their actual units or converted to the desired units. For example, the generated torque represented as a percentage of nominal torque. The industry commonly utilizes the following parameters which are shown as an example:

Data name	**Unit**	**Description**
Speed	1/min	The actual and set point speed
Current	A	Maximum allowed current to electric motor
Torque	Nm	The actual and set point torque
Position	m	The actual and set point position
Power	W	Mechanical power
Additional triggers	/	Additional reference signals and triggers

Table 2.1: The 6 main parameter groups

The data collection for PdM involves two key locations: the electric motor encoder and the frequency inverter. The frequency inverter provides the required voltages (V) to generate the desire torque. The voltage and current (I) drawn by the electric motor are measured and regulated. Utilizing an in-house motor model, the delivered torque can be calculated from the measured voltages and currents of the electric motor. Alternative features are available as well. By utilizing the encoder to measure the rotor position, it is possible to determine the rotational acceleration. In Equation 2.1 , the torque delivered by the electric motor (T_{motor}) is calculated by the product of the total driven inertia (J_{total}) and the angular acceleration ($\ddot{\theta}_{motor}$) of the electric motor. Through an iterative process that utilizes the acceleration of the electric motor, the delivered torque from the motor model, the total driven inertia can be determined. This approach can be used to verify and assess the correspondence of the driven inertia by the model and physical system. The assumption is made that the calculation for the generated electric motor torque is accurate and valid.

$$T_{motor} = J_{total} \cdot \ddot{\theta}_{motor} \tag{2.1}$$

The set point and actual values for the torque, speed and position are available. These parameters are used as the minimum required parameters for comparison of the physical system and the model. All parameters are used for comparison of the behaviour of the physical system and the model.

2.2. Conclusions State-Of-The-Art

This chapter addressed the sub-questions: *"What is the state-of-the-art of digital twins and condition monitoring in an industrial setting?"* and *"Is the currently available hardware sufficient for a digital twin and condition monitoring?"*. An overview is presented of the current software and tools utilized by SEW Eurodrive, along with the challenges encountered. The following section provides a summary of the crucial components required for the development of a digital twin in the industry:

1. The availability and quality of data are limiting factors, the gearmotor is the only sensor in the system
2. Collected data can be difficult to interpret and utilize effectively
3. Availability for models that can be applied in the industry is limited
4. Designed and operational systems contain unknown parameters, which are estimated by engineers
5. No established method for rating the performance of similar belt conveyor systems
6. The model must be capable of working with the data currently available, without additional requirements
7. Hardware limitations of an industrial setting must be taken into account
8. Currently available equipment can be used to create a digital twin

The current state of the industry and identified gaps serve as a benchmark for the subsequent section, Chapter 3.

Chapter 3

Literature Review

This chapter provides a broader context of the project by examining predictive maintenance, digital twins, condition monitoring and the modelling of the system. It begins with a brief review of predictive maintenance, followed by a more comprehensive discussion of digital twins and condition monitoring to provide a deeper understanding of the subjects matter. The following chapter explores the role of data in digital twins and condition monitoring. It examines the potential models identified for the subsystems in the literature and their use in a digital twin.

3.1. Predictive Maintenance

Predictive maintenance is an approach to maintenance in which the condition of equipment or systems is continuously monitored to predict and prevent potential issues before they occur. This involves collecting data from various sources such as sensors and visual inspections to assess the health of the equipment or system. The data is analyzed and used to identify patterns and trends that can be indicative for future failures. Predictive maintenance aims to optimize maintenance operations and improve equipment reliability and availability while minimizing maintenance costs and downtime. PdM can extend the useful life of equipment or systems and improve overall productivity. The implementation of predictive maintenance requires advanced data analysis techniques to effectively detect and predict anomalies and failures.

In the industrial setting, maintenance refers to the operations carried out to ensure that machinery and other physical equipment stays available for production. The primary objective of industrial maintenance is to maintain high levels of productivity while minimizing breakdowns and associated costs. Maintenance activities and their implementation are influenced by the production process and plant layout. Maintenance plays a crucial role in achieving customer-oriented performance parameters such as quality, cost, and productivity. Unexpected breakdowns can impact these three essential components of competitiveness. In today's industrial landscape, it is no longer optimal to wait for failures to occur, organizations must implement various maintenance procedures that are appropriate for their operations. Industry 4.0 has created new ways of improving technology in the industrial setting by utilizing "Smart Factory" concepts. This creates a environment that leverages the Internet-of-Things (IoT) to enable machines to collect and analyze data and act accordingly. The term IoT generally refers to scenarios where network connectivity and computing capabilities extend to objects and sensors. This allows devices to generate, exchange and consume data with minimal human intervention [19]. While the use of IoT has been criticized due to the individual addressability and network connectivity requirements of devices, its advanced sensors enable the detection of faults that are undetectable to the human eye. Predictive maintenance can provide early warnings in advance of failures, enabling machines or humans to take necessary action to minimize the frequency of failures [20].

Predictive maintenance has developed certain worldwide norms and references. There are four types of occurrence in maintenance:

1. *Corrective* - Performs maintenance when there are anomalies or a fault is detected
2. *Preventive* - Uses scheduled time frame interval maintenance
3. *Predictive* - Uses time frame information to signal predict a failure and preventing downtime
4. *Prescriptive* - Used so specific events can be prevented from happening

Predictive Maintenance is based on historic data, models and domain knowledge. It can predict trends, behaviour patterns and correlations by statistical, AI or machine learning models. This is utilized for anticipating pending failures in advance, to improve the decision-making process for the maintenance avoiding mainly downtime [21, 22]. A big part of Industry 4.0 is a future perspective of how manufacturing will become within years. The impact of maintenance costs can range from 15 % to 60% of the total operation of all manufacturing [7, 23]. However, there is a lack of knowledge on the actual production costs by companies which shows why PdM is so interesting for the industry.

The complexity, cost and accuracy of prognostics techniques is proportional to its applicability. Increasing prognostics algorithm accuracy with low cost and complexity is a big challenge. A representation is shown in Figure 3.1 [24]. The more accurate the models are developed, the more computational power and investments are required.

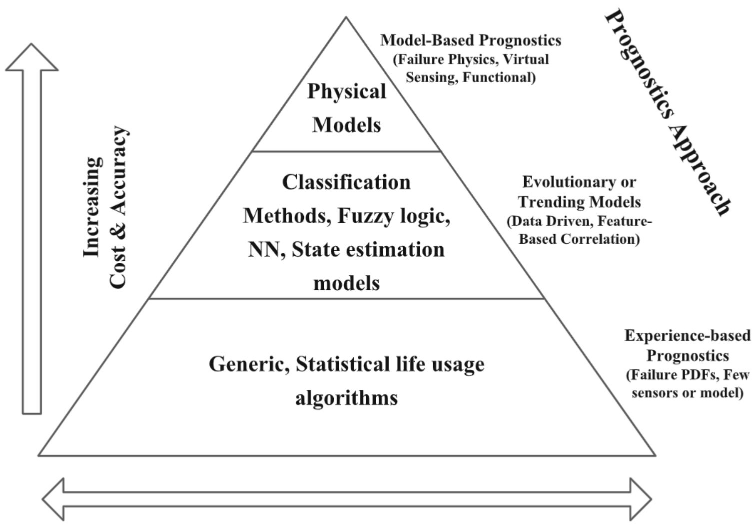


Figure 3.1: Prognostics approaches [25]

Numerous models can be created to facilitate predictive maintenance, with three distinct categories characterizing the methodological approaches employed in predictive maintenance forecasting [24, 26–28]:

1. *Physical model-based:* Features its primary characteristics on mathematical modeling with reflexes in a component's condition, demanding accuracy in the condition and measurement of failure, and statistical techniques to minimize these indices [28].

2. *Knowledge-based:* Approaches that reduce the complexity of a physical model, for this reason, are often used as a hybrid strategy. For example, expert systems or fuzzy logic [29, 30].

3. *Data-driven:* The models based on statistics, pattern recognition, artificial intelligence (AI) and machine learning algorithms are the most prevalent in the present development of PdM solutions.

Additionally there are other hybrid definitions such as Cloud-based, Deep-learning based, IoT-based, Fleet-based and Time-based which are referred to in [24].

3.2. Digital Twins and Condition Monitoring

A digital twin is defined as a virtual model that functions and behaves exactly like its physical counterpart, computed simultaneously with the physical system and with an automated transfer of data or information between the physical system and the model [31, 32]. Therefore, the digital twin is a digital representation of a physical system using real-time data to infer what is happening to the physical system. An illustration to visualize the idea is given in Figure 3.2. In reality there are specific models for the physical systems that are working real time with the collected data. This approaches a real time digital representation of the current physical system using the collected personalized data. By using these models, it is possible to infer the state of the physical system. In Industry 4.0, with technologies like the Internet of Things (IoT) combined with digital twins, it results in a powerful concept. Technologies like this allows for more precise data collection from parts of interest, collaboration between equipment and many more new things that could aid towards the goal of Industry 4.0.

Condition monitoring is the process of monitoring the health and performance of equipment and systems to detect potential issues or failures. A "significant change is indicative of a developing failure" [34]. This is the foundation for condition monitoring systems and comprise a combination of sensors and signal processing equipment [35]. These provide continuous indications of component condition based on techniques such as vibration analysis, acoustics, oil analysis and thermals. Monitoring can be real time/on-line (providing instantaneous feedback of condition) or off-line (data is collected and used afterwards) [36, 37]. It involves collecting data from various sources, such as sensors, measurements and visual inspections, which are then analysed to assess the condition of the equipment or system. Condition monitoring can provide real-time insights into the performance and behavior of equipment, allowing teams to identify potential issues before they result in downtime or production loss. The goal of condition monitoring is to prevent equipment failure and reduce maintenance costs by enabling proactive, and therefore predictive maintenance. In an industrial setting, condition monitoring is often applied to critical equipment, such as motors, pumps and turbines to ensure their reliable and efficient operation. Condition monitoring can include various techniques, including vibration

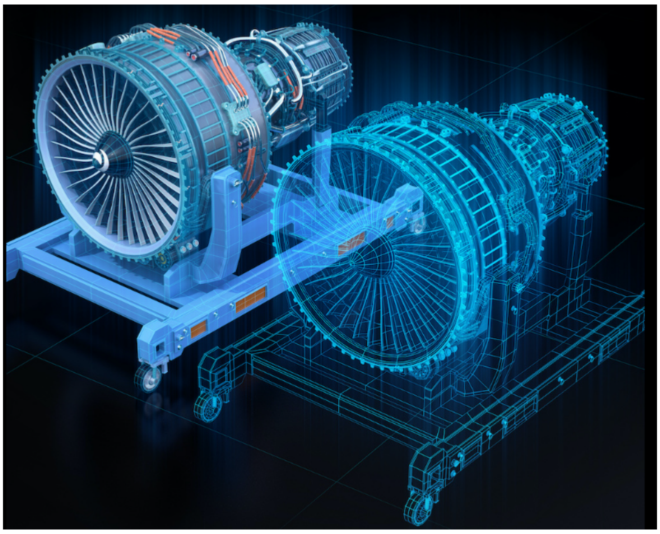


Figure 3.2: Illustration of a Digital Twin [33]

analysis, thermal imaging and oil analysis. These techniques can provide insights into the condition of the equipment. Such as, wear and tear, misalignment, imbalances and identify potential issues before they cause a failure. The successful implementation of condition monitoring requires the integration of various technologies, such as sensors, data analytics, visualization tools and a thorough understanding of the equipment and its operating conditions.

Using proper data collection and signal processing, faults can be identified when components are in operation and actions are planned preemptively to prevent damaged or failing components. Maintenance activities can be organized and timed more effectively, leading to enhanced reliability, availability, maintainability, and safety (RAMS) outcomes. In addition, downtime, maintenance and operational costs are reduced [38]. Condition monitoring techniques are therefore used throughout the industry [39, 40].

3.3. Modelling Approaches

The literature review is performed to find specific methods in scientific papers, which can be utilized for the modelling of the chain belt conveyor. Literature is mainly focused on belt conveyors for bulk material transport and very little on chain belt conveyors. The differences and similarities of these types of belts are analysed to determine the methodologies for chain belt conveyor systems. Industrial belt conveyors and industrial chain belt conveyors are two types of conveyor systems that are commonly used in industrial settings to transport materials or products from one place to another. While both of these types of conveyors serve similar functions, there are some differences in their design and construction that make them better suited for different applications. Determining the similarities of these systems, the theory for analyzing the belt conveyor models can also be applied to chain belt conveyors.

The general system is divided into subsystems. By analysing each subsystem, providing individual sanity checks and combining them afterwards, the complete model is constructed. To begin with, a literature review is performed to explore the possibilities of the subsystems. The general system consists of the electric motor, gear unit, coupling and the chain belt conveyor. A visual representation is provided in Figure 3.3.

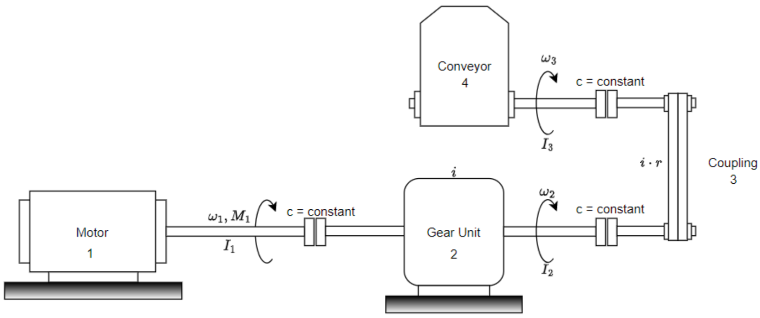


Figure 3.3: Schematic diagram of mechanical conveyor belt drive system [41]

3.3.1. Chain Belt Conveyors

The main focus for modelling chain belt conveyors is to predict the power consumption. There are different approaches to determine the consumption, depending on several factors. There is no first principle model available for the behaviour of the chain belt conveyor model. The choice of model will depend on the desired achievable goal and the level of accuracy and complexity desired. The behavior of a chain belt conveyor differs from other types and transmission systems. Chain belt conveyors rely on a closed form power transmission and hence do not need to be pre-tensioned like conventional belt conveyors.

Consequently, the chain slackens at the bottom section of the chain sprocket, where chain tension is minimal. The force gradually increases during the chain's reverse movement, owing to its mass and the friction between the chain and guide rail. After surpassing the reversal point, the conveying path initiates, and the tension substantially increases due to the added weight of the transported load. The tension peaks just before re-entering the chain sprocket. This general understanding of the chain belt conveyor can be helpful in understanding the system as a whole, shown in Figure 3.4.

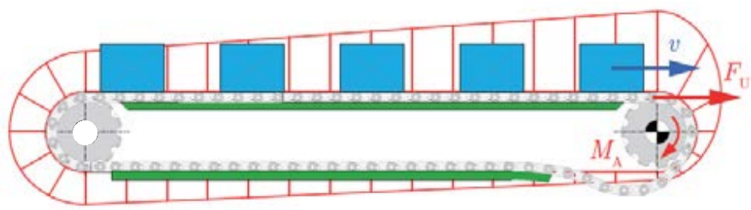


Figure 3.4: Simple tension force model of a chain conveyor [42]

To calculate chain belt conveyor systems forces, the driving force (F_u) is determined first. This force is necessary to move the chain and is primarily calculated from the frictional force at different sections of the system. The circumferential force is essentially used to calculate the required driving power. In the absence of a pre-tension force, the circumferential force is generally equal to the maximum chain tension force required to dimension the chain size or to support the permissible load. The radius of the driving sprocket and the circumferential force determine the required torque of the system. However, additional factors such as the startup acceleration rate may also need to be considered in the calculation [43].

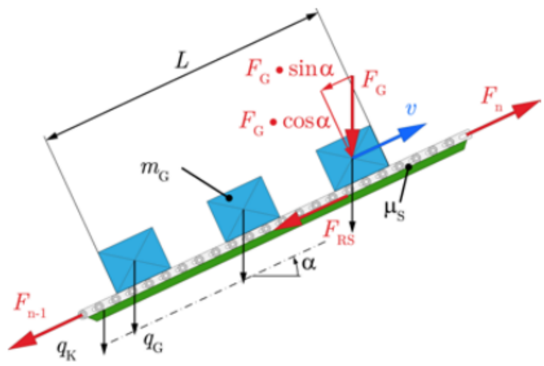


Figure 3.5: Straight section with slope[42]

The chain tension F_u that is at the end of the straight section can be generalized by the following Equation 3.1 [42]:

$$F_n = g \cdot L \cdot [\mu_s \cdot (q_k + q_G) \cdot cos\alpha] + (q_K + q_G) \cdot sin\alpha + F_{n-1} \tag{3.1}$$

Where g is the gravitational constant $[m/s^2]$, L the belt length of the desired section $[m]$, μ_S being the friction coefficient between chain and rail, q_G the specific weight of the goods $[kg/m]$, q_K the specific weight of the chain $[kg/m]$, the angle of the chain belt conveyor is indicated with α and F_{n-1} is the previous section if present.

Phenomenons of Chain Belt

Polygon Effect

The polygon effect is a dynamic phenomenon that can occur in chain belt conveyors, which is caused by the interaction between the chain and sprockets. This is also known as the sprocket-induced vibration or sprocket-induced dynamic instability. The polygon effect is characterized by the formation of a polygonal shape, as the chain passes over the sprockets, leading to high-frequency vibrations and noise. Factors such as the number of teeth on the sprocket, the pitch of the chain, the chain tension, the speed of the conveyor and the load on the conveyor can all contribute to the polygon effect. To mitigate the polygon effect, engineers can use several solutions such as increasing the number of teeth on the sprocket, increasing the pitch of the chain, increasing the chain tension, reducing the speed of the conveyor and reducing the load on the conveyor. This principle is visualized in Figure 3.7.

The model the polygon effect, the following approach can be used. The equation for a n-sided rotating polygon can be represented by the following equation:

$$y(t) = R \cdot sin(n \cdot t + \phi) \tag{3.2}$$

Where $y(t)$ are the coordinates of the polygon at time t, R is the radius of the polygon, n is the number of sides of the polygon, t is the time and phi is the initial phase angle of the polygon. This equation describes the movement of the polygon in a two-dimensional Cartesian coordinate system. The sine function is used to describe the movement of the polygon in the y-coordinates. This can be used to calculate the position of polygon at any

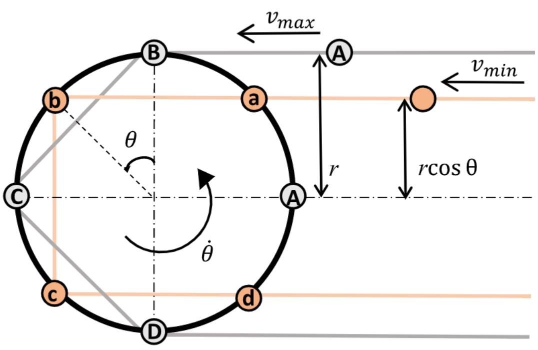


Figure 3.6: The polygon action of chain [44]

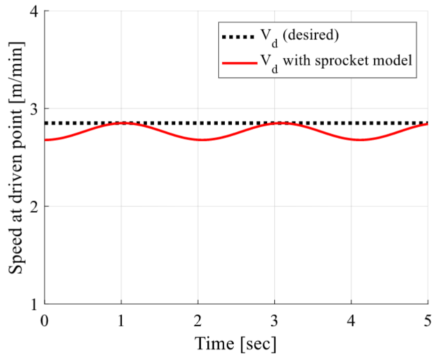


Figure 3.7: Linear speed at driven point [44]

given time, which can be used in the analysis of dynamic systems as chain belt conveyors. The relevance of the polygon effect for industrial chain belt conveyors is not determined. The change in the radius, combined with the point of engagement of the peripheral force results in a dynamic required torque.

