Development of a predictive maintenance model which provides fault identification and diagnostics on electrical gearmotor systems

An exploratory case study for SEW-Eurodrive

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Development of a predictive maintenance model which provides fault identification and diagnostics on electrical gearmotor systems

An exploratory case study at SEW-Eurodrive

Master Thesis

by

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Preface

With this thesis I will complete my Master of Science in Mechanical Engineering at the University of Technology in Delft. Withing the master of Mechanical Engineering I have specialized in the track of Transport Engineering and Logistics. The purpose of the master thesis research is to apply the theory and knowledge gained in the two-year program in an real-life problem situation. In this thesis I will cover the topic of applying fault detection and diagnosis of electric gearmotor systems in an industrial setting. Even though this topic was what I wanted to do for my graduation project, it was quite challenging nevertheless. However, I am happy with what I have achieved and believe I have made a valuable contributed to scientific and practical research.

This research was conducted for SEW Eurodrive in Rotterdam. I would like to start with thanking the staff of SEW Eurodrive, this includes the staff in Rotterdam, however also the people in the headquarters in Bruchsal Germany. I would like to specially thank to my supervisor Niels Maat for providing me with the opportunity to execute my thesis with him, and for the support and guidance. I'm also thankful to the graduation committee and the help that each member provided. I cannot thank Xiaoli Jiang enough for her unlimited assistance, thorough feedback and providing me with motivation no matter what. And lastly, Rudy Negenborn, for all his feedback during meetings which helped me step by step towards the final result.

Finally, I would like to thank my parents, friends and roommate(s) for their motivation, guidance and opportunities during this thesis and my entire studies at the TU Delft. This achievement is for you and your unconditional support throughout the difficult times and your sincere joy in the good ones.

I wish you a pleasant reading,

Ir. A.J. Robinson
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Summary

The industrial electric motor market size was 47 billion USD in 2020 and consumes roughly 70% of all industrial electricity (Mordor Intelligence, 2020; Waide and Brunner, 2011). These motors which are generally smaller than 5kW (and usually connected to a gearbox, called a gearmotor) are critical components to many industries and can be found in many machines, for instance conveyors and pumps. For these systems (motor, gearbox and the driven load), called electric gearmotor systems, it is crucial that they work without failure. In 2016 ITIC (Information Technology Intelligence Consulting) conducted a research across 300 companies and found that 98% of organizations report that a single hour of downtime can cost over 100.000 USD and for the automotive industry downtime can cost $22.000 per minute (ITIC, 2016; Nielsen Research, 2005). This downtime is not specifically related to the electric gearmotor systems, however considering their presence they play a large roll in this.

One of the current trends in regard to electric gearmotor systems is Industry 4.0. Industry 4.0, which stands for the modernisation of traditional manufacturing using automation and smart technologies (e.g. sensors, cloud storage, AI) (Lasi et al., 2014). Industry 4.0 contains many different topics, from supply chain integration to automation of robots to big data and lastly predictive maintenance (PdM). PdM is the most popular topic due to its high relevance and is a method to foresee failures or faults in a system that deteriorates over time through evaluating the state of the system (condition monitoring or fault detection and diagnosis (FDD)) and has been extensively covered by academic research over the last 20 years (Selcuk, 2017). Advanced techniques e.g. vibration, oil, thermal and acoustic analysis and by using artificial intelligence (AI) the condition of electric gearmotors systems can accurately be determined (Levitt, 2003).

A report by the US Department of Energy, Energy Efficiency & Renewable Energy found that PdM reduces maintenance cost by 25-30% and considering maintenance is between 15-70% of total productions cost, large amounts of savings can be achieved (You et al., 2010) (Sullivan et al., 2010). However, two thirds of the 256 manufacturing companies surveyed by PwC (PricewaterhouseCoopers) in 2018 still only conduct visual inspections and some basic instrument inspections (Haarman et al., 2018). Combining this information a gap can be found; even though there is an abundance of academic knowledge on PdM, in practice it has hardly been adopted by companies and organisations.

In recent years papers have been published addressing this scientific gap, however reasons why vary. Wickern, 2019 states that it is mainly due to financial and organizational obstacles. Tiddens, 2018 states that unavailability of high-quality data is a wide spread issue, that companies do not understand the value of PdM and literature focuses on technical part of PdM, ignoring other facets like organisational perspectives or maintenance strategies. Karuppiah et al., 2021 identified poor commitment from top management. Other reason that can be found are organisational culture issues (Freeman Gebler et al., 2016) and worries about data security and hesitance to share data through value chain (Bokrantz et al., 2017).

From an industrial perspective there are other problems and gaps that have been identified. First, the demand for PdM solutions for electric gearmotor systems has slowly been increasing, however solutions are not available yet. Second, every problem where PdM can be applied is unique and presents its own difficulties, requiring universal PdM models which are generally not researched in academic literature. Third, sensors are relatively expensive compared to gearmotors which makes them financially hard to justify. The main option is using the data generated by the variable frequency drive (VFD), this component powers the motor and also generates data about the current the motor uses and its rotational speed. Fourth, gearmotor systems are generally easy to replace, thus for maintenance engineers who are responsible for correct operation it is adequate to know that a machine is starting to fail (diagnosis), and do not need know when in the future (prognostic) the machine will fail exactly. Prognostics is important when it comes to expensive equipment which can take weeks to deliver. This diagnosis is

referred to as fault detection and diagnosis (FDD) and will be the focus of this thesis. The main faults that occur in electric gearmotor systems are blockages in movement, bearing failure and gear failure.

To study FDD a case study was needed, which was performed at SEW Eurodrive. SEW Eurodrive is a leading manufacturer of drive technology, which encompasses gearboxes, motors, gearmotors, AGV's (automated guided vehicles) and VFD technology. The practical gap was stated as followed: it is unknown what PdM and FDD models are available, that can be applied to current systems and what is possible with the available data. The research question is *"How to develop a fault detection and diagnosis model of an industrial applied electric gearmotor system?"*. The complete problem of PdM is larger than what is discussed here, however this will provide an overview of the possibilities and a general solution.

To be able to answer the above mentioned research question first the state-of-the-art of the industries that adopts electric gearmotors is defined. This was done through conducting an analysis of industrial reports and of SEW Eurodrive. Secondly, a literature review was conducted which showed how FDD works, the relevant models and how it can be applied to the current situation. The main faults were also analysed.

In the state-of-the-art six main problems were identified with regard to the development of FDD and PdM models. First, due to the large amount of (complicated) academic researches it is difficult to know where to start when researching models. Secondly, the customers and problems where PdM models need to be applied are very unique thus making universal solutions difficult. Thirdly, changes often happen in an industrial settings which makes training of artificial intelligence (AI) models difficult and requires adaptable solutions. AI is commonly used for fault detection throughout PdM and FDD. Fourth, there is a general lack of data, especially fault and failure data. The fifth problem is with false positive and false negative alarms in models. Sixth problem is system diagnostics (being motor, gearbox and load) being more difficult then component (single element) due to more noise and more possible failures. Lastly, the main faults the occur in gearmotor systems are first blockage in movement, bearing failure and gear failure (related to oil degradation).

In the next stage a literature research was conducted into FDD. FDD has two basic functions, first the behaviour of the process is monitored and secondly faults are detected. FDD consists of four stages, fault detection, fault isolation, fault identification and fault evaluation. Detection techniques can be generally categorised into two main categories, model-based and data-driven. Model-based uses mathematical formulas to describe the system while data-driven methods use artificial intelligence/machine learning (ML) to detect faults and failures. Fault identification can be done using model-based and data-driven techniques, however data-driven solutions are preferred due to accuracy and simplicity. Using model-based and data-driven methods depends on the problem and parameters making an universal solution impossible. Next, the characteristics of the three main faults were analysed to make identification possible. Gaps were found in academic literature. First, there is a lack of system level diagnostics in gearmotor systems. Secondly, lack in hybrid solutions consistent out of model-based and data-driven methods for gearmotor systems. Finally there is a lack of developed models which have been applied to real world systems.

Based on conclusions from the introduction, state-of-the-art of SEW Eurodrive and the literature research a model was designed in the methodology. Using an evaluation matrix with criteria based on the research scope model-based method was chosen for the fault detection phase. This was because model-based solutions are the most robust, adaptable and accurate in an industrial setting. The mathematical model will predict the torque that the motor uses. This is because the motor torque can simply be calculated from the current that the motor uses using data from the VFD. Using these two inputs a residual is generated, which is the measured torque subtracted from the calculated torque. From this residual features are extracted (e.g. max value, mean), which will be normalized and the mean taken from the values, this generates a health indication value. When a fault occurs the health indication value increases and when this reaches a pre-defined threshold, an alarm can go off. This threshold can be flexible to avoid false positive and false negative alarms which increases accuracy. When a fault is detected the next phase of the model can happen, fault identification. Here a data-driven method was chosen. This is because it excels in classification accuracy and easy of use. The complete model is referred to as a hybrid diagnostics model, because it utilises a model-based and a data-driven solution.

When the model is developed for a given system it is divided into two phases, the offline phase and the online phase. During the offline phase the mathematical model is generated from parameters about the system. Initial healthy running data is fed into the system and analysed, here threshold and values are saved in a file. When the gearmotor system is in operation the online code will run, it will use the values generated in the offline phase to calculate the health indication value of the scope and see if it breaches the threshold. If the threshold is broken the algorithm will see if it can classify the fault. Eventually, the maintenance engineer will see which motor is showing faults and an estimation of what the cause could be.

Key performance indicators (KPI) were specified to measure the performance of the fault detection and identification sections. A confusion matrix was generated to identify how well the methods classified the data. From here four KPI's were used, accuracy, precision, recall and F1-score were used.

To verify and validate the model a case study from SEW Eurodrive was taken. A lift was chosen which is operated by VDL Nedcar, a car manufactured in the south of The Netherlands. The lift elevates a car frame which in turn are welded on by robots. Data has been collected over the period 01/07/2020 until 30/7/2021, the data are recordings of 8 seconds, now called scopes. For the system a mathematical model was developed and inserted into the fault detection section of the FDD model. Sadly, fault data was not available, thus fault data was generated which utilized the characteristics of the faults which were identified in the literature review. A decision tree machine learning model was trained based on these faults. The model was verified and validated using various methods.

After this the model was evaluated using the identified KPI's. The KPI's were applied to the detection and to the classification part using healthy data and the simulated fault data. The fault data was simulated at three levels, namely, mild, moderate and severe. Next four different thresholds were defined, these are the mean of healthy measurements with multiple of the standard deviation. For each threshold and fault severity a confusion matrix was generated.

Four conclusions were drawn from the results, first, the algorithm has a high recall. A high recall shows a low classification of healthy scopes of being faults, this was one of the goals due to maintenance engineers conduct maintenance on healthy systems is counterproductive. Second, is that precision declines with higher thresholds. This is to be expected because not all faults breach the threshold value. However, this problem would be mitigated using a sliding window alarm, this only sounds an alarm if the threshold is breaches a certain amount of times. Third, the highest accuracy was the second deviation above the mean, with the highest accuracy being 94%. This was because at the threshold of one standard deviation healthy scopes were being classified as faults. Fourth, the f1-score which shows the mean between recall and precision is high overall. This is important because we want out model to identify all the healthy scopes and at the same time identify only positive cases. The results of the fault classification decision tree classifier have an accuracy's of 84%, 91% and 98%. Together with the precision, recall and f1-score all being balanced it shows that the algorithm is balanced and works properly.

In general the results from the hybrid diagnostic model are very promising, faults are identified and correctly identified in many cases. However, in reality accuracy would not be as high. The data that was used in the VDL Nedcar case study was taken of a system that had already been running for 7 years. It is unknown how an actual healthy system would perform and what the impact is of the age. Deterioration in lubrication could give higher torque values than expected for example. Another issue was that not all the parameters of the mathematical model were known. The exact weight of the car on the lift is unknown. Temperature was also not considered in the model. In reality temperature has an impact on how well the lubricant works, however also on the efficiency of the motor. These can differ the efficiency of the system with a couple of percent depending on the situation undermining accuracy. The low sample rate (250Hz) of the VFD limited the amount of information that can be extracted from a measurement and also limits early detection of faults. Simulating the faults was the only option to test the model, however simulating is an approximation of the actual faults and in reality will differ in size and noise. Due to this the decision tree classifier would also be less accurate.

In conclusion, this thesis studied fault detection and diagnosis and applied it to an electric gearmotor system in an industrial setting. Often models found in academic research can not be applied due to shortcomings meaning they have not been studied properly. To recapitulate the main research question is:

> *How to develop a fault detection and diagnosis model of an industrial applied electric gearmotor system?*

To develop a predictive maintenance model of an industrial applied electric gearmotor system first the state-of-the-art of the industry was analysed followed by an in depth literature research into fault detection and diagnosis. From here a hybrid diagnosis model was developed and verified and validated through data taken from SEW Eurodrive. Based on the results from the sub-questions the main research question can be answered. The model should be a hybrid model, implying that fault detection is done through a model-based solution and fault classification should be done through a data-driven algorithm. Fault detection which utilises a mathematical description of the movement of the system, this is used together with a measurement to calculate a health indication value. The fault diagnosis is done using a machine learning algorithm, namely a decision tree classifier.

Limitations of the research are: limited data VDL Nedcar and data was from 7 year old machine. Larger data set could have shown influence of seasons and of internal and external influences, e.g. temperature. Temperature has an large influence on the torque thus seeing impact would be interesting. Could not apply hybrid diagnostic model to other systems to compare accuracy and how accurate mathematical model is with different movement. Limited by the fault data. Other solutions from model-based and data-driven could have been used and tested, however limited by time.

The recommendation for scientific research are as followed. Even though, research into FDD and PdM have been going on for decades, the research is one sided and focuses on the technical part of PdM and FDD. There are five dimensions to PdM/FDD, such as technical, economic, environmental, social and safety and many papers focus only on the technical dimension. This can be achieved through combining knowledge from different universities or through having closer contact with industries where the technology is intended for. When researching for papers that are relevant to the literature review there were many papers that tried to use complex algorithms to find minuscule faults in components. While results were usually promising, these are difficult to use in an industrial setting. Thus, while pushing technological boundaries is good, extra focus should go towards models which add value and are simple to apply to industrial settings. Another problem is data, many models and algorithms use data that does not represent a real-life situation. Faults and failures are made in unrealistic methods (e.g. drilling large holes in bearings) which limits usage of models.

For SEW Eurodrive the following is recommended. Further research can be done into the model and how it can be implemented into the different systems of clients. Research can also be done into how the model could run locally on a computer or be integrated into a cloud which captures data. There are many PdM and FDD algorithms in literature. All work in separate ways and have advantages and disadvantages. To effectively understand these models trail and error method would be suggested. Next recommendation would to gather as much data as possible and also gather data from different industries as well. Gathering data from different industries helps to understand where certain failures are more likely to happen, how machines behave in different environments and to work towards helping as much clients as possible. Essential is to create simple products which cater towards the needs. When working products start getting developed a focus should move towards future products and how to easily integrate DriveRadar in these. To lower the threshold for companies to adopt PdM or FDD it would be the best if these solutions would come with the products. This not only would give better reliability to the customer, it would financially help SEW Eurodrive.

Contents

Abbreviations

Abbreviation	Definition
SEW	Süddeutsche Elektromotorenwerke
I4.0	Industry 4.0
IoT	Internet of Things
PdM	Predictive Maintenance
FDD	Fault Detection and Diagnosis
USD	United States Dollar
AI	Artificial Intelligence
ML	Machine Learning
ITIC	Information Technology Intelligence Consulting
PwC	PricewaterhouseCoopers
IG	Industrial Gear units
DRIG	DriveRadar Industrial Gear units
OEM	Original Equipment Manufacturer
R&D	Research and Development
VFD	Variable Frequency Drive
AC	Alternating Current
DC	Direct Current
KPI	Key Performance Indicators
EPU	Edge Processing Unit
SKF	Svenska Kullagerfabriken
RUL	Remaining Useful Life
HST	High Speed Train
RMS	Root Mean Square
FFT	fast Fourier transform
STFT	short-time Fourier transform
DL	Deep Learning
ANN	Artificial Neural Networks
LR	Logistic Regression
SVM	Support Vector Machine
DT	Decision Tree
RF	Random Forest
PCA	Principal Component Analysis
HVAC	Heating, Ventilation en Air Conditioning
MSCA	Motor Current Signature Analyse
ABS	Anti-lock Braking System
VDL	Van der Leegte (Family name)
BMW	Bayerische Motoren Werke
PLC	Programmable Logic Controller
PCC	Pearson correlation Coefficient
MDI	Mean Decrease in Impurity

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1 Introduction

1.1. Research Context

In 2020 the global industrial electric motor market size was 47 billion US dollars and it has been estimated that it account for roughly 70% of all industrial electricity consumption (Mordor Intelligence, 2020; Waide and Brunner, 2011). These motors which are generally smaller than 5kW (usually connected to a gearbox, called a gearmotor) are critical components to many industries and can be found in many machines, such as, compressors, heavy-duty equipment, conveyors, elevators, cranes and pumps. For these systems (motor, gearbox and load), called electric gearmotor systems, it is crucial that they work without failure.

Over the next seven years it is estimated that the global electric motor market size will grow by 67% due to the increase in worldwide general manufacturing (ReportLinker, 2020). This is a stable growth of roughly 7% per year and due to competitive pricing and technological advancements there is a large number of international competitors (The Business Research Company, 2020). For the involved companies it is crucial to stay technologically innovative and differentiate to meet needs of ever increasingly demanding customers. Two of the current largest trends in this branch are servitization and Industry 4.0. Servitization stands for the move from a product to a service-oriented business model, this means not only providing goods, also providing support, self-service and knowledge. This creates additional services for the customers which result in a higher revenue for the company. The other trend is Industry 4.0, which stands for the modernisation of traditional manufacturing through automation and using smart technologies (e.g. sensors, cloud storage, AI) (Lasi et al., 2014). Servitization and Industry 4.0 compliment each other through servitization focusing on adding value to the customer and Industry 4.0 adding value to the manufacturing process (A. Frank et al., 2019). Industry 4.0 contains many different topics, from supply chain integration to automation of robots to big data and lastly predictive maintenance (PdM).

PdM is a technology to foresee failures or faults in a system that deteriorates over time through evaluating the state of the system (condition monitoring) and has been extensively covered by academic research over the last 20 years (Selcuk, 2017). PdM has different exact definitions, however in general it is seen as an umbrella term for everything that has to do with fault detection and diagnosis, prognostics and condition monitoring. Advanced techniques e.g. vibration, oil, thermal and acoustic analysis are used and by utilising artificial intelligence (AI) the condition of electric motors can accurately be determined (Levitt, 2003).

Its attractiveness for organizations is also clear, in 2016 ITIC (Information Technology Intelligence Consulting) conducted a research across 300 companies and found that 98% of organizations report that a single hour of downtime can cost over 100.000 USD and for the automotive industry downtime can cost $22.000/minute (ITIC, 2016; Nielsen Research, 2005). This downtime is not specifically related to the electric gearmotor systems, however considering their presence they play a large roll in this. Another report by the US Department of Energy, Energy Efficiency & Renewable Energy found that

PdM reduces maintenance cost by 25-30% and considering the fact maintenance is between 15-70% of total productions cost, large amounts of savings can be achieved (You et al., 2010; Sullivan et al., 2010). These numbers are very promising for this technology, however outside of the universities PdM has hardly been adopted. Two thirds of the 256 manufacturing companies surveyed by PwC (PricewaterhouseCoopers) in 2017 still only conduct visual inspections and some basic instrument inspections (Haarman et al., 2017). In another survey by PwC it was found that only 11% of the companies had some type of PdM solution, while 60% of the companies have intentions to use PdM (this was 49% in 2017), thus adoption is low, however willingness is high (and increasing) (Haarman et al., 2018). Another survey by Siemens in 2018 which found that 93% of the 230 interviewed companies said that their existing maintenance processes are not very efficient (Milojevic and Nassah, 2018). To illustrate, companies where downtime is expensive will daily inspect a certain amount of electric drive systems on their conditions, these are almost always healthy resulting unnecessary maintenance time. Combining this information a gap can be found; even though there is an abundance of academic knowledge on PdM, in practice it has hardly been adopted by companies and organisations.

In recent years papers have been published addressing this issue, however reasons why vary. Wickern, 2019 states that it is mainly due to financial and organizational obstacles. Tiddens, 2018 states that unavailability of high-quality data is a wide spread issue, that companies do not understand the value of PdM and literature focuses on technical part of PdM, ignoring other facets like organisational perspectives or maintenance strategies. Karuppiah et al., 2021 identified poor commitment from top management. Other reason that can be found are organisational culture issues (Freeman Gebler et al., 2016) and worries about data security and hesitance to share data through value chain (Bokrantz et al., 2017).

Thus, even though science has started to address the issue that PdM adoption is slow, research has to be done into PdM models and techniques that adhere to real world parameters, not to laboratories tests where most papers are based on. Key is to identify current PdM techniques and understanding how these can be applied to a industrial application. This research addressed this scientific gap with a study on how PdM can be integrated into the manufacturing industry in a sustainable way.

1.2. Research Field

This research is conducted at SEW-EURODRIVE B.V. (from now on referred to as SEW Eurodrive) which is a subsidiary of SEW-EURODRIVE GmbH & Co KG. This family owned company produces gear units, motors, gearmotors, AGV's (automated guided vehicles) and variable frequency drives (VFD) in various sizes for a range of different applications, see figure 1.1. SEW Eurodrive has subsidiaries in 52 countries around the world and its headquarters are in Bruchsal Germany, this is also the main production facility and where most R&D is done. SEW Eurodrive The Netherlands employs 150 of the 18.000+ employees of the SEW Eurodrive Group. Over 2019/2020 the company had 3.3 billion euros in sales resulting in being one of the global market leaders in its sector (Sew-Eurodrive, 2021). Nevertheless, SEW Eurodrive would like to grow as a company and increase its revenue. To reach this goal the company must innovate and differentiate to meet customer demands.

SEW Eurodrive's is a player in a highly competitive market, so it is essential to differentiate. SEW Eurodrive does this through providing customers flexibility, quality, service, knowledge and expertise. Through this they have build a loyal customer base which appreciates a partner which provides not only products, but full solutions e.g. engineering, maintenance and 24/7 service. The servitization trend is not directly applicable for SEW Eurodrive. This is because 80% of SEW Eurodrive clients are OEM (original equipment manufacturers), these are company's that build machines that utilize the products of SEW Eurodrive. Examples of OEM machines are packaging machines, automated logistic warehouses and airport baggage handling machines. These are the companies that would be moving towards the servitization trend due to them being in direct contact with the customer and being value adding to their business. However, for SEW Eurodrive there is potential if they can help these OEM customers with the move to servitization. For the macro trend Industry 4.0, SEW Eurodrive has been developing products and gaining knowledge and is slowly helping clients adopt this into their factories. One of the most interesting technologies of Industry 4.0 for clients is predictive maintenance. For many clients this

Figure 1.1: Products of SEW-EURODRIVE

is not a new topic, however it has become increasingly popular due to financial benefits, nevertheless adoption among end users is still low. To cater to this SEW Eurodrive has been developing a PdM software called DriveRadar.

DriveRadar is an umbrella term for all software that has to do with intelligent, scalable services for Smart Factory's with the eventual goal of boosting productivity. DriveRadar is still actively being developed, however is far from being a finished product. DriveRadar will eventually prevent unforeseen failures and interference's in operation through detection of deterioration of products. R&D of DriveRadar has mainly focused on industrial gear units (IG), see figure 1.2. These IG are used in industries such as mining, steel production and timber and can deliver up to 5200kNm of torque (SEW-Eurodrive, 2014). They are usually found in essential places in production lines (e.g. conveyors, mills), thus it is important that they do not fail. SEW Eurodrive has test fitted IG units with an EPU (edge processing unit, which sends info to the cloud) and sensors that detects ambient, oil, electronics and IG temperature, vibrations, the input speed, oil level and the operating hours. This gives a complete overview of the current state of the IG and when something abnormal is sensed in the IG it is directly reported to the plant supervisor or maintenance engineer. In The Netherlands DriveRadar has been installed on two IG units at a steel manufacturing company which are very satisfied with the product. On a computer screen they can see the condition of the IG's (down to the health state of each single bearing) and if anything has to be done to it in terms of maintenance.

While DriveRadar for IG units has slowly gained traction over the last couple of years, it has not really been implemented in other SEW Eurodrive products. This is where SEW Eurodrive faces a bottleneck in the development of DriveRadar. This is because if failure occurs, replacement IG units can also take more than a week to be delivered resulting in extended production downtime. Secondly, it is simple to justify 2000 euros worth of sensors on a IG unit worth 100.000 euro's, however gearmotors are worth roughly 1000 euros which does not justify the price of sensors. To solve this issue SEW Eurodrive wants to utilise data from the VFD. They are used to control the AC motor speed and delivered torque through varying input frequency and voltage to the motor. These components can act as a basic sensor which creates data, see table 1.1, advantage is that that this data is created normally through the VFD and does not require additional sensors which saves costs. Active and output current are the same for most systems, they only differ for some AC motors. Setpoint and actual speed are almost identical, with the setpoint speed being the speed the controller assigns and the actual speed being the speed of the motor. DC Link Voltage, IxT channel and the two IPOS channels are mainly used to see what has happened with the system after failure has happened. SEW Eurodrive wants to be able to determine the health condition and fault identification through this data due to simple implementation, low cost and easy of understanding.

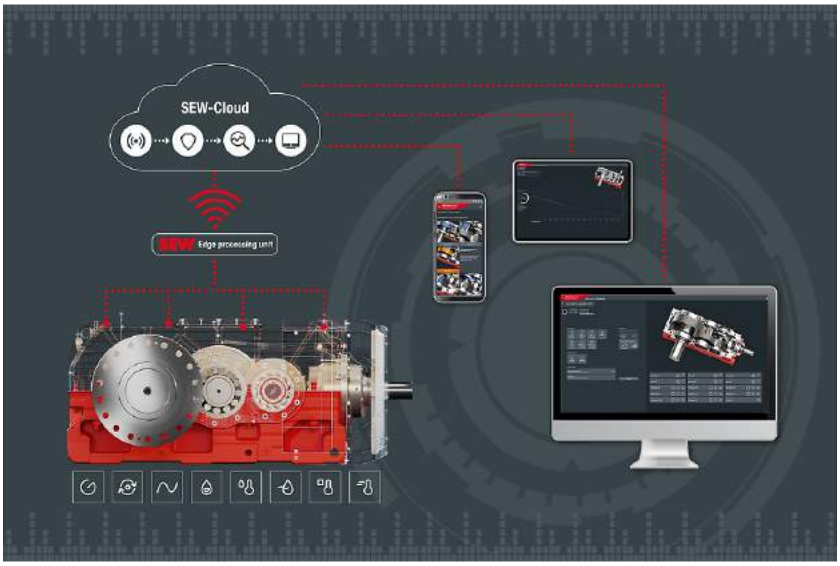


Figure 1.2: DriveRadar for industrial gear units (SEW-Eurodrive, 2019)

Data name	**Unit**	**Description**
Active Current	% A	Percentage of maximum allowed current to motor
Output Current	% A	Percentage of maximum allowed current to motor
Setpoint speed	1/min	Speed controller selects
Actual speed	1/min	Actual speed of motor
DC Link Voltage	V	Connects the VFD rectifier and inverter
IxT Channel	/	Burden on VFD (temp, current, etc.)
IPOS 511	deg	Rotation of system
IPOS 512	/	Number of rotations

Table 1.1: Data from variable frequency drive

The data gathered from the VFD will thus to analyse electric gearmotors systems, see figure 1.3. Gearmotors are homogeneous and compact units which consist of a gear unit and an electric motor. They are versatile and used in lifts, pumps, mixers and other machines and are found in industries like the automotive (press shops to final assembly), beverage (moving bottles to packaging units) and intralogistics (sorting to supplying goods). They are at the heart of many systems in industries thus it is important that gearmotors do not fail. Here there is another difference compared to IG units, due to the low price of gearmotors, replacements are inexpensive if they were to fail. However more serious is the fact that if gearmotors system fail, production lines stop working resulting in revenue losses. Another difference is with IG units, replacements can take more then a week because they are custom made and have to be shipped internationally. This makes PdM models that predict future failure, called prognostics, obvious due to limited downtime of IG's. Small gearmotors differ due to companies regularly keeping back-up gearmotors in storage due to their low cost, when a gearmotor fails they can be changed. Here having exact future date of failure is less relevant, simply knowing failure is imminent is enough, this is called diagnostics or fault detection and diagnosis (FDD).