Stick Slip Effect

The stick-slip effect is a phenomenon that can occur in chain belt conveyors, this is where the belt and chain experience periodic sticking and slipping movements [44]. This effect can be caused by the dynamic interaction between the chain and belt, as well as between the chain and the sprockets. It is typically characterized by high-frequency vibrations and noise. It can lead to increased wear and tear on the conveyor components, decreased efficiency and reduced lifetime of the conveyor system. Factors such as the coefficient of friction between the chain and belt, the chain tension, the speed of the conveyor, and the load on the conveyor can all contribute to the stick-slip effect. When the coefficient of friction is high and the chain tension is low, the chain will tend to stick to the belt, which can cause the belt to slow down and the chain to accelerate. When the coefficient of friction is low and the chain tension is high, the chain will tend to slip on the belt, which can cause the belt to speed up and the chain to decelerate. To mitigate the stick-slip effect, engineers can use several solutions such as reducing the length of the belt, increasing the chain tension, increasing the speed of the conveyor and reducing the load on the conveyor.

Interviews with chain belt suppliers are conducted to discuss the phenomena of stick-slip and the polygon effect. The verification of the industrial problems by contacting a global belt supplier Ammeraal Beltech is performed. This interview resulted in the confirmation of the industrial issue of the polygon effect for shorter belt conveyors and the stick-slip phenomenon for very long industrial belt conveyors.

To model stick-slip, a multi-mass spring dampener can be used as first seen in [43]. This modelling is very computationally intensive and allows for accurate calculations. When looking at short length chain belt conveyors, the functionality is assessed by the engineer that puts the system in operation. If the position of the belt is of importance, it is made sure the stick-slip effect is not present. The natural frequency of the chain belt conveyor significantly exceeds the natural frequency of the drive, resulting in no interaction between the two systems. Therefore, a rigid dynamics model can be used for the modelling of the chain belt conveyor. The calculations for the natural frequencies of a chain belt conveyor is shown in the case study in Section 6.2.3.

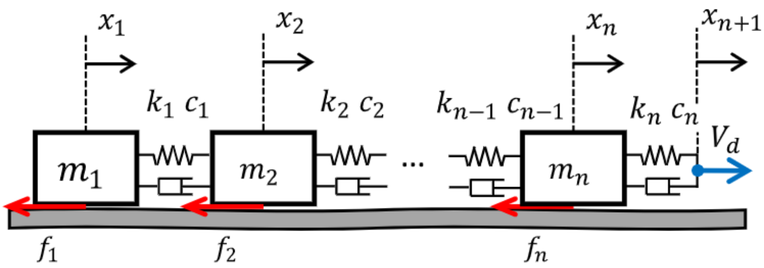


Figure 3.8: Multimass spring–damper model for conveyor system [44]

The static and dynamic friction of the belt are known requirements. The dynamic and static friction play a major role in the stick-slip phenomenon. As a result from the interview performed with Ammeraal Beltech, the conclusion is drawn that the exact static and dynamic friction are not known. The difference between the static and dynamic friction is different for the materials of contact. With the intention of a generalized model, the friction is only modelled by a Coulomb's friction model shown in Figure 3.9. The viscous friction is very low due to the materials used for the belt and the guiding rails. The viscous friction is captured in a different aspect of the model.

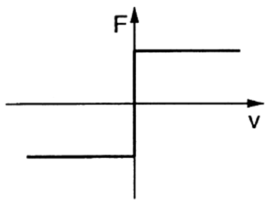


Figure 3.9: Coulomb friction model [44]

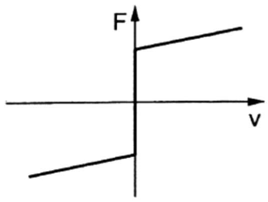


Figure 3.10: Coulomb and viscous friction model [44]

3.3.2. Electric Motor

The asynchronous induction motor is the core component of the system. This component is the start of the driving train and is where the torque to drive the physical system is generated. There are multiple ways to model the electric motor, methods that are often used are measuring the currents from the motor and a transfer function (TF). For modelling the electric motor with measured currents, the exact electric motor-model must be known. The control of the electric motor combined with the currents results in an accurate motor model to predict the generated torque.

In an industrial setting there are limitations like available space, investment costs, software, hardware and many more. Industrial manufacturers look for the lowest possible investment cost for the production equipment. Therefore, companies as SEW provide the minimum required hardware, as costs need to be as low as possible to be competitive. As previously mentioned in State-Of-The-Art (Chapter 2) , the available memory to measure parameters is limited. This results in a limitation of the amount of parameters that can be included in the scope. The more parameters included in a data set, the less time the data set contains. Due to this hardware limitations and the complexity of the electric motor model, a transfer function is considered as the optimal solution.

Generated Torque Transfer Function

A transfer function is a mathematical representation of the relationship between the input and output of a system. In the case of an asynchronous electric motor, the transfer function describes how the motor responds to changes in the torque set point and actual torque. The transfer function of an asynchronous electric motor is typically expressed in terms of the Laplace variable, "s", which represents the complex frequency domain. The transfer function is defined as the ratio of the output (the generated torque) to the input (the torque set point).

The transfer function of an asynchronous electric motor can be derived using the equations that describe the electric motor's behavior. These equations typically include the motor's electrical characteristics, such as resistance, inductance and capacitance, as well as its mechanical characteristics, including inertia, friction and load torque. Once the transfer function has been derived, it can be used to predict the motor's response to changes in the input voltage or current. This can be useful in designing motor control systems, as it allows engineers to optimize the motor's performance and efficiency. The transfer function is derived by experiments, using the same control and parameters as the motor of modelled physical system. A visual representation of the transfer function is provided below in Figure 3.11.

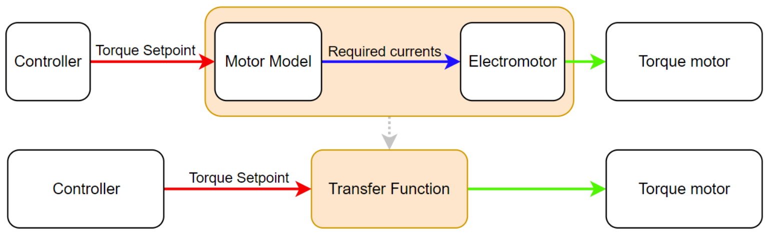


Figure 3.11: Representation of the transfer function input and output

3.3.3. Gear Unit

For gear units used in the gearmotors there are 2 main types of losses [45]:

1. Tooth friction losses
2. Churning losses

Tooth friction losses are the mechanical losses of the gear unit. Tooth friction losses in a gear unit refer to the energy dissipated due to the contact and relative motion between meshing gear teeth. These losses occur as a result of the sliding and rolling interactions between tooth surfaces, leading to energy conversion into heat and wear. The extent of tooth friction losses is influenced by factors such as the gear materials, surface roughness, lubrication, and operating conditions. SEW Eurodrive has a lot of knowledge on the mechanical efficiency of the gear units as these have to be determined individually. The efficiency of gear units is particularly reliant on the gear ratio and motor speed, therefore it must be determined case-by-case. This knowledge of mechanical losses is present at SEW Eurodrive and therefore are desired to be included in the model. Experiments can determine if these individual test of efficiencies are required.

Churning Losses are created by the gear wheels displacement effect in the oil. They are not required to be taken into account during the drive selection's initial approximation. However, in some cases these losses can be significant. If at least one of the following conditions holds true, high churning losses can occur [46]:

1. High rotational speeds, over 2000 rpm
2. The oil level being to high as a result of an unsuitable mounting location (depends per gear unit type)
3. High oil viscosity, which is temperature dependent
4. Low to very low temperature in working environment

As per [47], churning losses are the result of lubricant being struck, pumped, or otherwise agitated by the movement of the gears inside a gearbox. Prior research has established two key equations, each suited for either low-speed or high-speed gear applications. Refinement of the high-speed gear equation is essential, as substantial losses can arise in such systems. A refined equation, irrespective of the system's geometry, has been formulated that delivers optimal results under specific configurations.

The review in [48] examines a range of studies on churning losses, identifying rotational speed, gear geometry, confinement degree, and fluid density as relevant factors. However, the specific impacts and general solutions for power loss reduction remain uncertain due to the reliance on experimental correlations from distinct experiments. A universally applicable modelling methodology for examining fluid dynamics phenomena across gear types and configurations is necessary to better assess churning losses and devise potential solutions for minimizing power loss.

It is widely recognized that the losses can be divided into two parts. By segregating these losses into mechanical and churning losses, it may be possible to gain insights into which portion of the losses is attributable to churning losses. Currently, the loss ratio is unknown, and the industry is keen on identifying where energy losses occur in their machinery. Although it is feasible to use computational fluid dynamics (CFD) simulations to calculate losses [49], this is beyond the scope of this research project. It is difficult to employ a method that is scalable for industrial applications that provides in detail insights. Combining speed dependent losses for the entire system is suggested.

In conclusion, churning losses are dependent on speed, temperature and geometry. As the temperature and geometry of the gear unit are unknown, the churning losses will be captured using parameter estimation in the speed dependent losses.

3.4. Parameter Estimation

RLS, known as *Recursive Least Squares*, is a technique for estimating the parameters of a system using a recursive algorithm. In the context of a digital twin of a chain belt conveyor, RLS can be used to estimate the parameters of the conveyor's physical system. For example, the estimation of the friction coefficient and the transported mass on the chain belt conveyor. The basic idea behind RLS is to use a recursive algorithm to update the estimates of the system's parameters based on new measurements of the system's output. The algorithm starts with an initial estimate of the parameters, then uses the measurement data to update the estimates in a iterative fashion. The algorithm also uses a forgetting factor that allows it to weight the importance of older measurements relative to newer measurements, which is useful in cases where the system's dynamics may change over time.

The RLS algorithm is a form of adaptive filtering, and it is computationally efficient, which makes it well suited for real-time applications such as digital twins of chain belt conveyors [50]. However, it may not be susceptible to noise and model mismatch. Good initialization and fine-tuning of the parameters, as well as high-quality measurement data and proper model assumptions, are crucial for good performance. Additionally, the accuracy of the estimated parameters depends on the quality of the measurement data, and the assumptions made about the underlying model of the system. RLS is used in many papers to estimate parameters in parametric models [51–55].

Multiple techniques can be utilized to detect local minima and maxima during parameter estimation using Recursive Least Squares (RLS) for a digital twin model of a chain belt conveyor. Firstly, it is essential to define a suitable cost function that can provide meaningful results. Second of all, different initialization values can be used to start the optimization process, and the RLS algorithm can be run multiple times. This method helps to identify if different initialization values lead to different results, which could indicate the presence of local minima or maxima. The methods mentioned above can be used to refine the RLS estimates, providing a more accurate representation of the system's behavior.

The physical system used for data collection is known. Therefore, this physical system can be modelled and used to leverage the data and use parameter estimation. The general idea for parameter estimation for system identification is shown in Figure 3.12.

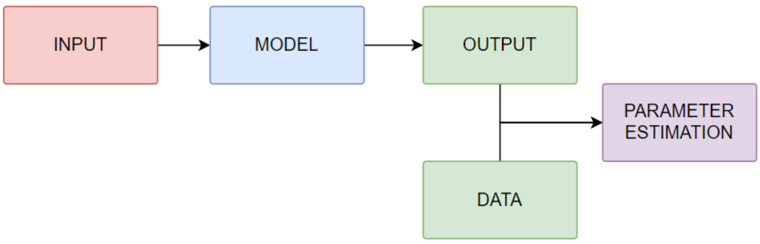


Figure 3.12: The general idea of leveraging the model and data for parameter estimation

3.5. Anomaly Detection

There are a number of methods that can be utilized to detect anomalies in the system. Multiple strategies are proposed for anomaly detection of the chain belt conveyor digital twin. Combining the insights created from these methods allows for a more broad and accurate analysis of the system. The combination of the current condition of the physical system and the over time trend provides great insights for predictive maintenance.

3.5.1. Fast Fourier Transform

Fast Fourier Transform (FFT) is a mathematical algorithm that is used to transform a time-domain signal into a frequency-domain signal [56]. The FFT treats amplitude versus time information globally as it transforms the data to an amplitude versus frequency description [57]. This is achieved by decomposing the signal into its individual sine and cosine components, each having a unique amplitude, phase and frequency. This technique enables the identification of the frequency components that make up the signal, as well as their respective amplitudes and phases. FFT is commonly used in signal processing and is a popular tool for frequency analysis. Furthermore, it is widely used in vibration analysis for rotary equipment [58]. When a chain belt conveyor is in operation, it generates vibrations that can be measured using sensors [59]. This is due to the fact that some faults occur very occasionally and also each type of machine has specific failure vibration patterns [60–63]. The vibrations are a measured in the time-domain signal that contains information about the conveyor's performance. It can be difficult to interpret this information from the raw time-domain signal. Therefore, FFTs are used to transform the time-domain signal into a frequency-domain signal, which is a representation of the signal in terms of its frequency components. This makes it possible to identify the different frequencies present in the signal and to understand how they relate to the conveyor's performance.

For example, by analyzing the frequency spectrum of the vibrations generated by the chain belt, it is possible to identify the natural frequencies of the chain belt. This can be used to predict its behavior and identify potential problems. Additionally, by analyzing the frequency spectrum of the vibrations rotational parts, it is possible to identify misalignment and other issues that can affect the conveyor's performance. This implies that FFTs can be used to analyze the sensor data and integrate the results into the digital twin. Increasing amplitudes of known frequencies in the system can be used as a marker for degradation of the system. Comparing FFT amplitudes of the same system in a different point in time can show over time degradation of the physical system [64].

Order Analysis

Order analysis is a frequency domain technique used to analyze the vibration signals of rotating machinery with a known rotational speed [65]. In order analysis, the vibration signals are transformed from the time domain to the frequency domain using the previously explained Fast Fourier Transform (FFT) algorithm independent of rotational speed. Order analysis can be used to identify gear mesh frequencies, bearing frequencies and other relevant frequencies that can indicate potential issues regarding the physical system [66]. Order analysis is utilized to determine the frequencies of the physical system independent of the rotor speed.

3.5.2. Residual Analysis

The prediction of the model is compared to the actual data from the physical system. The difference between the outputs are called the residuals and are derived using Equation 3.3 [67]:

$$e_i(t) = y_i(t) - \hat{y}_i(t) \tag{3.3}$$

Where $y_i(t)$ is the output of the physical system and $\hat{y}_i(t)$ the output of the model.

Residual analysis is an important aspect of a digital twin of a chain belt conveyor, as it allows for the identification of discrepancies between the simulation and the physical system. By analyzing the residuals, it is possible to identify any issues with the model's assumptions or input data, allowing for adjustments and improvements to be made to improve the model's accuracy and reliability. Residual analysis creates a better understanding of the underlying causes of these discrepancies. Popular strategies for residual analysis are:

Statistical analysis, time-series analysis and correlation analysis. It's important to note that the choice of residual analysis strategy will depend on the specific requirements, goal and desired level of detail of the digital twin. The analysis of the residuals can be performed to identify changes in the system, which can be an indication for anomalies. Therefore, the following statistical strategy is proposed. This statistical strategy requires data over a longer period of time, to establish the changes in residuals.

Statistical Residual Analysis

Statistical residual analysis is a statistical technique used to assess the residuals for the validity of a digital twin model [68]. The residuals can be analyzed using various statistical features to assess the model's accuracy and reliability [69]. Feature extraction techniques, including maximum, minimum, root mean square (RMS), mean, standard deviation, variance, correlation, kurtosis, and crest factor, are detailed in Table 3.1, with values varying based on failure. The statistical analysis can be performed in both time and frequency domain to detect anomalies in the system. For example, the maximum peak of a frequency will increase over time by developing failurs.

Statistical feature	**Purpose**
Mean	The average of a signal
Standard deviation	Measure of data dispersion around mean value
Variance	Average squared deviation from mean (dispersion measure)
Absolute maximum	Greatest value in a data set (extreme point)
Correlation	Degree of linearly relation between two variables
Kurtosis	Measure of data distribution's tails, relative to normal.
Root Mean Square	Square root of arithmetic mean of squared values
Skewness	Measure of data distribution's asymmetry around mean

Table 3.1: Possible features for statistical residual analysis

3.5.3. Transport Loss Factor

The *Transport Loss Factor* (TLF) is a way to show the specific mechanic energy consumption by using a method of transportation [70]. The TLF is utilized as an indication for the efficiency of the method of transport. This is insightful to determine the performance of the chain belt conveyor. As stated in the Introduction 1 there is currently no industrial standard used by SEW Eurodrive to determine the performance of a chain belt conveyor. Transport Loss Factor is a term used to describe the reduction in efficiency of a transport system due to various factors, such as friction, resistance or inefficiencies in the system itself.

There are different ways to measure the transport factor loss depending on the system, but the most generalized method is as follows. The transport loss factor is defined as the ratio of the mechanical work W_M (or energy E_M) required to drive the transport system and the transport work W_T (or performance E_T) for the displacement of a payload with weight of F_{pay} over a certain distance L [70–72]. In this equation for the TLF the assumption is made that the speed is constant. This is not applicable for the current experiment and therefore it is based on the kinetic energy [72].

The following general form is utilized for the transport loss factor as Equation 3.4:

$$f_T = \frac{W_M}{W_T} = \frac{\sum(F_{Di}|L_i| - F_{payi} \cdot H_i + \frac{1}{2} \cdot g \cdot (M_{pay,i} + M_{transport,i}) v_i^2)}{\sum F_{payi}|L_i|} \tag{3.4}$$

In this particular system there are no changes in height, simplifying the calculation. The total provided torque, the payload and the distance travelled is known. The weight could be determined by dynamic weighing. The transport loss factor can be utilized to determine the performance of the system.

It is of interest to compare similar chain belt conveyor systems or other transportation systems used in the industry. The TLF can be utilized to indicate the energy consumption of the system. This insight creates an indication on how efficient the system runs, and therefore the sustainability of the system can be addressed. The sustainability and efficiency of a system must be considered by industries.

3.5.4. Dynamic Weighing

Dynamic weighing is a technique used to measure the weight of material being transported on a gearmotor-driven chain belt conveyor using the collected data sets. By measuring the tension in the belt and calculating the weight of the material, dynamic weighing provides accurate weight measurements that can be used for process control and optimization, improving the system's performance and efficiency. The dynamic weighing process involves measuring the required torque for a section of the chain belt conveyor, which is then used to calculate the weight of the material being transported. For example, by measuring the weight of material being transported, it is possible to correlate the degradation of the chain belt conveyor to the transported mass.

Dynamic weighing is normally performed by a dedicated system that has to be calibrated. The idea proposed is to utilize the digital twin to approximate the weight being transported on the belt. An initialization run can be performed with an empty belt to set the initial parameters for the model. Here, the only unknown parameters in the system are the system losses and friction, as the weight of the driven belt is known. It is of interest in the future to link the weights on the belt to the degradation of the system.

3.6. Concluding Remarks

In the section above the sub-questions answered are: *"How are digital twins and condition monitoring defined in literature?"* and *"How can the subsystems of the digital twin be modelled?"*. An explanation is provided for digital twins and condition monitoring, along with an exploration of their importance and demand within the industry. The potential is shown but in reality implementation appears to be hard and requires more research. The adaptation in the industry will add great value to the PdM solutions, and therefore the efficiency of the production process.

Creating a digital twin for a chain belt conveyor involves modelling the physical system by combining multiple subsystems. Currently, no model for the chain belt model is available. The phenomenons (the polygon and stick-slip effect) of the chain belt conveyor are analysed. To make optimal use of the available memory to create data sets, a transfer function for the generated torque is proposed. The gear unit is split in mechanical and churning losses. The parameter estimation method to fit the model and the collected data is explained. Thereafter, the methods for anomaly detection are elaborated. These are FFTs, order analysis, statistical residual analysis and the TLF. The transport loss factor is used to to indicate the performance of the system. A new method for dynamic weighing using the collected data sets is proposed.

In the following Chapter Methodology 4 it is elaborated how the digital twin for condition monitoring of an industrial chain belt conveyor system is build.

Chapter 4

Methodology

The methodology outlines the development of a conceptual model, which is subdivided into multiple subsystems for detailed elaboration and explanation. Following individual subsystem testing through sanity checks, the properly functioning systems are verified and validated in Chapter 5. Sanity checks comprise assessments for verifying the accuracy and validity of model subsystems. These evaluations detect errors or inconsistencies, ensuring reliable and precise model outputs. A comprehensive overview of all subsystems and the general system's Input-Output diagram is depicted in Figure 4.1. The system is composed of multiple subsystems, these need to be combined to establish the final model.

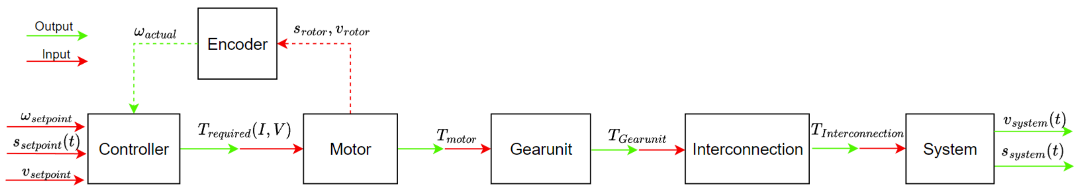


Figure 4.1: Input-Output diagram of the general system

The dynamics of the model are based on equations of motion (EoM). The general equation of motion used for the model is shown in Equation 4.1 [54]:

$$\ddot{\theta}_{motor} = \frac{T_{motor} - T_{load} - B \cdot \omega_{motor}}{J_{total}} \tag{4.1}$$

Here $\ddot{\theta}_{motor}$ represents the electric motor acceleration, the torque generated by the electric motor is shown as T_{motor}, the load torque induced by the transported mass as T_{load}, the losses (constant and speed dependent factor) in the physical system are represented as B and the total driven inertia as J_{total}.

The general system consists of a gear unit, which involves conversions when performing calculations. The decision is made to carry out the calculations for the entire system on the electric motor side of the gear unit. Therefore, all calculations are related to the rotor of the gearmotor [41].

4.1. Controller

The controller used in this model is a position controller for the position, speed and torque. The controller of the modelled physical system is recreated, tested and validated by conducted experiments. It is a cascade control as shown in Figure 4.2. The inputs for the controller are shown on the left-hand side in blue. These are the set points for acceleration, speed and position. The set points used from the collected data sets will be discussed in the upcoming section 4.2. The systems feedback, represented by position, speed and torque, is displayed in green. For the physical system these measurements are obtained from the encoder, which measures based on the rotor position. The feedback for the model is based on the EoM. The controller operates in discrete time and has a control loop time of 1 millisecond. This implies that every millisecond the controller adjusts to the present error and the frequency inverter drives the electric motor accordingly. The position controller outputs a torque set point for the electric motor. SEW Eurodrive uses an proprietary motor model for the frequency inverter to control the torque accordingly. The transition from torque set point to generated torque is discussed later in Chapter 4.3.

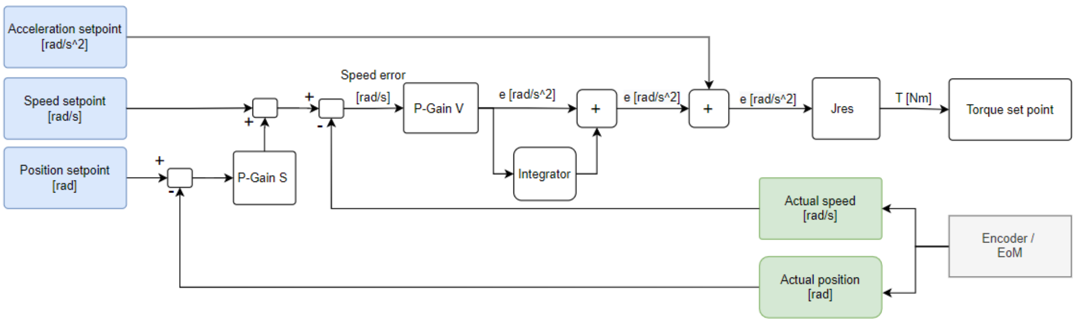


Figure 4.2: Overview of the position controller

4.2. Data

In Chapter 2 an overview of the commonly used parameters for data sets in the industry is given. Thereby, the explanation on how the generated torque of the electric motor is calculated. The position controller in the model uses same input as the physical system. The speed set points of the physical system are measured and used as an input for the model. This ensures the exact same trajectory to be used for the model by utilizing the input set points from the physical system. In total 7 parameters are obtained as information acquired from the physical system. By scoping the set point and the actual value (for position, speed and torque), the comparison can be made between the model and the physical system. The torque is considered as the main parameter of interest to show the interaction between the driven physical system (chain belt conveyor) and the gearmotor. The scoped parameters for every collected data set are:

Name	Unit	Description
Torque set point	Nm	The torque set point of the controller
Actual torque	Nm	The actual torque produced by motor
Position set point	rad	The position set point for the controller input
Actual position	rad	The actual position of the system
Speed set point	rad/s	The speed set point for the controller input
Actual speed	rad/s	The actual speed of the system
Digital input	/	Triggers in the system

4.2.1. Model Input

The model is provided with input in the form of speed and position set points from the physical system. This is a trapezoidal speed profile to generate the position and acceleration profile. In an industrial setting, the acceleration, deceleration and a maximum speed are provided for the system. The system accelerates to the maximum speed and will continue moving with this speed until a sensor is triggered for the deceleration. The prediction of when the position sensor is hit is complex. Therefore, the set points from the physical system are used as an input for the speed profile of the model. A visual representation of the speed, position and acceleration profile is shown in Figure 4.3. The acceleration movement is called a pulse-coast-pulse profile.

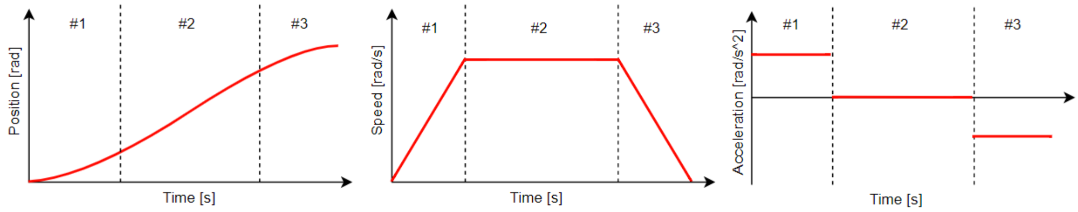


Figure 4.3: The trapezoidal position-speed-acceleration profile

The model recreates the speed, position and acceleration set points of the physical system. Since the speed set points are in discrete form, performing integration for the position and differentiation for the acceleration is not possible. The discrete form induces numerical errors that result in deviations from the original input profile of the physical system.

4.2.2. Sample Time

The sample time of the data set refers to the fixed time interval between consecutive data points in discrete-time. Furthermore, the cycle time is the total time of the cycle that is captured. For example, a 1 millisecond (1000 Hz) sample time implicates that every millisecond, measurements are taken and in a 3 second cycle time are 3000 samples. The hardware limitations of the system result in a limited amount of available memory. Shown in subsection 3.5.1, the sample time and the possible frequencies to capture are correlated. An illustration is provided in the following Figure 4.4.

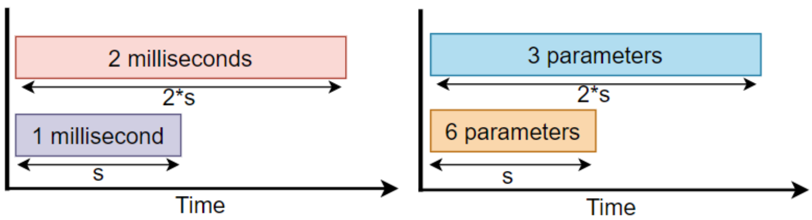


Figure 4.4: Comparison of different sample times and quantity of parameters

The sample time and cycle time correlation is established. The sample time also determining the frequencies that can be captured in the FFT. Specifically, the highest frequency that can be captured is half the sample frequency.

The frequencies of interest can be identified based on the known characteristics of the physical system, which may include the following:

1. Rotor speed and bearings
2. Gear unit stages
3. Mechanical frequencies of the physical system
4. Driving pulley behaviour
5. Natural frequencies of the chain belt conveyor

The amount of measured parameters is established, therefore the sample time can determine how much of the cycle is captured. It can be difficult to determine the sample time, therefore in experimental setups the following advice is given:

1. Use a high sample time. This allows to establish all the frequencies possible to capture, even though the entire cycle is not captured.

2. Use a sample time matched to the cycle of the physical system. By capturing the entire cycle, the acceleration and deceleration phase are both captured, these are insightful.

4.3. Electric Motor

In the Chapter 3 the methods for the modelling of the electric motor are discussed. By the limitations of the industrial setting, the amount of memory to measure parameters is limited. Therefore, the solution to model the electric motor as a transfer function is proposed. For the modelling of the electric motor, a transfer function is created by an experiment with a flywheel attached to a electric motor, shown in Figure 4.5. For the electric motor specifications, the nameplate is provided in Figure 4.6.

By utilizing a flywheel as the driven load, the dynamics of the driven system are decoupled from the electric motor. The utilisation of a flywheel is valid as the rigid body dynamics can be used since the natural frequencies of the chain belt and drive do not interfere. The approach is employed to ensure that the generated torque is only based on the motor and its dynamics. This experiment is performed to decouple the motor from the dynamics of the system and show the actual torque response. The experiment utilizes an identical electric motor as used in the physical system. The transfer function can suppress behaviour of the electric motor that can interfere with the system. The gearmotor system is the driving force of the system and is assumed to be fully functional. The assumption is made this is not present by performing frequency calculations and visual inspections presented in Chapter 5.

4.3.1. Transfer Function Experiment

The experiment to determine the transfer function (TF) is performed using a step function response and a flywheel. This transfer function closes the gap from torque set point to generated torque. A digital input is used to provide a step input. This simulates the step input as there is no build-up in signal, the torque set point is on or off. When a transfer function is created, the assumption is made that the initial conditions are zero, being correct for this case. The control loop operates with a cycle time of 1 millisecond, similar to the imitated system. Multiple experiments are performed on the torque response and it shows that the utilized way of electric motor control determines the torque response. SEW Eurodrive has

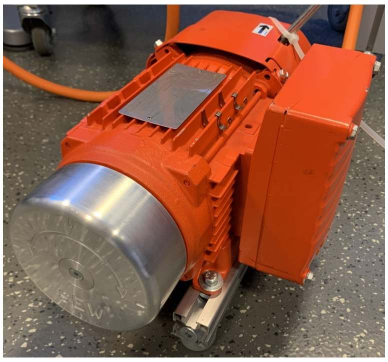


Figure 4.5: Flywheel experiment setup

Figure 4.6: Nameplate of motor for flywheel experiment

multiple ways to drive the electric motor, in this case the electric motor control is called "VFCplus".
To determine the transfer function the following experiment is deducted:

1. All the equipment is tested for proper functioning
2. The desired parameter scopes are set
3. A step function input is given and the measurement is started
4. The electric motor reacts to the signal by providing torque
5. The flywheel starts moving
6. The measurements of the experiment are acquired

After performing the experiments, the following response of the system is given, as shown in Figure 4.7. Given that the focus is on the initial response of the generated torque, only the first 0.5 seconds are presented. The data set shown recorded for 2.3 seconds, but no further variations in behavior were observed.

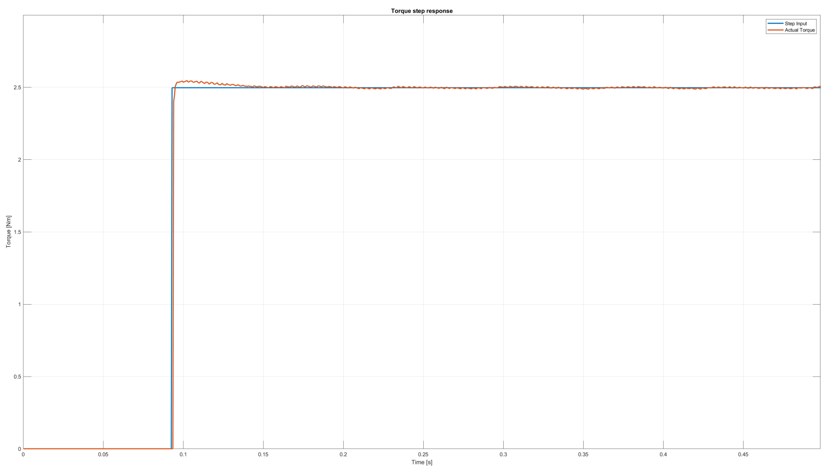


Figure 4.7: Step input and actual electric motor torque response

An overshoot and torque response delay can be identified in Figure 4.7. The delay in the torque response is caused by the sample time. It is not possible and realistic to create instant torque, which could neglect a time delay for a more realistic transfer function response. Based on this knowledge, only a time constant for the transfer function is used. In control systems engineering, the time constant is a well-known parameter that characterizes the behavior of a system in response to a step input. Specifically, it can be defined as the time required for the step response to rise up to 63% or 0.63 of its final value. This means that the time constant reflects the speed at which a system can reach its steady-state response after being subjected to a sudden change in input. The final derived transfer function, to represent the conversion from torque set point from the controller to actual torque delivered by the electric motor, is given by:

$$TF = \frac{1}{1+s\cdot\tau} = \frac{1}{1+s\cdot 9.8e-4} \tag{4.2}$$

The validity of the created transfer function is tested in two ways:

1. Torque step response
2. Speed cycle response

The step response is provided as an input and compared to the response of the system. By comparing the derived transfer function with the actual response of the system, its performance can be evaluated. The comparison between the system and transfer function is shown in Figure 4.8.

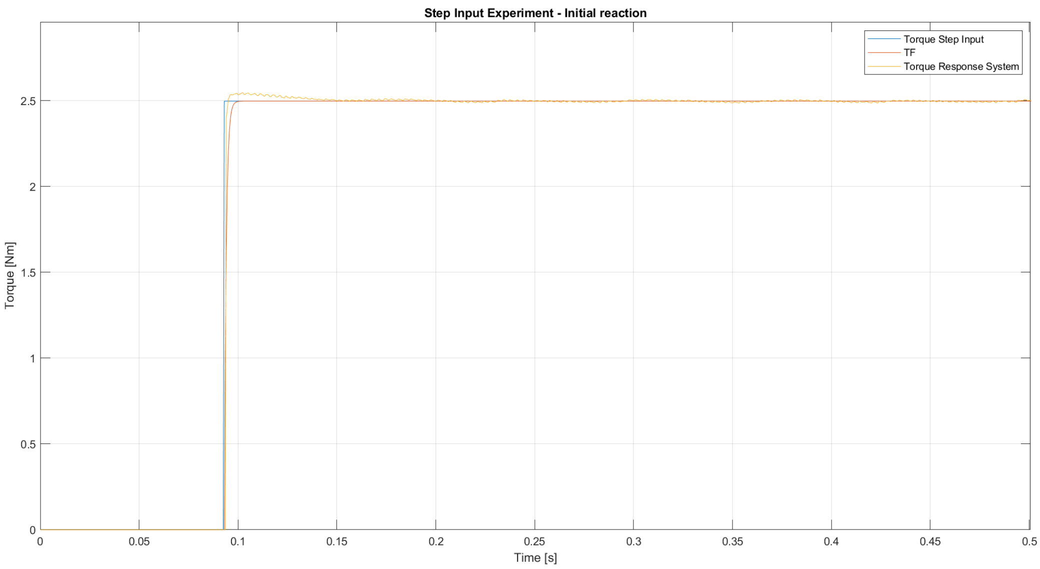


Figure 4.8: Step input, motor torque and transfer function response response

The speed cycle response shows the difference between the actual delivered torque by the system and the transfer function. This is tested by following the torque set point of a speed trapezoidal profile. This profile is chosen as it represents a frequently used input in industrial settings. The speed profile is shown along with the corresponding torque response in figure 4.9.

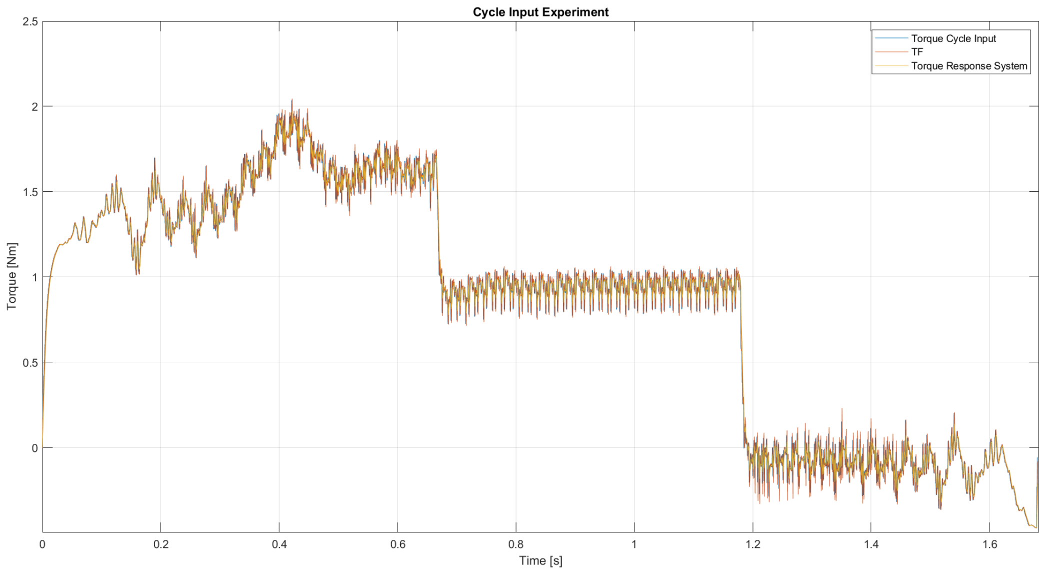


Figure 4.9: Torque set point, motor torque and transfer function response for a speed cycle input

The statistical analysis of the error between the transfer function and the electric motor torque response is performed. Both follow the same torque set point and are compared to analyse the fit. Looking at the statistics, the difference between the transfer function and the real response can be compared. The following statistical features are provided to assess the error, as shown in table 4.1.

Parameter	Description
T_error_Act-Sp [Nm]	Torque error of the actual generated torque and torque set point
T_error_TF-Sp [Nm]	Torque error of the TF torque and the torque set point
T_error_TF-Act [Nm]	Torque error of the TF torque of the system and the actual torque
REP_T_Act-Sp	REP of the actual torque and the torque set point
REP_T_Tf-Sp	REP of the TF torque and the torque set point
REP_T_Tf-Act	REP of the TF torque and the actual torque

Table 4.1: The parameters used for statistical analysis of the torque transfer function

The relative error percentage (REP) is used to show the relative error of the compared torque measurements. The percentage error is used, since the amplitude is relative to the signal. The mean, standard deviation, absolute maximum and the correlation are provided for the statistical analysis. The results are provided in Table 4.2.