Failures are not common, however can occasional occur which results in unwanted downtime. Gearmotor systems from experience from SEW Eurodrive have three main failure causes. The first is that there is a blockage in the system, here the movement is obstructed. Second, is a bearing failure in the system and third is a gear failure. If SEW Eurodrive could identify these failures after detecting failure the maintenance process could be done faster and through understanding the failure a knowledge will be gained which can help towards avoiding similar failures in the future.

These reasons result in developing DriveRadar for gearmotors a logical decision due to long term cost

Figure 1.3: SEW Eurodrive standard gearmotors

savings for companies. Especially if DriveRadar is also able to determine the health condition of the systems that are connected to the gearmotors through the data of the VFD, giving a complete condition monitoring solution.

1.3. Research Problem

SEW Eurodrive strives to become more competitive and qualitative gearmotor supplier worldwide. It wants to achieve this by further meeting customers expectations and providing more services. From the research field it was concluded that gearmotor systems benefit the most from diagnosis, e.g. understanding that a fault is happening, not when a fault will happen in the future (prognostics). Thus, from now failure detection and diagnosis (FDD) will be used instead of PdM. Key gaps have been identified in literature when it comes to the development of failure diagnostic models. Many failure diagnostic models, techniques and theories are inapplicable in industrial settings halting adoption. In the next two sections the scientific and practical problem statement are discussed.

1.3.1. Scientific Problem Statement

The scientific problem is comprised of two main issues. First, there is a limited amount of scientific research into bridging the gap between scientific FDD and industrial applications. In the last two years some papers have addressed the gap to a certain extend, however lack concrete solutions (Freeman Gebler et al., 2016; Jin et al., 2016; Bokrantz et al., 2017; Tiddens, 2018).

Secondly there is a gap between FDD models, techniques and theory which have been developed in academic (lab) environments and industrial settings. In literature FDD models mainly focus on the technical aspect, however ignore financial or managerial facets. The FDD models described in literature mainly use complex algorithms that have been developed in a controlled environment and use Machine Learning, concepts which are difficult to understand and implement in industrial settings. There is a need for accurate, reliable FDD models and software, which can be implemented into current industrial systems without requiring large financial and/or labor, which is regularly the case in literature.

1.3.2. Practical Problem Statement

Even though FDD and PdM promises less maintenance cost and increases in productivity, its actual implementation in industrial applications has been slow. This is characterized by the fact that in reality facets, for instance, finance, management, knowledge, culture and data quality play a role. This can result in a sub-par maintenance strategy which can be very costly and time consuming. This uncertainty leaves opportunities for SEW Eurodrive to help its customers with implementing FDD, however SEW Eurodrive still lacks understanding of how to achieve this. Secondly, knowledge about FDD models that can be applied to industrial situations is also limited making it difficult to help customers.

1.4. Research Objectives

This research is focused on developing a fault detection and diagnosis model which can be applied to an electric gearmotor system in an industrial setting. This is done in cooperation with SEW Eurodrive where the model is developed for a current system. Based on the research problem the following research objective was defined:

> *Develop a predictive maintenance model which provides fault identification and diagnostics on electrical gearmotor systems*

1.5. Research Questions

The following main research question was formulated based on the research objective:

Main Question

> *How to develop a fault detection and diagnosis model of an industrial applied electric gearmotor system?*

To answer the main question various sub-questions were formulated:

1. What is the state-of-the-art of fault detection and diagnosis in industrial settings?
2. How does literature describe fault detection and diagnosis models and what type of data is necessary?
3. What KPI's can be used to assess the fault detection and diagnosis model?
4. What fault detection and diagnosis model can be developed for an electric gearmotor system?
5. How can the model be verified and validated?

1.6. Research Scope

For the eventual objective of developing a FDD model for industrial setting, first understanding is necessary on all relevant aspects. This will be done with an analysis on the state-of-the-art of the industry and a literature review on fault detection and diagnosis models, the possibilities with the available data and characteristics of the main faults. Furthermore, focus will lay on FDD not on prognostics (prediction of future failures) (Ly et al., 2009). This has two reasons, first, before prognostics can be done diagnostics must be deeply understood. Secondly, in an industrial setting prognostics has limited added value, if it is known a machine is about to fail it will be replaced immediately.

From the information gathered above a diagnostic fault diagnostics model will be developed which can be implemented in an industrial setting. Industrial setting refers to an environment that is developed with industries where goods are manufactured. If a subsystem of a production facility starts to fail, maintenance engineers will get a notification that a system is showing abnormalities and an estimation of the fault. A model with these capabilities would add the most value due to first identifying a failure before it happens, together with an estimation of what it could be to accelerate the maintenance work. No prognostics will happen, the model will solely focus on diagnosis. The model will only use data that comes out of the VFD, see table 1.1, advantage of this is the fact no extra sensors are necessary and the financial savings. Using the data the condition of the mechanical components will be determined, it is assumed the VFD, cables, the controller and other electric components are healthy and will not fail. The mechanical components are the motor, gearbox and the load that is being powered. Load referring to the machine that is being powered, e.g. conveyor or mixer. Being an industrial setting it is important that the model has a low development cost, cost revering to time and money designing takes.

To validate and verify the fault detection and diagnostic model a case study will be conducted using data and parameters of a system SEW Eurodrive has already gathered data on. The system is a lift used in a car manufacturing plant which has been gathering data from July 2020 until October 2021.

A summary of the scope is presented below with all delimitation's (boundaries research) and limitations (restrictions research)

- Model will utilise the given eight data sources (table 1.1)
- Focus on gearmotor and load
- Will be a diagnostic model
- Focus on robust and adaptable model (requirements industrial setting)
- Identify blockage, bearing and gear failure

1.7. Research Outline

The structure of the report will follow the the different subquestions. In chapter 2 the state-of-the-art of the development of PdM and FDD in industrial settings can be found, this is defined using SEW Eurodrive. Thereafter a literature review on all aspects of FDD can be found which are relevant to the scope and a detail view of the main faults can be found in chapter 3. In this chapter different solution methods for fault detection and for fault diagnosis will be discussed. In chapter 4 all aspects of the designed model will be presented. This chapter also includes the KPI's which will be used to evaluate the different parts of the model. Subsequently in chapter 5 the model will be applied to a case study and shown how it can be implemented in a system. This will be used to verify and validate the system, eventually the KPI's are evaluated and results discussed. Lastly in chapter 6 the conclusion, limitations and recommendations can be found.

2
State-of-the-art SEW Eurodrive

To understand a problem it is essential to understand the state-of-the-art of the current industrial setting, being company and literature related. Thus, in this chapter the state-of-the-art of the industry will be analysed and summarized using knowledge from experts and SEW Eurodrive, a key player in the industry. The sub-question that will be answered in this chapter is: *What is the state-of-the-art of fault detection and diagnosis in industrial settings?*

2.1. State-of-the-art at SEW-Eurodrive

The state-of-the-art has been identified through using relevant company papers/reports and through conducting interviews with SEW Eurodrive employees. An overview of the findings can be found below with key issue that have been identified. These issues are summarized in the synthesis. Important is that, even though SEW Eurodrive will be used as source, it will reflect the state of the general industry and players that are working on the same problem.

At SEW-Eurodrive everything that has to do with Smart Factories is captured under the umbrella term DriveRadar (SEW-Eurodrive, 2019). The concept *Smart Factory* is an expression for the end goal of digitization of manufacturing, where machines continuously share data which is used for self-optimizing devices or across organizations to address issues (Roda et al., 2018). The eventual goal is to improve productivity and efficiency in the production industry to boost profits. When it comes to FDD/PdM DriveRadar determines the status using data that is recorded during the operation of their drive systems (this is everything from frequency inverters to AC motors). Through predictive analytic procedures together with expert knowledge this data is evaluated and translated into actions. This leads to unforeseen failures and interference's in operations, detection of wear and decrease downtime.

However, DriveRadar is still in the development phase and requires extensive R&D. A problem SEW Eurodrive faces is that the models, algorithms and knowledge from academic literature cannot directly be applied in an industrial situation in many cases. Every customer and project is unique and has its own requirements, some customers just want the data from the products of SEW Eurodrive and other customers want a complete PdM solution. Another issue is that in reality industrial plants continuously change, examples are machines running at different speeds, loads and temperature over time making it difficult to train models. This combined with the overall lack of data, including failure data extremely limits Machine Learning possibilities. The last issue that the industry in general faced are false positive and false negative alarms. False positive is an error in fault classification where the algorithm or model believes a fault has happened when this is not the case and false negative being the test believes there is no failure when there is a failure. These results in unnecessary maintenance and in some cases unnecessary downtime. Especially important here are false positive alarms, these will trigger maintenance to be done without actual maintenance being necessary. Examples can be when the oil is cold the efficiency of the gearbox will be lower resulting in a higher current to the motor to perform the same movement. This could result in an error or alarm due to the increased torque, however in reality this is not a problem. These issues makes creating a single, reliable and universal PdM program a complex problem. To reach the final goal SEW Eurodrive requires structured information, trail-and-error between models/algorithms to find working solutions and data in bulk.

To understand how far the development of PdM solutions are in industrial practises is the simplest to break PdM down into steps. According to the European Standard *EN 13306*, 2018 there are four main maintenance concepts for maintenance, namely, reactive maintenance, preventative maintenance, predictive maintenance and proactive maintenance, see figure 2.1. The first category is the simplest, it is based on components running until failure has occurred and stops the system from running. However, because of the unexpected downtime and extra maintenance expenditures this is usually more expensive (Zhang et al., 2019). Preventative maintenance is conducted through regularly replacing components or planning maintenance, however leading to extra operation costs and increased unexploited lifetime (Wan et al., 2017). Predictive is based on assessing the health condition of systems and their sub-systems to predictive when maintenance is necessary. Pro-active is done through determining the reason machines fail and eliminating the cause, however this is overkill for many properly engineered systems. Predictive maintenance when applied in the correct way to the right system is the most cost effective maintenance technique that can be applied (Qiao and Lu, 2015; Hashemian and Bean, 2011; Barajas and Srinivasa, 2008). In general the industry determines which maintenance strategy is used. Traditional industry's such as mining or steel production prefer a reactive strategy, however nuclear power-plants work with proactive due to safety reasons. In production and logistics it depends on the company, however in general it is reactive with some type of preventative. SEW Eurodrive therefor wishes to develop predictive solutions to cater to the Industry 4.0 development.

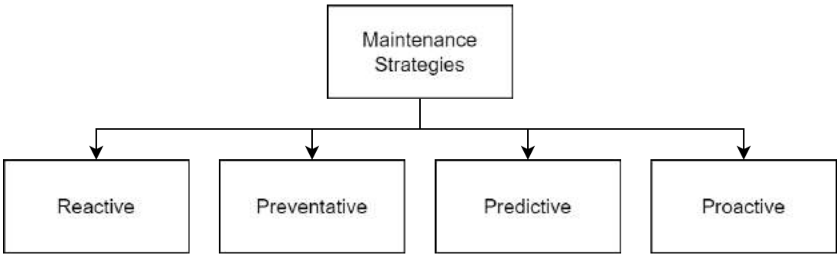


Figure 2.1: Four types of maintenance strategy's (*EN 13306*, 2018)

A PdM model has five stages in total, from capturing the data to the actual prediction, see figure 2.2. Collecting the data is the first phase, next is pre-processing where the most relevant information is extracted. This is followed by assessment, where the data can be judged on its quality and quantity and features can be extracted. Then it is analysed through algorithms and then a prediction of the (remaining) health is done. When it comes to products SEW Eurodrive is at the pre-processing phase, two products, namely DriveRadar DataCollector and DriveRadar DataConverter have been released already. The first product simply collects data and the second can convert the data into readable files. These products belong to the capturing phase, thus pre-processing phase is what SEW Eurodrive is currently focusing on. This includes defining what type of data to extract (e.g. vibration, current, DC voltage), how to analyse it and how to save it. SEW Eurodrive has also developed a product called DriveRadar IoT Suite, this is a web application which can display the condition of the systems and components. It is still being developed however one can currently see an overview of the collected data and see some pre-processing techniques that have been applied. This is currently being developed and is not public yet.

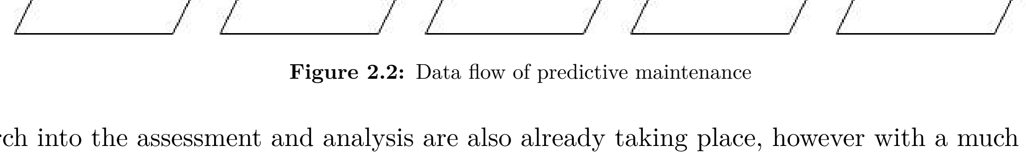


Figure 2.2: Data flow of predictive maintenance

Research into the assessment and analysis are also already taking place, however with a much broader scope. This is because the best parameters are still being defined in the pre-processing stage. Various AI and ML algorithms are being tested together with evaluating different analysis techniques. However, options are limited due to the lack of quality data. Products of SEW Eurodrive can last up to 30 years and the systems which are attached to the gearmotor system in general also last for a long time. This results in a lack of failure data which is necessary for AI. To try and create fault data SEW Eurodrive has multiple test rigs, however it can takes months or years before failure happens. AI is being developed which can create this fault data, however it will not be the same as real world data.

A problem when developing FDD solutions is the difference of component vs system level diagnostics. Traditionally many papers in literature focus on component level diagnostics, examples being simply focusing on the gearbox bearing of a drive-system (Randall, 2004). This can be seen in the Industrial Gear units of SEW Eurodrive which already have a DriveRadar solution, they are relatively simple components which makes PdM straightforward. However, in reality operators and maintenance engineers of production facilities want to be able to detect the condition of full systems, not individual components. System level diagnostics is considerably more difficult compared to component level diagnostics due to the fact more (critical) faults can occur and there is more noise.

Another problem when developing FDD solutions is the identification of the main failures from electric gearmotor systems. From interviews with engineers of SEW Eurodrive three main failures were identified. These failures are based on experience from engineers and have not been recorded with DriveRadar. The first main failure of a system is blockage of movement in the load. Depending on what the load is this can differ, however examples are blocked rotation of a pump, obstruction of movement of a lift or a pile up on a conveyor. This results in a peak load in the current send to the motor which can result in extensive damages. The second main failure is bearing failure, bearings are responsible for transferring motion through the system through supporting and guiding components which turn relative to each other. These crucial components are subjected to heavy loads thus are the most likely component to actual fail in a system. The last main failure is gear failure, gears are found in the gearbox and occasionally in the load. They transfer the torque through the system thus are also subjected to heavy loads. When lubrication of systems degrades the gears are subjected to increased wear and heat which results in degradation over time.

Outside of the monitoring side of DriveRadar there are other issues that also have to be addressed, examples are data security, network loading and if it is financially viable as a product. All these issue makes this a complex problem with how to solve PdM being one of it. Important now for the development of DriveRadar is gathering relevant and useful data and knowledge from the internet which can in turn be applied. Secondly it is essential to conduct tests with the data that is already available, this will give an insight into what works and which does not and this is important in the research and development stage of a product.

2.2. Concluding Remarks

In this chapter the sub-research question *What is the state-of-the-art of fault detection and diagnosis in industrial settings?* was answered. The chapter explored at what stage in development SEW Eurodrive is, gave an overview of FDD and the problems the company faces. An overview of the main points of the state-of-the-art of SEW Eurodrive in the development of DriveRadar can be found below.

1. Lack of knowledge of how to create Smart Factory concept that satisfies all customers in their dynamic environments
2. Currently at the pre-processing phase, knowledge about this and the next stages (assessment and analysis) necessary
3. Lack of data (especially failure data)
4. Lack of models/algorithms which can directly be applied to an industrial setting
5. Searching for methods to avoid false positive and negative alarms in models/algorithms
6. Difficulty in identifying system level diagnostic models
7. Three main failures: blockage in movement, bearing failure and gear failure

In the next chapter a literature review is conducted where all relevant information is gathered on the given problem and how it can be solved. The problem and given situation is defined in chapter 2, solutions identified in chapter 3 and in the following chapters a solution is given.

3

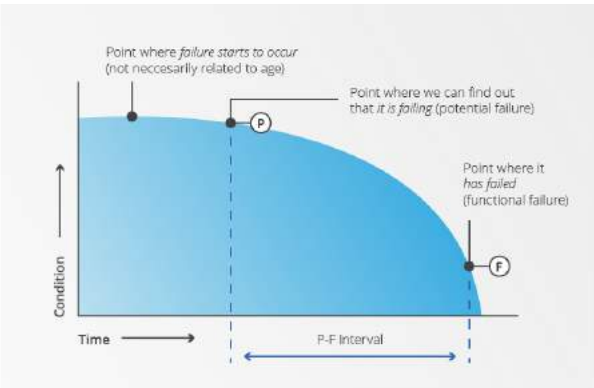
Literature Review

In this chapter the context of the problem is described in more detail by means of a literature review. First, a short review over fault detection and diagnosis (FDD) is given. Secondly, the different FDD techniques are given which can be applied to the system and are also compared. Thirdly, the main faults are analysed and determined how they can be detected. In this chapter the sub-question 2 will be answered: *How does literature describe fault detection and diagnosis models and what type of data is necessary for these?*

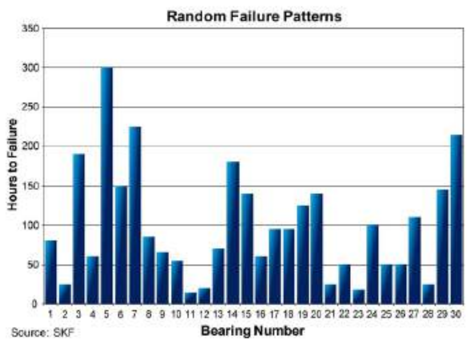
3.1. Fault Detection and Diagnosis

Fault detection and diagnosis (FDD) lets operators and maintenance engineers know exactly when and what is wrong with the machines and systems they are responsible for and what they need to do to repair it. This results in advantages in a safer environment for humans, less downtime and a better understanding of the system (Abid et al., 2020). In recent decades a lot of work has been done on FDD with various techniques being developed. A full predictive maintenance solution involves diagnosis and prognosis, and here FDD fits in the diagnosis stage. With the advent of Industry 4.0 current industrial processes, systems and components are becoming smart, thus generating process-related data to discover faults which arise which makes FDD very relevant.

The potential of FDD can be seen in a P-F curve, see figure 3.1a. It shows the behavior of an asset before failure happens. The x-axis is time, and the y-axis is the condition of the asset. The curve shows the time interval between the time of potential failure (P) and actual failure (F). At point P one can already determine that failure (F) is going to happen, F is typically a distribution of the possible failure times for the failure mode under examination (Bellstedt, 2020). SKF (Svenska Kullagerfabriken), one



(a) Predictive maintenance in the context of the P-F curve (Bellstedt, 2020)



(b) Flaws of time based maintenance due to random bearing failure (Hashemian and Bean, 2011)

Figure 3.1: Why predictive maintenance is important

of the largest bearing manufacturers worldwide, tested 30 identical bearings under identical conditions until they failed. As figure 3.1b shows, some failed after 15 hours and one lasted for 300 hours. Despite the bearings being identical, time-to-failure varied immensely.

Before going into detail about FDD, first the definition of a fault is defined, namely: an unpermitted deviation of at least one characteristic property or parameter of the system from the acceptable/usual/standard condition (Yang et al., 2015). Faults may be already existing in the process or appear at an unknown time and the speed of appearance of faults can be different. Faults can be classified into three categories, abrupt faults, incipient faults (drifting faults) or intermittent fault. A failure is defined as an eternal system interruption to execute a function (Yang et al., 2015).

FDD has two basic functions, first monitor behavior of a process and secondly, reveal the fault and its root causes (Park et al., 2020). The second stage can also be divided, namely fault detection, fault isolation, fault identification, and fault evaluation, see figure 3.2. Fault detection is observing a fault, isolation and identification is naming the fault, which is also referred to as diagnosis. Fault evaluation is an assessment of the impact on the system and how to respond to it, this is based on the opinion of the maintenance engineers and will not be discussed. In some literature fault evaluation stage is used to calculate the remaining useful life (RUL) process which predicts the life cycle of the component (Saufi et al., 2019). This is performed through determining the size of the fault and the component where it is occurring. However, this is outside the scope and will not be researched.

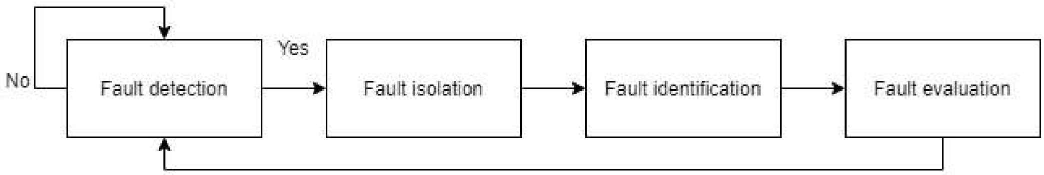


Figure 3.2: Procedure FDD (Park et al., 2020)

Fault detection methods have been research extensively in recent decades, they can be classified into model-based and data-driven. In certain papers knowledge-based FDD is categorised as data-driven due to it using previous knowledge (data). To simplify it has been left out of the overview. Data-drive approaches consider detection and diagnosis as classification (Tidriri et al., 2016). It does this in two stages, first stage detects whether the system behavior matches the expected one and the second stage determines the type of fault. The two stages can be performed independently or combined with each other. Model-based generally uses a model, based on the physics of the process which will be monitored creating residuals which will be analysed. Model-based can be used for classification however has not really been researched in recent years due to data-driven methods excelling at the task. Each method has each own advantages and disadvantages, which can be mitigated through combining, called hybridisation.

The rest of the chapter will be paragraphed by each stage of FDD giving information within the given research scope. Unique to this situation is that limited data options are available, in a full FDD system data such as vibration, audio, air pressure etc. are available. This results in the isolation phase, where the root cause is identified and the fault isolated from the data difficult. A focus will lay on a more general fault identification which in industrial settings is enough. Before the research a term is defined, uni- and multivariate data, univariate data analysis involves only one dependent variables and multivariate involves more than two dependent variables. In the rest of the chapter the steps of FDD will be presented with relevant literature.

3.1.1. Data Acquisition

In the introduction the eight data streams were defined which are available from the VFD, see table 1.1. The motor armature current can be converted to torque the motor generates using the motors torque constant k_T and formula 3.1. k_T determines the torque-current relationship and is in Nm/amp, i_a stands for armature current. Torque can show the health condition of the overall machine (e.g. load,

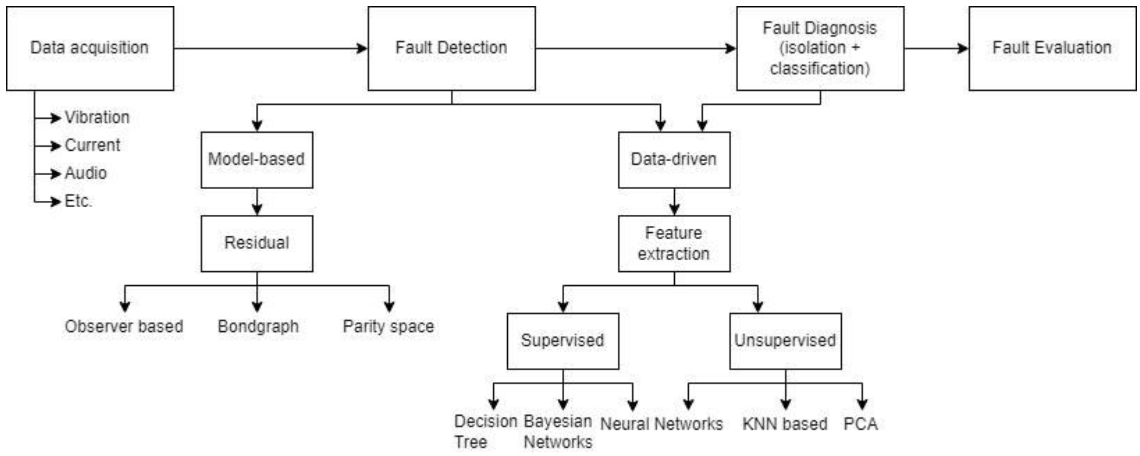


Figure 3.3: Overview FDD and methods (Tidriri et al., 2016 Abid et al., 2020)

gearbox and motor), because it *flows* through the machine, the servomotor generates the torque which is converted through the gearbox and then utilized at the load (Zhou et al., 2007). If anything happens in the system (e.g. increase friction, degradation oil) the torque is influenced. One disadvantage is that upcoming failures can only subtly change the torque which results in, or, too late identification or simply faults not being seen until failure happens. This can be mitigated through correct fault detection and isolation. Faults can be detected when there is a good model and torque estimation. In literature vibration sensors are used due to high accuracy and clear failure detection, many papers have compared vibration and current data for fault detection the the conclusions are similar (Corne et al., 2015 ,Bellini et al., 2008). While vibration signals are more accurate and can detect very early failure onset, current signals also show fault signs when the right features are extracted. An example of current fault detection is by Guzinski et al., 2009 who through using torque could identify the messing frequency of the gearbox of a High Speed Train (HST) to monitor gearbox failure. In general, current-based fault diagnosis can be categorised into two methods, residual-based fault diagnosis and features-based fault diagnosis. Residual-based employs an analytical model to represent the system which is subtracted from the system input to provide a base value, when faults occur the residual value increases. Feature-based characterizing attributes are modeled and use features in the time and feature domain for in machine fault diagnosis.

$$T_{motor} = k_t i_a \tag{3.1}$$

Using the setpoint speed and actual speed of the servomotor have been used in literature for FDD with some techniques. Faults were identified in helical gears (commonly used in manufacturing) at low speeds through using optical encoder signal (Shao et al., 2016). Another possibility is an algorithm that was developed which can detect failures in gears in a planetary gearbox powered by a servomotor (Zhao and Lin, 2018). In Hamadache et al., 2015 a method was proposed based on rotor speed signal which is advantageous in terms of cost and simplicity. Problem with all these papers is that they use sensors with a high sampling frequency, some higher than 25.000 Hz. The data out of the variable frequency drive (VFD) is 250 Hz thus not accurate enough for precise failure detection. The other four data channels, DC link voltage, IxT Channel and IPOS 511 and 512 cannot be used for fault detection. These channels are mainly used by engineers for system checks or occasionally health checks. The IxT channel shows the load on the VFD over a time period, one could argue that when an increased motor load this value would change too, however this has not been researched in literature.

3.1.2. FDD Detection

Fault detection is the first task which determines if there is a fault or not in the system. The method used for this depends on the data and the requirements. Model-based and data-driven are analysed and compared.

FDD detection methods
According to Skliros et al., 2018, the FDD methods that can be found in literature are divided into two categories. First is called **model-based**, where a mathematical model is derived which simulates the systems movement or degradation. Second is called **data-driven**, this methods is based in artificial intelligence (AI) or machine learning (ML) and is most commonly found in literature. Below an extensive overview of the categories can be found, mainly based on papers by Zonta et al., 2020, Zhang et al., 2019 and Kwon et al., 2016.

Model-based
Model-based or physic-models, are based on mathematical equations that describe a system or component. In literature model-based methods use a physics (mathematical) model of a system or component to calculate physical parameters which are compared with system observations. By using various techniques to compare results faults and root causes are isolated (Skliros et al., 2018). A second method in literature to use a physics model of a system is to describe a systems failure mechanism (e.g. fatigue, wear or corrosion) to define a system's degradation process (Liao and Köttig, 2016). Failure mechanisms are captured in a mathematical model, which relates the usage or loading of a system to degradation rate or lifetime prediction (Tinga and Loendersloot, 2019). When the load/usage is monitored it is possible to predict the remaining useful life (RUL), this is known as prognostics. These two methods can also be defined as quantitative vs qualitative models (Khalastchi and Kalech, 2018). Quantitative models involve mathematical equations, which typically describe the functionality of components. Qualitative models involve logic-functions, which typically describe the behavior of components by describing qualitative relations between the observed variables.

Model-based methods create residuals which are analysed to detect faults. It can be described by equation 3.2, $y_i(t)$ is the measured output of a system and $\hat{y}_i(t)$ is the estimated output. A residual (or $e_i(t)$ is a signal that is zero when the system under diagnosis is fault-free, and non-zero when particular faults are present in the system (Svärd, 2015).

$$e_i(t) = y_i(t) - \hat{y}_i(t) \tag{3.2}$$

In literature three main methods are used for residual generation, namely, bond graph modeling, diagnostic observers and parity relations. First, bond graph modeling is a graphical representation of a dynamical physical system (Kothamasu et al., 2006; Samantaray and Bouamama, 2008). Bond graph utilises an energy-based methodology for modeling, the energy (current, voltage) are modeled and if abnormalities are sensed by sensors a fault is detected. Another method is diagnostic observers, here a system is observable (i.e. determining system behaviour through system outputs) and because the process parameters are known, the process can be estimated and residuals generated, usually using equation 3.2 (Tidriri et al., 2016). The last approach is through parity space which transforms the state-space model of a system to obtain parity relations (Gertler, 1991). The purpose of generation these parity relations is to provide equations which only depend on known or measured variables. These are sensitive to change this can detect faults.