The transfer function demonstrates a level of reproducibility deemed acceptable for this application. The following evaluation is concluded:

1. *The mean* of the transfer function and the actual torque are both close to zero. Therefore considered acceptable.

2. *The standard deviation* are both within 8% reach of each other, considered acceptable.

3. *The absolute maximum* is just over 1% in difference, considered acceptable

4. *The correlation* is under 0.1% difference, considered acceptable

Parameter	Mean	Std	AbsMax	Corr
T_error_Act-Sp [Nm]	0.00040405	0.073037	0.361	0.9941
T_error_TF-Sp [Nm]	1.4989e-17	0.067626	0.36476	0.99493
T_error_TF-Act [Nm]	-0.00040405	0.036381	0.21714	0.99854
REP_Act-Sp [%]	0.17334	6.9711	101.11	\
REP_Tf-Sp [%]	0.075891	7.1643	100	0.86412
REP_Tf-Act [%]	-0.091166	4.3684	100	\

Table 4.2: Statistical analysis of the system response and transfer function

The usage of the transfer function could result in suppressing behaviour of the electric motor. The natural frequencies of a gearmotor can be determined by a Campbell diagram, which is not available at SEW Eurodrive. This indicates that Campbell diagrams are not widely available in the industry. If available, the frequencies of the system and the motor can be checked to look for frequencies of resonance. The assumption is made that the transfer function does not suppress resonance of the electric motor and physical system. The requirement of visual inspection is proposed. As this model is simulating operational real-life systems working properly, this assumption is assumed valid for this scenario.

4.4. Gear Unit

The gear unit of the model is a three-stage gear unit, as shown in Figure 4.10. The pinions are indicated as **P** and the gears as **G**. A gear unit has mechanical and churning losses, which are discussed in Section 3.3.3. The three stages enable the identification of generated vibrations generated by gear meshing. The frequencies of interest are determined by utilizing the rotational speed of the rotor and the gear ratios. The product of the individual stage gear ratios is the total gear ratio i, in this case i=30.99.

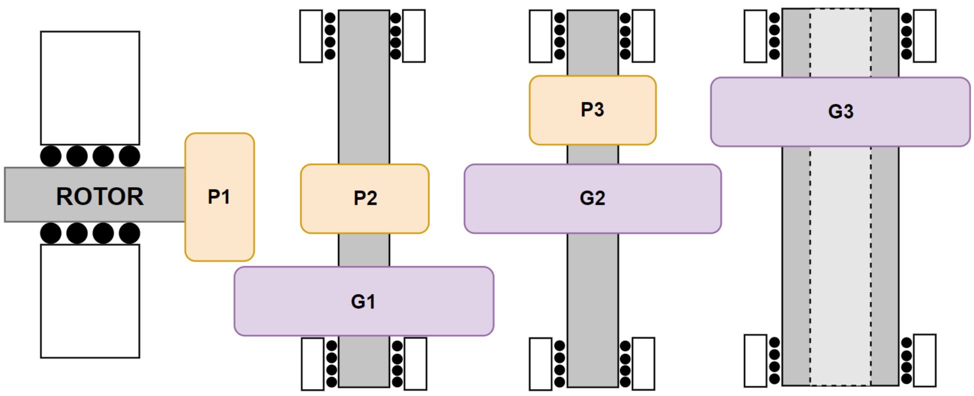


Figure 4.10: Schematic overview of the three-stage gear unit

The mechanical losses of the gear unit are acquired from SEW Eurodrive. Ranging from low speed and high torque load, to high speed and low torque load, the efficiency is 93% and approximated as a constant. The churning losses are speed, temperature and geometry dependent. Only the speed is known and for churning losses is little information is available at SEW. This parameter will be estimated and captured in the speed dependent losses of the model. The speed dependent losses are captured in the Equation 4.3:

$$T_{loss} = B_{total} \cdot \omega_{motor} \tag{4.3}$$

The assumption is made that the driving shafts of the electric motor and gear unit are infinitely rigid and therefore will not be modelled as a compliant shaft. This can be assumed because the stiffness of the shaft is negligible compared to the belt. Note that the losses of the gear unit counteract the movement of acceleration of the physical system, but aids in the deceleration phase. An overview of the gear unit conversion calculations is given in Table 4.3.

Parameter	Symbol	Equation
Motor output power	P_{motor}	$P_{motor} = T_{motor} \cdot \omega_{motor}$
Motor angular velocity	ω_{motor}	$\omega = \omega_{gearunit} \cdot i$
Gear unit output power	$P_{gearunit}$	$P_{gearunit} = \eta \cdot P_{motor}$
Gear unit output torque	$T_{gearunit}$	$T_{gearunit} = T_{motor} \cdot \eta \cdot i$
Gear unit angular velocity	$\omega_{gearunit}$	$\omega_{gearunit} = \frac{\omega_{motor}}{i}$

Table 4.3: Description of gear unit conversion calculations

4.4.1. Inertia Calculations

In chain belt conveyor systems the use of a gearbox is a common practice to increase torque, decrease speed and reduce the reflected inertia of the load on the electric motor. To determine the total reflected inertia, it is necessary to consider the inertia of the transported mass. This includes the applied load, belt, pulleys and coupling. Inertia's before and after the gear unit have to be calculated accordingly. The resulting total reflected inertia can be utilized for the appropriate sizing and selection of the motor. The inertia of the system is calculated from the electric motor side of the gear unit. It is common practice for the inertia of the belt to be simplified to a point mass rotating around the drive pulley, as shown in Equation 4.4.

$$J_{load} = m_{belt} \cdot r_{pulley}^2 \tag{4.4}$$

Where J_{load} is the inertia of the belt and applied load $[kg \cdot m^2]$, m_{belt} is the mass of the belt and applied load $[kg]$ and r_p is the radius of the driven pulley $[m]$. To determine the total weight of the belt the total length has to be calculated as shown in Equation 4.5 and Figure 4.11.

$$L_{belt} = 2 \cdot L + 2 \cdot \pi \cdot r_p \tag{4.5}$$

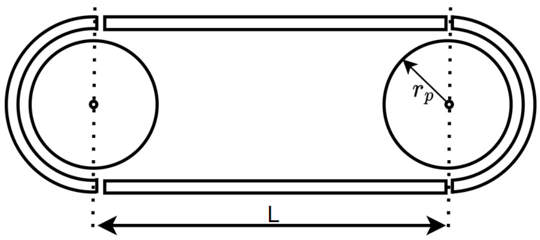


Figure 4.11: Calculation for the length of belt

The pulleys can be considered as thin-walled cylinders that are rotating around their axis. Their inertia is calculated as show in Equation 4.6:

$$J_{pulley} = \frac{1}{2} \cdot m_{cylinder} \cdot (r^2_{cylinder} \tag{4.6}$$

Here J_{pulley} is the inertia of the pulley as a cylinder $[kg \cdot m^2]$, $m_{cylinder}$ is the mass of the pulley $[kg]$ and $r_{cylinder}$ is the radius of the cylinder $[m]$.

To determine the total load deflected on the motor Equation 4.7 is used:

$$J_{total} = \frac{J_{load} + 2 \cdot J_{pulley} + J_{coupling}}{i^2_{gearbox}} + J_{gearbox} + J_{motor} \tag{4.7}$$

With J_{total} being the total inertia reflected to the motor, if present $J_{coupling}$ for the inertia of the coupling, $J_{gearbox}$ being the inertia of the gearbox and J_{motor} the inertia of the electric motors rotor $[kg \cdot m^2]$. The gearbox reduction is indicated as i. The magnitude of J_{pulley} can be considered negligible as it very small relative to the total inertia.

4.5. Chain Belt Conveyor

The general explanation for a chain belt conveyor is provided in Chapter 1. The basic analysis of the physical system is a chain belt conveyor is sliding over a guiding rails. This action can be simplified to a mass with a Coulomb's friction force with the sliding surface, as shown in Figure 4.12 [73]. The dynamics of a rigid body can be mimicked in practice with a setup of a gearmotor, driving a flywheel [74]. As flywheel loads exhibit no dynamics, this serve as suitable setups.

The model can be extended adding a spring stiffness K showed in Figure 4.13, instead of rigid body dynamics as shown in Figure 4.12. This stiffness K is unique to the driven chain belt and the specifications of the chain belt have to be determined in collaboration with the manufacturer. The collaboration required with the chain belt manufacturer to develop the K-stiffness model results in a limitation for the applicability. In the industrial setting the belt specifications are rarely known. This model would be less suitable for a generalized model for a chain belt conveyor.

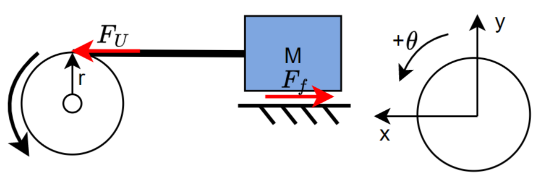


Figure 4.12: The rigid body simplification of the system

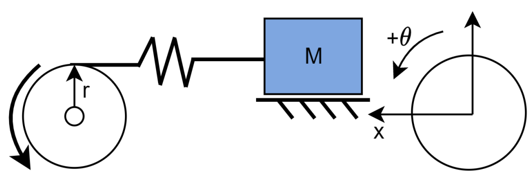


Figure 4.13: The spring mass model simplification of the system

The K-stiffness model is elaborated more to show the suggested model based on the "trailer-truck" principle. The mass of the gear unit and the belt interact and therefore this model is suggested. The equations of motion for Figure 4.13 for the electric motor part are:

$$J_{m+gb} \cdot \ddot{\theta}(t) = -B \cdot \dot{\theta}(t) + T_m + F_{spring} \cdot r_{pulley} \tag{4.8}$$

$$F_{spring} = k(x(t) - r \cdot \theta(t)) \tag{4.9}$$

The equations of motion for the part of the chain belt are suggested as:

$$m_{belt+load} \cdot \ddot{x}(t) = -\mu_s \cdot m_{belt+load} + k(r \cdot \theta(t) - x(t)) \tag{4.10}$$

The combination of the wide and easy applicability, little requirements for chain belt specifications and computational power, the rigid dynamics model is chosen. The K-stiffness model is suggested for future research with the preliminary work suggested. To determine the T_{load} Equation 4.11 is used:

$$T_{load} = F_{driving} \cdot r_{pulley} \tag{4.11}$$

Where $F_{driving}$ is defined as Equation 4.12 [42]:

$$F_{driving} = g \cdot L \cdot [\mu_s \cdot (q_K + q_G) \cdot cos\alpha + (q_K + q_G) \cdot sin\alpha] + F_{n-1} \tag{4.12}$$

Here g is the gravitational constant $[m/s^2]$, q_K is the weight per meter of the belt $[kg/m]$, q_G is the weight per meter of the transported mass $[kg/m]$, as shown in Figure 3.5.

Natural Frequencies Chain Belt Conveyor

To determine the natural frequencies of the belt the following calculations are performed. The frequencies of interest are induced by the belt characteristics. These characteristics are often not known by field engineers and is suggested for a more in-depth analysis of the system. The prediction of natural frequencies are not relevant for the field engineers that only have interest in the proper functioning of the chain belt conveyor. The spring stiffness of the chain belt conveyor is defined as shown in Equation 4.13:

$$K = \frac{E \cdot A}{L} \tag{4.13}$$

With K being the belt stiffness [N/m], E is the Young's modulus [Pa], A is the cross-section area $[m^2]$ and L the length of the element [m].

The lateral speed stress waves in the chain belt are determined by equation [43]:

$$c_1 = \sqrt{\frac{E}{\rho}} \tag{4.14}$$

Where E is the Young's modulus [Pa] and ρ the material density of the chain belt $[kg/m^3]$.

To determine the lateral natural frequencies of the chain belt, as Equation 4.15 follows [43]:

$$\omega_n = \frac{n \cdot \pi}{L} \cdot c_1 (1 - \frac{v_b}{c_1^2}) \tag{4.15}$$

Considering the dependency on length L the following stiffness profile can be assumed, as shown in Figure 4.14. This combined with Equation 4.15, shows the frequencies of the belt in Figure 4.15. The closer the transported mass is located to the driving pulley, the higher the stiffness and the generated frequencies of the chain belt conveyor, as shown in Equation 4.13. When the chain belt conveyor is in operation, the produced natural frequencies of the chain belt are changing over time. Note that the chain belt conveyor does not create one distinct frequency in the FFT analysis.

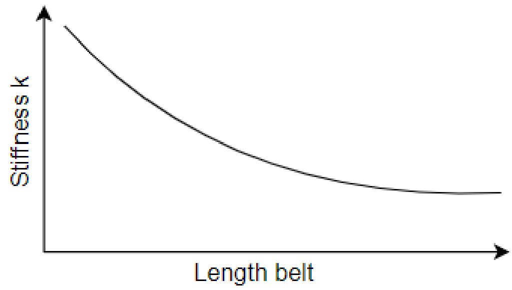


Figure 4.14: Stiffness of chain belt dependent on the length

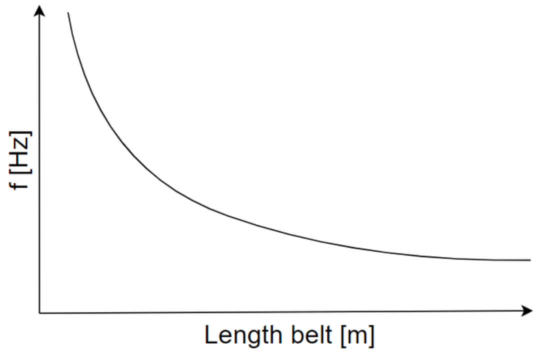


Figure 4.15: Natural frequencies of chain belt dependent on the length

4.5.1. Coulomb's Friction

The friction implemented in the model is the Coulomb's friction model. The friction is always in opposite direction of the motion, this is shown as a free body diagram (FBD) in Figure 4.16. The model is based on rigid dynamics,

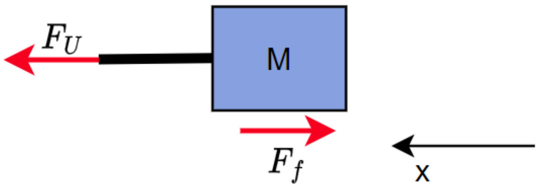


Figure 4.16: Free body diagram for the Coulomb's friction

The Simulink implementation is shown in Figure 4.17. Before the mass can move, the motor must first overcome static friction as seen in the main equation of motion 4.1. The absolute-block in combination with the sign-block is used to correct for negative and positive directions. This ensures that the rigid connection of the chain belt can move in positive or negative direction.

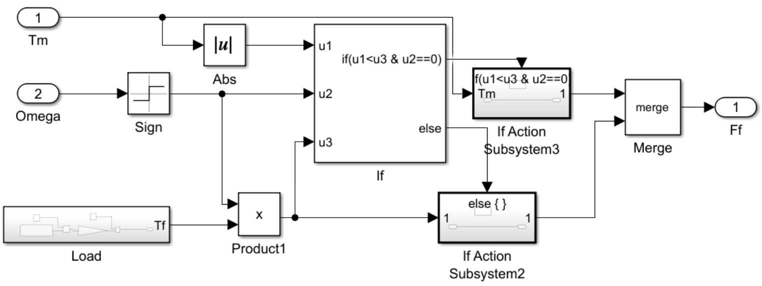


Figure 4.17: Matlab Simulink Implementation of the Coulomb's friction

4.6. Parameter Estimation

To identify unknown parameters of the system a parameter estimation method recursive least squares is used [75]. Recursive Least Squares (RLS) is a widely used method for parameter estimation. RLS is known for its fast convergence and adaptability to changes in the system. The convergence of RLS depends on various factors, such as the choice of initial parameter estimates, the accuracy of the data and the presence of noise in the data. The cost function used is the sum of the squared error.

In some cases, RLS may converge to a local optimum instead of the global optimum. This can happen if the initial parameter estimates are too far away from the true values, or if the data is noisy and contains outliers. In such cases, the algorithm may get trapped in a local minimum and fail to converge to the global optimum. To improve the chances of RLS converging to the global optimum, it is important to choose appropriate initial parameter estimates. Pre-processing the data to remove noise and outliers can improve the parameter estimation, but is not performed. The in-depth analysis of the convergence (global and local minima and maxima) of the estimated parameters is outside of the scope of this research project.

To determine the coefficients, an initial guess is provided. For example, the coefficient of friction is known to be approximately 0.25. Therefore, this is provided as the initial condition with desired boundaries (Lower boundary, initial guess, upper boundary). The parameter estimation can be showed as followed in Table 4.4:

Parameter	Description	Threshold	Unit
μ_s	Coefficient of friction of chain belt and rails	[0.1 ; 0.25 ; 0.5]	/
$mass_{load}$	Transported mass of the load on the belt	[0 ; 10 ; 100]	kg
BmA	Constant loss factor	[0 ; 0.13 ; 1]	Nm
BmB	Speed dependent loss factor	[0 ; 0.29 ; 1]	$Nm/(rad/s)$
BmC	Quadratic speed dependent loss factor	[0 ; 2.8e-20; 1]	$Nm/(rad/s)^2$

Table 4.4: Estimated parameters with the initial guess and boundaries

When the coefficients of interest are determined, the model is updated to the best fitting model. This implies the model will have the best fit according to the provided data set. By initializing the model in a healthy state, the estimated parameters can be identified and compared to estimated parameters in later stages. A healthy state is considered as t_0, and is used to initialize the healthy state estimation of the parameters, as shown in Figure 4.18. A desired threshold can be used to determine anomalies in the system. These boundaries have to be established based on experience of the field engineer and over time data sets. The threshold in predicted values can be compared to outliers in a fuzzy logic approach, as shown in Figure 4.19 [76]. If the estimated parameter is out of the expected thresholds in multiple data sets, this can be an indication for anomalies in the physical system.

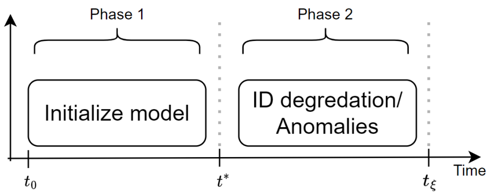


Figure 4.18: The initialization and anomaly detection phase of the model

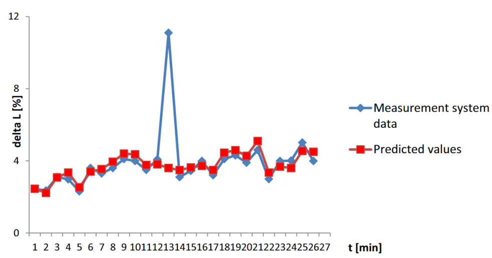


Figure 4.19: Example of outlier in predicted value and measured data [76]

4.7. Frequency Domain

Fast Fourier Transform

The fast Fourier transform (FFT) is used to create insights on the frequencies present in the analysed signal. Using a logarithmic amplitude scale allows for clear distinguished amplitudes of frequencies in the FFT. By comparing amplitudes of FFTs the frequencies of interest can be determined. The frequencies of interest can also be predetermined based on known parameters such as the rotor speed, number of stages in the gear unit and number of teeth on the sprocket. The frequency analysis and amplitude comparison is performed in Matlab.