After generating a residual signal it is analysed (Abid et al., 2020). This can be done in two ways, first is defining threshold values which when reached an alarm goes off. The second is defining fault decision indicators which are features which change when distinct failures happen. Usually a mathematical model of a system is used and compared to information from sensors and actuators to generate residuals. However, in industrial settings plants are subjected to disturbances and noise which induce model-based errors (Gertler, 2008). Important is to create a *robust* model that is as insensitive to noise as possible. The issue with this is a wide variety of data is necessary to diagnose the different possible faults.

Figure 3.4 illustrates model-based fault detection, on the left a system receives an input which the system performs, this input also goes to a model. The action is simulated and the result is compared to the actual system, when the system deviates from the simulation it can be assumed something has happened (Khalastchi and Kalech, 2018).

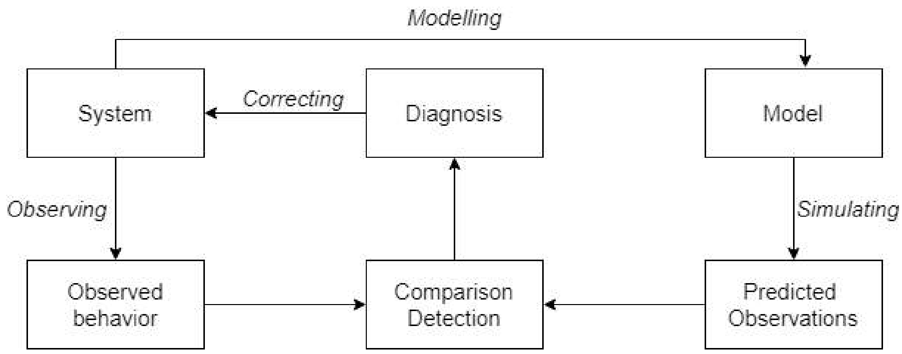


Figure 3.4: Principle of Model-based Diagnosis (Jannach and Gut, 2008)

The downside of model-based FDD is that they take time to develop compared to data-driven model, this is due to data-driven solutions requiring large amounts of data, however this is explained in the paragraph *data-driven models*. Advantages of model-based is that they work for situations previously not encountered, are robust and that they do not need large data sets (which in industrial settings can be hard to get a hold of, see Haarman et al., 2018). Model-based diagnostics is limited to a certain amount of data sources due to increased complexity which comes with multivariate data sources (Tidriri et al., 2016). Models-based solutions also work better in systems that operate in variable environments (e.g. wind turbines, ships, military systems) due to the constantly changing environment and the many possible failure modes, support for can be found in papers by Tinga and Loendersloot, 2019, Jardine et al., 2006, Farrar and Lieven, 2007 and Zio, 2009.

Data-driven model

Data-driven methods are based on large amounts of data from systems where data analytics is applied e.g. AI or ML. These analytic techniques discover patterns and relationship in data sets which in turn can predict failure of systems when abnormalities appear. Advantage of this is that no previous knowledge of the system characteristics or failure behaviour is necessary, which makes this approach popular and accessible. However, this knowledge gap of failure modes can make the model draw incorrect conclusions. For example, a high correlation could be found between the current and the temperature of an electric motor, however from an engineering point this makes sense. Another downside with AI/ML is that they are trained with a data set which includes distinct failures, however when a new type of failure happens the model will not know how to react if not trained for it. This makes data-driven solutions excel in component failure analysis, however with system level diagnostics the increased amount of failures makes it difficult to train a data-driven model. However, data-driven models excel in classification accuracy, in Zhang et al., 2019 review they found data-driven solutions could predict failure with 100% accuracy. Data-driven works well for diagnostics and for prognostics, the only requirement is the necessary data.

The increase of popularity of data-driven PdM models is due to the easy of use, slow increase of availability of (industrial) data, recent developments of AI and decrease data storage cost (Zhang et al., 2019). Development of an AI model has two phases, first a learning process based on raw historical data, secondly the model is applied to a situation to identify failures. There are two main data-driven solutions, first is using machine learning (ML) and second is using deep learning (DL) or artificial neural network (ANN) algorithms, see figure 3.5. ML algorithms (e.g. logistic regression (LR), support vector machine (SVM), decision tree (DT)) require collecting large data sets on health conditions and various failure scenarios for model training. After this feature engineering is conducted, this is the process of using domain knowledge to extract features (characteristics, properties, parameters) from data based on the time, frequency and time-frequency domain (explained below) (Canizo et al., 2017). The representation of the health is determined through the extracted features. DL or neural network models are different because it avoids feature engineering and does all that itself. DL does this through using multiple layers to extract features from raw input, this can give it a deeper understanding of patterns. Downside is that even though a model can be extremely accurate, it is impossible to understand why the algorithms makes a decision (*black box model*). However, DL applications in articles use experimental datasets for FDD analysis with few studies that use a real machinery system (Saufi et al., 2019). This is due to the quality difference between experimental and real machine datasets. One last common technique used in data-driven solutions is Principal Component Analysis (PCA) (Tidriri et al., 2016). PCA is a multivariate statistical analysis technique which reduces dimensionality of data while retaining essential information to make data analysis easier. In appendix A an overview of all relevant data-driven algorithms can be found, first the pro's and con's and second an evaluation matrix, taken from Robinson, 2021.

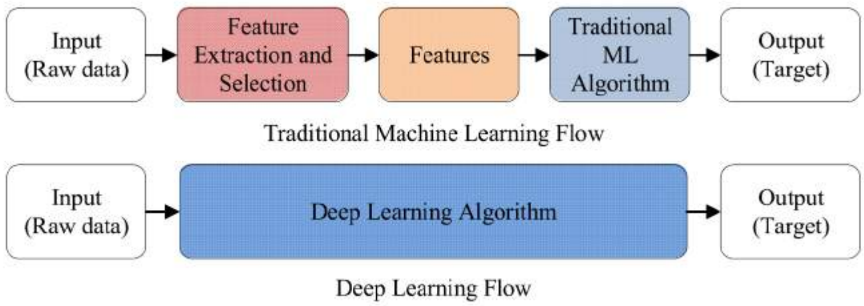


Figure 3.5: Flow of a ML or DL data driven model (Zhang et al., 2019)

When large amounts of data are available they are usually compressed through feature extraction. Signals convey useful information about system status and fault detection depends on examination of various features extracted from system signals. Failure detection is conducted using three common methods, namely, time, frequency and time-frequency (Ghafari, 2008). Signal processing techniques in the time-domain is the most attractive approach due to its simplicity. Feature extraction such as, max or minimum value, root mean square (RMS), mean, standard deviation, variance, correlation, kurtosis and crest factor. These features and more are explained in table 3.1 and give a value which can change depending on the failure. Frequency domain (or spectral analysis) is popular in literature where time domain signals are converted to the frequency domain using fast Fourier transform (FFT). Here faults are found in the low-range frequencies and defect identified by changing amplitudes and noise. Using an envelope detector, which takes a high frequency modulated signal as input and gives a signal of the peaks as output, see figure 3.6 is also a thoroughly researched topic with promising results (Yan et al., 2017). The last technique is time-frequency domain analysis, which uses techniques that analyse signals in both time and frequency domain simultaneously. The most common time-frequency analysis is short-time Fourier transform (STFT), here the sinusoidal frequency is determined of local sections of a signal as it changes over time. All these features can be extracted from signals and used by data-driven algorithms to detect and classify faults.

Comparison of different approaches

To compare the different approaches a table is given with the advantages and disadvantages of each method, see table 3.2. These are general advantages and disadvantages and every problem has a unique set of requirements making a different method more applicable. In general, data-driven approaches are accurate when it comes to simple systems (components) compared to model-based. A drawback of data-driven methods is the availability of data in industrial settings (Medjaher and Zerhouni, 2013). This is due to how systems and sub-systems are used changes often (e.g. different loads or speeds). This renders the trained data-driven models useless and the system has to be trained all over again. An example is the Fast Fourier transform (FFT), this technique is an algorithm that converts a signal from the time to the frequency domain. In the frequency domain a data-driven model can be trained to identify bearing faults due to there being a peak at 30 Hz. However, when rotation speed changes this peak will change location on the frequency domain making it difficult for data-driven problems to identify bearing failures. The last downside of data-driven models is that the systems where a model is applied to have to be in a new state. This is because the models identify a new, perfectly working machine and then identify when something bad happens (in the FFT for example). Once again in

Feature Names	**Brief definition**
Mean	Average of signal
Variance	Measures dispersion of signal around mean
RMS	Square root of the mean square
Peak Value	Maximum of signal
Minimum Value	Lowest value of signal
Peak to Peak value	Difference between maximum and minimum
Correlation	Extend two which two variables are linearly related
Standard Deviation	Measurement of the amount of variation of set of values
Kurtosis	Measure whether data is heavy or light-tailed relative to normal distribution
Skewness	Measure of symmetry of dataset compared to the centre data point
Crest Factor	Ratio of peak value to RMS value
Mean Square Error	Average of the squares of the errors of two variables
Impuls Factor	Maximum value divided by the mean value
Shape Factor	Value that is affected by an objects shape

Table 3.1: Brief review of time-domain features

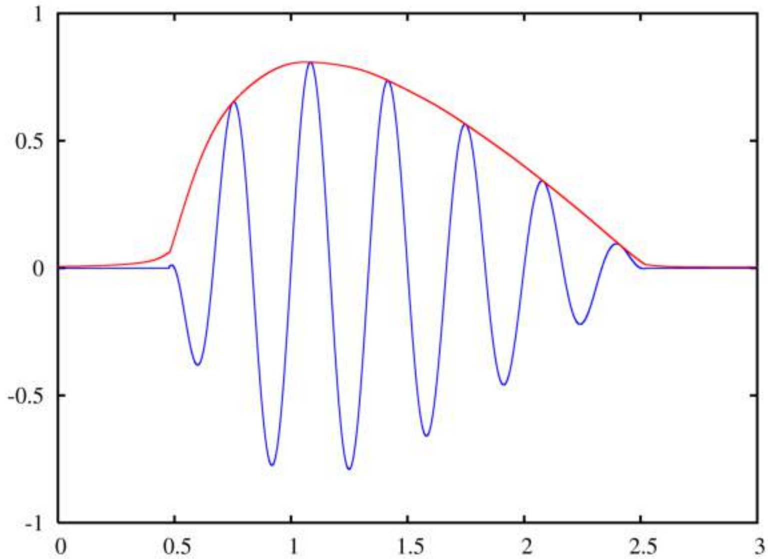


Figure 3.6: Envelope signal detector (Damato, 2021)

reality machines are not always new, gearmotor units can last 30 years before they need to be replaced (Sew-Eurodrive, 2021). However, data-driven models do excel when it comes to cost and simplicity of implementation thus is regularly preferred to model-based. Model-based can be difficult when it comes to formulating the correct physical model that represents the system.

3.1.3. FDD Diagnosis

Fault diagnosis consists of fault isolation and identification. When a fault has been detected the model should try to isolate it, this is because it gives additional useful information about what has happened

	Advantages	Disadvantage
Model-based	-Requires non or hardly historic knowledge (data) of the system - Rate of false alarms to misdetections can be adjusted - Dynamic of states can be estimated at each time	- Requires knowledge of the engineering of the system or component - Higher cost (time & effort)
Data-driven	- Can be used without knowledge of performance of the system - Combining algorithms enhances results - Low cost (time & effort)	- Results depend on quality of data - Algorithms difficult to adjust for false alarms (black box method) - Struggle variable operating conditions

Table 3.2: Model-based vs data-driven (Skliros et al., 2018, Medjaher and Zerhouni, 2013)

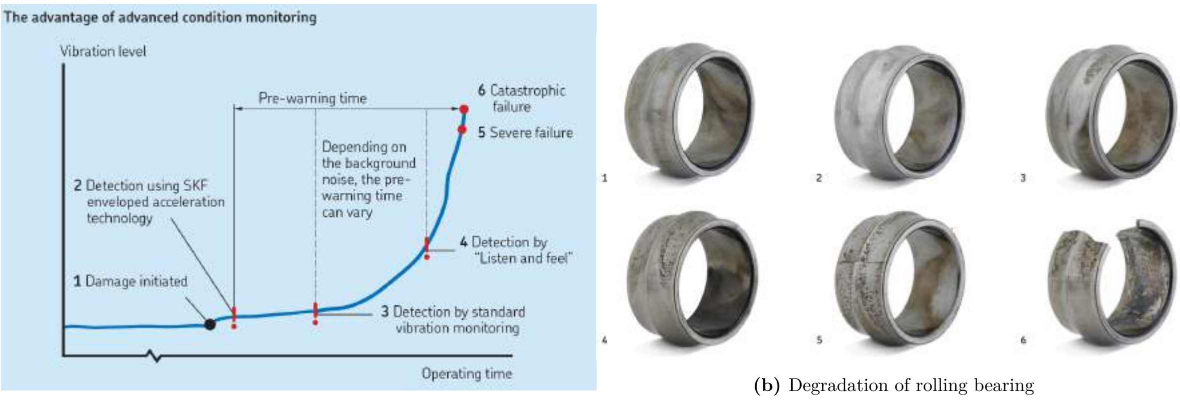
which increases accuracy, example is the root causes of the fault (Severson et al., 2016). Fault isolation is not always applied and is mainly used when multivariate data is available. Fault identification is the examination of the location and type of faults in the systems components, otherwise known as classification (Saufi et al., 2019). Fault location can be where in the system the fault has occurred, usually this is the bearings components, e.g. inner or outer race fault. Fault type is for instance the type of gear fault, e.g. chipped tooth or gear spalling. These faults or anomalies all have characteristics which makes them detectable, examples are increased peak value or higher kurtosis. These values are called data features and are well researched.

Traditionally, fault classification was done through the use of model-based detection. However, with the increase of industrial data (and Industry 4.0 development) data-driven methods have been increasingly used in literature for classifications and excel model-based methods (Abid et al., 2020). Model-based classification requires multivariate data from different parts of the system, e.g. different parts of an HVAC, see Appendix C. Classification through data-driven methods can be done using three methods, supervised, unsupervised and semi-supervised learning, see paper Robinson, 2021 for a literature review on machine learning methods. Supervised methods use labeled data which has the goal of mapping a label to a new input data. In FDD classification a data-driven model is trained using different labeled fault data with the goal of identifying the fault that has occurred. Unsupervised uses unlabeled data with the goal of identifying the underlying distribution or structure, called clustering. Unsupervised FDD is generally used for classification between normal and faulty conditions, however this can easily be effected by noise and changing environmental conditions. When using data-driven methods for (fault) classification there are two phases, an offline phase where the dynamic model is trained to classify using data which can be saved. The next step is the online phase where the data-driven models are applied to a FDD model to detect and classify faults (Medjaher and Zerhouni, 2013).

Fault characteristics Below the main faults are stated which were identified in the introduction. These are blockages, bearing and gear failure. Below an explanation of how the failure happens can be found, its characteristics and its impact on data from the VFD.

Blockages in the movement of the load of the gearmotor system are the most common failure in an industrial setting and are classified as an abrupt failure. Examples can be goods blocking a conveyor movement or an object stopping the rotation of a fan. The gearmotors are usually a feedback system, feedback systems use measurements of the output as part of the input to perform actions with higher accuracy. Thus, when the movement is blocked, the controller senses that there is a sudden decrease in rotation speed of the motor. To compensate this the controller will increase the current to the motor to overcome the delay in the movement, this results in a high current peak. The VFD will be overloaded when this happens, which means it delivers more than 100% its rated capacity. VFD's are designed to do this for short periods of time, if afterwards they can cool down. To ensure safety the VFD has a 0.2 second window where this high peak is allowed. After this the VFD will stop all current to the motor and show an error.

Rolling bearing failures are incipient faults and are the most common researched failure in literature due to ease of understanding and relatively high occurrence. Bearing failures are responsible for up to 90% of all failures in some cases, depending on the industry (Immovilli et al., 2012). In general faults are detected through vibrations, however other methods, e.g. current, speed and motor flux have been researched. Field studies have indicated that 90% of rolling bearing failures are related to inner or outer face failure (Subrahmanyam and Sujatha, 1997). The two main failure reasons are 33% due to fatigue and 33% due to lubrication problems, these are average values and are depended on the industry or application (Group, 2017). The exact damage to the bearing varies in the beginning, usually on one spot small damage appears which grows into a concept called spalling, see figure 3.7. Symptoms of spalling are excessive shaft movement and increase frictional moment to rotate shaft. Bearing failure results in a drastic increase in noise due to gear misalignment and increase of wear (Kharche and Kshirsagar, 2014). Mechatronic systems have many different bearings thus locating which bearings fails is almost impossible, however knowing that a bearing is failing already helps maintenance engineers. Internal bearing damage to the motor will be easier to detect compares to external bearings, this is because the damage signature has to be transmitted through the system before it gets to the servomotor (Lessmeier et al., 2016). This has a dampening impact on how detectable it is, however an increase of noise happens with a increase in torque that is necessary to turn the system. This is due to in the gearbox the gears not being perfectly aligned with each other, resulting in the gears not connecting (meshing) at the right part requiring more torque to move them. K. F. Brethee et al., 2016 states that there is an increase of 2% power increase due to the change in friction coefficient. When in the load which the gearmotor power bearings fail different things can occur, in general imbalances happen in the system resulting in increased noise and increase in torque. As previously mentioned these characteristics would first be filtered by the gearbox, however eventually will have an impact on the measurements.



(a) The progress of rolling bearing damage

(b) Degradation of rolling bearing

Figure 3.7: Bearing failure characteristics Group, 2017

Gear failures fail for the same reasons as bearings, excessive loading or lubrication errors and are also classified and incipient failures (Sharma and Parey, 2016). Some sources state that 90% of gear failures are the result of lubrication failures and contamination problems (Service, 2018). The failure starts on one of the teeth of the gearbox or pinion gear and then slowly spreads to other gears. This failure is mainly found in the frequency domain through converting the signal with the FFT. Lu et al., 2017, K. Brethee et al., 2016 and Mallikarjuna et al., 2020 state various characteristics of gear failure. Increase of the supply line frequency which is the current frequency that the motor receives means failure is imminent. General increase in FFT peaks shows gear failure, this can be understood because the degradating tooth rotates mainly at a certain frequency. This will clearly show in the FFT of the current together with an increase of the kurtosis. Praveenkumar et al., 2017 compares vibration, acoustic pressure and stator current for detecting gear failure through MSCA using two Machine Learning techniques namely support vector machine (SVM) and artificial neural network (ANN) and for detecting gearbox failures current analysis had a higher accuracy than vibration.

In table 3.3 the main faults are given with how their signal values changes due to the failure. This is followed by how these faults can be identified through the available data.

Fault name	What is it	Impact on torque
Blockage system	Obstruction movement	Drastic increase in torque until freq. inverter limit hit, continued for 0.2 seconds
Bearing failure	Outer- or inner-ring failure rotational bearing starts to fail	Shaft it is holding not aligned, increase noise due to bad meshing increase motor torque
Gear pinion failure	Gear teeth start to wear	Small increase noise, frequency peaks
Other	Random failure (e.g., stator, rack, shaft failure)	Depends on failure

Table 3.3: Faults system with identification

3.1.4. FDD Overview

Fault detection and diagnosis is a field that has been widely researched with many researched still happening due to advancements for instance Industry 4.0. Detection and classification of faults can be done in different ways and there is no universal best method due to every issue having different goals and challenges. An method which is become more popular in literature is using a hybrid of the detection and classification methods, refered to as hybrid models.

Hybrid-models

Hybrid models are algorithms that combine the methods with the aim of enhancing diagnostic results and accuracy (Skliros et al., 2018, Jardine et al., 2006). Sometimes data-driven algorithms are created by combining different AI/ML techniques and called a hybrid solution, however here these remain data-driven. The advantage of hybrid methods is individual model limitations can be compensated resulting in better results, however a universally best method is impossible due to variations on limitations of data, the application constraints and the complexity of the system (Liao and Kottig, 2014). Other interesting points based on Tidriri et al., 2016 are:

- It overcomes the weakness of a diagnostic method with the strength of another method to achieve a better performance.
- It enables to use a variety of information sources such as service history, operation and maintenance records, historical and on-line data, mathematical models, causal relationships...etc. when they are available.
- It enables to benefit from all the progress and achievements made by each community.

There are different ways to perform hybridization, one of the most common reasons is using data-driven and model-based to compensate each other due to insufficient historic data or when it is not possible to create a model-based option (Wallace et al., 2020). This results in on of the techniques handling diagnosis and the other technique handling prognostics, or one technique handling detection and the other diagnosis. Luo et al., 2010 applies a diagnostic methodology that uses FDD (model based) followed by a Machine Learning algorithm called support vector machine (SVM) on an anti-lock braking system (ABS) of a car. They create a physical model of the system and consider four faults which they identify through SVM. Liang and Du, 2007 develop a hybrid fault diagnosis algorithm to detect and isolate failures which is applied to a heating, ventilating and air-conditioning (HVAC) system. Simulations were conducted of healthy condition and three component failures which could accurately be identified with the use of a SVM. Medjaher and Zerhouni, 2013 builds a hybrid prognostic method which is applied to a mechatronic system. The method relies on two phases, first in the offline phase a behavior and degradation model is created and in the online phase the health state of the system is monitored with the RUL.

3.2. Concluding Remarks

This chapter aims to provide more insight in the scientific problem context by answering the sub-research question: *How does literature describe fault detection and diagnosis models and what type of data is necessary?*

Fault detection and diagnosis (FDD) has two basic functions, first monitor behavior of a process and secondly, reveal the fault and its root causes (Park et al., 2020). FDD has four stages, detection, isolation, identification and evaluation. Fault detection methods have been research and be classified into model-based and data-driven. Model-based method create a (mathematical) model of a system to describe it and data-driven methods use artificial intelligence to detect faults. First in a FDD algorithm is the data acquisition stage, given the data that is available from the VFD the main options are using the current and rotational speed. The current can be converted into the torque that the motor delivers which has been used in papers for fault detection. Abnormalities in rotational speed have also been used to detect faults. Fault detection can be achieved through model-based or data-driven methods. The advantage of model-based are that previous data is not necessary, adjustable false alarm rate and dynamic states can be estimated. Downsides are knowledge of engineering of the system and higher cost (time and effort). Advantages of data-driven are that no previous knowledge of the system necessary, combining algorithms can enhance results and low cost (time and effort). Disadvantages are results depend on quality of data, difficult to adjust algorithms due to them being black boxes and struggles in variable operating conditions. Fault diagnosis (isolation and identification) can be done using model-based and data-driven methods. However, data-driven excel when it comes to classification of data. Mulitvariate data is also required for model-based solutions. Hybrid models are algorithms that combine the methods with the aim of enhancing diagnostic results and accuracy.

The main faults were identified in chapter 2, namely, blockage, bearing and gear failure. Below a short overview of characteristics and impact of the faults

- Blockage
  - Obstruction movement
  - Increases current flow to motor which spikes until VFD shuts off
- Bearing
  - Outer- or inner-ring failure rotational bearing starts to fail
  - Shaft it is holding not aligned, increase noise due to bad meshing increase motor torque
- Gear
  - Gear teeth start to wear, usually lubrication related
  - Increase noise, frequency peaks, small amount of noise

The main identified gaps of literature about FDD and relevant systems can be found below.

1. Lack of system level diagnostics in mechatronic systems (which are essential for many industries)
2. Lack of hybrid diagnostic models applied to mechatronic systems
3. In available papers no real world feedback

4

Model Selection and KPI's

In this chapter the framework will be developed for the eventual FDD model. An analysis will be done of the state-of-the-art and the literature review to find a model to fit the problem. Next the model will be discussed in detail and all relevant details presented. Last the KPI's will be determined which will evaluate the model. In this chapter the following two research questions will be answered: *What fault detection and diagnosis model can be developed for an electric gearmotor system?* and *What KPI's can be used to assess the fault detection and diagnosis model?*

4.1. Model Selection

In chapter 2 the state-of-the-art of the current industrial setting was analysed to define the gaps and the necessities of an FDD model. The goal of the literature research was to summarise what is currently possible when it comes to FDD, and all of the stages that are part of it. This was conducted to eventually complete the objective of creating a FDD model which could be applied in an industrial setting. In this chapter the information will be analysed and a relevant FDD model chosen which will complete the objective the best.

Fault Detection

For the FDD detection stage a choice must be made between model-based and data-driven fault detection, which are compared in table 3.2. From the scope and from chapter 2 conclusions can be drawn, there is a limited amount of different data sources, there is (generally) no fault data, industrial settings change often and simplicity is important. To do choose the right method an evaluation matrix will be used, an evaluation matrix is a tool to assess different choices over different criteria. For our given system five criteria are selected which are also assigned a weight depending on how important they are, they are explained below. The five criteria were defined using the research scope of the thesis, these points were identified to be important for the model. The grades of the system are based on table 3.2.

- Robustness: how a model performs if variables or assumptions are altered
- Accuracy: how close measurements are to the true value
- Ease of implementation: how simple the model can be applied to a situation
- Adaptability: how simple the model can be changed to fit a situation
- Development cost: how expensive it is to develop (time/money)

Table 4.1 shows the filled in evaluation matrix with the given score. Data-driven scores the lowest, which is mainly due to the points robustness and adaptability. This is because once a model is trained for a certain system, it cannot be converted to a different system even though they might be similar. Small changes in rotational speed, temperature or wear can make a data-driven model invalid requiring the whole training process to happen again for reliable diagnostics. Model-based has more points, advantage being adaptability and robustness while still being accurate. It is also the most intuitive due

	Weight (1-5)	Data-Driven	Model-based
Robustness	4	1	4
Accuracy	5	4	4
Ease of implementation	4	5	2
Adaptability	5	1	4
Development cost	3	5	2
Total		64	70

Table 4.1: Evaluation matrix data-driven and model-based

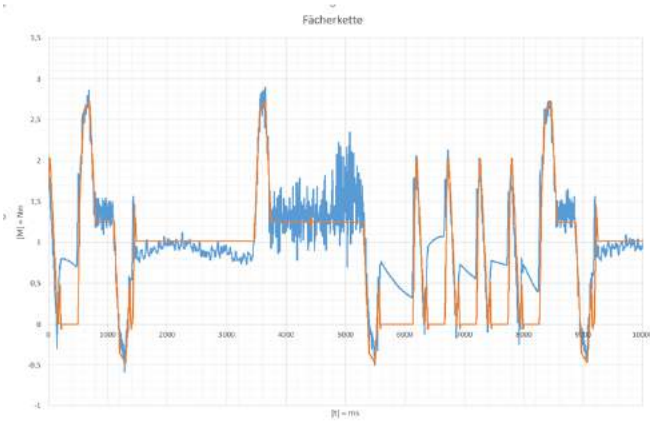
to it being mathematical equations describing a system, while data-driven model requires (black-box) algorithms. Model-based in general does lack in relative ease of implementation due to it requiring more effort then data-driven. In the literature research it was also stated that model-based diagnostics is in general better at system-level based diagnostics compared to data-driven which is usually better at component-level diagnostics. Thus for the detection stage model-based solution will be utilised.

The next part is defining how the faults will be detected. The most common and successful solution in literature is done with creating residuals through observers, bond graphs or parity space. Parity space requires state-space model of the system with multivariate data. Bond graph also requires multivariate data on the energy flow through the system. The remaining is observer based, this is the simplest and utilises the formula 3.2. The residual that will be used will be the armature current of the motor. This can be converted to the torque that the motor produces (*measured torque*), parallel to this the torque that is required to move the load can be calculated from the setpoint speed (*reference torque*). The calculated (reference) torque will remain the same and be used as reference, the measured load changes over time if abnormalities happen in the system. This technique has been suggested in literature as stated in chapter 3, however information is limited (Zhou et al., 2007). Thus, this model will be an extension of academic literature to further develop torque as a fault detection method. The difference with many papers is that data comes in a continuous flow, however the data in this situations comes every hour with an eight second scope. A possibility is with the model-based solution to recreate the eight second scope and subtract the model-based solution from the new measurement. In theory, this should give a flat line around 0, in reality this is not the case however can serve as a reference point.

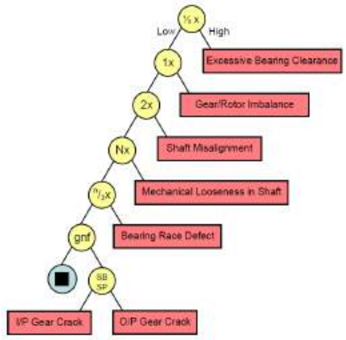
SEW Eurodrive has a proof of concept of this idea, see figure 4.1a. SEW Eurodrive conducted a lab test with a small conveyor with a servomotor where they measured the torque (blue) and estimated the reference torque (orange). This graph has a Pearson correlation coefficient (PCC) of 0.93. The Pearson correlation coefficient is a normalised measurement of the covariance over two scopes, always has a value between -1 and 1 as result, 1 being perfect match and -1 being perfect opposite. However, this experiment was a lab research, thus everything was in perfect condition and they had data which in an industrial setting is not always available. Examples are exact inertia and friction data from the VFD and the pre-determined acceleration from the controller of the system. These are not always available in reality.

If a fault starts developing then the mean of the residual will deviate from 0 indicating change in the system. To more accurately detect abnormalities other features can also be extracted, these can be combined to give a health indication value. For example, when bearings start to fail noise drastically increases, however the mean will initially remain the same, thus using other features besides the mean helps. Below an overview of the detection features are given which will detect if there is a fault. Correlation defines the relation between the model-based solution and the measurement. Mean, median, RMS, peak value (max), kurtosis, crest factor all say something about the residual and will change if anomalies start to occur. Some of the features have similarities, however all say something unique about the residual. In table 4.2 the features with there formulas can be found.

The next step is to define when a fault actually occurs. In the scope and chapter 2 it was concluded that false positive and false negative alarms should be mitigated. This can be achieved through flexible fault thresholds as defined in the literature. Another conclusion that besides the main faults (blockage,



(a) Comparison of measured (blue) and estimated (orange) torque of a belt conveyor



(b) Diagnostic decision tree for a gearbox (Saha and Vachtsevanos, 2006)

Figure 4.1: Hybrid-model proposal

Feature	**Fault detection**	**Formula**
Correlation	Decreases with increasing noise	$\frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i-\bar{y})^2}}$
Mean	Increases/decreases when more/less torque is necessary	$\frac{\sum_{i=1}^{n} x_i}{n}$
Median	Increase/decrease when more/less torque is necessary	$\frac{(n+1)}{2})observation$
Max peak	Faults create higher values	$maximumvalue$
RMS	Increase/decrease with failure	$\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}$
Kurtosis	Faults result in more peaks	$n \cdot \frac{\sum_{i=1}^{n}(x_i-\bar{x})^4}{\sum_{i=1}^{n}(x_i-\bar{x}^2)^2}$
Crest Factor	Increases before RMS when failure occurs due to peakness	$\frac{max}{RMS}$

Table 4.2: Features with fault detection capability and formula

bearing and gearing failure), other unknown faults can develop thus the fault detection algorithm must be robust to also detect these. As previously defined when an anomaly occurs the extracted features will start to differ from their normal values. In the beginning some features will probably change faster than others, to summarise the values of the features and easy analysis a *health indication value* will be generated, see formula 4.2. This value will reflect the health of the system and will give maintenance engineers an easy method for understanding the health of the system. The health indication value will rely on the extracted feature from table 4.2, which are scaled between 0 and 1 (normalized) to all have the same weight, using formula 4.1. Some limited data should be available to define x_{max} and x_{min}, taken from a healthy system. The mean of these seven features will be then be taken which will show an indication of the overall health of the system. Advantage of this system is that it is easy to understand, the health of the system is scaled between 0 and 1, which could be visualised which is simple to interpret. The values x_{max} and x_{min} will be used to analyse every new measurement, when a fault occurs the value of x will be outside x_{max} which gives a value higher that 1 which can show a fault has happened. All values have the same weight, however an algorithm could be used which assigns a higher weight to certain features which change more dramatically when failures occur. When a fault starts to occur the indicator value will breach a pre-determined threshold and in theory slowly increase until failure happens. This will be referred to as the anomaly detection machine. These values for x_{max} and x_{min} for the extracted features will be generated in the offline mode and used in the online mode to compare new measurements with the offline measurements.

$$x_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{4.1}$$

$$health\,indication\,value = \frac{correlation + mean + median + max + RMS + kurtosis + crestfactor}{7} \tag{4.2}$$

Fault diagnosis
The next step in FDD is diagnosis. Fault identification or classification can be done through the usage of model-based and data-driven solution. From literature, model-based classification depends on multivariate data to isolate and classify the faults. This problem has an univariate data source which results in data-driven solutions being the better option. The faults that need to be classified are (1) blockage, (2) bearing fault, (3) gear fault and (4) other unknown fault. Unknown faults will be used by the classifier as an option when a scope does not fit into the first three choices, thus a fault will be present however it is not known what has happened. As from the literature data-driven methods excel in simple classification. This would be a simple supervised learning problem where a model is trained with the use of classified data and afterwards can be used to recognize scopes.

Based on the the literature review Robinson, 2021 and appendix A various machine learning algorithms are available for this problem. All having their own advantages and disadvantage and also having their own application. In literature the most common is support vector machine (SVM), random forest (RF), decision tree (DT) and artificial neural networks (ANN) (Carvalho et al., 2019). SVM is widely used due to its high precision in separation of classes of data and ease of understanding. RF has good performance when the numbers of variables is higher than the number of samples. DT is a series of sequential decisions made to reach a specific result. ANN is the most complicated, however has advantages that include no expert knowledge necessary, robust and with enough data very accurate. For this specific problem one algorithm stands out which is decision tree (DT). This is because it is one of the few algorithms that is good at classifying multiple inputs due to its design of multiple branches. Example of a DT can be found in appendix C and in figure 4.1b. A model is trained to identify the faults and at every 'branch' can choose if the fault matches to trained fault or it does not.

To classify the different scopes, features will be extracted. The difference here compared to the anomaly detection machine, which uses residuals, is that due to a univariate data source more features need to be extracted to clearly identify the faults. Blockage is the simplest to detect due to the sudden, high peak, this will result in high value for features such as peak and crestfactor. However, bearing and gear failure are very similar when it comes to characteristics. In chapter 3 the differences between the two were stated, being gear failure results in higher peaks in the frequency domain due to the bad meshing of gears. The general noise will also increase. Bearing failure increases noise and a higher mean and RMS in time domain. In table 4.3 all the features are shown, there is an overlap with the features from table 4.2, however here an analysis is done on the scope directly from the system without removing the predicted torque. Example can be seen in figure 4.1a, the blue line is the measured torque directly from the inverter, this will be taken for the analysis. The features for the fault detection will use the residual which is the orange line subtracted from the blue line of figure 4.1a. In table 4.3 the features can be seen that the classifier will use.

4.2. Conceptual Hybrid Diagnostics Model

In figure 4.2 the conceptual hybrid diagnostics model can be found. It is divided into two sections, an online and an offline part. In the offline part the model will be trained and fault indicator values generated which will define thresholds and the machine learning algorithm will be trained. These values will be used by the online phase, this is a much simpler code which will analyse new data and compare and analyse it with the values from the offline phase. *Important* here is that this thesis will focus on the *offline* part of the model. The reason for this is that this is where the knowledge is applied and is what makes the model unique. The *online* part is when the model it is applied in an industrial setting, e.g. a company. This is not relevant in this thesis and will not be discussed, however is illustrated to demonstrate how the model would work in an industrial setting. When the system changes parameters, like speed or more knowledge is gathered then the offline model can be trained again and the values for the online phase updated.

Feature	Fault detection	Formula
Time domain		
Mean	Increases/decreases when more/less torque is necessary	$\frac{\sum_{i=1}^{n} x_i}{n}$
Median	Increase/decrease when more/less torque is necessary	$\frac{(n+1)}{2})observation$
Max peak	Faults create higher values	maximum value
RMS	Increase/decrease with failure	$\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}$
Kurtosis	Faults result in more peaks and this defines that	$n \cdot \frac{\sum_{i=1}^{n}(x_i-\bar{x})^4}{\sum_{i=1}^{n}(x_i-\bar{x}^2)^2}$
Crest Factor	Increases before RMS when failure occurs due to peakness	$\frac{max}{RMS}$
Frequency Domain		
Kurtosis (FFT)	Faults result in more peaks and this defines that	$n \cdot \frac{\sum_{i=1}^{n}(x_i-\bar{x})^4}{\sum_{i=1}^{n}(x_i-\bar{x}^2)^2}$
Mean (FFT)	Increases/decreases when more/less torque is necessary	$\frac{\sum_{i=1}^{n} x_i}{n}$
Max peak	Faults create higher values	maximum value

Table 4.3: Fault classification features

When training a model for a new system first the offline phase is performed. From the physical system eight different data scopes are captured over a certain time, could be a week or a month, the system only has to be healthy. Then two scopes, namely, active current and setpoint speed are send to the next two step, called measured torque and predicted torque. The measured torque is the armature current of the motor converted into torque, which is the torque the motor delivers. This is done using the motor constant k_t and formula 3.1. The set-point speed is sent to the predicted torque, where together with information about the system (e.g. inertia, load torque, friction) and a mathematical model (see paragraph 4.2.1) a predicted torque curve is generated. These two graphs are send after this to the anomaly detection machine, here the model identifies fault through feature extraction and creates a health indication value. How this is done and with what features is explained in paragraph 4.1. These values which represent a healthy state are saved and are later used in the online phase to detect failure by comparing the features of new scopes with the previous healthy scopes of the system.

Important for the FDD model is to avoid alarms for false positive and negative scopes. This was already achieved to a certain extent with the use of flexible thresholds. The second way is creating two types of alarms, now called alarm 1 and alarm 2. Alarm 1 will sounds if a threshold is breached only once, this can occur due to cold gearbox oil on startup or a test run being performed without load and does not immediately mean there is a fault. Alarm 2 will work with a sliding window looking at the previous x number of scopes, if in the window a certain percentage is alarm 1 then alarm 2 will sounds giving a more reliable chance of there being a fault. The size of the window and percentage of faults can be defined and changed to avoid wrong error messages. However, this will not be analysed in this thesis. Reason for this is that it would require fault data of a system which develops over time. At the time of the thesis this was not available, thus is for future work.

4.2.1. Mathematical Model

The idea behind calculating the torque the motor delivers is simple, all movements must adhere to the basic physics formulas, e.g. $F = ma$ or $M = Fr$. The gearmotor system will be divided into three blocks, application (load), gearbox and motor. This is because every stage has a unique inertia, acceleration and efficiency which makes the calculations easier when isolated. This also makes switching to another system simpler due to the fact only some basic values like inertia change. The application torque is calculated with the formula 4.3, every movement has a dynamic and static part.

$$M_{tot} = M_{dynamic} + M_{static} \tag{4.3}$$

Next there are three main movements which are considered in this model, which cover most industrial applications. These are horizontal (rolling resistance), vertical (gravitational force) and rotational movement (bearing resistance). *Important* is that these are general formulas which might have to be

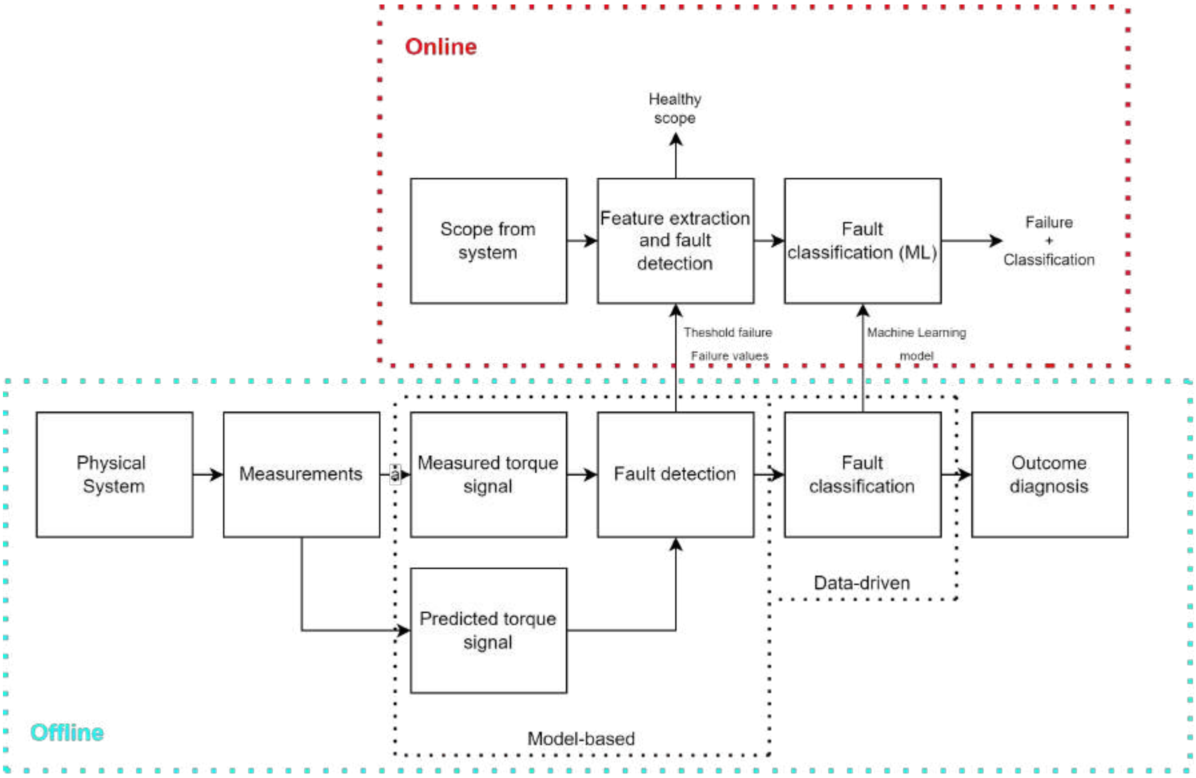


Figure 4.2: Conceptual hybrid diagnostic model

adapted to fit the application. The M_{static} is different when it comes to movements, moving horizontally could be accomplished with a conveyor or a ballscrew, both requiring different formulas. When a gearmotor system is developed the formulas for torque are used to calculate the size of the gearmotor, these could be used again for the model-based fault detection.

$$M_{v.tot} = J\alpha + m_{tot} * g * \frac{d}{2} * \frac{1}{\eta} \tag{4.4}$$

$$M_{h.tot} = J\alpha + m_{tot} * g * \frac{d}{2} * (\frac{2}{d} * (0,005 * \frac{d/5}{2} + f) + 0,003) * \frac{1}{\eta} \tag{4.5}$$

$$M_{r.tot} = J\alpha + m_{tot} * g * 0,005 * \frac{dKL}{2} * \frac{1}{\eta} \tag{4.6}$$

- M = torque [Nm]
- m = mass [kg]
- α = rotational acceleration [rad/s2]
- J = inertia [kg m2]
- g = gravitational constant [m/s2]
- d = diameter pinion [m]
- f = rolling resistance[/]
- K = scaling factor [/]
- L = length object [m]
- i = gearbox ratio [i]
- η = efficiency [/]

The structure of the torque predictor can be seen in figure 4.3. On the left the velocity and acceleration are inserted into the system, the setpoint speed is converted to acceleration before this. These are two vectors with a length of 2048. This goes through formulas 4.4, 4.5 or 4.6 and the torque that is necessary to move the load over the given time is produced. This is then inserted into the gearbox where the torque and inertia necessary to move the load is calculated. The gearbox has a input/output ratio defined by i, the load torque is divided by the ratio, see formula 4.7. Inertia of the load is divided by i^2, see formula 4.8. This is finally inserted into the motor where the load remains the same, however the inertia of the motor is added. After this a torque scope of eight seconds is available of an estimation of what the motor should deliver. The output will roughly correspond to orange line of figure 4.1a. The difference between figure 4.1a and this model is the rotational data because in the figure the rotational speed is measured from the controller not from the VFD. The controller does not see noise in the system, it just instructs the machine to rotate at a certain speed. The VFD however measures the rotation of the motor directly thus will have more disturbances in it.

$$M_{gearbox} = \frac{M_{load}}{i} \tag{4.7}$$

$$J_{gearbox} = \frac{J_{load}}{i^2} \tag{4.8}$$

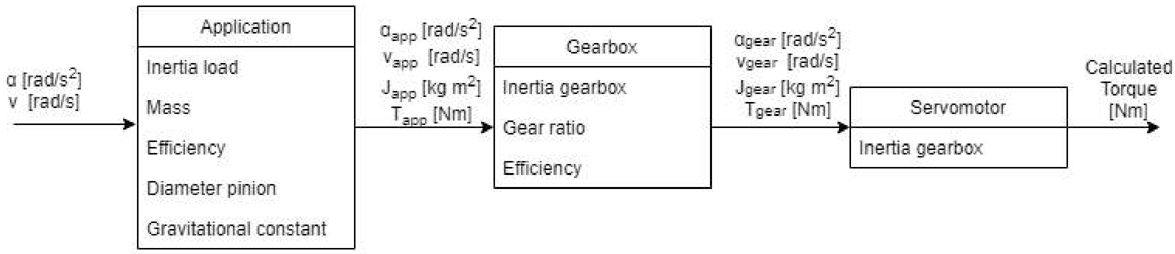


Figure 4.3: Structure of the mathematical model to calculate the torque

4.2.2. Decision Tree Classifier

The fault classification will be done through a trained decision tree (DT) model, as explained in paragraph 4.1. It is a supervised machine learning algorithm which splits data according to certain parameters. It is called a decision tree due to its similairties to an actual tree. DT has two entities called decision nodes and leaves, leaves are the final outcome and the nodes are where the data is split. To train the model fault data is necessary, however these are not available in many cases. To use the model fault data will be simulated from the healthy scopes with the use of the characteristics of the faults which were defined in the literature review. The faults are blockage, bearing, gear and other/random faults. When actual fault data becomes available the model can be trained with real data, however until that point an estimation of the faults is simulated and used to train the models. The fault will be randomly simulated in a certain range to remain realistic. The simulated artificial faults will not perfectly represent the faults due to other disturbances, however they will give an estimate of what the fault could be which is enough for maintenance engineers to understand what is happening. The decision tree model, together with the threshold values of faults and the values of failure are saved on the computer. In the online scripts these can be imported and used to analyse new scopes coming into the system. Output will be if the input scope is healthy and if fault has been detected the machine will give an alarm and the predicted failure.

4.3. Key Performance Indicators

To assess the model that has been designed on how well it performs key performance indicators (KPI's) are designed. KPIs are variables that are used to indicate how specific configurations of the processes is performing. The hybrid model has two specific process which can be measured, namely the anomaly detection machine and the machine learning code. These are both models which classify scopes, thus the same KPI's will be utilized with both, however analysed separately. Important is to first define what a confusion matrix is. It is a tabular representation of the predicted value and the actual values of the dataset. It provides a better understanding and clear visualisation of a model's result.

Confusion matrix		Actual class	
		Actual positive	**Actual Negative**
Predicted class	**Predicted Positive**	True Positive (TP)	False Positive (FP)
	Predicted Negative	False Negative (FN)	True Negative (TN)

Table 4.4: Confusion matrix representation

- True positive (TP)
  - Number of predictions where the classifier correctly predicts the positive class as positive
- True negative (TN)
  - Number of predictions where the classifier correctly predicts the negative class as negative
- False positive (FP)
  - Number of predictions where the classifier incorrectly predicts the negative class as positive
- False negative (FN)
  - Number of predictions where the classifier incorrectly predicts the positive class as negative

Below the KPI's are shown and defined, based on Alpaydin, 2014, Bohutska, 2021 and Shah, 2020.

- Accuracy
  - Number of correct predictions made by the model
  - $\frac{TP+TN}{TP+TN+FP+FN}$
- Precision
  - How correctly the model has detected positive outcomes
  - $\frac{TP}{TP+FP}$
- Recall
  - Measure of the positive points predicted with respect to all positive points
  - $\frac{TP}{TP+FN}$
- F1-score
  - Identifies overall performance by combining precision and recall
  - $2 * \frac{Precision*Recall}{Precision+Recall} = \frac{2TP}{2TP+PF+FN}$

4.4. Concluding Remarks

In this chapter the following two research questions are answered: *What fault detection and diagnosis model can be developed for an electric gearmotor system?* and *What KPI's can be used to assess the fault detection and diagnosis model?*.

The model that is chosen is a hybrid diagnostic model which was based on research and interviews from chapter 2 an 3. The detection phase of the FDD model is done through a model-based mathematical model which describes the torque of the system. This is used to create a residual together with the measured torque. This residual is analysed through feature extraction and a fault indicator value is generated. When this reaches a threshold an alarm 1 goes off, if alarm 1 goes off too many times alarm 2 will happen which indicates imminent failure.

Next the fault is classified using data-driven method with a decision tree machine learning algorithm. The following faults will be simulated to train the model, (1) blockage, (2) bearing fault, (3) gear fault and (4) unknown fault. The trained model will recognize these main faults in the given system.

The KPI's that are developed can be seen below.

- Accuracy
  - Number of correct predictions made by the model
- Precision
  - How correctly the model has detected positive outcomes
- Recall
  - Measure of the positive points predicted with respect to all positive points
- F1-score
  - Identifies overall performance by combining precision and recall

5

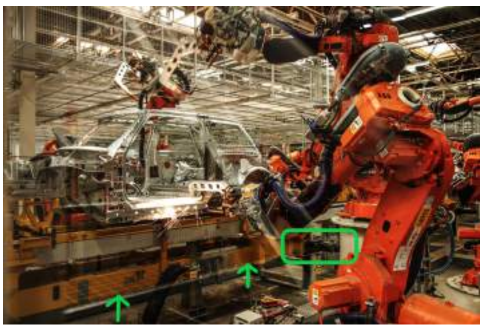
Model Implementation, Verification and Validation

In this chapter the following sub-research question is answered: *How can the model be verified and validated?* The model that was developed in chapter 4 has to be tested to validate and verify the results. To this it will be tested by a case study of a client of SEW Eurodrive called VDL Nedcar where data is collected. This will be validated and verified through multiple test and the KPI's assessed.

5.1. Model Case Study: VDL Nedcar

To validate en verify the FDD model it is applied to a running system which has data. SEW Eurodrive has been gathering data from different companies to start building a database with data from different applications and industries. However, information is only available of system installed in The Netherlands. In The Netherlands there are two locations where data is gathered, first is the production hall of SEW Eurodrive itself and secondly is at a company called VDL Nedcar. The information from the SEW Eurodrive production plant has a limited run-time and the data that has been captured is not of the highest quality, thus the model will be applied to VDL Nedcar. VDL Nedcar is an automotive manufacturing company which produces 240,000 vehicles a year for BMW and Mini (VDL Groep B.V., 2019). The factory is based in Born, The Netherlands and the factory has a total size of 1,500,000 square meters.

Currently, VDL Nedcar has applied DriveRadar to two different systems, first is are car turntables and secondly a car elevator, see figure 5.1 for the lift. Every month a SEW Eurodrive project engineer reviews the data and writes a report about the health of the system and if there are any abnormalities. VDL Nedcar itself is very positive about the system, the feedback gives them a better understanding of the system which in turn gives more confidence.



(a) VDL Nedcar production facility with lift ("VDL Nedcar in zee met Duitse automotive", 2014)

(b) VDL Nedcar lift while plant was being constructed

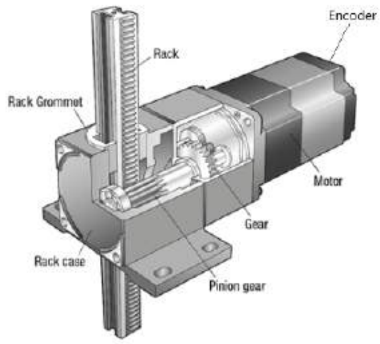
Figure 5.1: VDL Nedcar car lift system

Time (s)	0-1	1-1,25	1,25-1,75	1,75-2,5
Action	Stand still, brake active	Brake active, build torque	Release brake, accelerate till 3200 rpm	Move vertically steady state
Time (s)	2,5-2,8	2,8-3,4	3,4-3,6	3,6-4
Action	Slow down system	Pick up car chassis	Stop car chassis at final position	brake active

Table 5.1: Explanation of movement of VDL Nedcar lift

The hybrid diagnostic model will be applied to the lift, not the turntable. The main reasons is that at VDL Nedcar (and in other factories) lifts are more common than turntables, making this research more interesting and meaningful. Other reasons are that the vertical movement is simple, predictable and linear. In figure 5.1 the system can be seen, in figure 5.1a the working manufacturing plant is shown with welding robots and in figure 5.1b the system is shown when it was being constructed. In figure 5.2 a detailed view of the the rack and pinion system which moves the lift vertically. A rack and pinion system consists of a bar with a rectangular cross section (the rack) which has teeth on one side which mesh with the teeth on a small gear (pinion). Specifications of the VFD, the gearmotor and rack-and-pinion can be found in appendix B.

(a) Picture of the rack and pinion system on the lift



(b) Integrated rack and pinion system with gearmotor(Act In Time, 2021)

Figure 5.2: Rack and pinion system

VDL Nedcar's production plant works as followed, the car frame is moved to the welding robots (in orange) by a moving platform, here it is lifted by the system (green arrows) by a rack and pinion gear-motor system (green square), in order for the welding robots to have the same welding location every time. When the lift has reached its location it is held in place by a brake on the motor. This vertical movement is roughly a meter and the lifting takes 4 seconds from start to finish, see table 5.1 for a breakdown of the movement. After welding the movement is reversed and the car is put back onto the moving platform below, where the car is moved to the next welding station and the next car arrives. The system is part of a long welding *street* with many stations for welding, thus failure in one of the stations would result in the complete welding street being interrupted.

The system consists of many different components and in turn these components consist out of different parts, see figure 5.3. The named parts are most critical in the given system, thus most likely to fail. As defined in the introduction, blockage impact the whole system, bearings can be found in every mechanical component and lastly, gears can be found in two of the mechanical systems.

Data has been recorded over the last year, the first date of recording was 2nd of July 2020 and has run until 30th of July 2021 (and continuing). In total there were 1532 scopes available. The recordings are scopes of 8 seconds which capture a complete movement, recorded over 2048 bits resulting in a record-

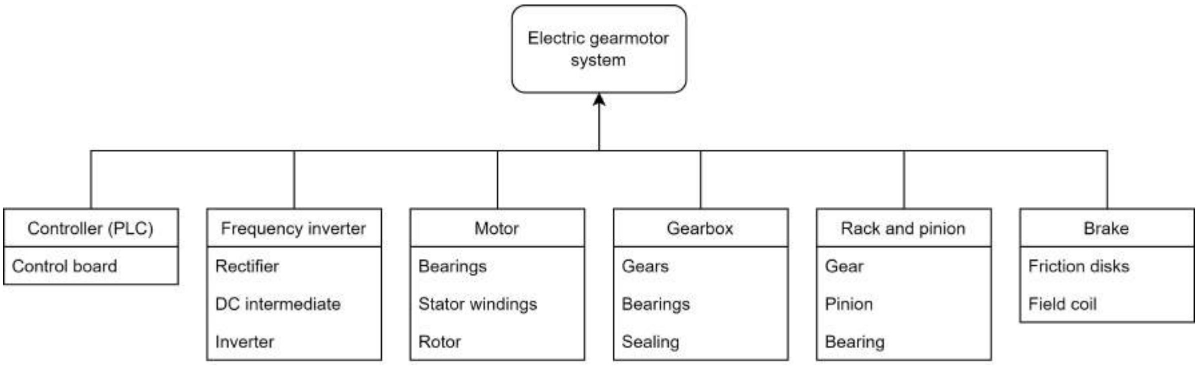


Figure 5.3: Breakdown of the gearmotor system with relevant components

ing frequency of 250 Hz (3.9 milliseconds between recordings). The scopes are recorded as followed; every hour the factory is working DriveRadar DataCollector waits for the system to move and then records this movement for 8 seconds and saved internally at VDL Nedcar. In figure 5.4 two scopes of five seconds are shown of the system, the rotational speed of the servomotor is shown and the motor current can be seen. The reason they are five seconds long is because after five seconds nothing else happens. Table 5.1 shows a breakdown of the movement of the system. The vertical movement which is roughly 1 meter starts with a fast movement to raise the lifting platform, afterwards it is slowed down to make sure it does not violently crash into the car chassis. At the top the car is kept in position by the brake and the robots start welding, afterwards the movement is repeated in the opposite direction.