Order Analysis

The order analysis is used to create insights in specific frequencies associated with the rotational speed of the motor. By comparing the vibration signals obtained at different times, it is possible to identify changes in the system. The order analysis can provide insights, as frequency analysis on rotary machinery is heavily correlated to rotational speed. The order analysis is performed in Matlab.

The main difference is the FFT is used to analyse the frequency content and amplitude of the signal, while the order analysis identifies specific frequencies associated with the rotational speed. Both methods are used as they provide a broader spectrum of frequency analysis of the data sets. Changes in amplitudes for specific frequencies are an indication for anomalies.

Mechanical Frequency Prediction

The mechanical chain belt conveyor system generates natural frequencies, which are of interest for possible resonance. By predicting the frequencies of interest, more insights in the frequency domain is created. The natural frequencies depend on characteristics of the mechanical system. By acquiring these specifications, frequencies of interest can be determined. The predicted frequencies are not always distinct frequencies in the FFTs. The difference in present generated frequencies depends on the mechanical component.

4.8. Residual Analysis

The residual analysis is the analysis of the error between the actual data collected from the system (y) and the predicted data from the model ($\hat{y}$), as shown in Equation 3.3. First, the parameter estimation is performed to approach the optimal fit of the model and the collected data set from the physical system. This minimizes the error based on the cost function of the parameter estimation. The residuals are analysed to understand the statistical features of the residuals. The following statistical approach is proposed. Due to the lack of data over longer periods of time, this is seen as exploratory and a method of comparison data.

4.8.1. Statistical Residual Analysis

The statistical analysis of the residuals is a proposed method to analyse the statistical characteristics of the residuals. By comparing statistical features, residuals of different data sets can be compared and insights can be gained. To determine the thresholds for the statistical features, the analysis with failure data over longer periods of time need to be performed. By mapping the changes of a feature, the threshold for failure can be established. Failure data plays a role for statistical analysis to be valuable. Since failure data is not present, the statistical analysis is used to create insights in the analysis and comparison of the residuals. The used statistical analysis features are shown in Table 4.5.

Statistical feature	Anomaly Detection
Mean	When more/less torque is required, it increases/decreases.
Median	When more/less torque is required, it increases/decreases.
Max Peak	Anomaly results in higher peaks
RMS	With failure, increase/decrease
Kurtosis	Anomalies cause more peaks.
Correlation	Decreases when the level of noise rises

Table 4.5: Features for statistical residual analysis

4.9. Transport Loss Factor

The Transport Loss Factor is defined as the ratio of the mechanical work W_M (or energy E_M) required to drive the transport system and the transport work W_T (or performance E_T) for the displacement of a payload with weight of F_{pay} over a certain distance L [70–72]. The efficiency of the electric motor is not included, since only the driven physical system is of interest. Similar chain belt conveyor systems can be compared for performance, providing an indication of performance, efficiency and anomalies. The efficiency of the system can be assessed to promote the importance of efficiency and sustainability.

The chain belt conveyor systems of interest do not have any elevation differences. The transport loss function, without accounting for differences in heights, is shown in Equation 4.16:

$$f_T = \frac{W_M}{W_T} = \frac{\sum(F_{Di}|L_i)}{\sum F_{payi}|L_i|} \tag{4.16}$$

4.10. Concluding Remarks

The dynamics of the model are based on the main equation of motion. The position controller is replicated from the actual chain belt conveyor of interest. The data sets acquired from the physical system provides the inputs for the model and serves as comparison. The electric motor is modelled using a transfer function derived by experiments using a flywheel model. The gear unit is modelled by the mechanical efficiency and the speed dependent losses. For the belt two models are proposed. Due to simplicity, the easy applicability and the little requirements of the model, the rigid body dynamics is selected. The parameter estimation of RLS is proposed to estimate parameters of the physical system for system identification and to estimate the weight transported on the chain belt. The frequencies of the data are analysed using FFTs and order analysis. The statistical residual analysis is proposed to analyse the statistical nature of the residuals. This creates insights of the residuals and allows for comparison. The transport loss factor is used to determine the performance of a chain belt conveyor. If differences occur in the results, an implication for anomalies can be suggested. To ensure anomalies, it is suggested to have an "X" amount of anomalies in a "Y" amount of data sets as a threshold. For example, in 3 out of 10 data sets, an error must occur to confirm the anomaly. This to prevent flagging every single anomaly, as the industrial setting is prone to creating faulty data sets.

Chapter 5

Model Verification and Validation

The implementation of the model is presented in the Methodology (Chapter 4). To demonstrate the proper functioning of the model, verification and validation is performed. Creating a digital twin model of a chain belt conveyor requires a thorough verification and validation process to ensure that it closely mimics the physical system it is based on.

5.1. Verification

The verification of the model implies ensuring that the model and its implementations are "correct". The verification is ensuring that the model is performing as intended, based on the reasonable presented theory. The model is verified in three ways: code inspection, visual checks and the results of test case scenarios.

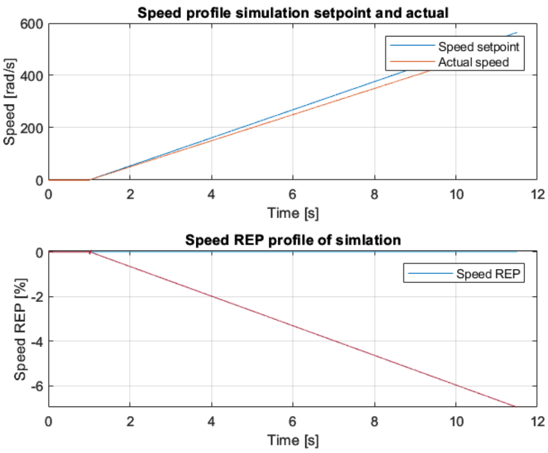
First of all, the model has been thoroughly inspected to ensure the right equations and principles are used. By individually checking components, the working of each component is ensured. Secondly, in collaboration with SEW engineers the model is checked for the mathematical model and implementation. Finally, the results of the model are tested and inspected. It should be noted that the use of this specific controller with feedback loops is expected to result in a lagging behavior. The use of a feedback loop will always result in lagging behaviour. The exact position controller used replicated from the physical system, therefore the assessment of the performance of the controller is not the goal. There is no tuning of gains or other parameters. The exact same parameter settings are used in the model as for the physical system. The objective of verification is to verify the behaviour of the model. To test the model, different inputs are provided and results are analysed. These inputs are not always representative for industrial applications. These different cases for inputs show the model is made correct.

The initial speed profile consists of a positive and negative ramp profile, shown in Figure 5.1a and A.2. This profile is not used in the industry, but the model follows the input nicely for a positive and negative ramp. This case is assumed valid.

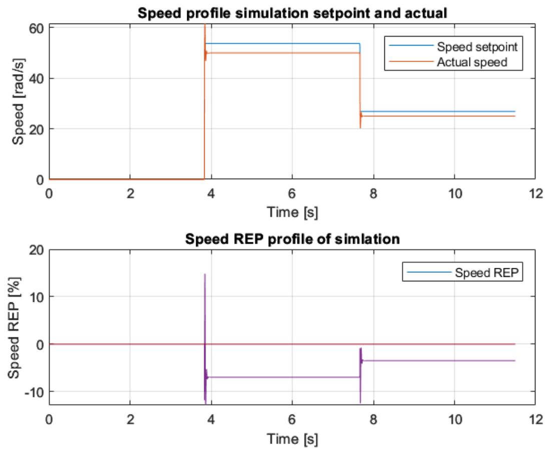
The second speed profile includes a positive and negative stairs profile, shown in Figure 5.1b and A.4. The stairs profile is not used for the speed profile, as the sudden steps result in a lot of strains on the system. These steps result in fast accelerations of the system, potentially damaging the system. The model follows the inputs as expected. This case is assumed valid.

The third speed profile consists of a trapezoidal speed profile with both positive and negative slopes, shown in Figure 5.1c and A.6. This profile is widely used in the industry and very representative for a verification. Both the negative and positive slopes are followed properly. This case is assumed valid.

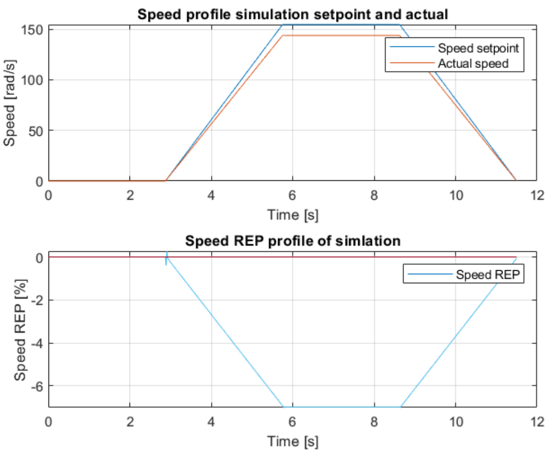
The fourth speed profile consists of a positive and negative trapezoidal profile with 2 different accelerations, shown in Figure 5.1d and A.8. The two accelerations are chosen as this is of interest to see the reaction of the model. The model follows the speed profile with two accelerations properly. This final case is assumed valid.



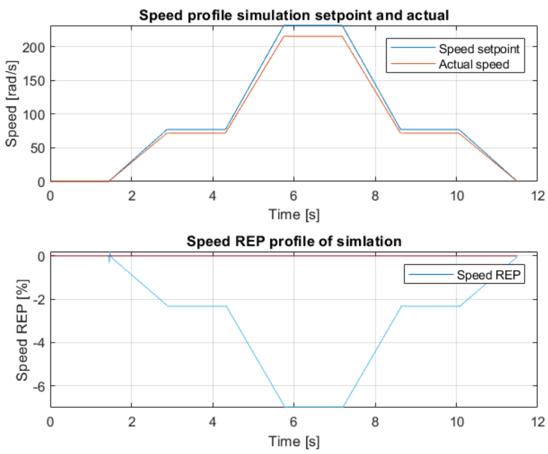
(a) Speed profile and REP for a positive ramp speed profile input



(b) Speed profile and REP for a positive Stairs speed profile input



(c) Speed profile and REP for a positive trapezoidal speed profile input



(d) Speed profile and REP for a positive trapezoidal speed profile input with 2 different accelerations

Figure 5.1: The results of different input profiles and the REP profile

5.2. Validation

To show the validation of the model the following method is used. The modelled chain belt is compared to the actual data acquired from the operating physical chain belt conveyor systems. By comparing the model in two ways, the validation is performed. The transported weight is known, so the only unknown parameters are the parameters for physical system. This can be considered as the system identification part of the parameter estimation.

Simulation Analysis and Comparison

The used belt is from now on referred to as "The white chain belt". The derived transfer function is based on the same electric motor used for the white chain belt conveyor. This gearmotor is commonly used in chain belt conveyor systems. The data set used is for the transportation of 10 kilogram weights on a tray that weighs 10 kilogram (20 kilograms total). The data set is collected with a sample time of 6 milliseconds. This is done to ensure the entire movement cycle of the tray is captured. The white chain belt conveyor torque profile is shown in Figure 5.2 and speed profile in Figure 5.3.

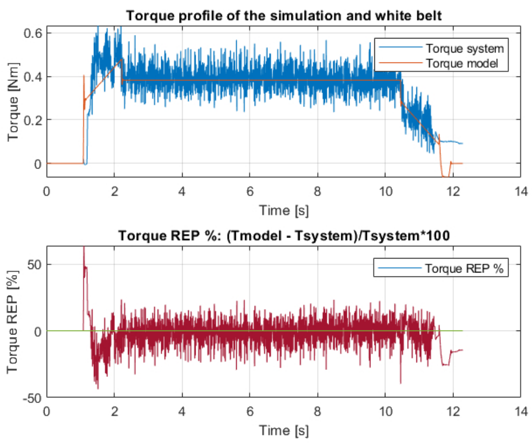


Figure 5.2: White Chain Belt: The torque profile of the model and physical system compared

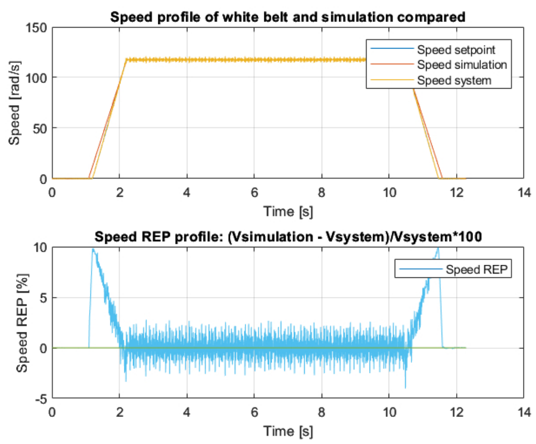


Figure 5.3: White Chain Belt: The speed profile of the model and physical system compared

The model follows the movement of the white chain belt conveyor properly. The REP is used to indicate the error of the model and physical system. The start-up phase shows the largest discrepancy. The acceleration phase of the system covers all phenomenons and initial misalignment's of the system. The largest REP is as expected in the acceleration phase. When looking at the speed

Parameter Estimation Analysis

The analysis of the estimated parameters is performed for the validity of the model. The estimated parameters are system identification of the physical system. The estimated parameters, when transporting 20 kilograms, are shown in Table 5.1. The friction coefficient is in range with the expected value for μ of 0.20-0.25. This results from an interview with the manufacturer of the chain belt conveyor Ammeraal Beltech. The quadratic speed dependent losses BmC are very small compared to BmA and BmB. These can potentially be neglected in the future case study. The speed dependent losses BmB are the dominant factor and BmC are very small relative to the other factors and can therefore be neglected.

Parameter	μ_s	BmA $[Nm]$	BmB $[Nm/(rad/s)]$	BmC $[Nm/(rad/s)^2]$
White Chain Belt	0.23	1.1e-4	2.1e-3	4.1e-21

Table 5.1: The estimated parameters of the two belts with 10kg load

Residual Analysis

The residuals of the white chain belt are statistically analysed. This allows the analysis of the statistical nature of the residuals. The analysis is performed to provide insights, but requires more research for decisive conclusions. The statistical residual analysis is performed and presented in Table 5.2. The closer the mean of the residuals are to zero the smaller the overall error. Looking at the standard deviation this is in range. The correlation of the transfer function and the actual torque is within the industrial 5% benchmark. The high kurtosis indicates a signal with a lot of peaks. This is confirmed by visual inspections.

Parameter	Mean [Nm]	Std [Nm]	AbsMax [Nm]	Corr	Kur	RMS [Nm]
Residuals White Belt	-0.016	0.099	0.526	0.962	214.560	0.072

Table 5.2: The statistical residual analysis of the white chain belt conveyor

FFT and Order Analysis

To analyse the detection of anomalies in an FFT and the Order Analysis the following experiment is conducted. In an experimental setup 5 data sets are acquired, using the same weight for the belt. This means that the same weight has been transported 5 times by the same chain belt conveyor. No data over longer periods of time is available, so changes in FFTs can not be shown. What can be shown is no changes show in the FFTs when comparing 5 different collected data sets transporting the same weight. The 5 original data sets are analysed for frequencies with FFTs on the torque parameter. As this parameter contains the most frequencies in relation to the system, this parameter is selected. First the four FFTs of the data sets are shown in Figure 5.4. As the y-scale is logarithmic, the amplitudes can be assumed similar. The small amplitude differences are very small in comparison. The conclusion can be drawn that 5 unique data sets transporting the exact same weight do not have different amplitudes in the FFT.

Parameter Estimation Convergence

To test the behaviour of the model regarding to parameter estimation for local maxima and minima, the following test is conducted. In the Literature Review 3, the importance of the initial conditions of the parameter estimation are discussed. To test for convergence, the parameter estimation is performed with multiple initial conditions. By changing the initial conditions of the parameter estimation, the importance of the chosen initial conditions are emphasized.

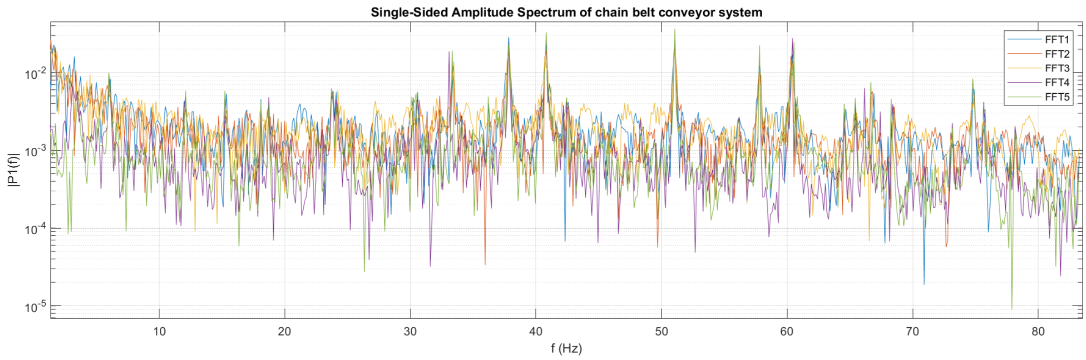


Figure 5.4: All five FFTs plotted

The initial conditions of the estimated parameters are determined by an initialization run. Thereafter, the mass is estimated with different initial conditions of the parameters. Test one: Estimating the mass transported by the chain belt conveyor. The model is initialized with a 10 kilogram mass on a 10 kilogram tray. The parameters associated with this initialization are chosen as initial parameter constants.

Parameter	Value
Mass	20 kg
μs	0.22
BmA	1.1e-4
BmB	2.6e-3
BmC	4.1e-21
Parameter tolerance	1e-05
Function tolerance	1e-05

By changing the initial condition, the convergence of the parameter estimation can be studied. The guessed initial condition is including the tray. So an initial guess of 30 kilogram indicates the 10 kilogram tray and a 20 kilogram mass. The change in convergence is presented in Table 5.3. The influence of the initial conditions is presented when estimating weight.

Initial Condition Guess	10	20	30	40	50
Estimated Mass	19.05	/	20.07	20.15	20.16
Initial Condition Guess	60	70	80	90	100
Estimated Mass	20.64	20.37	20.35	20.40	20.49

Table 5.3: Table of difference in mass estimation with different initial conditions

The following test is performed to see how well the model can estimate parameters without any predefined knowledge. The following initial conditions and boundaries are provided, shown in Table 5.4. It is shown that initializing the model decreases the levels of freedom of the system and allows for a more accurate identification of the systems parameters.

The conclusion can be drawn that the initial conditions and initialization of the model are of great importance for the parameter estimation for system identification. Minimizing

Parameter	Initial condition	Predicted value	Estimation with mass known
Mass	10	9.37	20 (Set)
μ_s	0.3	0.23	0.21
BmA	0	5.7e-07	1.1e-4
BmB	0	2.8e-3	2.6e-3
BmC	0	1.5e-34	4.1e-21
Parameter tolerance	1e-05	/	/
Function tolerance	1e-05	/	/

Table 5.4: Table of comparison in parameter estimation with different initial conditions

the amount of estimated parameters results an increase in accuracy. This is expected and has to be taken into account. The effect of the initial conditions of estimated parameters is suggested to be studied in a future continuation of this project. The behaviour of the convergence is out of the scope of the project. The importance of the initial conditions is emphasized and has to be taken into account when performing parameter estimation for system identification using the model.

5.3. Concluding Remarks

The verification and validation of this model has been shown in this chapter. By providing multiple different inputs for the model, analysing the output of the model with the predicted behaviour, the verification of the model has been shown. The validation has been shown in multiple ways. The chain belt conveyor model is compared to data from an physical chain belt conveyor. The parameter estimation coefficients, used for system identification, are explained and analysed. The statistical analysis is performed to show the statistical nature of the residuals. Since no data over longer periods of time is available, the ability to show differences in amplitudes of FFTs can not be validated. It is shown that the FFTs from multiple different data sets of the exact same transported weight do not change. Finally, the convergence of the parameter estimation is shown. Using an initialization using a 10kg weight on a tray, the method to determine initial conditions has been established. The importance of the initial conditions and initialization is demonstrated by changing initial conditions and comparing the outcomes.

Chapter 6

Case Study - SEW

6.1. Model Case Study: SEW Eurodrive

A case study was conducted at the SEW Eurodrive facility in Rotterdam, The Netherlands. This site houses a manufacturing plant where numerous SEW Eurodrive products are assembled. In order to optimize production and reduce the workload for production workers, various chain belt conveyor systems are utilized. The case study focuses on these chain belt conveyors to utilise the developed chain belt conveyor model. The primary objectives include estimating unknown system parameters for system identification, investigating anomaly detection, testing dynamic weighing techniques and evaluating system performance.

Figure 6.1: White chain belt conveyor SEW Eurodrive

Figure 6.2: Blue chain belt conveyor SEW Eurodrive

Facility Overview

A total of three sequentially placed chain belt conveyors were analyzed. The first and last chain belt conveyors consist of straight sections, the middle chain belt conveyor features a turn. From now on, the first belt will be addressed as the "Blue belt" and the last belt as the "White belt". These two straight section belts are the belts of interest. When assembling the SEW Eurodrive gearmotors, they are placed on a solid plastic tray that weighs approximately 10 kilograms. The chain belt conveyor is designed to pause at specific locations to facilitate final tests and inspections on the gearmotor. After the tests and inspections are completed, a SEW worker manually activates a switch, resulting the tray to proceed to the next defined position.

The entire motion, consisting of acceleration, constant speed and deceleration, is referred to as a "cycle". Each tray carrying a gearmotor undergoes five cycles to reach the end of the chain belt conveyor sequence. Consequently, a total of five data sets are collected for analysis. To simplify the system, a schematic overview was developed, illustrating each individual cycle. For this case study, the systems of interest are the blue and the white of the belt conveyors, as illustrated in Figure 6.3.

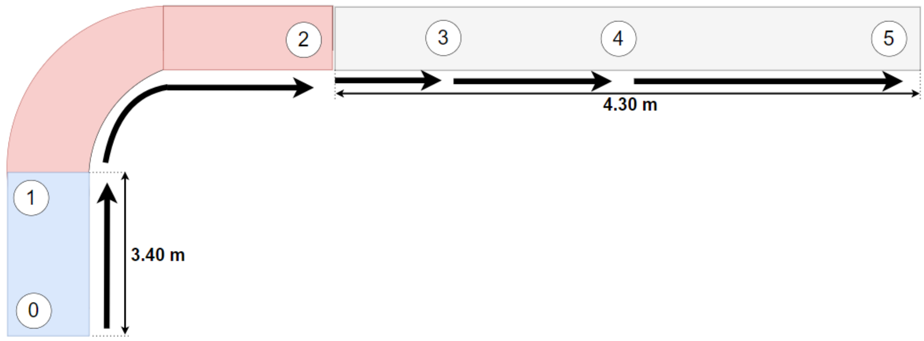


Figure 6.3: Schematic lay-out of the chain belt conveyors at SEW Eurodrive facility

Collected Data

The following procedure is performed to collect the data sets from the chain belt conveyors. First, the parameters of interest have to be selected. For this case study there are 7 parameters of interest, as explained in Chapter 4.2. The correct 7 parameters have to be selected as there are many different possibilities of the specific units of the parameter. The torque parameter is considered the main parameter of interest as it allows for the analysis of the interaction between the gearmotor and driven system. Using these parameters, the measurement is created and needs to be activated for the system to collect data sets.

The creation of all the data sets for this case study is as follows. Weights are placed on the plastic trays and transported by all three chain belt conveyors. The trays are the exact same as the trays used by SEW Eurodrive employees in the production process. The weights used are weighed individually and labeled, as shown in Figure 6.5. The data sets created consist of the belt being empty (no tray), an empty tray and weights on the trays. The weight is varied from 0 to 100 kilograms, in steps of 10 kilograms. This results in 11 different kinds of data sets by weight. Every data set is created by manually changing the amount of weights on the tray. Every combination of weight on the tray is measured at least 2 times. This ensures that the data sets match and faulty data sets are not assumed to be correct. In an industrial setting, like the production facility of SEW Eurodrive, the collection of data sets can be prone to faults. This results in data sets not capturing the full cycle of the chain belt conveyor. In total there are 335 data sets created for this case study.

The data sets collected from the physical system always follow a speed trapezoidal input per cycle. This speed trapezoidal input is collected as the speed and position set points and are used for the inputs of the model. By using this as the input for the model it is ensured the model uses the exact same input as the physical system. The acceleration, maximum speed and deceleration is the same for every cycle, this is shown in Figure 6.6. The gap indicates the amount of time the belt moves with a constant velocity, which is varying per cycle

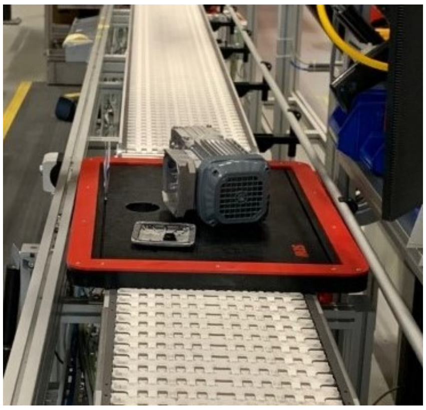


Figure 6.4: A transported gearmotor

Figure 6.5: The labelled transported weights

depending on the length of the belt.

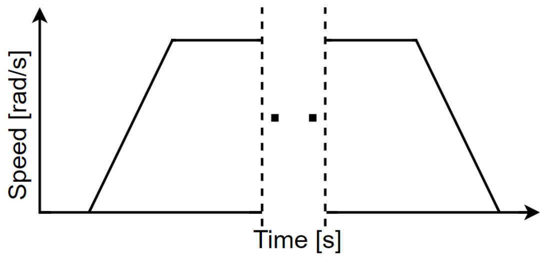


Figure 6.6: Speed trapezoidal per cycle

The data sets collected from the system contain 7 parameters, shown in Table 6.1. These parameters are selected as the fundamental requirements to model the physical system. Previously, it has been discussed that the industrial setting is a limiting factor for the duration of the measurement. Therefore, the choice has been made to use 3 different sample times. To capture the most detailed behavior of the system, a sample time of 1 millisecond (the highest possible sample time) is used. Using a 1 millisecond sample time only partially captures the cycle of the belt, which is limiting the model. To capture the full cycle of motion, a minimum sample time of 6 milliseconds for the final white belt must be used. To capture the entire cycle of the first blue chain belt, a sample time of 12 milliseconds is used. This difference in sample time results in a different window of captured frequencies by the FFT.

Number	**Parameter**	**Unit**
1	Speed setpoint	rad/s
2	Actual speed	rad/s
3	Position setpoint	rad
4	Actual position	rad
5	Torque setpoint	Nm
6	Actual torque	Nm
7	Digital inputs	/

Table 6.1: All parameters measured in a single data set

6.1.1. Specification of Systems of Interest

The chain belts of interest are the first (blue) and the third belt (red). In collaboration with Ammeraal Beltech and online research, the specifications of the last white belt is acquired. The specifications of the blue belt are unknown except the length, width and estimation of weight. The white chain belt conveyor type is a plastic modular belt, the "Uni Flex ONE K1200" from Ammeraal Beltech. The maximum amount of known parameters for the model are collected. The following set of parameters for the belts are known, shown below in Table 6.2:

Parameter	**Blue: Value**	**White: Value**	**Unit**
Material density	\	1410	kg/m^3
Young's modulus	\	2.7	GPa
Length belt	3.4	4.3	m
Weight belt per meter	\	4.1	kg/m
μ_s	/	0.2-0.25	/
Diameter pulley	0.08	0.121	m

Table 6.2: Table of predefined parameters of the physical system

6.2. Experiments

In order to utilize the obtained data, multiple experiments are conducted. The results are compared and analysed to demonstrate the practical application of the model. By creating distinct cases, the results and highlights of the functionality are presented. Besides this, any relevant analysis or observations are elaborated and explained.

Figure 6.7 presents a graphical illustration of various data sets corresponding to driving weights in the system. For a better visual distinction between the data sets, a cut-off filter is used. A clear distinction among the weights can be observed. The model is expected to exhibit discrepancies primarily in the acceleration and deceleration phases, as these stages encompass numerous phenomena and intricate behaviors.

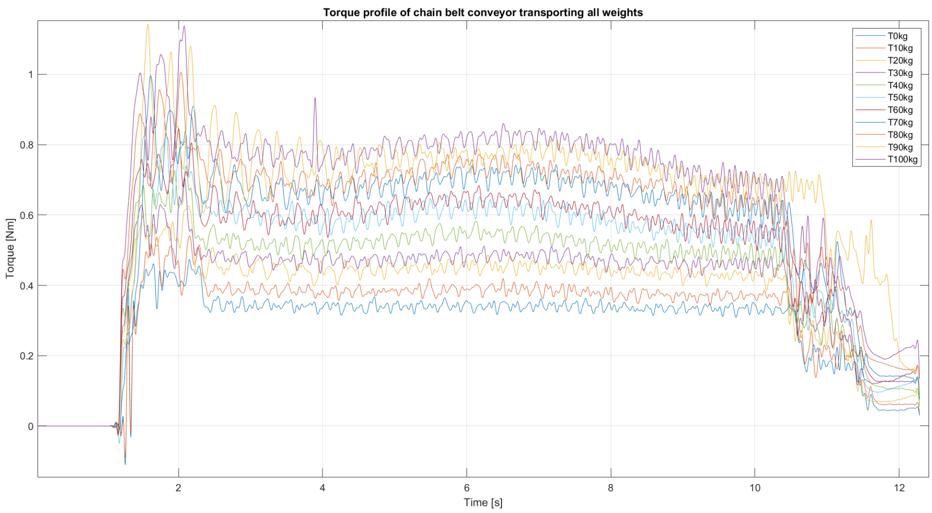


Figure 6.7: Overview of the generated torque plot for all weights

6.2.1. Experiment One

In the first experiment, addressed as "Experiment One", the purpose is to identify unknown parameters of the physical system for system identification. The data sets with known weights ensures minimizing the free variables for parameter estimation. The less variables for parameter estimation, the more accurate the parameter estimation for system identification. This approach can be used as a benchmark to show the most accurate estimation of the physical systems parameters. This case uses the maximum possible known parameters and therefore chosen as the first conducted experiment. Initial conditions play an important role for parameter estimation, all initial values for the parameter estimation are based on the empty tray (0 kg) estimation.

The estimated coefficients are the losses BmA (friction constant in Nm), BmB (viscous dampening $Nm/(rad/s)$) and the coefficient friction μ of the chain belt conveyor. The coefficient BmC, for the quadratic speed dependent losses in $Nm/(rad/s)^2$, is neglected to its minimal contribution. The initial incentive of the quadratic speed dependent loss coefficient was to capture losses from the fan attached to the rotor (for cooling purposes). All parameters are constrained within a range of 0 to 1. The initial conditions are the same for every performed parameter estimation, the importance was shown in the validation. The results are presented in the following Table 6.3:

Parameter	0 kg	10 kg	20 kg	30 kg	40 kg	
μ_s	0.23	0.23	0.22	0.23	0.22	
BmA	1.1e-4	1.1e-04	1.1e-04	1.1e-04	4.6e-5	
BmB	2.3e-3	2.1e-3	2.5e-3	2.3e-3	2.6e-3	
Parameter	50 kg	60 kg	70 kg	80 kg	90 kg	100 kg
μ_s	0.24	0.22	0.20	0.22	0.22	0.20
BmA	8.9e-4	1.0e-4	1.1e-4	1.1e-4	1.1e-4	1.4e-4
BmB	2.2e-3	1.6e-3	2.5e-3	2.5e-3	4.8e-3	3.4e-3

Table 6.3: The parameter estimation for system identification of the white belt

The results are analysed and the following conclusions are drawn. The amount of weight transported does not change the coefficient of friction of the belt. The coefficient of friction for 100 kilograms decreases by 10-15% compared to the empty tray. The following analysis is made. The more weight is transported by the system, the more efficient it runs. This can not be shown since there is no data with higher mass. The other possibility is that, as seen in Figure 6.7 the amount of torque required for the constant speed is not constant. Comparing the empty tray versus the 100 kilogram tray, the constant speed section results in an arch. This is an increasing trend with increased weight. The industrial setting can generate inconsistent data sets, more data sets allows for testing the accuracy for outliers. The physical system can be tuned to a different weight or bending due to the amount of weight. This results in an increase of torque over the constant speed section of the cycle. The model does not account a change in coefficient of friction. Real life observations of the system showed that the belt would move more smooth and constant when the amount of transported weight is increased. The increased weight on the belt ensures more tension in the belt. This pretension ensures less influence of phenomenons like stick slip. This conclusion is also drawn from the interview with Ammeraal Beltech. The proportion of speed dependent losses BmB related to the total generated torque ranges from a minimum of 30% to a maximum 80%. The chain belt is operational by SEW Eurodrive in the 10 to 40 kilogram range for transported weight. This implies that all the higher weights are part of the case study and do not occur in the factory.

The parameter estimation is used to identify coefficients in the system and the overall results are consistent, indicating a robust model. For the coefficient of friction this is as expected, as the amount of transported weight should not change this parameter. The cost function, characterized by the sum of squared errors, is impacted by the cyclical nature of the system, with variations in transported distance during acceleration, constant speed and deceleration phases potentially affecting the accuracy of the parameter estimation. The speed dependent losses, BmB, are dominant compared the constant loss factor BmA. More research is required to pinpoint the churning losses and to decouple them from the system. It is of great importance for the data set to contain the complete cycle of the movement.

Statistical Residual Analysis Case One

The statistical analysis is performed on all residuals of all data sets for different weights. The model is fit using parameter estimation, the coefficients used can be seen in Table 6.3 and the residuals are statistically analysed. Comparing the statistical analysis of the residuals gives insights in the behaviour of the weight increase on the model and physical system. This is presented in Table 6.4.

Parameter	Mean [Nm]	Std [Nm]	AbsMax [Nm]	Corr	Kur	RMS [Nm]
0 kg	-0.003	0.117	2.473	0.927	238.690	0.117
10 kg	-0.016	0.099	2.138	0.915	216.660	0.101
20 kg	-0.002	0.059	0.312	0.942	4.097	0.059
30 kg	-0.010	0.072	0.388	0.933	3.267	0.073
40 kg	0.025	0.068	0.400	0.948	3.897	0.072
50 kg	0.014	0.122	1.070	0.905	9.048	0.123
60 kg	0.006	0.072	0.488	0.909	5.725	0.072
70 kg	-0.001	0.075	0.430	0.945	5.154	0.075
80 kg	0.004	0.084	0.537	0.949	5.249	0.084
90 kg	-0.036	0.153	0.939	0.933	8.048	0.157
100 kg	-0.003	0.152	1.770	0.954	11.223	0.152

Table 6.4: Statistical analysis of the residuals

The mean shows that the residuals are close to zero. Taking the standard deviation into account this shows no odd behaviour. The standard deviation is in the same ballpark for all estimations. This is a good indications for disparsity of the data compared to the mean. The increase of the standard deviation for 90 and 100 kilograms is of interest, as expectation of the increase in weight was a lower standard deviation. The absolute maximum is a difficult parameter to interpret as the industrial setting can result in peaks because of the systems behaviour. This will show as the maximum torque value in the data set but is not always representative. The maximum torque changes for many data sets of similar weight. When the same weight is transported a different maximum torque can be generated due to the belt being stuck or other reasons. The correlation is based on the actual generated torque by the physical system and simulated torque. The results show the correlation is all in the same ballpark around the 93%. The correlation is used to check that the generated torques are matching. The kurtosis relates to the tailedness of the residuals. As expected the lower weights perform worse, as an increase in weight results in a more stable cycle. This is confirmed from visual inspection and by an interview with Ammeraal Beltech. The RMS decreases as the weight increases. This indicates that the magnitude of discrepancies between the model and system are decreasing. Similar to the standard deviation, the 90 and 100 kilogram data sets are higher than expected. The RMS and standard deviation are used together for the analysis of the discrepancies.

6.2.2. Experiment Two

In the second experiment, addressed as "Experiment Two", the belt, the friction coefficient μ_s and losses (BmA, BmB) are initialized. Initialization is carried out using the known weight of the belt and tray. This is done to minimize the parameters for the initialization of the belt. By using these initialized values for parameter estimation, the following load estimations are obtained and presented in the table 6.5 The results are collected for the results

Parameter	0 kg	10 kg	20 kg	30 kg	40 kg	50 kg
mass (mu=0.23)	/	9.6	19.3	29.6	40.4	50.8
Parameter	60 kg	70 kg	80 kg	90 kg	100kg	
mass (mu=0.23)	60.3	71.5	76.6	92.7	104.9	

Table 6.5: The estimated load when initializing the coefficients with an empty tray

of dynamic weighing when initialising the model with an empty tray. The worst performers are the estimation of 80 kg and 100 kg. Both are within approximately 5% of the actual weight transported by the physical system. The 95% accuracy is achieved, meeting industry standards. The chain belt operates in the 10 to 40 kilogram transported weight range. Future research in the operational field of transported weight can improve the model for a specific situation.

Frequency Domain Analysis

The analysis of the frequency domain is performed to show present frequencies in the signals. Calculations are performed to predict frequencies of the mechanical system. Thereafter, the FFT and Order Analysis is performed on the data sets of interest. This shows the use case of the predicted frequencies and the generated frequencies based on the transported amount of weight.

6.2.3. Frequencies of the System

The mechanical system has natural frequencies and these are calculated to determine the presence of possible resonance. For the case study the properties of the belt are known, which allows for the frequency analysis. As chain belt conveyors have different operating situations, multiple conditions apply to them (for example different speed and weight). The operating conditions are dynamic and can be unique, which creates different frequencies in the system as a result.

The following calculations require extensive knowledge of the chain belt conveyor system and are not possible for every system. This frequency analysis is seen as an in depth analysis, as for the blue belt the specifications are unknown. Currently, chain belt conveyor specifications are hard to find and generally it takes too much time for engineers to find out. In this case study, only the specifications for the white belt are know. There has been a collaboration with the manufacturer, Ammeraal Beltech, which provided great insights on the belt. The Uni Flex ONE belt (white belt) has the property that consists of single links that are connected. The chain belt conveyor system has the following frequencies of interest:

1. Frequency for the lateral wave of the belt
2. Frequency of the stiffness of the belt
3. Frequency of the driving sprocket

The natural frequency for the lateral wave of the belt is as follows. For the lateral wave speed of the chain belt the following equation is used [43]:

$$c_1 = \sqrt{\frac{E}{\rho}} = \sqrt{\frac{2.7Gpa}{1410kg/m^3}} = 1400m/s \tag{6.1}$$

If the belt is modelled as a string, the following equation is used for the lateral natural frequencies of the chain belt [43]:

$$\omega_n = \frac{n \cdot \pi}{L} \cdot c_1 \left(1 - \frac{v_b^2}{c_1^2}\right) = 1020Hz \tag{6.2}$$

The calculated ω_n shows the valid assumption for the decoupling of the chain belt and electric motor. The calculated lateral natural frequencies are almost two times higher than the maximum possible captured frequency. The maximum frequency that can be captured in this research project is limited by the equipment available in the industrial setting.