Since DriveRadar has started recording, there have not been any failures in the system, however there have been small abnormalities, see figure 5.5. The figure shows the maximum value of the current of the scopes over all the recording dates. In the figure there are two gaps, in August and in December. These were due to a production stop for a couple of weeks in august and secondly a Christmas pause. The system is healthy and the system has been running for 6 years.

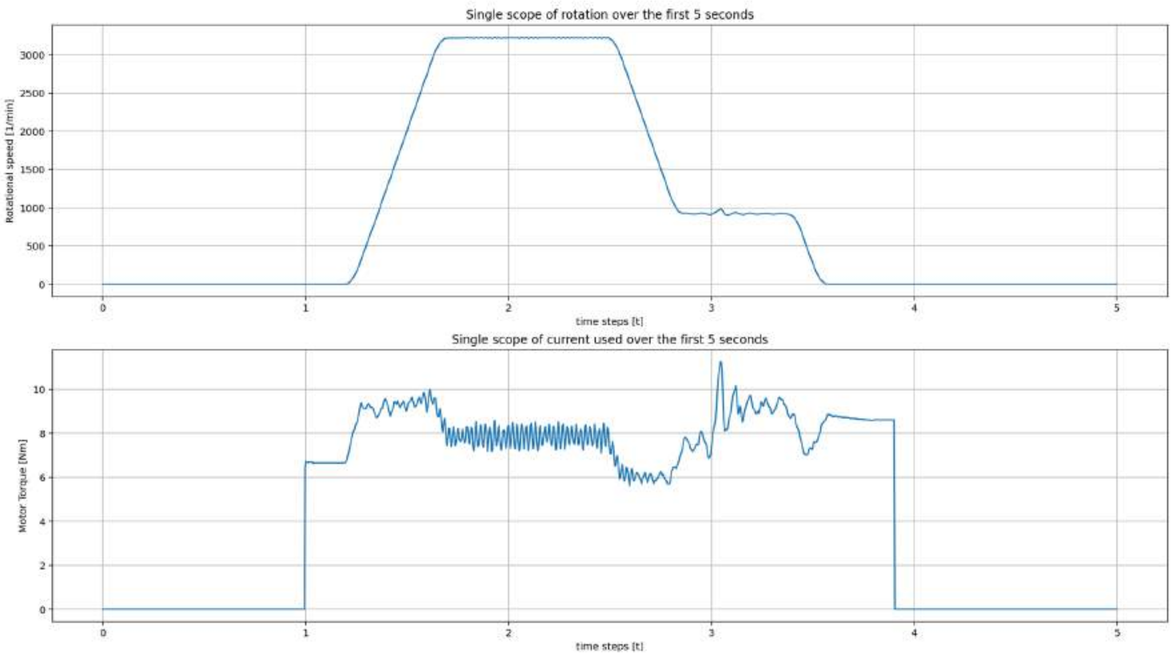


Figure 5.4: 5 second scope of the rotation and current of the servomotor

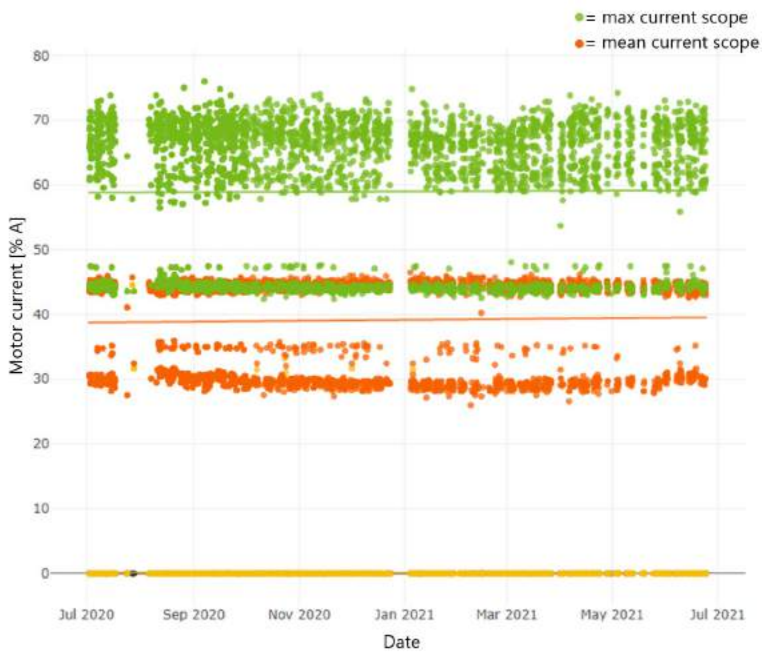


Figure 5.5: Output current of VDL Nedcar lift over a year

5.2. Implementation Model

In this research, Python 3.9 is used as the programming software. For the offline phase Jupyter Notebooks are used to define threshold values for the online phase, this is because Jupyter Notebooks are simple to understand and easily adaptable. For the online phase a Python script is used which utilises the threshold values of the offline phase to define failure and classify. A Python script is utilised due to simple implementation into other systems.

5.2.1. System Simplification

A schematic view of the given system is given in figure 5.6 with all relevant parts, namely, the motor, the gearbox and the rack and pinion. The brake that stops the system is also left out of the system, because it only holds the system still, it does not actually stop the system while moving. This means there is not a lot of wear in the brake compared to other components. In figure 5.6 a current goes to the motor which is translated in rotational movement and torque. This is converted by the gearbox into a higher torque with lower rotational speed which is translated to the rack and pinion system which moves the system vertically.

5.2.2. Mathematical Model

In paragraph 5.2.1 the VDL Nedcar system is simplified. From here the mathematical equations can be formulated, based on the formulas in paragraph 4.2.1. Important is that even though these formulas are based on the formulas in paragraph 4.2.1, most systems are different and will require some form of adoption depending on the application. However, when a gearmotor system is developed these formulas are usually used to estimate the size of the gearmotor, thus being available. At every step the torque, inertia and rotational speed and acceleration have to be calculated. Below the three calculation steps are presented with the formulas to calculate the torque the motor delivers. The load acceleration is calculated using the rotational speeds scope integrated over every time step.

1. Load
   - $J_{load} = m_{load} \cdot \frac{{d_{pin}}^2}{4} + \frac{1}{8} \cdot m_{pin} \cdot {d_{pin}}^2$

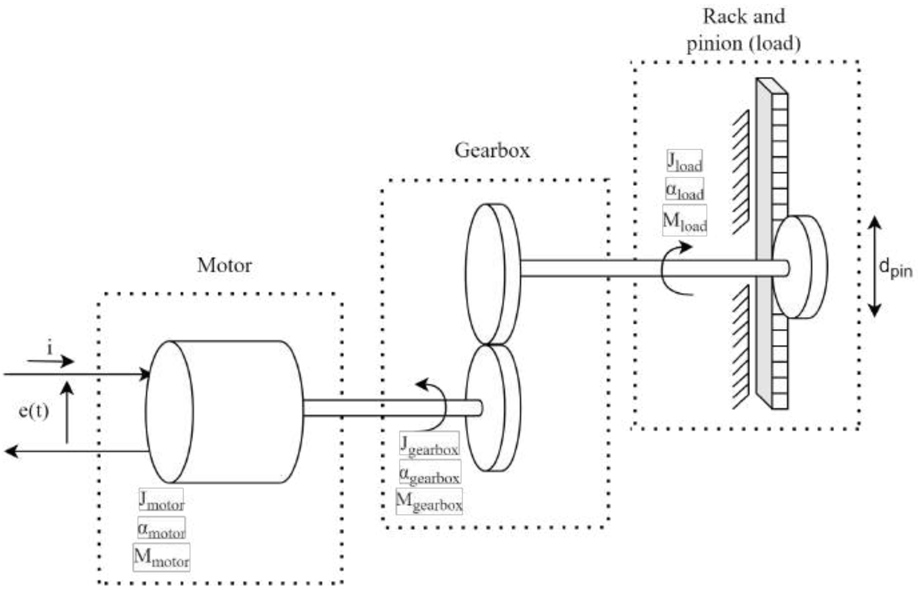


Figure 5.6: Schematics of rack and pinion mechanical system

- $\alpha_{load} = \alpha_{load}$
- $M_{load} = J_{load} \cdot \alpha_{load} + m_{load} \cdot g \cdot \frac{d_{pin}}{2} \cdot \frac{1}{\eta}$

2. Gearbox

- $J_{gearbox} = \frac{J_load}{i^2} + J_{gearbox}$
- $\alpha_{gearbox} = \alpha_{load} \cdot i$
- $M_{gearbox} = J_{gearbox} \cdot \alpha_{gearbox} + \frac{M_{load}}{i} \cdot \frac{1}{\eta}$

3. Motor

- $J_{motor} = J_{gearbox} \cdot J_{motor}$
- $\alpha_{motor} = \alpha_{gearbox}$
- $M_{motor} = J_{motor} \cdot \alpha_{motor} + M_{gearbox}$

5.3. Verification and Validation

Now that the FDD model has been applied to a system it will be verified and validated. Verification is the process of ensuring that the model "is right". This means assessing if the model has been implemented in the correct way and works as satisfied. This will be done by analysing the different outputs of the model and discussing the results. Model validation is the process of ensuring that sufficient accuracy is achieved by the model for its purpose. For the VDL Nedcar case study only normal operation running data was available because no faults occurred over the running time. To validate the model for fault detection artificial faults were generated using the characteristics determined in the literature review. The hybrid diagnostic model which was defined in chapter 4 is analysed using various methods to ensure validity. The model was developed to be applied in an industrial setting where limited data is available. For this reason the model is validated in two ways, first using only one month of running data (146 measurements) and also using a year of data (1532 measurements). These results are in turn discussed.

The verification and validation is broken down into two parts, fault detection and fault diagnosis, see figure 5.7. This is because these two parts work separately in the model and because there is no fault data the model could not be tested as a whole. This is because a faults gradually occur and it is unknown how this mechanism actually happens. The model is going to be validated with artificially generated faults to verify that faults can be detected.

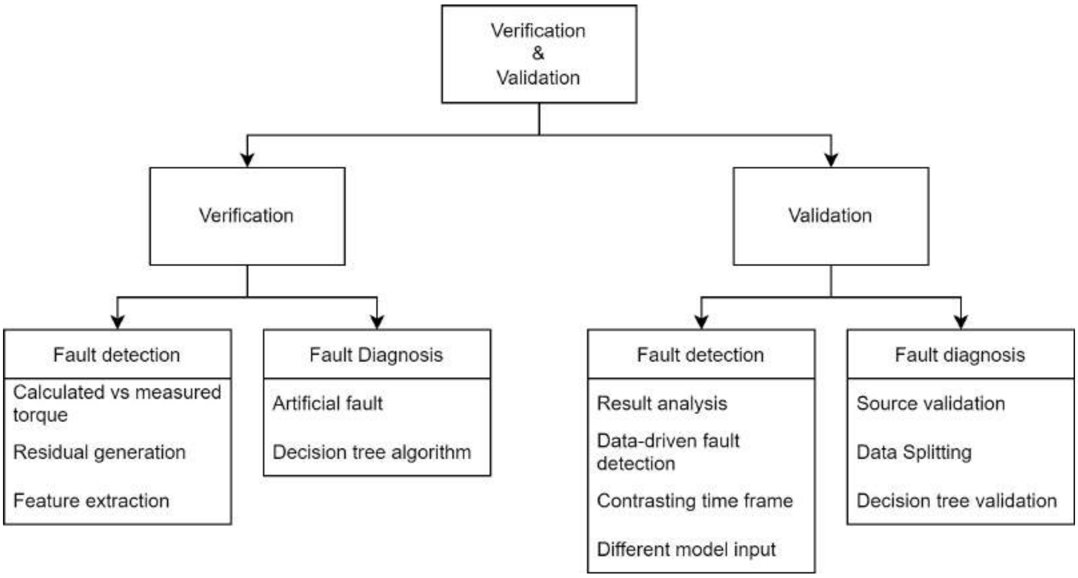


Figure 5.7: Verification and validation

5.3.1. Verification

The code is verified in three ways, first through inspecting the code, visual checks and inspecting results. First, the code was checked throughout the coding to ensure the right data and formulas were used. The code, mathematical model and faults were checked during the development by a SEW Eurodrive data engineers and a project engineer. Visual checks are performed in the following paragraph. The final results of the code are also inspected, the results can be found in paragraph 5.3.3 and are also discussed below.

Fault Detection Verification

In figure 5.8 the calculated torque (orange) can be seen next to the average of the scopes from July 2020 (healthy state). In general the calculated torque is similar to the measured torque. As stated in chapter 4 the calculated torque has two parts, the static and dynamic torque. In table 5.1 the movement is described in detail, the static parts are 1.75-2.5 and 2.8-3.4 and dynamic are 1.25-1.75, 2.5-2.8 and 3.4-3.6. Looking at figure 5.8 it can be concluded that the static parts have the correct torque. The dynamic parts of the movement, especially the first two are over estimated by roughly 1 Nm. This can have a couple of reasons, seeing that the dynamic part is based on $F = ma$ the mass and/or acceleration one of them can be off. Acceleration is taken directly from the set-point speed thus can be assumed to be correct. The mass, which involves the inertia, is likely to be off, reasons can vary from production mistakes, to wear in the system, to incorrect data or something else. Nevertheless, the calculated torque is used as reference thus small abnormalities do not matter if they remain constant.

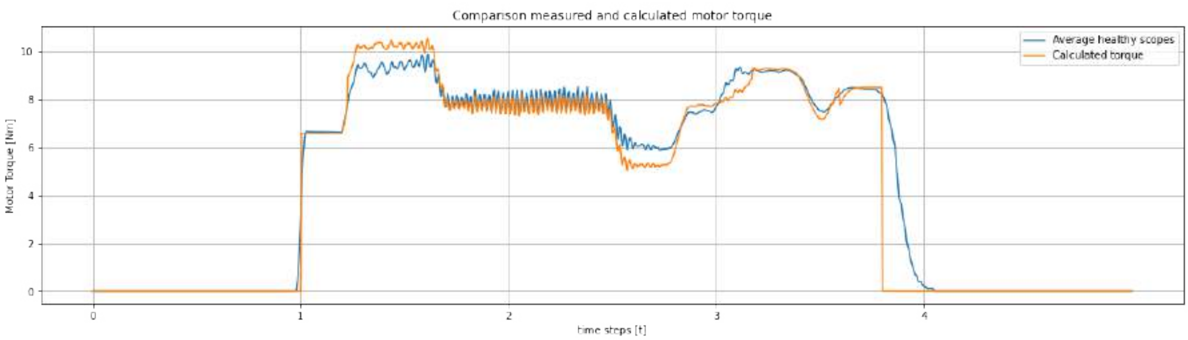
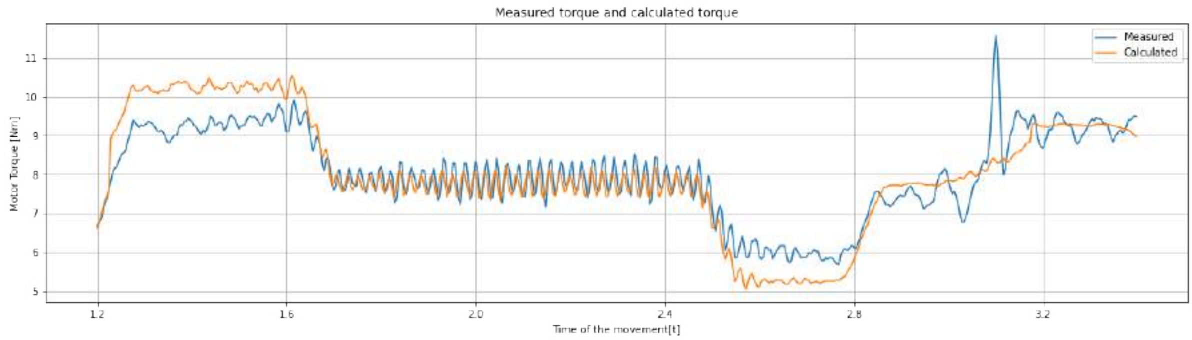
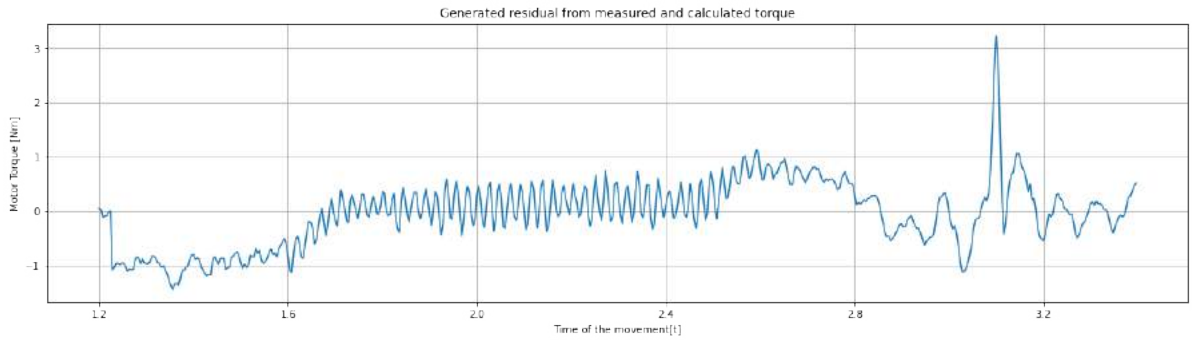


Figure 5.8: Calculated vs measured torque

In figure 5.9 a healthy scope is plotted next to the average calculated torque with the residual that is generated, explanation can be found in paragraph 4.1. The peak occurs when the car is picked up by the lift which causes vibrations in the system and a sudden increase in necessary torque. This is normal for the given system thus a peak does not necessary mean there is a failure. In the hybrid model after correlation is calculated, the other features (peak value, kurtosis) are generated from the residual. For the first five scopes the value of the features can be found in table 5.2. These features are as expected and show no abnormalities. All of the scopes that were used had been inspected and all show a normal movement of the system. In table 5.3 the same table can be seen, however here the features have been normalized and include their health indication value. Based on these results the fault detection section performs as expected.



(a) Measured torque scope versus calculated torque



(b) Generated residual

Figure 5.9: Residual generation from a scope

	Correlation	**Mean**	**Median**	**Max**	**Rms**	**Kurtosis**	**Crest-factor**
2020-07-01 T00:26:32	0.092	0.0041	0.026	3.73	0.64	6.59	5.79
2020-07-01 T07:26:32	0.058	0.088	0.076	2.67	0.58	3.35	4.57
2020-07-01 T10:26:32	0.076	-0.010	0.083	3.13	0.60	4.96	5.25
2020-07-01 T14:26:33	0.071	0.030	0.10	3.23	0.59	5.78	5.49
2020-07-01 T15:26:33	0.075	-0.0081	0.089	2.85	0.60	4.30	4.72

Table 5.2: Extracted features from 5 scopes

	Correlation	Mean	Median	Max	Rms	Kurtosis	Crest-factor	Health indicator
2020-07-01 T00:26:32	0.72	0.33	0.26	0.89	0.65	0.65	0.82	0.61
2020-07-01 T07:26:32	0.14	0.51	0.37	0.47	0.20	0.13	0.52	0.33
2020-07-01 T10:26:32	0.44	0.30	0.38	0.65	0.29	0.39	0.69	0.44
2020-07-01 T14:26:33	0.37	0.38	0.42	0.69	0.22	0.52	0.75	0.47
2020-07-01 T15:26:33	0.43	0.30	0.39	0.54	0.35	0.28	0.55	0.40

Table 5.3: Normalized extracted features from 5 scopes with the health indicator value

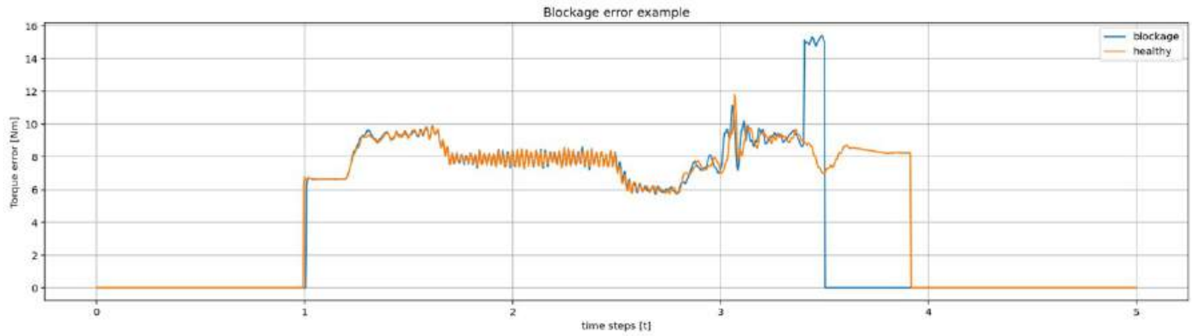
Fault Diagnosis Verification
No fault data was available when the system was being developed thus fault data was artificially simulated, this was explained in chapter 4. This was done by taking 584 healthy scopes of the system and applying the characteristics of the faults to all these scopes, see table 3.3. To ensure the faults were as realistic as possible a random factor was added to the noise, peaks, increased torque and other characteristics. In figures 5.10a, 5.10b and 5.10c the artificial faults can be found. The faults are all at the severe range of random to illustrate the differences better. The blockage fault (figure 5.10a) is clear to understand, the movement is impeded thus the VFD increases the current which gives the drastic peak. As stated in the literature review (chapter 3) bearing and gear failures are very similar. The differences were that bearing failure results in a increase of noise and higher necessary torque to move the system. Gear failure will have a sinusoidal wave through the movement which size and frequency depend on the failing gear. This will also increase the noise in the system due to vibrations of the bad gear tooth. In reality the failures can differ which can be expected. The artificial failures have the goal to test the hybrid diagnostic model, and because they do mimic reality to a certain extend they will be used and will give valid results. When actual fault data becomes available this can be used to test the model and the artificial failures can be validated.

Fault classification is done through a decision tree algorithm. Python has a library called scikit-learn which has almost all machine learning algorithms in it. As previously stated, the model is trained using the first month of data (146 scopes), however to make the increase accuracy the 146 scopes will be duplicated four times, thus there will be 584 scopes. After this these 584 scopes will have the four faults applied to them, thus there will be four tables with 584 scopes of blockage, bearing, gearing and other faults. Each of these faults has 584 unique scopes because when the faults are applied there is a random factor which makes every one unique. These scopes are split, 70% are used for training and 30% are used for testing the data. How this works is of the 584 scopes, 409 scopes are used for training and 175 for testing. With the 409 scopes the features are analysed and the decision tree algorithm is trained with these values. After this the 175 test scopes are presented to the trained model. The model has not yet seen these scopes yet and are used to define the KPI's, namely accuracy, precision, recall and f1 score. This ensures reliable results from the model.

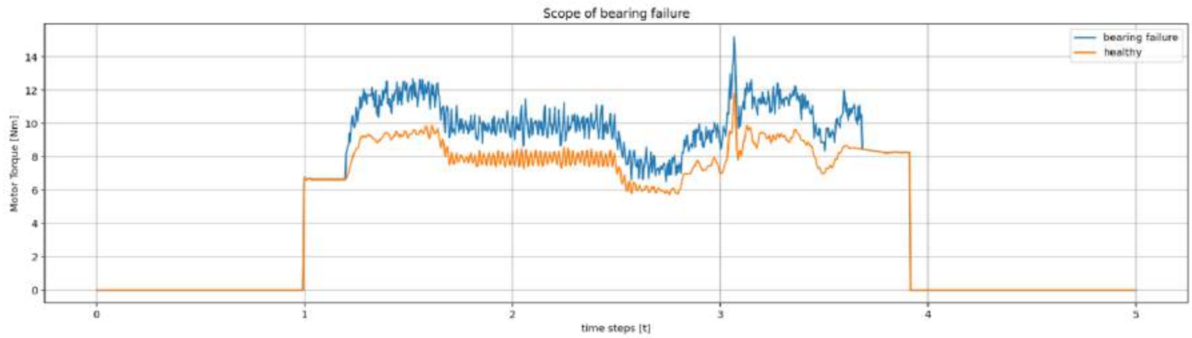
5.3.2. Validation
Validation of the hybrid diagnostic model is done only using the VDL Nedcar case study. Data, parameters and mathematical models were not available of other systems at the time. To ensure valid validation of the model the complete model is validated in sections, below an overview can be found. The first the model-based fault detection is validated and secondly the fault generation and classification is validated.

The model-based fault detection is validated using the following methods:

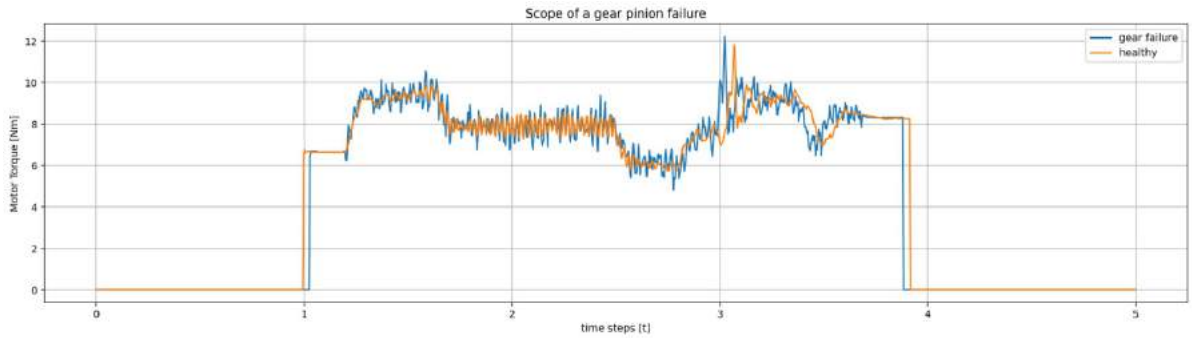
- *Analysing model-based results*: comparing measured and calculated torque and validating results
- *Data-driven for fault detection*: utilizing data-driven instead of model-based to detect faults



(a) Blockage fault compared to normal scope



(b) Bearing fault compared to normal scope



(c) Gear fault compared to normal scope

Figure 5.10: Three artificial faults simulated using healthy scopes

- *Contrasting time frame fault detection*: comparing values of fault detection
- *Contrasting time frame fault diagnosis*: comparing values of fault diagnosis
- *Analysing different model input*: analysing how the model-based section reacts to a new input

The data-driven fault diagnosis is validated using the following methods:

- *Source validation*: validation of simulated faults
- *Data splitting*: randomly dividing data into train and test data with a 70/30 split
- *Decision tree validation*: validating decision tree as the best algorithm

Due to the absence of fault data and especially data of a developing fault the complete model could not be validated. A fault usually slowly develops over time where the severity increases slowly, however how a fault develops was not known. For example, in the morning when a system is cold the fault might be detected faster, however during the day the fault might not be as clear because the system is at running temperature. Without knowing how faults develop it is difficult to validate the complete model, to still have proper validation the model is analysed using other methods. In the model the fault detection and diagnosis parts work separate from each other and do not influence each other. Thus they can be validated separately to ensure validity of the sections. The whole model is validated using other methods, see below.

First complete model validation, the model was presented to those who have knowledge about the model and of the VDL Nedcar system to validate the values that had been used and overall correctness. The fault detection mathematical model was checked by the appropriate engineer to ensure the correct parameters and formulas were used. The anomaly detection machine was presented to two SEW Eurodrive workers, a data and a project engineer. Both seeing and understanding how it could function and seemed to be built on realistic features. The characteristics of the faults came from literature and different websites which specialise in the subject. Eventually when actual failure occurs then the artificial faults can be validated, however more detail can be found in paragraph 5.3.2.

Fault Detection Validation
In model-based validation the mathematical model and fault detection machine are considered. Sadly the mathematical model could not be applied to another system, however the idea behind the mathematical model is simple. All movements, being horizontal, vertical or rotational must adhere to the basic formulas of nature, see paragraph 4.2.1. Thus, if the mathematical model would be applied to another system, and all parameters are known then the mathematical model will always approach the actual measurements. In chapter 4 the mathematical model was also applied to a conveyor belt, see figure 4.1a which also showed a close correlation.

In the VDL Nedcar case study the average measured torque and the calculated torque can be compared to each other, see figure 5.8. Over the 5 second scope the PCC (explained in chapter 4) is 0.90, reason for just five seconds not eight is that this captures the whole movement and outside the five seconds the system does not move. In table 5.4 the difference between the measured and calculated torque can be found for the model. It is done by taking the mean over a certain time of the movement, see table 5.1 for which time of the movement. The first time was chosen because here the system was accelerating, the second because the system was moving at a constant speed (steady state) and last is when the car has been lifted thus there is a heavier weight. During the acceleration part the average is the largest, the exact reason is not known, however after discussing the results with SEW Eurodrive engineers some conclusions can be drawn. First is general wear in the system due to the system being old (7 years), second is influence of temperature on the system, third is manufacturing defects which can result in higher torque values. The last conclusion is that, the acceleration part adhere to the formula $F = ma$, acceleration is known, thus the mass could be off. The exact weight of the car frame was not known thus this could be the case, however exact reasons vary.

	Measured [Nm]	Calculated [Nm]	Difference
1.25-1.6 seconds	9.36	10.24	10%
1.8-2.4 seconds	7.90	7.75	1.9%
3.2-3.5 seconds	9.21	9.24	0.5%

Table 5.4: Comparison measured torque to calculated torque for mathematical model

The second validation method to apply data-driven solution to fault detection. In chapter 4 it was concluded that for the problem model-based solution would work the best. However, data-driven has shown multiple times in literature that is works well for fault detection, thus will also be applied to the problem. First the four faults (blockage, bearing, gear and other) were simulated in three different levels of severity, namely, mild, moderate and severe. Then the healthy scopes were taken and noise, a wave and/or a sinusoidal wave applied to them based on conclusion of the literature review. The the three severity's has fault characteristics applied to them in a certain range, e.g. between 1.5-2.5% increase of a step. This was done to mimic a fault that would happen in a real life situation. The three severity's of faults will be used in further paragraphs for validation of the system. In table 5.5 the mean health indication values can be found of the faults when simulated with a moderate fault level.

In table 5.6 and 5.7 the results can be seen of the KPI's. They both used the simulated faults which were defined above. Looking at the numbers the overall results are very similar. Accuracy of both model-based and data-driven are high, going up to 94% for model-based and 92% for data-driven. When

Failure	**Mean health indicator value**
Blockage	4.4
Bearing	0.85
Gear	0,64
Other	0,59
Healthy	0,45

Table 5.5: Mean health indication value of the simulated faults

looking at the F1-score there is a larger difference, with the mild faults model-based has a significantly higher score. This being essential to avoid false positive alarms means that model-based is better given the case. This justifies the choice for model-based for fault detection in terms of accuracy. There are other advantages to this, examples are the data-driven model is now trained to recognise the faults its has been given however new types of faults might not be recognised correctly. Model-based, which uses health indication values with thresholds for fault detection have a higher precision in mild faults which means less false positives. Additionally because model-based uses extracted features from a residual it will handle other faults in a stronger way then data-driven which is trained to only recognise certain faults.

Model-based	**Mild**	**Moderate**	**Severe**
Accuracy	0.79	0.88	0.94
Precision	0.77	0.81	0.91
Recall	0.83	0.99	0.99
F1-score	0.80	0.89	0.95

Table 5.6: Model-based vs data-driven fault detection 146 measurements, model-based results

Data-driven	**Mild**	**Moderate**	**Severe**
Accuracy	0.77	0.89	0.92
Precision	0.71	0.87	0.92
Recall	0.70	0.86	0.92
F1-score	0.71	0.86	0.92

Table 5.7: Model-based vs data-driven fault detection 146 measurements, data-driven results

The third validation method is using all the available data at the time, e.g. 1532 scopes compared to 146. 146 Scopes were used for training, the reason behind this was to mimic a situation where a limited amount of data is available of the system (e.g. just started operation). However, after a while more data will be available, thus 146 is compared to 1532 scopes. In table 5.8 the average values for the features can be found before normalization together with the eventual health index value. Comparing the two the values are very similar with hardly any difference. Interesting is that the health value decreases when looking at more scopes. When looking at the values of 5.8 this makes sense due to median, max, kurtosis and crestfactor having a lower average value. The main reason for this would be the influence of temperature on the system. In the winter the system will be colder when it starts which will create higher peaks in the features, higher torque due to less efficiency. The rest of the measurements during the day will be normal because the system will working at normal temperature. This results in more high peaks, however average will roughly remain the same. When the system is normalized with equation 4.1 the x_{max} of will be higher pushing the normal values down resulting in a lower average and a lower health value. This results in the natural question, will this have an impact on the trustworthiness of the model? Theoretically it should not, if over time the system will start the fail the health value will gradually increase resulting in an alarm. Taking the values over a longer time will actual increase the changes of recognizing a failure making the system better.

	correlation	mean	median	max	rms	kurtosis	crestfactor	health
mean 146	0.080	0.025	0.079	3.085	0.617	5.163	4.988	0.454
mean 1532	0.082	-0.022	0.015	2.990	0.626	5.029	4.768	0.411

Table 5.8: Mean values of 146 and 1532 scopes with the health index value

Next we will look at the results if 1532 scopes are used instead of 146 scopes. This uses the data over a full year of operation. In table 5.9 and 5.10 the results can be found of the analysis. Interesting to see is that on average the data-driven shows a higher results overall. This is to be expected because the algorithm has more data to work with which results in a better understanding of the characteristics of the faults. Higher accuracy is 95% in this case which is very good. Secondly, the model-based solution overall has lower values overall. Why this happens exactly is unknown, however in the following paragraph an explanation is given for the difference between 146 and 1532 scopes.

Model-based	Mild	Moderate	Severe
Accuracy	0.70	0.84	0.90
Precision	0.67	0.77	0.87
Recall	0.83	0.92	0.96
F1-score	0.76	0.84	0.91

Table 5.9: Model-based vs data-driven fault detection 1532 measurements, model-based results

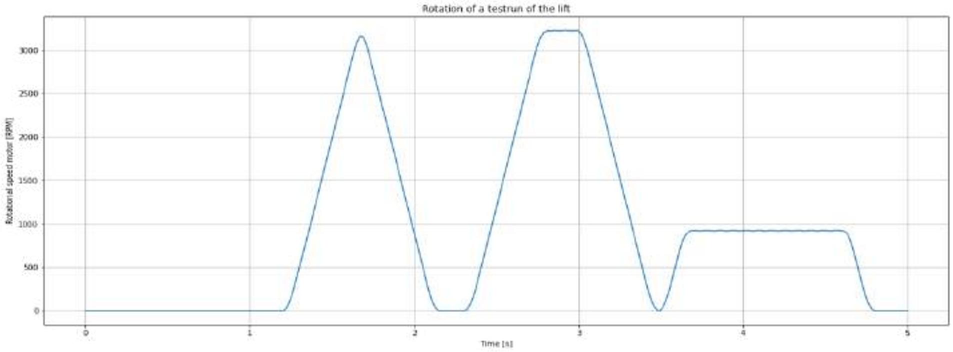
Data-Driven	Mild	Moderate	Severe
Accuracy	0.83	0.92	0.95
Precision	0.77	0.88	0.94
Recall	0.80	0.89	0.93
F1-score	0.78	0.89	0.93

Table 5.10: Model-based vs data-driven fault detection 1532 measurements, data-driven results

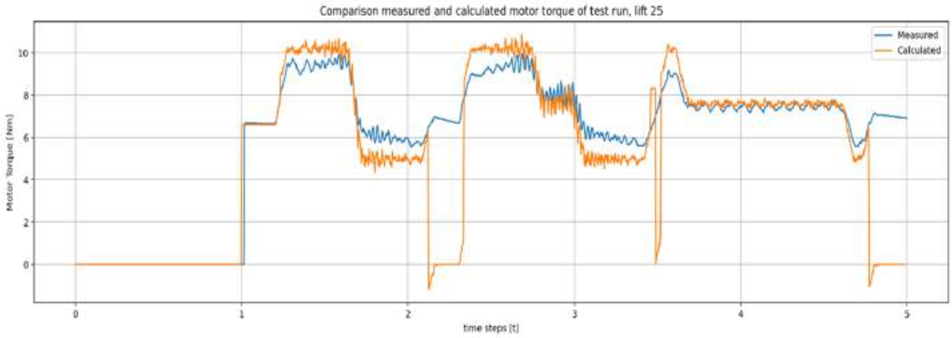
A fifth model-based validation method is to have different inputs into the model and see if the outputs are still valid. VLD Nedcar has data of scopes of movements which move differently to the normal movement of the system, see figure 5.11. In these scopes VDL Nedcar was testing the system without a car to see the condition of the machine. The movement has two accelerations and de-accelerations to 3000 RPM and then a short steady-state of roughly 900 RPM. In figure 5.11b the measured and calculated torque can be seen. The same characteristics can be seen as described in paragraph 5.2.2. In the acceleration phase there is a slight overestimation of the torque and the steady-state is almost the same. Abnormalities can be seen when the system stops moving, this is where the calculated torque drops to 0. This is because in the actual system the brake is activated to stop the system from moving, however torque is still send to the motor, called pre-loading. The goal of this pre-loading is to avoid the lift from slightly dropping down when the brake is released. Technically no torque is flowing through the system thus the calculated torque is zero, this characteristic can also be seen in figure 4.1a.

Fault Diagnosis Validation

The faults that were simulated will be validated through various methods. The first is verifying the sources where the characteristics of the faults were defined. Second was presenting the faults to experts from SEW Eurodrive. The project engineer stated that the faults that were generated would resemble the actual faults. When more data of the actual faults is collected the artificial faults can be directly compared to actual faults. Characteristics of the actual faults could also be integrated into artificial faults to make them more accurate.



(a) Rotation speed test run of lift



(b) Measured and calculated torque of test run of lift

Figure 5.11: Black-box validation model-based diagnostic model

The second part of the artificial faults is to validate that the decision tree algorithm works and is the best algorithm for the model. First and simplest validation step was though splitting the data 70/30 which shows what happens when the model is faced with data that it has not seen before, this is explained in detail in paragraph 5.3.1. The model has an average accuracy of 91% which is very good. The splitting was done randomly to avoid sampling bias, which is defined as systematic error due to non-random sampling of data. In table 5.11 an overview of eight classification algorithms can be found with their average accuracy, precision, recall and F1-score over 10 test. As stated in chapter 4 decision tree classifier was defined to be algorithm with the highest accuracy for this problem which is justified by the results. The second highest was random forest classifier which works similar to decision tree which explains the higher accuracy. In many cases in the table precision and recall are very similar, looking at the formulas defined in paragraph 4.3 this means that false positive and false negative are equal. In this case it is a good thing because the algorithm is equally balanced because the data set is equal, meaning all healthy and faulty scopes are the same. Neural networks (or deep learning) scored one of the lowest even though it is in theory the strongest, based on conclusion from the literature study. This is mainly due to there not being enough data to properly train a NN model. If more data was available this could have excelled

	Accuracy	**Precision**	**Recall**	**F1-score**
Decision tree	0.91	0.92	0.92	0.92
Logistic regression	0.76	0.73	0.74	0.73
Linear discriminant	0.89	0.90	0.89	0.90
K neighbors	0.74	0.73	0.74	0.73
Neural network	0.66	0.53	0.65	0.58
Gaussian NB	0.88	0.88	0.88	0.88
SVM	0.50	0.42	0.51	0.43
Random forest	0.90	0.91	0.90	0.91

Table 5.11: Accuracy and standard deviation of eight machine learning classification algorithms used to classify the faults

5.3.3. Evaluation KPI's

In chapter 4 KPI's were defined to evaluate the detection and classification algorithm. Exact values can be found in Appendix D.

First the evaluation of the detection algorithm. To test the KPI's of the model four different thresholds are evaluated, they are based of the standard deviation from the mean of the healthy scopes. These four thresholds were chosen to determine the general accuracy. When the results are known the threshold could be adapted for a higher accuracy, basing it of values from table 5.12.

Threshold name	Threshold Value
Mean:	0.45
Standard deviation*1 + mean	0.59
Standard deviation*2 + mean	0.73
Standard deviation*3 + mean	0.87
Standard deviation*4 + mean	1.01

Table 5.12: Value for threshold fault detection algorithm

In the VDL Nedcar case study 146 scopes were chosen, these were all the scopes of the first month of operation are used and when it is sure that the machine was in a healthy state. These 146 scopes had features extracted as explained above and a health indicator score generated. The mean of these were calculated and the standard deviation was multiplied by 1,2,3 or 4 and added to the mean, see the values in table 5.12 and visualisation in figure 5.12. Figure 5.12 can be interpreted in the following manner, on the start of the x-axis is 1st of July and the end is the 31st of July. They fluctuate around the mean 0.46, differences can be caused due to various reasons, e.g. cold morning runs or other small running time abnormalities. Exact values do not matter and serves as an indication of where the threshold could potentially be which faults will breach.

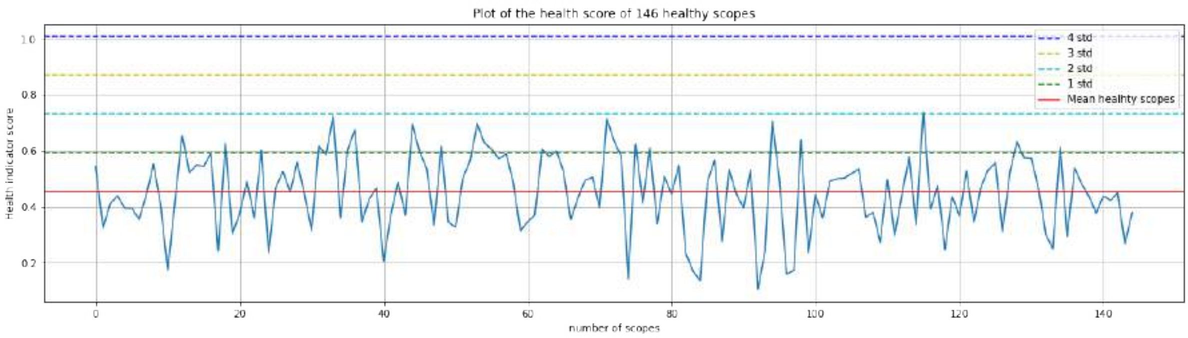


Figure 5.12: Plot of the health score of 146 healthy scopes

The healthy scopes and the artificial faults, blockage, bearing, gear and random failure were compared to the thresholds and if they were exceeded. To have an even divide between healthy and faulty scopes the 146 healthy scopes were multiplied by four, which meant that there were 580 healthy scopes. From these values a confusion matrix was build for every threshold and for the three severity of faults, these can be found in table 5.13 and 5.14 and in detail in Appendix D. In chapter 4 it was stated that using a sliding window alarm false positive alarms could be mitigated by only sounding an alarm if a threshold was breached a certain number of times. In theory this would work, looking at the values from table 5.5 all failures have higher health indication values which in theory sound the alarm. However, to test this actual healthy data would be necessary. It is unknown how actual faults appear in systems and in which intervals. This would be a good topic for future research and will be mentioned in the conclusions. Furthermore, in general a couple of conclusions can be drawn from the results.

Threshold	Severe fault level accuracy	Moderate fault level accuracy	Mild fault level accuracy
Mean + 1 Std	0.89	0.87	0.79
Mean + 2 Std	0.94	0.88	0.78
Mean + 3 Std	0.91	0.81	0.70
Mean + 4 Std	0.85	0.77	0.65

Table 5.13: Fault detection accuracy values of multiple thresholds

Threshold	Severe fault level F1-score	Moderate fault level F1-score	Mild fault level F1-score
Mean + 1 Std	0.88	0.86	0.80
Mean + 2 Std	0.95	0.89	0.82
Mean + 3 Std	0.91	0.84	0.77
Mean + 4 Std	0.87	0.81	0.74

Table 5.14: Fault detection F1-score values of multiple thresholds

First, the algorithm has a high precision due to a low classification of healthy scopes being a fault, especially with 2 standard deviation and higher. This is one of the goals because having engineers conduct maintenance on healthy systems is counterproductive. Precision would have the lowest score on the first standard deviation due to 25 health scores being above the line which coheres to being the first standard deviation because it will include some values above the mean. Second conclusion is that precision declines with higher thresholds. This is to be expected because not all faults breach the threshold value, however, this problem should be mitigated with using a sliding window. This is because a certain percentage does breach the threshold which the sliding window will pick up. Third, the threshold that had the highest accuracy was the second deviation above the mean with the highest accuracy being 94%. This was due to the low classification of healthy scopes being faults while still categorising faulty scopes correctly. The highest accuracy of the mild fault level was 79%, this was mainly caused by faults being predicted as healthy scopes. In general this is still an acceptable accuracy for algorithms. Reasons for this is that the 'other' fault itself had a high deviation from its own mean due to randomly simulated artificial faults which were sometimes more severe than others. The three other faults were still classified with a reasonably high accuracy, with gearing being classified with an accuracy of 65%. Lastly, the f1-score which shows the mean between recall and precision is overall high. This is important because we want out model to identify all the healthy scopes and at the same time identify only positive cases. This can be a trade-off, however with the lowest f1 score being 80% and highest being 95% gives the model a good performance.

The results of the fault classification decision tree classifier can also be found in table 5.15 and extended in Appendix D. With accuracy's from 84%, 91% and 98% it excels in classifying the faults. Together with the precision, recall and f1-score all being balanced it shows that the algorithm is balanced and works properly. In figure 5.13 the mean decrease in impurity (MDI) can be seen of the features used by the tree decision classifier. This represents how important each feature is in classifying the faults. The median and the FFT mean are the most important. The mean of the features is 0.125, all features are relatively close to this which shows they all played a part. The least important was kurtosis of the frequency domain, this was probably due to the fact it was only used in classifying the gear faults.

KPI diagnosis	Mild fault	Moderate fault	Severe fault
Accuracy	0,84	0,91	0,98
Precision score	0,86	0,92	0,99
Recall score	0,85	0,92	0,98
F1 score	0,85	0,92	0,98

Table 5.15: KPI values for the decision tree diagnosis algorithm

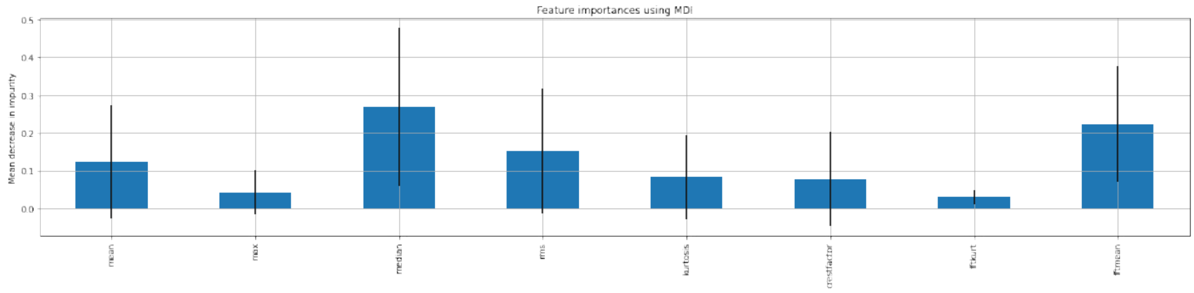


Figure 5.13: Importance of the features using MDI

The results from the diagnostic model are very promising, faults are identified and correctly identified with a relatively high accuracy. However, in reality accuracy would be less. The data that was used in the VDL Nedcar case study was taken of a system that was 7 years old. This was the best option even though it can be assumed some deterioration had developed. It is unknown how an actual healthy system would perform and what the impact is of the age. Deterioration in lubrication could give higher torque values and more noise than expected for example. Another issue was that not all the parameters of the mathematical model were known. The exact weight of the car that was picked up is unknown. Temperature was also not considered in the model. In reality temperature has an impact on how well the lubricant works, however also on the efficiency of the motor. These can differ with a couple of percent depending on the situation undermining accuracy. The low sample rate (250Hz) of the VFD limited the amount of information that can be extracted from a measurement and also limits early detection of faults. Simulating the faults was the only option to test the model, however simulating is an approximation of the actual faults and in reality will differ in size and noise. Due to this the decision tree classifier would also be less accurate.

5.4. Concluding remarks

In this chapter the following research question is answered: *How can the model be verified and validated?*. This chapter was based on the hybrid diagnostic model developed in chapter 4.

First the case study is defined. This was done by analysing a system operated by VDL Nedcar, a car manufacturer. The system is a lift which elevates a car chassis over a 4 second time period. The rack and pinion, gearbox and load were simplified and a mathematical model developed. The model was implemented in Python and the results demonstrated. The calculated and measured torque were shown, the residual that is generated and the features shown. No actual fault data was available of the system (or in general) thus the faults (blockage, bearing and gear failure) were generated based on the healthy scopes.

After implementation the hybrid model it was verified and validated. The model and code is verified through three ways: checking the code, visual checks and inspecting results. The model was validated using the following methods.

- The model was presented to those who have knowledge about the model and of the VDL Nedcar system to validate the values that had been used and overall correctness.
- All movements must adhere to the basic formulas of nature, thus if done correctly the mathematical model will describe the system
- Difference between using 146 and 1532 scopes for fault detection and fault diagnosis were shown and conclusion drawn
- Different inputs were put into the model to check how it would react

The fault classification was, first, validated through verifying the sources of the fault characteristics. Second, by splitting the data 70/30 into training and testing data. Thirdly, by comparing different machine learning classification algorithms.

6 Conclusion & Recommendation

This chapter will present the research conclusion by answering the main research question. The six sub-questions have been answered in the concluding remarks of each chapter. Through combining the answers the main research question will be answered. This is followed by recommendations and lastly a discussing is held. In the discussion the limitations of the research are discussed with the contribution to scientific and practical research.

6.1. Conclusion

In chapter 1 the main research question and the sub-questions were introduced, the main research question being:

> ***How to develop a fault detection and diagnosis model of an industrial applied electric gearmotor system?***

This thesis studied fault detection and diagnostics (FDD) for small gearmotor system, which consists out of an AC motor, gearbox (or reducer) and the load it is attached to, which is applied in an industrial setting. These gearmotor system can be found throughout industries such as automotive, logistics and transport, the food industry and many more. They are cheap and in general reliable components which are critical to smooth operation of these industries. However, faults and failure do occur with unexpected and usually expensive downtime as a result. In literature, fault detection is generally accomplished through using sensors, complicated algorithms and utilising data generated in a lab. However, in an industrial settings expensive sensors are not financial variable, complicated algorithms are not robust enough and the data is filled with noise and anomalies. Thus, there is a gap between literature research and industrial needs. Furthermore, simple, accurate and robust models are necessary which can easily be applied to gearmotor systems.

To research the above mentioned gap a study was executed in two stages, first, a research into the state-of-the-art of a player in the gearmotor industry called SEW Eurodrive. Secondly, a literature research was conducted into the different aspects of the research problem.

The first subquestion was answered in chapter 2: *'What is the state-of-the-art of fault detection and diagnosis in industrial settings?'*. In order to answer these questions research was conducted at SEW Eurodrive, a player in the industry. The research was conducted through interviewing employees and reading company articles. The conclusions of this research reflects the state of the current industry. Six main problems were identified when it came to the development of fault detection models. First, due to the large amount of (complicated) academic researches it is difficult to know where to start when researching models. Secondly, the customers and problems where models need to be applied are very unique thus making universal solutions difficult. Thirdly, in industrial settings changes happen often which makes training AI models difficult and requires adaptable solutions. Fourth, general lack of data, especially fault and failure data. Fifth, problems with false positive and negative alarms in models. Sixth problem is system level diagnostics being more difficult then component due to more noise and more possible failures. Lastly, the main faults the occur in gearmotor systems are first blockage in movement, bearing failure and gear failure (related to oil degradation).

In chapter 3 the following subquestion was discussed: *'How does literature describe fault detection and diagnosis models and what type of data is necessary?'*. Fault detection and diagnosis (FDD) has two basic functions, first the behaviour of the process is monitored and secondly faults are detected. FDD consists of four stages, fault detection, fault isolation, fault identification and fault evaluation. Detection techniques can be generally categorised into two main categories, model-based and data-driven. Model-based uses mathematical formulas to describe the system while data-driven methods use artificial intelligence/ machine learning to detect faults and failures. Fault identification can be done using model-based and data-driven techniques, however data-driven solutions are preferred due to accuracy and simplicity. Using model-based and data-driven methods depends on the problem and parameters making an universal solution impossible. Further, the characteristics of the three main faults were analysed to make identification possible. Gaps were found in academic literature. First, there is a lack of system level diagnostics in gearmotor systems. Secondly, lack in hybrid solutions consistent out of model-based and data-driven methods for gearmotor systems. Finally there is a lack of developed models which have been applied to real world systems.

Based on conclusions from the introduction, state-of-the-art and the literature research a model was designed in chapter 4. The subquestions that were answered are: *'What fault detection and diagnosis model can be developed for an electric gearmotor system?'* and *'What KPI's can be used to assess the fault detection and diagnosis model?'*. First, using an evaluation matrix with the criteria robustness, accuracy, ease of implementation, adaptability and development cost model-based method was chosen for the fault detection phase. The mathematical model will predict the torque that the motor uses. This is because the motor torque can simply be calculated from the current that the motor uses using data from the VFD. Using these two inputs a residual is created, which is the measured minus the calculated torque. From this features will be extracted (e.g. max value, mean), which will be normalized and the mean taken from the values, this generates a *health indication value*. The health indication value represents the health of a recording of a movement, the higher the value the higher the chance something is wrong with the system. A healthy recording will be between 0 and 1 with faulty recordings having higher values than 1. Thus, when a fault occurs the health indication value increases and when this reaches a pre-defined threshold, an alarm can go off. This threshold can be flexible to avoid false positive and false negative alarms which increases accuracy. This method of fault detection is a extension of what has been done in academic literature, literature suggest torque and it has been applied in certain cases. However this case has certain features requiring a slight different model. n When a fault is detected the next phase of the model can happen, fault identification. Here a data-driven method was chosen. This is because it excels in classification accuracy and easy of use.

When the model is used it is divided into two phases, the offline phase and the online phase. During the offline phase the mathematical model is generated from parameters about the system. Initial healthy running data is fed into the system and analysed, here threshold and values are saved in a file. When the gearmotor system is running the online code will run, it will use the values generated from the offline phase to calculate the health value of the scope and see if it breaks the threshold. If the threshold is broken the algorithm will see if it can classify the fault. Eventually, the maintenance engineer will see which motor is showing faults and an estimation of what the cause could be. In this thesis the focus was on the offline part. The reason for this is that this is where the knowledge is applied and is what makes the model unique. The online part is when the system is applied in an industrial setting and not as relevant to this thesis.

Key performance indicators (KPI) were specified to measure the performance of the fault detection and identification sections. A confusion matrix was produced to identify how well the methods classified the data. From here four KPI's were used, accuracy, precision, recall and F1-score were used.

The last subquestion to be answered is: *'How can the model be verified and validated?'*. To verify and validate the model a case study from SEW Eurodrive was taken. A lift was chosen which is operated by VDL Nedcar, a car manufactured in the south of The Netherlands. The lift elevates the car frames which are welded on by robots. Data has been collected over the period 01/07/2020 until 30/12/2021, the data came from the VFD and were short recordings of 8 seconds, now called scopes. In total there were 1532 recordings available. For the system a mathematical model was developed and inserted into the fault detection section of the FDD model. Sadly, fault data was not available, thus fault data was simulated which utilized the characteristics of the faults which were identified in the literature review. A decision tree machine learning model was trained based on these faults. The model was verified and validated using various methods. Verification was conducted by analysing the fault detection and fault diagnosis results and discussing the results. Validation was done through analysing the model in parts. This was done due to only one system being available where data could be taken from and due to there being no fault data the model could not be tested to detect a fault over time. To mitigate this issue fault detection and fault diagnosis was validated using numerous methods.

After this the model was evaluated using the identified KPI's. The KPI's were applied to the detection and to the classification part using healthy data and the simulated fault data. The fault data was simulated at three levels of severity, namely, mild, moderate and severe. This was done to test how sensitive the model was to faults, mild being only a small change (roughly 2% increase torque for example). Severe faults would mimic a situation where the machine is about to fail. Next threshold had to be chosen for the fault detection part to detect faults with. Four different thresholds were defined, these are the average of healthy measurements with multiple of the standard deviation. These thresholds were chosen to test the model, in future research the best threshold could be found which would improve accuracy. For each threshold and fault severity a confusion matrix was created.