The stiffness of the belt $K[N/m]$ is determined from experiments by Ammeraal Beltech and not widely known. The stress-strain curve is shown in Appendix B and only operates in the initial linear section. Thereby, a manual test is performed for validation and is shown in Appendix B. The frequency for the stiffness of the belt is calculated with the following equation:

$$K = \frac{F}{\Delta L} = \frac{6250N}{0.00625m} \approx 1.000.000N/m \tag{6.3}$$

The natural frequencies of the chain belt modelled as a spring (with L=1 m and mass = 20kg) are calculated as follows:

$$\omega_s = \sqrt{\frac{K}{m}} = \sqrt{\frac{1.000.000}{20}} \approx 224Hz \tag{6.4}$$

The calculations of the natural frequencies of the belt show that they are not in range of the FFT. As mentioned in the Methodology 4.7, the length of the belt between the transported mass and the driving pulley becomes shorter while in transport. Therefore, no peaks are expected but can be an explanation of the "base-noise" in the signal. As the natural frequency of the chain belt conveyor is changing during the operational cycle.

For the frequency calculation of the sprocket the following calculations are performed. The operational nominal speed is 1415 rpm, with a 30.99 gear reduction, indicates a 0.76 Hz frequency of the outgoing shaft. The sprocket has 10 teeth, so a frequency around 7-8 Hz is of interest for the driving sprocket.

The frequencies related to the transfer functions and the electric motor are assumed to have no interference or natural frequencies, explained in Section 4.3. This can now be shown by the Equation 6.2.

6.2.4. FFT

The FFT shows the frequencies in the signal that is collected. An Order Analysis shows the frequencies related the a specific speed. The changes in frequencies can be of great interest and is widely used in the industry to show anomalies in system. There are no data sets available over long periods of time. This implies that the over time change of the system is not captured. To prove that the frequencies are inherent to the current condition of the system, multiple FFTs are compared of the same transported weight and different weight. If there is hardly any change in the amplitudes, the conclusion can be drawn that the mechanical system is consistently producing frequencies based on the transported weight.

First, 5 FFTs are compared with data sets collected with a 20 kg mass on the *white chain belt conveyor*, shown in Figure 6.8. The frequencies are also plotted logarithmic, which will clearly show significant changes in amplitudes, as shown in Figure 6.9. The conclusion can be drawn, that within 5 data sets, the differences in amplitude are minimal. It can be concluded that there are no significant changes in the frequencies of the same transported weight. The conclusion is drawn there are no changes in the collected data sets. The suggested order analysis is not provided as it will not result in new insights of the system. The suggestion is made that for future research the frequencies depending on the rotatory speed can be analysed, as they can provide great insights.

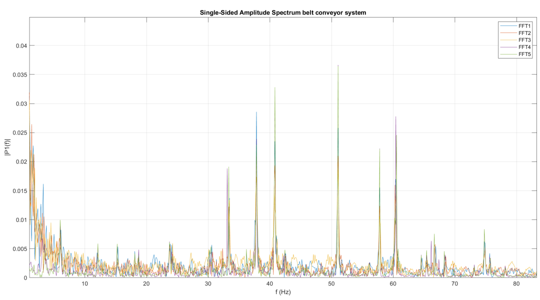


Figure 6.8: FFT comparison of 5 data sets for 20 kilogram

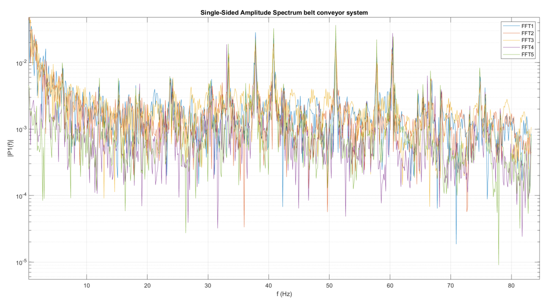


Figure 6.9: Logarithmic FFT comparison of 5 data sets for 20 kilogram

Thereafter, the FFTs of three different data sets with weights of 10, 60, 100 kilograms are compared. This analysis is performed to see the differences in the FFTs by changes in transported weight. This can be used to identify frequencies of interest and test for frequencies that are consistent with different transported weights. The 10, 60 and 100 kilograms FFT comparison is shown in Figure 6.10. After analysing the following conclusions are drawn. The method to use FFTs for anomaly detection is possible when data over longer periods of time are available. In the situation of this case study the analysis is difficult. The clear trend of the difference in weight can be seen, as the frequencies show in sequence. The peaks aligned peaks are all similar for the three data sets. Besides the change in weight and frequency, more research is required to create distinct conclusions. Over time data is suggested for the analysis of FFTs, as there are many frequencies that are difficult to trace.

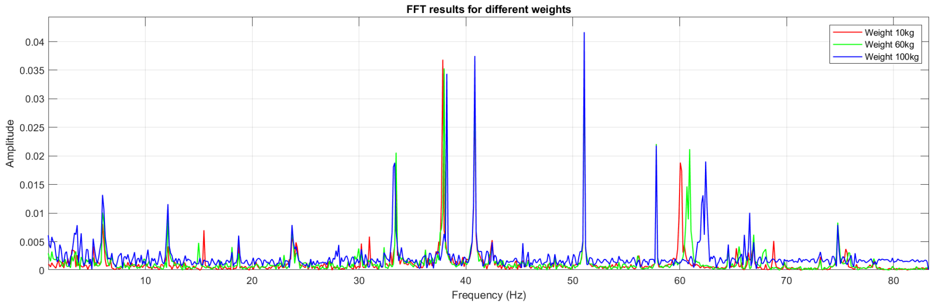


Figure 6.10: FFT comparison of 20, 60 and 100 kilograms

Transport Loss Factor

The system's performance is evaluated using the transport loss factor (TLF). In "Case One" the TLF is calculated using the known weights, which involves estimating only the losses and the coefficient of friction. In "Case Two" the TLF is determined by initializing the belt weight and subsequently estimating the weight, which involves estimating additional parameters. The estimated weight result in an error based on the weight estimation. This indicates the importance of the dynamic weighing accuracy when using this to determine the TLF. For the working environment of SEW Eurodrive the 95% accuracy is achieved. Only for 100 kilograms the industrial standard for accuracy is not achieved.

Parameter	10 kg	20 kg	30 kg	40 kg	50 kg
TLF Case One	0.022	0.018	0.014	0.013	0.011
TLF Case Two	0.023	0.018	0.014	0.012	0.011
Parameter	60 kg	70 kg	80 kg	90 kg	100 kg
TLF Case One	0.009	0.011	0.009	0.009	0.010
TLF Case Two	0.008	0.010	0.009	0.009	0.008

The comparison can be made with other transporting systems using the transport loss factor. The TLF of the physical system is compared to the continuous transport TLF of 0.023 [70]. The corresponding decrease in TLF is as expected when transporting more weight. The trend of the transport loss factor is as expected, since the increase in generated torque and transported load are not linear. The following figure allows for a global overview of the chain belt conveyor system, shown in Figure 6.11.

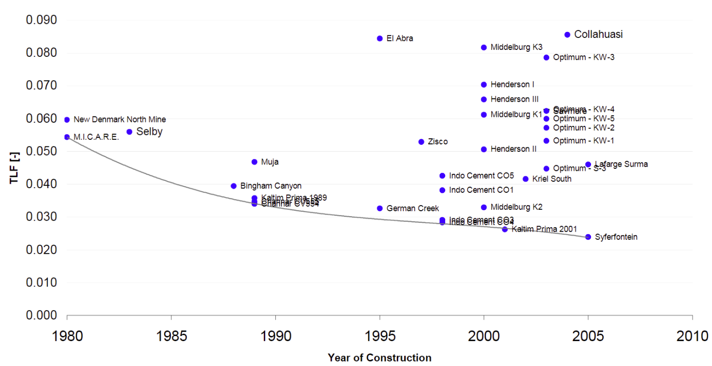


Figure 6.11: Transport loss factor overview [72]

6.2.5. Experiment Three

For the third experiment the blue belt is used. This is the first belt of the three belt sequence, as shown in Figure 6.3. This chain belt conveyor interacts differently to the transported trays. A situation is created where the tray is placed on the chain belt conveyor, while the chain belt conveyor is already in operation. The weight on the belt changes while the cycle is performed.

The unique operational setting is the weighted tray being placed on the blue chain belt while already being in operation. This can be seen by the torque and speed profile shown in Figure 6.12. The change in transported weight while the system is in operation is not accounted by the model. The disparity can be clearly shown in Figure 6.13. The separation lines in the figures show where the tray is completely on the belt, or starting to leave the belt. Therefore, the suggestion for future research is given for the expansion of this model so these changes can be accounted for.

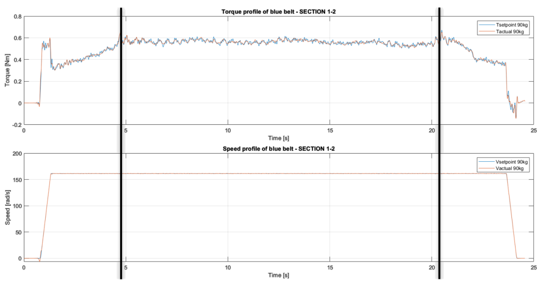


Figure 6.12: Torque and speed of the operational blue belt

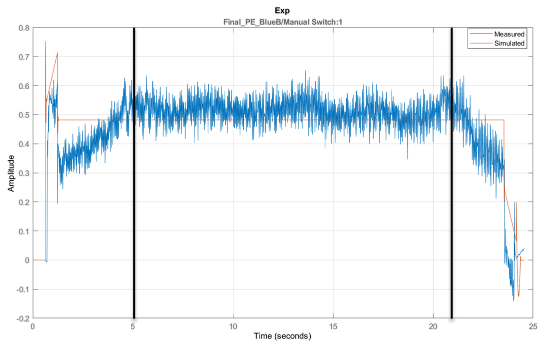


Figure 6.13: Torque of the physical system and prediction of the model

6.3. Concluding Remarks

The case study has been performed on the facility of SEW Eurodrive in Rotterdam, The Netherlands. The data sets are created by placing weights on a tray, which is transported along chain belt conveyors. In total 335 unique data sets are created. The data sets contain 7 parameters of interest. The main parameter of interest is the generated torque, as it represents the interaction of the gearmotor and the physical system. For the case study, straight section belts are used.

For the case study the following experiments have been conducted. First, using the known weights the amount of estimated parameters is minimised. Parameter estimation is performed for system identification, compared and analysed. Thereafter, a statistical residual analysis is performed to show the statistical nature of the residuals.

Second, the model is used for dynamic weighing. The model is initialized using the parameters of a tray with no weights. These parameters are used to estimate the weight on the belt. The accuracy is a minimum of 95% if the used data sets contain the complete cycle of the belt. The importance of the acceleration and deceleration phase is emphasized. The industrial setting is prone to faulty data sets and should be taken into account when performing experiments.

The natural frequencies of the system are analysed. The natural frequencies of the system are calculated to predict possible resonance frequencies for the systems. The transfer function can suppress behaviour induced by the electric motor and therefore this analysis was performed. A frequency analysis was performed to show that without the presence of data over longer periods of time, the amplitudes of the frequencies are similar. This experiment was proposed for future research when proper data is available.

The performance of the system was indicated using the transport loss factor. The importance of the knowledge for the transported weight is shown by the error induced for the TLF when using the estimated weight. An indication of the performance of the system was provided using the transport loss function. This method was suggested as the industry standard for the performance indication of the system.

Finally, in "Experiment Three" the importance of no changes in weight while operational was emphasized. It was clearly shown that the model does not account for these changes and can not be used for this situation. The expansion for this situation is suggested as future research.

Chapter 7

Conclusion & Recommendations

This chapter presents the research conclusions by providing a comprehensive response to the main research question by combining the findings from the six sub-questions. Consequently followed by recommendations and a discussion. The discussion highlights the research limitations and contributions to both scientific and practical domains.

7.1. Conclusion

Chapter 1 provided an introduction to the main research question and sub-questions, with the main research question being as follows:

"How to Develop a Digital Twin for Condition Monitoring of an Industrial Gearmotor Driven Belt Conveyor System?"

This research studied digital twin models for the condition monitoring of industrial gearmotor driven chain belt conveyor. Chain belt conveyors can be found throughout many industries and therefore, methods of PdM are of high interest. Industrial settings are competitive and dynamic. The desire is expressed for a robust model that is applicable without required changes to operational systems. Currently, the degradation or performance of a chain belt conveyor is unknown and collected data is hard to interpret. Chain belt conveyors do not have an indication for the operational performance or efficiency. Most models for digital twins and condition monitoring are created in a test environment, which is not representative for the industrial setting. The knowledge gap between the literature and the industry is defined and established. The industry has expressed a demand for a digital twin for condition monitoring that is generalized, robust and easy applicable.

To address the identified knowledge gap, a two-stage study was conducted. First, a review of the state-of-the-art was conducted, focusing on SEW Eurodrive as a prominent figure in the drive industry. Secondly, a literature review was carried out to explore various aspects of the research problem.

The first subquestion was answered in Chapter 2: *"What is the state-of-the-art of digital twins and condition monitoring in an industrial setting?"*. Research was conducted at SEW Eurodrive to address the questions at hand. SEW Eurodrive was considered as a key player and therefore representative for the drive industry. The research was performed in collaboration with the engineers and studying company documents. By establishing the benchmark of the industry, the current situation is defined and the following problems were identified. The availability of usable data is limited. The only sensor available for collecting data from the physical system is using the gearmotor and the VFD. Additionally, more understanding is required regarding the necessary data and the potential applications. The model must be generalized, as this requires no changes or adaptations in the currently operational systems. Engineers lack insight into the system's parameters, often resorting to approximations during the design process. These approximations can be high compared to the actual values, which leads to over-dimensioning. Mapping these parameters could enable tracking of degradation over longer periods of time. However, currently no methods are available for predicting or mapping degradation or breakdowns. The performance and efficiency of the physical systems can not be compared as there is no method used as the industrial standard. Hardware limitations also restrict advancements, as the components are typically designed to "just" meet requirements in order to maintain a low price to be competitive. Given the harsh industrial setting, clients prioritize cost and reliability.

The second subquestion answered in Chapter 2: *"Is the currently available hardware sufficient for a digital twin and condition monitoring?"*. To optimize the application of digital twins for condition monitoring, the model should be widely applicable and the necessary parameters for the model should be readily available and universally employed. Analysing the currently used parameters, the indication is made that a minimum of 7 parameters are required. All these parameters are collected by the gearmotor and the VFD. The torque is the main parameter of interest. SEW Eurodrive utilizes an proprietary motor model to compute the generated torque. The torque, speed and position set point and actual value are measured, as they provide insights for the comparison of the model and the physical system.

In Chapter 3 the following subquestion was discussed: *"How are digital twins and condition monitoring defined in literature?"*. Predictive maintenance is an approach to maintenance in which the condition of equipment or systems is continuously monitored to predict and prevent potential issues before they occur. Digital twins are a concept with various interpretations and in this research defined as followed; A digital twin is a virtual representation of a physical object or system that provides real-time and historical data on its performance, behavior and condition. It is a digital model that replicates the physical properties and processes of the object or system. Furthermore, it can be used to simulate and analyze different scenarios and outcomes. Condition monitoring is the process of monitoring the health and performance of equipment and systems to detect potential issues or failures. Digital twins and condition monitoring serve as a tool for implementing PdM. These concepts are explained to show the potential of this research.

Subsequently, the subquestion answered is: *"How can the subsystems of the digital twin be modelled?"*. Literature research has been performed to explore the possibilities to model the general system. Belt conveyors for bulk mass material transport are a highly researched topic and are in line with chain belt conveyors. Distinctions are made for the two different systems, this determines what literature for belt conveyors is applicable for chain belt conveyors. The chain belt conveyor uses a chain consisting of interconnected links, is closed form and does not rely on friction to drive the belt. A sprocket with teeth interconnecting the belt is used, resulting in no slip. The belt is always under tension, as the belt slows down faster than the deceleration profile. The methodologies and analysis of the belt conveyor are used as a guideline throughout this research.

A new model for chain belt conveyors based on first principles is proposed. This model is based on the fundamental mechanical analysis of the system. A Coulomb's friction model of a sliding mass is proposed as this represents the sliding of the chain belt over the guiding rails. Phenomenons for industrial chain belt conveyors, such as stick-slip and the polygon effect were examined. Data collection limitations in an industrial setting led to the proposal of a transfer function to represent the electric motor. Using a transfer function minimizes the measured parameters per data set. The gear unit generates two main type of losses, being mechanical losses (tooth friction) and churning losses. A rigid body model is proposed as this allows for minimal required specifications and is a widely applicable model. A K-stiffness model is proposed for future research, this requires more specifications of the chain belt conveyor.

To continue, the following subquestions are answered: *"How can data be leveraged to identify unknown parameters in the system?"* and *"How can the model be used to identify anomalies in the system?"*. The parameter estimation method *Recursive Least Squares* is proposed for system identification. Recursive least squares is a technique to estimate parameters of the physical system using collected data sets. The data is leveraged to identify the best fit of the model and the collected data from the physical system. This model-based approach is possible as the physical system of interest is known and leveraged for system identification. The parameters of the system can be compared, creating insights into the characteristics and losses of the system.

Multiple methods are proposed for anomaly detection. For the estimated parameters used for system identification, thresholds are used. If the estimated parameters are out of bounds, this can be an indication for possible occurring anomalies. The collected data sets are analysed using a *Fast Fourier Transform* (FFT). This allows to create insights into the frequencies that are present in the collected signals. If specifications of the chain belt conveyors are known, ranges for frequencies of interest can be determined. The difference in amplitude of the frequencies can be an indicator of anomalies in the system. Order Analysis is performed to show the produced frequencies at specific velocities. These methods are used for the frequency analysis and are of great use to detect over time changes in the physical system.

The residuals are the error between the predicted value of the model and the data collected from the physical system. A *statistical residual analysis* is performed to acquire information on the statistical nature of the residuals. By comparison and changes of the statistical features, valuable insights into the physical system can be obtained.

To indicate the performance of the physical system the *Transport Loss Factor* is proposed. This implies the factor of the mechanical work compared to the work to transport the payload. This allows for comparison of chain belt conveyors and other methods of transportation. This method for rating the performance of the chain belt conveyor is suggested to be used as the industry standard.

The method of *dynamic weighing* is proposed. This implies the measuring of the transported mass on the belt, only by using the torque from the data set collected from the physical system. The possibility of knowing the weight without needing any adjustments to physical systems can be very insightful. For example, to determine the correlation of degradation and the transported weight. An initialization method is proposed in the case study. Dynamic weighing is currently only performed with dedicated sensors. Dynamic weighing can be applied to a wide range of chain belt conveyors without any adjustments using this model.

In the Chapter 4, the model is created in Matlab Simulink. The dynamics of the model are based on the equation of motion used for belt conveyors. The position controller has been replicated to precisely imitate behaviour of the physical system. The data sets collected from the physical system are used as an input for the model. A transfer function for the generated torque is conducted via experiments using a flywheel model. The specifications of the gear unit are known by SEW Eurodrive and are separated in mechanical and speed dependent losses. The chain belt conveyor system is modelled as a rigid Coulomb's friction mass model. This is the first time this model is utilized for a chain belt conveyor.

In Chapter 5, the model is verified and validated. First, the model is verified by performing multiple different input cases. These are ramps, stairs and trapezoidal speed profiles in positive and negative direction. The behaviour of the model is evaluated and subsequently demonstrates the model is valid. The validation has been performed by comparing the model to data generated by a chain belt conveyor. There is no data available that is collected over a longer period of time to show degradation in the system. Five unique data sets are created using the same transported weight. Subsequently, these data sets are analysed using FFTs resulting in no significant discrepancies in amplitude. The initial conditions for parameter estimation are tested by showing the inputs and outputs based on different initial conditions.

In Chapter 6, a case study is performed at SEW Eurodrive, Rotterdam. Only straight chain belt conveyors are of interest. Furtermore, a white chain belt conveyor is selected for the case study. Data sets are manually created using weights on trays, that are transported by the chain belt conveyor. Empty trays and trays with 0 to a 100 kilograms in increments of 10 kilograms are examined during testing. This results in 11 different situations for the load case. Experiments have been performed for the system identification of the white chain belt conveyor. Thereafter, the dynamic weighing is tested. In the end, dynamic weighing can be performed with a minimum of 95% accuracy, meeting industry standards. An analysis of the frequencies of the physical system is performed to show the validation of the model and the used assumptions. This is only possible by collaboration with the chain belt manufacturer, as belt specifications are required. It is shown by using FFTs that the frequencies do not change with the currently used data sets and therefore, future research is proposed to examine over time changes of the chain belt conveyor. The statistical analysis of the residuals is performed, analysed and compared. The performance and efficiency of the system is expressed using the Transport Loss Factor and compared between different weights. The transport loss factor is in line with the expected factor for continuous transport. The limitations of the model are shown by a case that has changing transported mass.

In conclusion, a digital twin for condition monitoring of an industrial gearmotor driven chain belt conveyor is developed. The novelty presented by this research is a first principle model for a chain belt conveyor based on Coulomb's friction with the capability of system identification, anomaly detection, dynamic weighing and the performance comparison of chain belt conveyors. The model is created only using the data collected from the gearmotor using the VFD, which enables the development of a model with extensive adaptability, suitable for numerous chain belt conveyor systems within the industry, without the need for any adjustments to operational systems. This results in a generalized and robust model with wide-ranging applicability throughout the industry to gain insights into currently operational chain belt conveyors. The ability to compare chain belt conveyors and use system identification for insights into the system allows for more efficient operational systems in future.

7.2. Recommendations

The following recommendations are proposed for the future of a research project. Firstly, the collection of data sets over an extended period is necessary. The availability of data sets is related to the many possibilities and limitations for PdM models. Data sets over longer periods of time can facilitate the mapping of parameters through time and enable the use of prediction methods such as ARIMA to forecast trajectories. The determination of anomaly thresholds in the system requires failure data, these thresholds can also serve as a basis for performing statistical residual analysis on the model. The correlation of the transported weight and the degradation of the system could also be examined using data over longer periods of time. When collecting data sets over extended periods of time, it's important to minimise the possibility of generating faulty data sets caused by the industrial environment.

In the second place, the subsystems of the model can be developed in greater detail. The installation of new sensors to measure parameters such as temperature and vibrations could facilitate further research on the mechanical and churning losses of the gear unit. The chain belt can be modelled using the proposed K-spring stiffness. By enhancing the modelling for the subsystems, it could potentially provide even more comprehensive insights into the system, which could lead to improved predictions and analysis.

The final recommendation pertains to utilize this model for the evaluation of the chain belt conveyor's efficiency and energy consumption. The industry can evaluate the performance of operational systems to assess the sustainability of the production facility. By maximising the efficiency the energy consumption is minimised. The goal of achieving a sustainable future is attainable, utilizing this digital twin model is one example of a promising approach to reach this goal.

7.2.1. Academic Contribution

The scientific contribution of this research is the new model for chain belt conveyors. The model is based on first principles and has shown feasibility. The main interest of available literature and research is focused on belt conveyors for bulk material transport. The literature has been analysed and the applicable theory for chain belt conveyors is selected. The novelty presented by this research is a first principle model for a chain belt conveyor with the capability of system identification, anomaly detection and dynamic weighing. The position controller for the electric motor of the modelled physical system is implemented in the model. A transfer function is derived by experiments, to bridge the gap between the torque set point and generated torque.

The model is created only using the data collected from the gearmotor using the VFD, which enables the development of a model with extensive adaptability, suitable for numerous chain belt conveyor systems within the industry, without the need for any adjustments to operational systems. The performance of the chain belt conveyor can be compared to other systems using the transport loss factor. The model is validated using a case study. The case study consists of 335 data sets, with varying transported weights and sample times. The simplicity of the model leads to a reduced demand for computational power, making it more resource-efficient. The boundaries imposed by the industrial setting have been established and the gap between the industry and the academics has been bridged. This digital twin for condition monitoring creates insights into the performance of chain belt conveyors, aiding in the perspective of a more sustainable future.

7.2.2. Industrial Contribution

This proposed model presents a new model for the chain belt conveyor that can be used in the industrial setting. The data acquired from the systems is leveraged to gain insights and information into currently operational chain belt conveyors. The system identification can be used to compare similar operational systems. These insights can be studied to analyse different stages of degradation or health indication of chain belt conveyors. The position controller is included in the model to ensure robustness and an optimal simulation. The controller can easily be adjusted to other settings of different systems. The creation of the transfer function to bridge the gap between the torque set point from the controller to actual set point has been acquired by experiments. The transfer function minimizes the amount of measured parameters, creating more flexibility for the model.

This research showed SEW Eurodrive the boundaries of the current operational industrial environment. The need for data sets and the utilization of data was emphasized. The limitations of the hardware were established, allowing deliberate choices for future products. The possibility of system identification allows for the analysis of operating systems. The model allows for more insights and comparison when selecting equipment for new systems. This results in more optimal specifications, resulting in a more sustainable operation.

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Appendix A

Appendix A

A.1. Verification Controller

For the verification of the position controller, all tests are performed in the positive and negative direction.

The following results are acquired for the positive and negative ramp, stairs, speed trapezoidal and extended speed trapezoidal inputs:

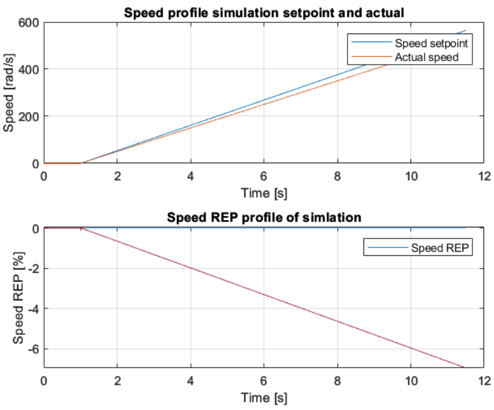

Figure A.1: Speed profile and REP for a positive ramp speed profile input

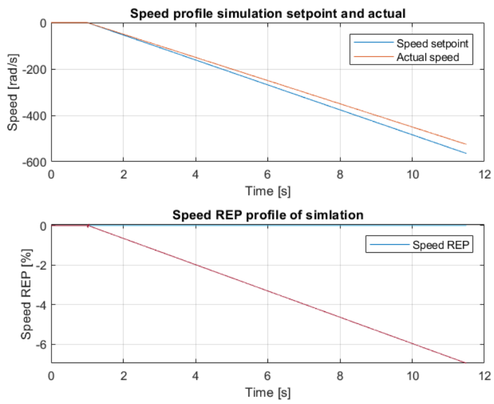

Figure A.2: Speed profile and REP for a negative ramp speed profile input

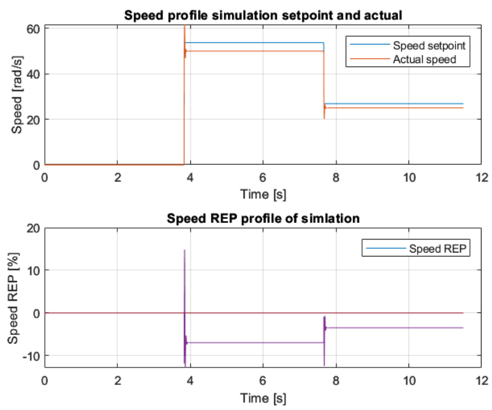

Figure A.3: Speed profile and REP for a positive Stairs speed profile input

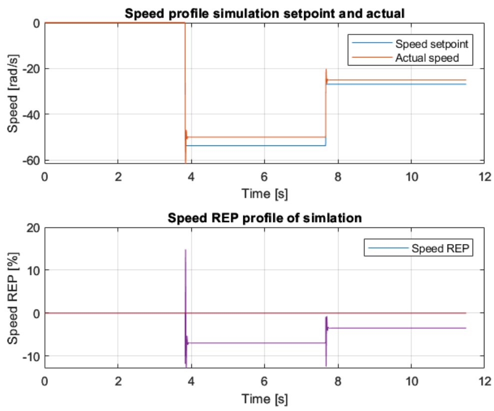

Figure A.4: Speed profile and REP for a negative Stairs speed profile input

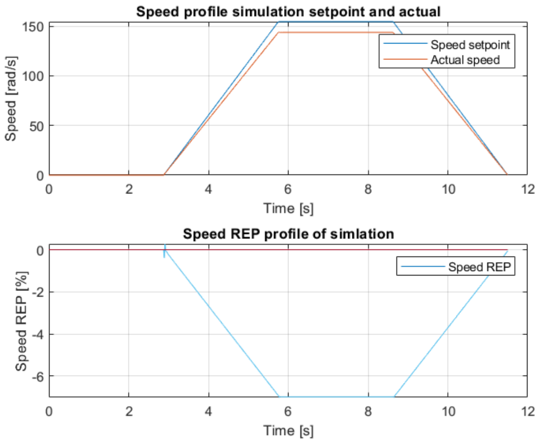

Figure A.5: Speed profile and REP for a positive trapezoidal speed profile input

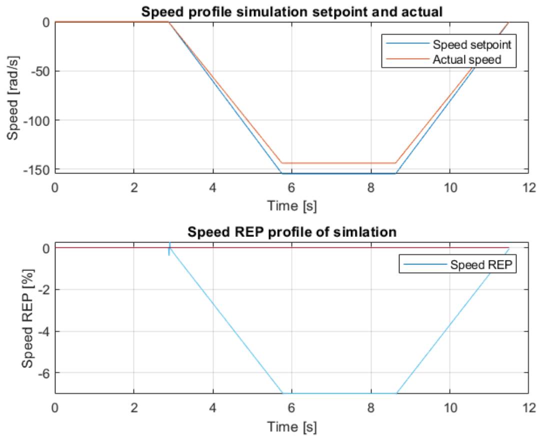

Figure A.6: Speed profile and REP for a negative trapezoidal speed profile input

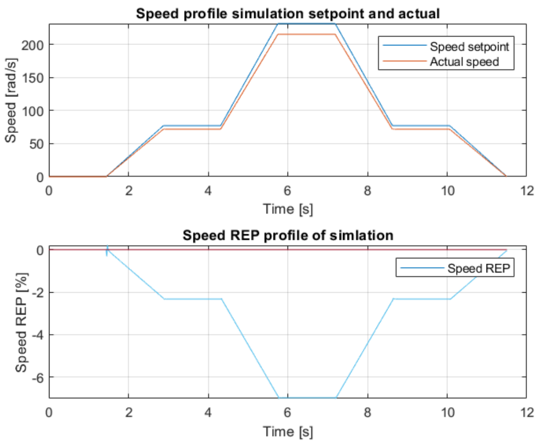

Figure A.7: Speed profile and REP for a positive trapezoidal speed profile input with 2 different accelerations

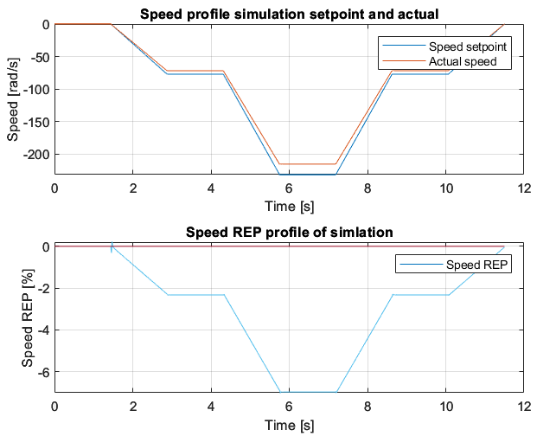

Figure A.8: Speed profile and REP for a negative trapezoidal speed profile input with 2 different accelerations

Appendix B

Appendix B

B.1. Information Mechanical System - Chain Belt Conveyor

For the stiffness of the chain belt an experiment was performed and the manufacturer has been contacted. The experiment was performed as a validation of the S-N curves provided.

The chain belt conveyor has been stretched using a known mass, measuring the extension on three different locations. The measurements in the experiment have been performed multiple times to ensure an accurate result. The experiment is shown in Figure **??**.

Figure B.1: Stress-Strain curve experiment for the UNI Flex One chain belt

In collaboration with the manufacturer of the chain belt conveyor, Ammeraal Beltech, the S-N correlation is acquired for the chain belt. Note that the only the initial linear part is used and not the entire curve to determine the stiffness of the chain belt. The conditions of the experiment have been calculated and checked to match the provided documentation. The S-N curve for an Uni Flex One chain belt is shown in Figure B.2.

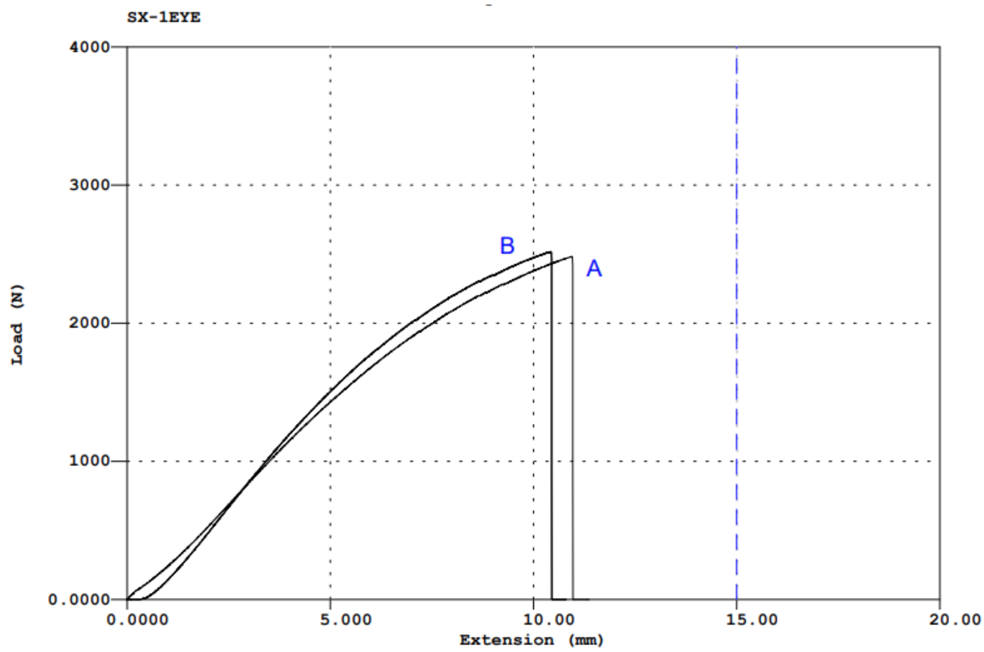

Figure B.2: Stress-Strain curve of an UNI Flex One chain belt

Appendix C

Appendix C

C.1. Transfer Function Experiment

To determine the transfer function for the electric motor and experiment is performed. Multiple setups have been tested to ensure the validity of the transfer function. This Appendix C is intended to show the broad analysis for the transfer function.

Multiple tests have been performed to determine the transfer function:

1. Step input torque - Free rotor
2. Step input torque - Locked rotor
3. Speed cycle input

The step inputs of both free and locked rotor are tested and analysed. No differences occur in the generated torque. For the free rotor the speed limiters are initiated after approximately 0.5 seconds.

The speed cycle and the generated torque is as presented in Figure C.2. This situation is a representation of the industrial setting and of importance to test the actual generated torque to the transfer function.

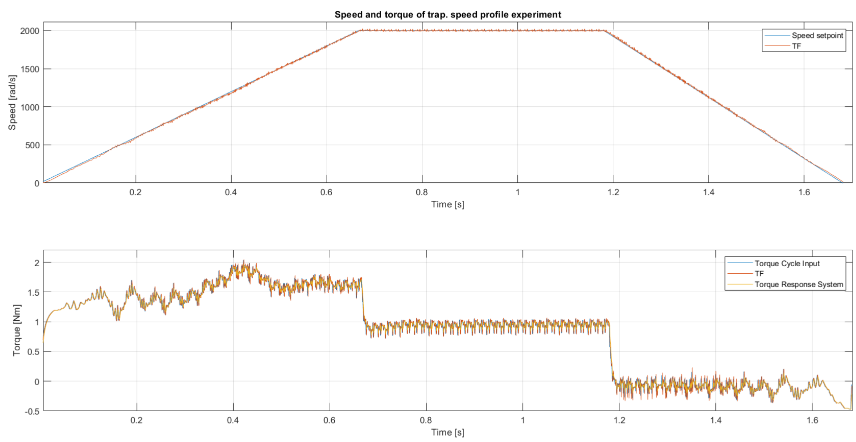

Figure C.1: Speed cycle and generated torque of flywheel experiment

The FFT of the torque signal is performed to gain insights into the torque signal. This data set is analysed at it uses a 1 millisecond sample time. This is allows for the highest possible frequencies captured. To capture higher frequencies, different equipment must be used. A clear distinction can be made of base noise and mechanical frequencies (sub 50 Hz). The 300 Hz peak is cause by the full bridge rectifier. Other peaks are hard to elaborate on and are assumed to be generated by the electronics. This FFT provides the most information possible on the present frequencies possible using the equipment from the conducted case study at SEW Eurodrive, Rotterdam.

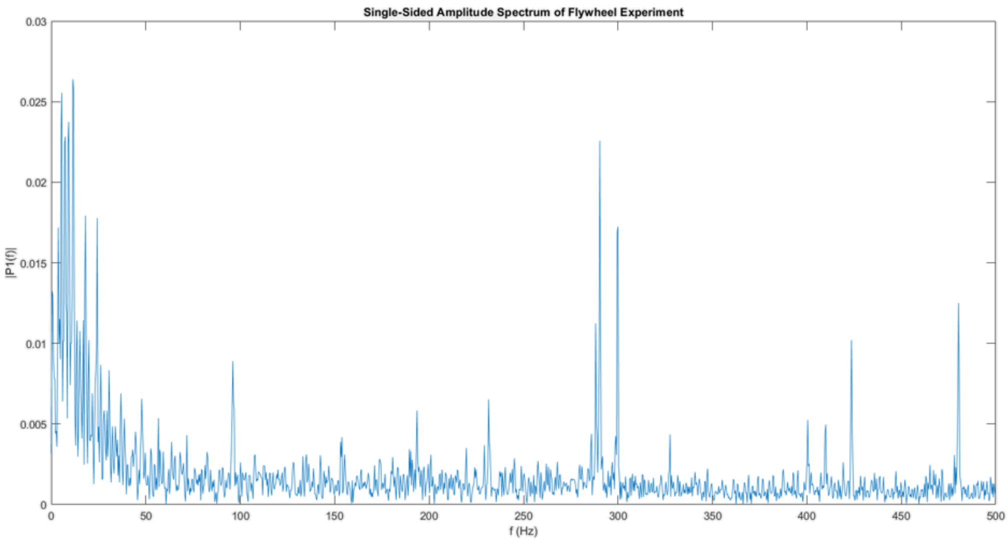

Figure C.2: FFT of generated torque signal by flywheel experiment