Four conclusions were drawn from the results. First, the algorithm has a high precision due to a low classification of healthy scopes being a fault, especially with the threshold of 2 standard deviation. This is one of the goals because having engineers conduct maintenance on healthy systems is counterproductive. Second, is that precision declines with higher fault thresholds which is caused by faults being classified as healthy scopes because the threshold has a higher value than the health indication value of the faulty scopes. This problem could be mitigated using a sliding window. A sliding window alarm initiates when a certain percentage of the fault breach the threshold value (e.g. if in the last 10 scopes 5 breach the threshold the alarm will go off). Third, the highest accuracy was the second deviation above the mean, with the highest accuracy being 94%. The highest accuracy of the mild fault level was 79%, this was mainly caused by faults being predicted as healthy scopes. In general this is still an acceptable accuracy for algorithms. Reasons for this is that the 'other' fault itself had a high deviation from its own mean due to randomly simulated artificial faults which were sometimes more severe than others. The three other faults were still classified with a reasonably high accuracy, with gearing being classified with an accuracy of 65%. To avoid false positive results it was desired that precision is as high as possible. For mild faults precision was 77% and for severe faults as high as 94%. The 77% precision is an acceptable due to the high amount of faults that are correctly predicted. To avoid false positives it was noted that this could be avoided using a sliding window, however this could be researched in future work. In practise, the results are satisfactory. In the introduction the goal was to develop an accurate, robust and reliable fault detection model and this was achieved. A 79% accuracy on mild faults is good when considering how small the difference is between healthy and mild fault scopes and as stated would probably increase with a sliding window. These results would give maintenance engineers a reliable model that they could use for fault detection and prevent unexpected downtime.

Fourth, in chapter 4 model-based was chosen for fault detection, after implementing data-driven for fault detection some conclusions can be drawn. The accuracy of both methods are similar (within 2% of each other), however f1-score is higher for model-based (average 4.5% higher). Thus, combining the results that model-based is as accurate as data-driven, together with other advantages justifies its choice for fault detection. Fifth, the f1-score which shows the mean between recall and precision is overall high. This is important because we want out model to identify all the healthy scopes and at the same time identify only positive cases. The results of the fault classification decision tree classifier with the three faults (mild, moderate and severe) have an accuracy's of 84%, 91% and 98%. Together with the precision, recall and f1-score all being balanced it shows that the algorithm is balanced and works properly.

In conclusion, this thesis studied what type of fault detection and diagnosis model could be developed for an industrial setting. Given the importance of a robust, accurate, adaptable model a hybrid diagnosis model was developed. It used a model-based method for fault detection and a data-driven solution to identify which fault could have happened. The fault detection method extracts features of possible faults which together form a value that determines the health of the system. This gives an easy understanding of the healthy of the system. To make maintenance faster the main possible faults were identified.

6.2. Limitations of this Research

Predictive maintenance and fault detection diagnosis (and Industry 4.0) are trending topics which, even though have been research for a long time, still require academic research and remain complex issues. Due to this there were limitations during this research. When it came to the case study VDL Nedcar there was limited data (1 year of data), and the data was of a system that had already been running for 7 years. The system was nevertheless in a healthy state, however being able to compare the mathematical model with a healthy state might have resulted in a higher accuracy. Using a larger data set would have also resulted in identification of external influences such as seasonal differences due to temperature. It would also have made future predictions of faults more accurate. While the artificial faults were simulated as accurately as possible, they still differ from an actual fault which limit accuracy of the model.

Applying the hybrid diagnostic model to other systems would have also given the possibility for comparison in accuracy. This could have led to development of a better model potentially, however it is for SEW Eurodrive to further research the topic. It would have also been interesting to see how to model would have worked with different types of motors (AC, DC, etc.), different types of gearboxes and especially different types of loads. The load tends to fail before the gearmotor system, thus understanding the failure mechanisms of different loads would have been interesting. The mathematical model of the loads could also have been compared and potentially interesting conclusions found. In the model external factors were not integrated, examples are temperature or wear. The efficiency of a gearbox relies heavily on the oil, which in turn relies on being at the right temperature. The motor constant, which is used to convert current to torque also depends on temperature which has also not been taken into account. In cold winter months it could be expected that more torque is required from the motor, this does not necessarily mean that there is a fault however.

The thesis had a focus on diagnostics with the argument that prognostics would not have as much added value to the system. However, there could be cases where knowing the remaining life of a system would be interesting. Based on this research future work could be done into using the FDD model and expanding it for prognostics. Another algorithm which is used in literature are Auto-regressive–moving-average models which predict future values in a continuous measurements. These could be applied in this case to adapt to potential seasonal changes or wear over time. Lastly, the model was limited to the identified failures, however in some cases (e.g. conveyor belt) the belt could be the first to fail. Thus, in future work other failures should be concidered depending on the application.

6.3. Recommendation

In this paragraph, first the recommendations for industries that utilise gearmotor systems are presented. These recommendations were made with regard to the research from the state-of-the-art of SEW Eurodrive and from the literature study. These were split into scientific research recommendations and SEW Eurodrive (industry) recommendations.

6.3.1. Recommendation for Scientific Research

In chapter 3, a literature review was performed on FDD for gearmotor systems. Research into FDD and PdM have been going on for decades and only intensified with the Industry 4.0 trend. However, research is one sided and focuses on the technical part of PdM and FDD. Examples are how to apply algorithms to complex data or prognostic models for certain components. Karuppiah et al., 2021 states that there are five dimensions to PdM/FDD, technical, economic, environmental, social and safety and many papers focus only on the technical dimension. Thus, recommendations for academia is also think and research the other dimensions. This can be achieved through combining knowledge from different universities or through having closer contact with industries where the technologies is intended for.

When researching for papers that are relevant to the literature review there were many papers that tried to use complex algorithms to find minuscule faults in components. While results were usually promising, these are difficult to use in an industrial setting. Thus, while pushing technological boundaries is good, extra focus should go towards models which add value and are simple to apply to industrial settings. Another essential subject to this problem is data. Many models and algorithms use data that does not represent a real-life situation. Faults and failures are made in unrealistic methods (e.g. drilling large holes in bearings) which limits usage of models. Combating the general lack of industrial data would also help development. This can be done through using AI to generate realistic data.

Finally, PdM and FDD are part of the Industry 4.0 revolution which is happen in manufacturing. The technology promises, and to a certain extent, improved efficiency and reliability of many industries. PdM and FDD financially make the most sense for companies due to the probable increase in productivity. Researching anything that has to do with these topics will help and they will help guide the way for other Industry 4.0 technologies. PdM and FDD are large problems with lots of different problems. Other issues that have not been mentioned in this research are data security and sharing or impact network usage of extra sensors.

6.3.2. Recommendations SEW Eurodrive

In this thesis, a FDD model was designed which could be applied to a gearmotor system to monitor the condition and detects and classify faults. This system had good results when it was validated and verified, however applying to other systems would show the real effectiveness. Further research can be done into the model and how it can be implemented into the systems of clients. The theory on which the model is based is simple, all movement have to adhere to the basic movements of nature thus changing to another system should work. The model could run locally on a computer or be integrated into a cloud which captures data. Other recommendations have been mentioned to a certain extent in the conclusion, however will be explained further below.

As previously mentioned, there are many PdM and FDD algorithms in literature. All work in separate ways and have advantages and disadvantages. To effectively understand these models trail and error method would be suggested. Try out models in different situation and see how they behave and if they work. When trying these advice would be to start as simple as possible, how do faults behave in different conditions and how can they be detected the best. Next recommendation would to apply DriveRadar DataCollector to as much systems as possible to gather data and also apply it to different industries as well. Data is necessary to understand behaviour of systems and for AI algorithms. Advantage of gathering as much data as possible is that the chance of gathering fault data increases. Problem with this is that DriveRadar would have to already be applied at clients, difficult about this is that it would not benefit the customers immediately thus motivating customers can be difficult. Together with the fact that many customers do not understand PdM technologies yet makes this difficult. However, it is known that more companies (especially bigger companies) are starting to understand the benefit of PdM. Applying DriveRadar in different industries helps to understand where certain failures are more likely to happen, how machines behave in different environments and to work towards helping as much clients as possible.

Essential is to create simple products which cater towards the needs. When working products start getting developed a focus should move towards future products and how to easily integrate DriveRadar in these. To lower the threshold for companies to adopt PdM or FDD it would be the best if these solutions would come with the products. This not only would give better reliability to the customer, it would financially help SEW Eurodrive.

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A

Overview Machine Learning Algorithms

Below an overview of all relevant data-driven algorithms can be found. The first table A.1 compares the algorithms when it comes to various grading criteria, for example ease of understand and speed of learning. The criteria are ranked from 1 until 4, here 4 means it performs the best and 1 means it performs bad. In the second table A.2 all the pro's and con's of the various algorithms are mentioned, these are general pro's and con's and are not specific for data-driven diagnostics. The aim of these tables is to give an easy overview and summary of all the algorithms. These tables are taken from a previous literature research done by the author, more information can be found here Robinson, 2021.

Machine Learning Paradigms	**ML algorithm**	**Ease of understanding**	**Accuracry in general**	**Speed of learning**	**Data necessary**	**Tolerance to missing values**	**Tolerance to Noise**	**Tolerance to overfitting**	**Tolerance to high dimensional datasets**
Supervised									
	Naïve Bayes	4	1	4	1	4	3	2	3
	Decision trees	4	2	3	1	3	2	1	3
	SVM	3	4	1	2	2	2	3	4
	K-nearest neighbour	4	2	4	1	1	1	2	1
	Linear Regression	4	2	4	2	1	1	2	1
	Decision trees	4	3	3	1	3	2	2	3
Unsupervised									
	SVM	3	4	1	2	2	2	3	4
	k-Means	4	2	3	1	2	1	2	2
	Hidden Markov models	1	2	1	3	/	4	/	3
	Principle component analysis	2	\	3	1	3	1	/	4
	K-nearest neighbour	4	2	4	1	1	1	2	1
	K-means clustering	4	2	3	1	2	1	2	2

Table A.1: Machine learning paradigms, techniques and algorithms and their scores Kotsiantis, 2007 Shanthamallu et al., 2017 N. and Kaur Raina, n.d. Dey, 2016 Choudhary and Gianey, 2017 Kotsiantis et al., 2006 Chapelle et al., 2009

ML algorithm	Data process task	Pro's	Con's
Linear Regression	Regression	• Easy to understand and visualise • Easy to program	• Assumes linear relationship, not always the case • Sensitive to outliers
SVM	Classification	• Performs well in high dimensions • Considered best algorithm when classes are separable • Outliers do not have a high impact	• Slow • Bad when classes overlap • Choice of hyper-parameters is important
K-nearest neighbour	Classification/Outlier detection	• Easy to understand and program (one hyper-parameter) • Easy to add new data • Multi-class problems solvable • No assumptions about data	• Slow training large datasets • Cannot handle high dimensions • Datasets must be scaled • Sensitive to outliers
Naïve Bayes	Classification	• Fast predictions • Can hangle large datasets • Effective with multi class predictions • Performs well in high dimensions • Good will unimportant features	• Bad estimator • Assumption of independence can be its weakness
Decision trees	Regression/ Classification	• Easy to understand and visualise • Not necessary to normalize data	• Sensitive to new data • Prone to overfitting • Can be slow to train
k-Means clustering	Cluster analysis/ Outlier detection	• Easy to understand and implement • Can handle large datasets • Easily handle new examples	• Need to choose right hyper-parameters (k) • Division of data classes necessary • Sensitive to outliers • Not good with high dimensions
Hidden Markov models	Latent variable models	• Strong statistical foundation • Flexibility due to unobserved variables	• Difficult to understand • Computationally expensive • Large data needed for training
Principle component analysis	Dimensionality reduction	• Improves performance of algorithms • Reduces Overfitting • Improves Visualization	• Data must be normalized • Information loss can occur • Loss of independent variables
Q-learning	Model-free learning	• Does not require model • Good with real life examples	• Learning ability can be restricted due to no knowledge • Learning can take very long
Markov Decision Process	Model-based learning	• Able to model sequential decision problems • Relative small computational time	• Extensive data requirements • Assumes transition probabilities and rewards are stationary • Difficult to program

Table A.2: Pro's and con's of the Machine Learning algorithms side by side Kotsiantis, 2007 Shanthamallu et al., 2017 N. and Kaur Raina, n.d. Dey, 2016 Choudhary and Gianey, 2017 Kotsiantis et al., 2006 Chapelle et al., 2009

B

Information Mechanical System

Three tables can be found below with extensive specifications of the main components of the lift.

Product data Servomotor	
Speed [r/min]	3000 / 104
Total ratio [i]	28,88
Mounting position	M6
Input speed nepk [rpm]	4500
Output speed na_pk [min-1]	156
Output torque Mapk [Nm]	435
Drive with special feature	Yes
Electrical regulation	Y_UL/CSA
ISO code	CLP 220
Lubricant type	Miner.Oil
Lubricant volume [l]	1,6
Rated speed nN [rpm]	3000
Standstill torque M0 [Nm]	13,4
Max. limit torque Mpk [Nm]	42,1
I0 standstill current [A]	10
Max. permitt. current Imax [A]	47
Cyclic duration factor S1-S10	S1
Motor voltage [V]	400
Max. permitted frequency [Hz]	250
Thermal class/Enclosure[IP]	F / 65
Electrical regulation	Europe (CE)/USA (UR)/ Canada (CSA)
Ambient temperature min. [°C]	-20
Ambient temperature max. [°C]	40
Brake type+size	BY4F
Brake voltage [V]/-torque [Nm]	400 AC / 28
Brake rectifier nameplate	None
Nameplate	German
Nameplate text	YBS.10205
Weight	41.00 kg

Table B.1: Information gear-servomotor unit

Product data Inverter	
Inverter part number	08279616
Size	2S
Rated power [kW]	5.5
Voltage [V]	3x380-500
Nominal input current [A]	11.3
Output voltage [V]	3X0-UIN
Rated output current [A]	12.5
Ambient temperature min. [°C]	0
Ambient temperature max. [°C]	+50
Degree of protection IP	20
Weight [Kg]	6.6
International efficiency class	IE2
Relative apparent power loss at performance point (90	100) [%]

Table B.2: SEW Eurodrive MDX61B0055-5A3-4-00 data

Lift specifications	
Lifting power [N]	8000
Lifting speed [m/s]	0,6
Acceleration [m/s2]	30
Torque [Nm]	240
Pitch diameter [mm]	60
lifting gear ratio [mm]	188,5
Efficiency [η]	0,8
Temperature resistance [C]	-10 to +100

Table B.3: Leantechnick SL 5.3 specifications

C

Hybrid-model diagnostics

In this appendix various hybrid-model based techniques are shown which have been found in literature which fit the parameters of the system. These will act as an inspiration for the model that will be used in this paper. A brief explanation of every model is given which is taken from the papers.

S. Frank et al., 2016
Figure C.1 summarizes our proposed hybrid AFDD algorithm. Conceptually, it consists of two distinct stages: fault detection and fault diagnosis. The fault detection engine compares measured building performance (typically, interval energy consumption data) with expected performance using a statistical model constructed from historical measurements, weather history, and, if available, a whole-building physics-based model.2 Significant deviation between measured and expected performance indicates a fault. Given a detected fault, the fault diagnosis engine classifies the type of fault using data-driven models constructed from a large database of simulated fault behavior. Data-driven algorithms require large and comprehensive training data sets, but comprehensive measured data for faults are rarely available. The hybrid algorithm addresses this weakness by leveraging a pre-simulated database of modeled faults to provide rich training data.

Liang and Du, 2007
In this paper, a new kind of MBFDD scheme is proposed based on a combination of the model-based FDD method and the Support Vector Machine (SVM) method. The physical model is derived based on the mass and energy balance of the HVAC system, so high modeling accuracy is assured. Meanwhile, to avoid the complex modeling and intensive computation, the model is simplified by employing the lumped-parameter method. On the other hand, an SVM method is used to design a fault classifier, which is

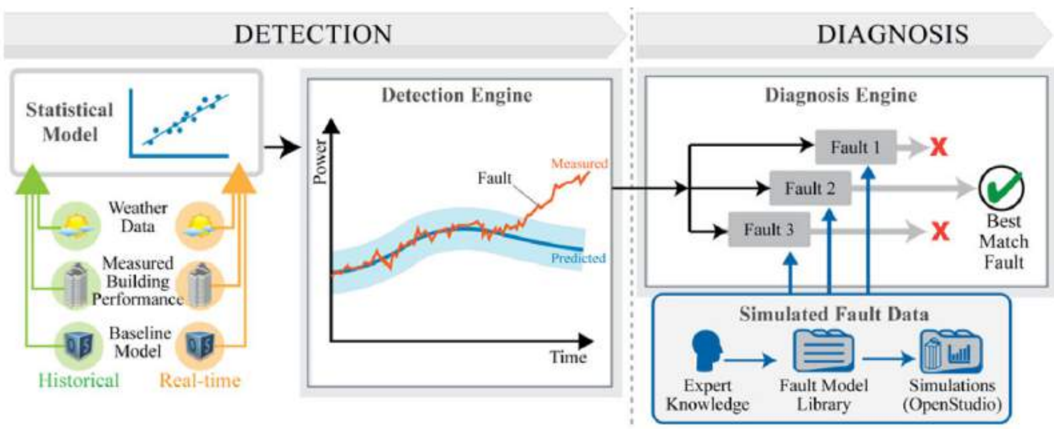

Figure C.1: Illustration of a hybrid diagnosis model for commercial buildings

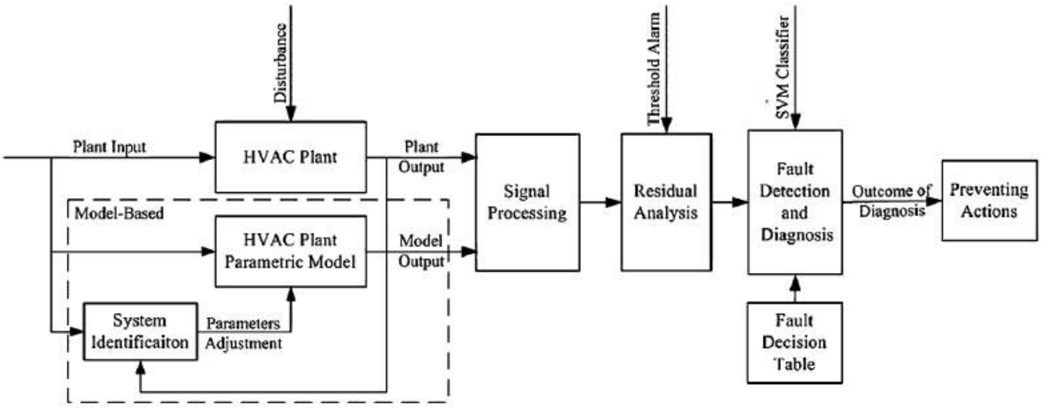

Figure C.2: Block diagram of a hybrid fault diagnosis for a HVAC systems

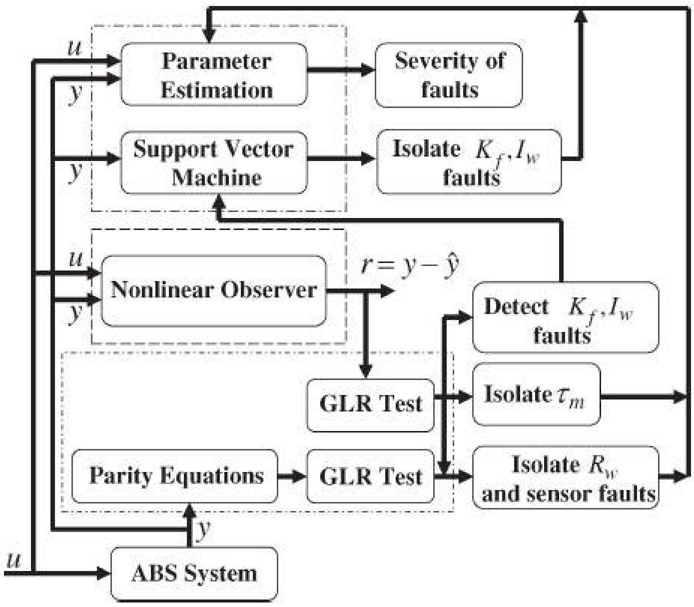

Figure C.3: FDI scheme for a car ABS system

based on the statistical learning theory that transforms the signal to a higher-dimensional feature space for optimal classification.

Luo et al., 2010

Figure C.3 shows a hybrid approach, which combines model-based and data-driven techniques to obtain better diagnostic performance than the use of a single technique alone, and demonstrate it on an anti-lock braking system. In this approach, we first combine the parity equations and a nonlinear observer to generate the residuals. Statistical tests, particularly the generalized likelihood ratio tests, are used to detect and isolate a subset of faults that are easier to detect. Support vector machines are used for fault isolation of less sensitive parametric faults. Finally, subset selection (via fault detection and isolation) is used to accurately estimate fault severity

D
In-Depth KPI's

In this Appendix all the KPI analyses can be found on the detection and classification of the data. They range from mild, moderate and severe fault level.

D.1. KPI's fault detection

In this section the KPI's of the fault detection can be found.

Confusion matrix		actual class	
		Actual positive	Actual Negative
predicted class	Predicted positive	480	145
	Predicted Negative	100	435

Accuracy	0,79
Precision	0,77
Recall	0,83
F1score	0,80

Table D.1: Fault detection, mild fault, mean + 1 * standard deviation

Confusion matrix		actual class	
		Actual positive	Actual Negative
predicted class	Predicted positive	576	248
	Predicted Negative	4	332

Accuracy	0,78
Precision	0,70
Recall	0,99
F1score	0,82

Table D.2: Fault detection, mild fault, mean + 2 * standard deviation

Confusion matrix		actual class	
		Actual positive	Actual Negative
predicted class	Predicted positive	580	344
	Predicted Negative	0	236

Accuracy	0,70
Precision	0,63
Recall	1,00
F1score	0,77

Table D.3: Fault detection, mild fault, mean + 3 * standard deviation

Confusion matrix		Actual class	
		Actual positive	Actual Negative
Predicted class	Predicted positive	580	401
	Predicted Negative	0	179

Accuracy	0,65
Precision	0,59
Recall	1,00
F1score	0,74

Table D.4: Fault detection, mild fault, mean + 4 * standard deviation

KPI Decision tree	
Accuracy	0,84
Precision	0,85
Recall	0,85
F1score	0,85

Table D.5: Decision tree KPI assessment

Confusion matrix		Actual class	
		Actual positive	Actual Negative
Predicted class	Predicted positive	480	50
	Predicted Negative	100	530

Accuracy	0,87
Precision	0,91
Recall	0,83
F1score	0,86

Table D.6: Fault detection, moderate fault, mean + 1 * standard deviation

Confusion matrix		Actual class	
		Actual positive	Actual Negative
Predicted class	Predicted positive	576	133
	Predicted Negative	4	447

Accuracy	0,88
Precision	0,81
Recall	0,99
F1score	0,89

Table D.7: Fault detection, moderate fault, mean + 2 * standard deviation

Confusion matrix		Actual class	
		Actual positive	Actual Negative
Predicted class	Predicted positive	580	218
	Predicted Negative	0	362

Accuracy	0,81
Precision	0,73
Recall	1,00
F1score	0,84

Table D.8: Fault detection, moderate fault, mean + 3 * standard deviation

Confusion matrix		Actual class	
		Actual positive	Actual Negative
Predicted class	Predicted positive	580	270
	Predicted Negative	0	310

Accuracy	0,77
Precision	0,68
Recall	1,00
F1score	0,81

Table D.9: Fault detection, moderate fault, mean + 4 * standard deviation

KPI Decision tree	
Accuracy	0,91
Precision	0,92
Recall	0,92
F1score	0,92

Table D.10: Decision tree KPI assessment moderate fault

Confusion matrix		Actual class	
		Actual positive	Actual Negative
Predicted class	Predicted positive	480	31
	Predicted Negative	100	549

Accuracy	0,89
Precision	0,94
Recall	0,83
F1score	0,88

Table D.11: Fault detection, Severe fault, mean + 1 * standard deviation

Confusion matrix		Actual class	
		Actual positive	Actual Negative
Predicted class	Predicted positive	576	60
	Predicted Negative	4	520

Accuracy	0,94
Precision	0,91
Recall	0,99
F1score	0,95

Table D.12: Fault detection, Severe fault, mean + 2 * standard deviation

Confusion matrix		Actual class	
		Actual positive	Actual Negative
Predicted class	Predicted positive	580	108
	Predicted Negative	0	472

Accuracy	0,91
Precision	0,84
Recall	1,00
F1score	0,91

Table D.13: Fault detection, Severe fault, mean + 3 * standard deviation

Confusion matrix		Actual class	
		Actual positive	Actual Negative
Predicted class	Predicted positive	580	177
	Predicted Negative	0	400

Accuracy	0,85
Precision	0,77
Recall	1,00
F1score	0,87

Table D.14: Fault detection, Severe fault, mean + 4 * standard deviation

KPI Decision tree	
Accuracy	0,98
Precision	0,99
Recall	0,98
F1score	0,98

Table D.15: Decision tree KPI assessment severefault

Development of a predictive maintenance model which provides fault identification and diagnostics on electrical gearmotor systems

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Abstract

Industrial electric motors are at the heart of almost every industry. They are a 47 billion USD market in 2020 and consume 70% of all industrial electricity. They are generally paired with a gearbox and load, which is referred to as an electric gearmotor system. Being so essential means that it is important to avoid failures, 98% of 300 researched companies by ITIC reported a cost of 100.000 USD every hour of downtime. To detect failures a technology called fault detection and diagnosis (FDD) is used, which is a method to foresee failures or faults in a system that deteriorates over time through evaluating the state of the system. It is an extensively academically research subject, however, has hardly been adopted in industrial settings where electric gearmotor systems are applied. Thus, a FDD model was developed to provide insight, knowledge, and a practical example into the necessities of an industrial FDD model. This was achieved through conducting an analysis on the state-of-the-art of FDD in industrial settings and conducting a literature review on FDD. Based on an analysis of the conclusions a hybrid diagnostics model was developed. For the fault detection a model-based solution was used, it compared the predicted torque to the measured torque of a motor to create a health indication value. If this value crosses a pre-determined threshold an alarm would go off. For fault identification a decision tree machine learning algorithm is used to identify: blockage, bearing, gear or random failure in a system. To verify and validate the hybrid diagnostics model it was applied to a client of SEW Eurodrive where data was available of a known system. The system had a fault detection accuracy as high as 94% and could classify failures with an accuracy of 93%.

Keywords: Predictive Maintenance, Fault Detection and Diagnosis, Electric Gearmotor System, Model-based, Residual Generation, Feature Extraction, SEW Eurodrive

Introduction

Research context

The industrial electric motor market size was 47 billion USD in 2020 and consumes roughly 70% of all industrial electricity (Mordor Intelligence, 2020; Waide and Brunner, 2011). These motors which are generally smaller than 5kW (and usually connected to a gearbox and load, called an electric gearmotor system) are critical components to many industries and can be found in machines, such as conveyors and pumps. It is crucial these systems work without failure. In 2016 ITIC (Information Technology Intelligence Consulting) conducted a research across 300 industrial companies and found that 98% of organizations report that a single hour of downtime can cost over 100.000 USD and for the automotive industry downtime can cost $22.000 per minute (ITIC, 2016; Nielsen Research, 2005). This downtime is not specifically related to electric gearmotor systems, however considering their presence they play a large roll in this.

One of the current trends in regard to electric gearmotor systems is Industry 4.0. Industry 4.0, which stands for the modernisation of traditional manufacturing using automation and smart technologies (e.g. sensors, cloud storage, AI) (Lasi et al., 2014). Industry 4.0 contains many different topics, from supply chain integration to automation of robots to big data and lastly predictive maintenance (PdM). PdM is the most popular topic due to its high relevance (3.030.000 results in Google Scholar for predictive maintenance) and is a method to foresee failures or faults in a system that deteriorates over time through evaluating the state of the system (condition monitoring or fault detection and diagnosis (FDD)) and has been extensively covered by academic research over the last 20 years (Selcuk, 2017). Advanced techniques e.g. vibration, oil, thermal and acoustic analysis and by using artificial intelligence (AI) the condition of electric gearmotors systems can accurately be determined (Levitt, 2003).

A report by the US Department of Energy, Energy Efficiency & Renewable Energy found that PdM reduces maintenance cost by 25-30% and considering maintenance is between 15-70% of total productions cost, large amounts of savings can be achieved (You et al., 2010) (Sullivan et al., 2010). However, two thirds of the 256 manufacturing companies surveyed by PwC (PricewaterhouseCoopers) in 2018 still only conduct visual inspections and some basic instrument inspections (Haarman et al., 2018). Combining this information a gap can be found; even though there is an abundance of academic knowledge on PdM, in practice it has hardly been adopted by companies and organisations.

In recent years papers have been published addressing this scientific gap, however reasons why vary. Wickern, 2019 states that it is mainly due to financial and organizational obstacles. Tiddens, 2018 states that unavailability of high-quality data is a wide spread issue, that companies do not understand the value of PdM and literature focuses on technical part of PdM, ignoring other facets like organisational perspectives or maintenance strategies. Karuppiah et al., 2021 identified poor commitment from top management.

Research Field

This research is conducted for SEW Eurodrive. It is a lead manufacture of gearmotors and serve many clients which operate in industrial settings. Here key problems and gaps have been identified when it comes to the development of PdM solutions. Firstly, the demand for PdM solutions for electric gearmotor systems has slowly been increasing, however solutions are not available yet. Secondly, every problem where PdM can be applied is unique and presents its own difficulties, requiring universal PdM models which are generally not researched in academic literature. Thirdly, sensors are relatively expensive compared to gearmotors which makes them financially hard to justify. The main option is using the data generated by the variable frequency drive (VFD), this component powers the motor and also generates data about the current the motor uses and its rotational speed. Fourth, gearmotor systems are generally easy to replace, thus for maintenance engineers who are responsible for correct operation it is adequate to know that a machine is starting to fail (diagnosis), and do not need know when in the future (prognostic) the machine will fail exactly. Prognostics is important when it comes to expensive equipment which can take weeks to deliver. This diagnosis is referred to as fault detection and diagnosis (FDD) and will be the focus of this thesis. The main faults that occur in electric gearmotor systems are blockages in movement, bearing failure and gear failure.

Research Problem & Question

The scientific problem is comprised of two main issues. First, there is a limited amount of scientific research into bridging the gap between scientific FDD and industrial applications. Secondly there is a gap between FDD models, techniques and theory which have been developed in academic (lab) environments and industrial settings. The practical problem was stated as followed: it is unknown what PdM and FDD models are available, that can be applied to current systems and what is possible with the available data. The research question is *"How to develop a fault detection and diagnosis model of an industrial applied electric gearmotor system?"*. The complete problem of PdM is larger than what is discussed here, however this will provide an overview of the possibilities and a general solution.

Research Scope

A summary of the scope is presented below with all delimitation's (boundaries research) and limitations (restrictions research).

- Model will utilise data from the VFD
- Focus on gearmotor and load
- Will be a diagnostic model
- Focus on robust and adaptable model (requirements industrial setting)
- Identify blockage, bearing and gear failure

Research Structure

To be able to answer the above mentioned research question, first the state-of-the-art of the industries that utilise electric gearmotors is defined. This was done through conducting an analysis of industrial reports and of SEW Eurodrive. Secondly, a literature review was conducted which showed how FDD works, the relevant models and how it can be applied to the current situation. The main faults were also analysed. The conclusions of these were analysed and am model developed which could solve the identified problems. Key performance indicators (KPI) were defined to measure how well the model works. This model was verified and validated by applying the model to a case study.

State-of-the-art Industry

In the state-of-the-art six main problems were identified with regard to the development of FDD and PdM models in an industrial setting. The issues were identified using industrial reports and interviews with employees of SEW Eurodrive (Haarman et al., 2018; Coleman et al., 2017; Tiddens, 2018). First, due to the large amount of (complicated) academic researches it is difficult to know where to start when researching models. The models are usually very complicated and focus on detecting small differences in data which in many cases would not be as relevant in an industrial setting. Many academic papers use data from laboratories environments which produce data which does not mimic industrial situations. Secondly, the customers and problems where PdM models need to be applied are very unique thus making universal solutions difficult. Thirdly, changes often happen in an industrial settings which makes training of AI models difficult and requires adaptable solutions. AI is commonly used for fault detection throughout PdM and FDD which halts adaptation of the models that are developed.

Fourth, there is a general lack of data, especially fault and failure data. In recent years companies and organisations have started applying sensors and record data from the machines however fault data is still hard to create due to machines having lifetimes of 20+ years. The fifth problem is with false positive and false negative alarms in models. False positive is an error in fault classification where the algorithm or model believes a fault has happened when this is not the case and false negative being the test believes there is no failure when there is a failure. These errors result in unnecessary maintenance and in some cases unnecessary downtime. Sixth problem is system diagnostics (being motor, gearbox and load) being more difficult then component (single element) due to more noise and more possible failures. Lastly, the main faults the occur in gearmotor systems are first blockage in movement, bearing failure and gear failure (related to oil degradation).

Literature Background

A literature review was conducted, first an analysis was done on what was possible with the available data. Second, fault detection and diagnosis was analysed in two stages, detection and diagnosis. Fault detection and diagnosis (FDD) lets operators and maintenance engineers know exactly when and what is wrong with the machines and systems they are responsible for and what they need to do to repair it. This results in advantages in a safer environment for humans, less downtime and a better understanding of the system (Abid et al., 2020). The main papers used for the analysis of FDD are: Saufi et al., 2019, Severson et al., 2016, Park et al., 2020 and Abid et al., 2020. Thirdly, the three identified faults were analysed on their characteristics.

VFD Data

As mentioned in the introduction, the data that is available comes from the variable frequency drive. The data can be found in table 1. Active and output current are the same for most systems, they only differ for some AC motors. Setpoint and actual speed are almost identical, with the setpoint speed being the speed the controller assigns and the actual speed being the speed of the motor. DC Link Voltage, IxT channel and the two IPOS channels are mainly used to see what has happened with the system after failure has happened. The motor output current can be converted to the torque the motor generates using the motors torque constant k_T and formula 1.

$$T_{motor} = k_t i_a \tag{1}$$

Torque can show the health condition of the overall machine (e.g. load, gearbox and motor), because it *flows* through the machine, the servomotor generates the torque which is converted through the gearbox and then utilized at the load (Zhou et al., 2007). If anything happens in the system (e.g. increase friction, degradation oil) the torque is influenced. Using the setpoint speed and actual speed of the servomotor have been used in literature for FDD with some techniques. Faults were identified in helical gears (commonly used in manufacturing) at low speeds through using optical encoder signal (Shao et al., 2016). Another possibility is an algorithm that was developed which can detect failures in gears in a planetary gearbox powered by a servomotor (Zhao and Lin, 2018). Problem with all these papers is that they use sensors with a high sampling frequency, some higher than 25.000 Hz. The data out of the frequency inverter is 250 Hz thus not accurate enough for precise failure detection.

Data name	**Unit**	**Description**
Active Current	% A	Maximum allowed
Output Current	% A	Maximum allowed
Setpoint speed	1/min	Speed controller selects
Actual speed	1/min	Actual speed of motor
DC Link Voltage	V	Voltage rectifier and inverter
IxT Channel	/	Burden on VFD
IPOS 511	deg	Rotation of system
IPOS 512	/	Number of rotations

Table 1 Data from variable frequency drive

Fault detection and diagnosis: detection

FDD has two basic functions, first the behaviour of the process is monitored and secondly faults are detected. FDD consists of four stages, fault detection, fault isolation, fault identification and fault evaluation, see figure 1. Fault detection is observing a fault, isolation and identification is naming the fault, which is also referred to as diagnosis. Fault evaluation is an assessment of the impact on the system and how to respond to it. Detection techniques can be generally categorised into two main categories, model-based and data-driven. Model-based uses mathematical formulas to describe the system. This is then used create residuals which are analysed to detect faults. Residuals can be described by equation 2, $y_i(t)$ is the measured output of a system and $\hat{y}_i(t)$ is the estimated output. A residual (or $e_i(t)$ is a signal which is zero when the system is fault-free, and non-zero when particular faults are present in the system (Svärd, 2015). Fault detection with residuals can be done in two ways, first is defining threshold values which when reached an alarm goes off (Abid et al., 2020). The second is defining fault decision indicators which are features which change when distinct failures happen. After generating a residual signal in some cases it is analysed and features extracted to gain a deeper understanding of what is happening, a full review on features can be found in Nguyen et al., 2018 and Ghafari, 2008. In industrial settings plants are subjected to disturbances and noise which induce model-based errors (Gertler, 2008). Important is to create a *robust* model that is as insensitive to noise as possible.

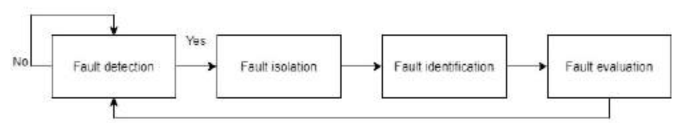

Figure 1 Procedure FDD (Park et al., 2020)

$$e_i(t) = y_i(t) - \hat{y}_i(t) \tag{2}$$

Data-driven methods are based on artificial intelligence or machine learning where large amounts of data are available. Advantage of this technique is that no previous knowledge of the system characteristics or failure behaviour is necessary, which makes this approach popular and accessible. Data-driven models excel in classification accuracy, in Zhang et al., 2019 review they found data-driven solutions could predict failure with 100% accuracy. Data-driven works well for diagnostics and for prognostics, the only requirement is the necessary data. Fault detection can be done using supervised or unsupervised learning, the difference is labeled data. Supervised uses labeled data to put data in the right categories, unsupervised learning clusters data with similar characteristics to categories data. Both these techniques are used to discover patterns and relationship in data sets which in turn can predict failure of systems when abnormalities appear. Example algorithms are support vector machines, k-nearest neighbour or decision tree classification. More information can be found in the literature review Robinson, 2021.

Fault detection and diagnosis: diagnosis

Traditionally, fault classification was done through the use of model-based detection. However, with the increase of industrial data (and Industry 4.0 development) data-driven methods have been increasingly used in literature for classifications and excel model-based methods (Abid et al., 2020). Model-based classification requires multivariate data from different parts of the system. When using data-driven methods for (fault) classification there are two phases, an offline phase where the dynamic model is trained to classify using data which can be saved. The next step is the online phase where the data-driven models are applied to a FDD model to detect and classify faults (Medjaher and Zerhouni, 2013). Using model-based and data-driven methods depends on the problem and parameters making an universal solution impossible.

Fault Characteristics

Next, the characteristics of the three main faults were analysed to make identification possible, see table 2. Blockage is when the movement is obstructed, an example is foreign contaminate blocking the movement of a pump. Bearings failure is when the outer- or inner ring fail which results in higher friction and noise in the system (Immovilli et al., 2012; Group, 2017). Gear failures, which are mainly caused by lubrication failure, start to occur on one of the teeth of a gear and gradually other teeth start to wear (Sharma and Parey, 2016; Service, 2018).

Gaps were found in academic literature. First, there is a lack of system level diagnostics in gearmotor systems. Secondly, lack in hybrid solutions consistent out of model-based and data-driven methods for gearmotor systems. Finally there is a lack of developed models which have been applied to real world systems.

Fault name	**Impact on torque**
Blockage system	Drastic increase in torque until VFD limit hits, continued for 0.2 seconds
Bearing failure	Shaft it is holding not aligned, increase noise due to bad meshing increase motor torque
Gear pinion failure	small increase noise, frequency peaks, small amount of noise

Table 2 Faults system with identification

Methodology

Based on conclusions from the introduction, state-of-the-art of the industry and the literature research a model was designed in the methodology. Using an evaluation matrix with criteria based on the research scope, model-based was compared to data-driven, see table 3. Model-based was chosen for detection. This was because model-based solutions are the most robust, adaptable and accurate in an industrial setting. Based on the literature review, the mathematical model will predict the torque that the motor uses, this is based on the fact that movements almost always can be described with basic physics formulas, e.g. $F = Ma$ or $M = Fr$. There are three main movements which are considered in this model, which cover most industrial applications. These are formula 3; horizontal (rolling resistance), formula 4 vertical (gravitational force) and 5 rotational movement (bearing resistance).

	Weight (1-5)	**Data-driven**	**Model-based**
Robustness	4	1	4
Accuracy	5	4	4
Ease implementation	4	5	2
Adaptability	5	1	4
Development cost	3	5	2
Total		64	70

Table 3 Evaluation matrix data-driven and model-based

$$M_{h.tot} = J\alpha + m_{tot} * g * \frac{d}{2} * (\frac{2}{d} * (0,005 * \frac{d/5}{2} + f) + 0,003) * \frac{1}{\eta} \tag{3}$$

$$M_{v.tot} = J\alpha + m_{tot} * g * \frac{d}{2} * \frac{1}{\eta} \tag{4}$$

$$M_{r.tot} = J\alpha + m_{tot} * g * 0,005 * \frac{dKL}{2} * \frac{1}{\eta} \tag{5}$$

- M = torque [Nm]
- m = mass [kg]
- a = rotational acceleration [rad/s2]
- J = inertia [kg m2]
- g = gravitational constant [m/s2]

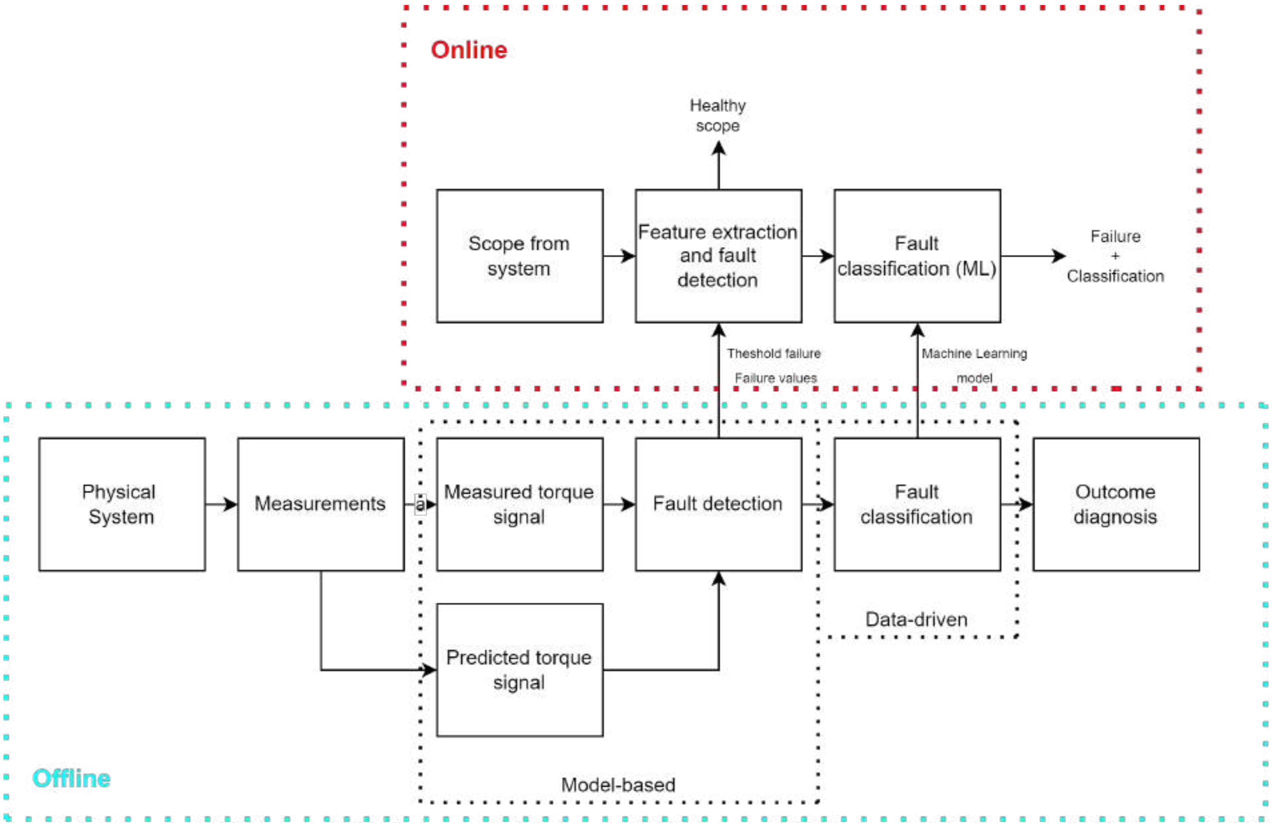

Figure 2 Hybrid-diagnostics model

- d = diameter pinion [m]
- f = rolling resistance[/]
- K = scaling factor [/]
- L = length object [m]
- i = gearbox ratio [i]
- η = efficiency [/]

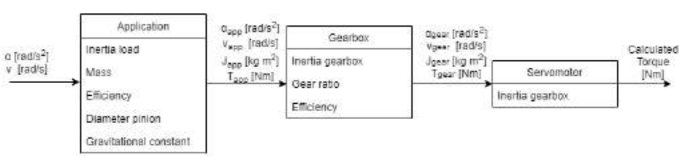

Figure 3 Structure of the mathematical model to calculate the torque

The structure of the torque predictor can be seen in figure 3. On the left the velocity and acceleration are fed into the system, the setpoint speed is converted to acceleration before this. This goes through formulas 3, 4 or 5 and the torque that is necessary to move the load over the given time is produced. This is inserted to the gearbox where the torque and inertia necessary to move the load is calculated. This is finally fed to the motor where the load remains the same, however the inertia of the motor is also added. After this a torque is available of an estimation of what the motor should deliver. After this two measurements will be available, the predicted and the actual measured torque. The measured torque is the current of the motor converted to torque using the motor constant k_T which can be found for every electric motor. The predicted torque is subtracted from the measured torque, this is called a residual. In theory the residual should have a mean of 0, however due to deviations in the measurements this can vary. From this residual features are extracted, see table 4. The reason residuals are generated, is that, with for example bearing failure, noise increases. This results in the mean remaining 0, however the peak and kurtosis will be higher. After this, the values will be normalized so they all have the same weight, which is a value between between 0 and 1, using formula 6. After this the mean taken from the values, this generates a health indication value.

$$x_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{6}$$

When a fault occurs the health indication value increases and when this reaches a pre-defined threshold, an alarm can go off. This threshold can be flexible to avoid false positive and false negative alarms which increases accuracy. When a fault is detected the next phase of the model can happen, fault identification. Here a data-driven method was chosen. This is because it excels in classification accuracy and easy of use. The complete model is referred to as a hybrid diagnostics model, because it utilises a model-based and a data-driven solution, see figure 2.

Feature	Fault detection
Correlation	Decreases with increasing noise
Mean	Increases/decreases when more/less torque is necessary
Median	Increase/decrease when more/less torque is necessary
Max peak	Faults create higher values
RMS	Increase/decrease with failure
Kurtosis	Faults result in more peaks
Crest Factor	Increases before RMS when failure occurs due topeakness

Table 4 Features with fault detection capability

When the model is developed for a given system it is divided into two phases, the offline phase (blue) and the online phase (red). During the offline phase the mathematical model is generated from parameters about the system. Initial healthy running data is fed into the system and analysed, here threshold and values are saved in a file. When the gearmotor system is in operation the online code will run, it will use the values generated in the offline phase to calculate the health indication value of the scope and see if it breaches the threshold. If the threshold is broken the algorithm will see if it can classify the fault. Eventually, the maintenance engineer will see which motor is showing faults and an estimation of what the cause could be.

Key performance indicators (KPI) were specified to measure the performance of the fault detection and identification sections. A confusion matrix was generated to identify how well the methods classified the data. The diagnostic hybrid model has two specific process which can be measured, namely the fault detection and fault diagnosis. These are both models which classify scopes, thus the same KPI's will be utilized with both, however analysed separately. Important is to first define what a confusion matrix is. It is a tabular representation of the predicted value and the actual values of the data set. It provides a better understanding and clear visualisation of a model's result. From here four KPI's were defined, accuracy, precision, recall and F1-score.

Verification and Validation

Case study: VDL Nedcar lift

To verify and validate the model a case study from SEW Eurodrive was taken. A lift was chosen which is operated by VDL Nedcar, a car manufactured in the south of The Netherlands. The lift was the only applicable application with data at the time. The lift elevates a car frame in about 4 seconds which in turn are welded on by robots, the rotational speed of the motor can be seen in figure 4. Data has been collected over the period 01/07/2020 until 30/7/2021, the data are recordings of 8 seconds, now called scopes. For the system a mathematical model was developed and inserted into the fault detection section of the FDD model. In figure 5 the averaged measured torque over the first month of operation can be seen next to the calculated torque of the system. In general the two scopes are very similar, around 1.5 seconds and 2.6 the system is accelerating and there is a small difference. The exact reason is not known, however the systems was already 7 years old at the time which could influence data. In the offline phase of development 145 scopes were used, these were taken from the first month of operation. From here an average health score was calculated, this was 0,45 with a standard deviation of 0,14. Four thresholds were defined, these are the mean with one, two, three or four times the standard deviation added to it, e.g. 0,59, 0,73, 0,83 and 1,01. These values were chosen to test the fault detection machine, in reality the threshold could be changed to have the highest accuracy.

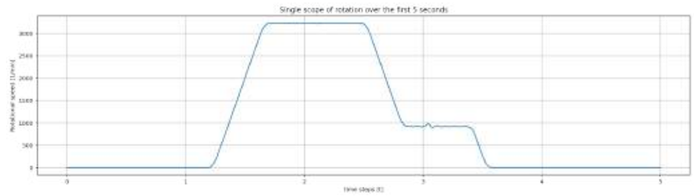

Figure 4 5 second scope of the rotation the motor

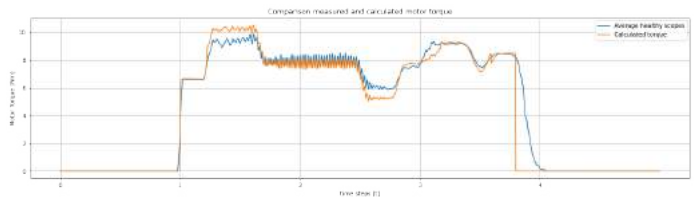

Figure 5 Calculated vs measured torque

Verification and Validation

The code is verified through three ways: checking the code, visual checks and inspecting results. The code was checked throughout the coding to ensure the right data and formulas were used. The code, mathematical model and faults were checking during the development by a SEW Eurodrive data engineers and a project engineer. Visual checks were conducted through the plotting of graphs showing various results of the code. The final results of the code we also inspected, the results can be found below.

Validation of the hybrid diagnostic model is done only using the VDL Nedcar case study. Data, parameters and mathematical models were not available of other systems at the time. To ensure valid validation of the model the complete model is validated in sections. The first the model is validated as a whole, second the model-based fault detection and third is the fault generation and classification validation. First general model validation, the model was presented to those who have knowledge about the model and of the VDL Nedcar system to validate the values that had been used and overall correctness.

In model-based validation the mathematical model and fault detection machine are considered. Sadly the mathematical model could not be applied to another system, however the idea behind the mathematical model is simple. All movements, being horizontal, vertical or rotational must adhere to the basic formulas of nature. Thus, if the mathematical model would be applied to another system, and all parameters are known then the mathematical model will always approach the actual measurements. A second model-based validation method is to have different inputs into the model and see if the outputs are still valid. A scope was used of a test run, here the calculated torque matched the measured torque in the same way as figure 5. The third validation method is using all the available data at the time, e.g. 1532 scopes compared to 145. The average health value of the 145 scopes is 0.473 and for the 1532 the value is 0.411. The main reason for this would be the influence of temperature on the system. In the winter the system will be colder when it starts which will create higher peaks in the features, higher torque due to less efficiency. The rest of the measurements during the day will be normal because the system will working at normal temperature. This results in more high peaks, however average will roughly remain the same. When the system is normalized with equation 6 the x_{max} of will be higher pushing the normal values down resulting in a lower average and a lower health value.

No fault data was not available, thus fault data was generated which utilized the characteristics of the faults which were identified in the literature review. A decision tree machine learning model was trained based on these faults. The model was verified and validated using various methods. The first is verifying the sources where the characteristics of the faults were defined. Second was presenting the faults to experts from SEW Eurodrive. The project engineer stated that the faults that were generated would resemble the actual faults. The second part of the generated faults is to validate that the decision tree algorithm works and is the best algorithm for the model. First and simplest validation step was though splitting the data 70/30 which shows what happens when the model is faced with data that it has not seen before. The model has an average accuracy of 93% which is very good. Other AI algorithms (support vector machine, random forest) were also applied an results compared. Decision tree classification had the highest accuracy.

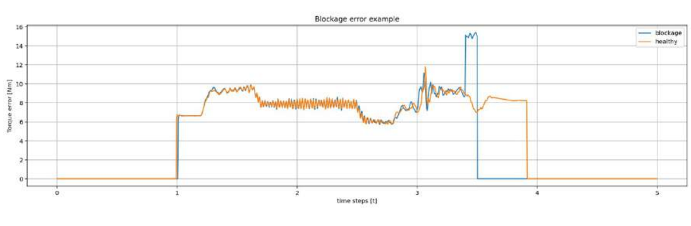

Figure 6 Blockage fault compared to normal scope

Evaluation KPI's

After this the model was evaluated using the identified KPI's. The KPI's were applied to the detection and to the classification part using healthy data and the simulated fault data. The fault data was simulated at three levels, namely, mild, moderate and severe. Next four different thresholds were defined, these are

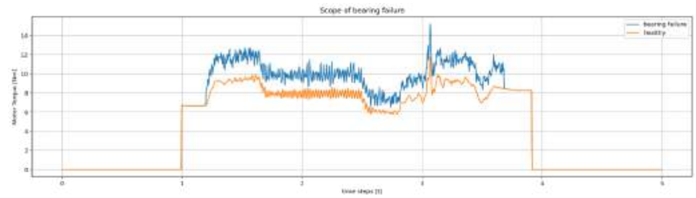

Figure 7 Bearing fault compared to normal scope

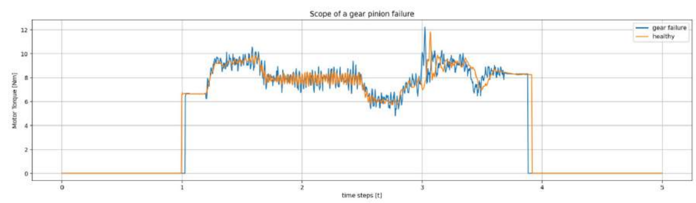

Figure 8 Gear fault compared to normal scope

the mean of healthy measurements with multiple of the standard deviation. For each threshold and fault severity a confusion matrix was generated.

	1 std	2 std	3 std	4std
Accuracy	0.79	0.78	0.70	0.65
Precision	0.77	0.70	0.63	0.59
Recall	0.83	0.99	1.00	1.00
F1 score	0.80	0.82	0.77	0.74

Table 5 KPI's Fault Detection, Mild Fault

	1 std	2 std	3 std	4std
Accuracy	0.87	0.88	0.81	0.77
Precision	0.91	0.81	0.73	0.68
Recall	0.83	0.99	1.00	1.00
F1 score	0.86	0.89	0.84	0.84

Table 6 KPI's Fault Detection, Moderate Fault

	1 std	2 std	3 std	4std
Accuracy	0.89	0.94	0.91	0.85
Precision	0.94	0.91	0.84	0.77
Recall	0.83	0.99	1.00	1.00
F1 score	0.88	0.95	0.91	0.87

Table 7 KPI's Fault Detection, Severe Fault

Four conclusions were drawn from the results, first, the algorithm has a high recall. A high recall shows a low classification of healthy scopes of being faults, this was one of the goals due to maintenance engineers conduct maintenance on healthy systems is counterproductive. Second, is that precision declines with higher thresholds. This is to be expected because not all faults breach the threshold value. However, this problem would be mitigated using a sliding window alarm, this only sounds an alarm if the threshold is breaches a certain amount of times. Third, the highest accuracy was the second deviation above the mean, with the highest accuracy being 94%. This was because at the threshold of one standard deviation healthy scopes were being classified as faults. Fourth, the f1-score which shows the mean between recall and precision is high overall. This is important because we want out model to identify all the healthy scopes and at the same time identify only positive cases. The results of the fault classification decision tree classifier have an accuracy's of 84%, 91% and 98%. Together with the precision, recall and f1-score all being balanced it shows that the algorithm is balanced and works properly.

In general the results from the hybrid diagnostic model are very promising, faults are identified and correctly identified in many cases. However, in reality accuracy would not be as high. The data that was used in the VDL Nedcar case study was taken of a system that had already been running for 7 years. It is unknown how an actual healthy system would perform and what the impact is of the age. Deterioration in lubrication could give higher torque values than expected for example. Another issue was that not all the parameters of the mathematical model were known. The exact weight of the car on the lift is unknown. Temperature was also not considered in the model. In reality temperature has an impact on how well the lubricant works, however also on the efficiency of the motor. These can differ the efficiency of the system with a couple of percent depending on the situation undermining accuracy. The low sample rate (250Hz) of the VFD limited the amount of information that can be extracted from a measurement and also limits early detection of faults. Simulating the faults was the only option to test the model, however simulating is an approximation of the actual faults and in reality will differ in size and noise. Due to this the decision tree classifier would also be less accurate.

Conclusion

In conclusion, this thesis studied fault detection and diagnosis and applied it to an electric gearmotor system in an industrial setting. Often models found in academic research can not be applied due to shortcomings meaning they have not been studied properly. To recapitulate the main research question is:

> ***How to develop a fault detection and diagnosis model of an industrial applied electric gearmotor system?***

To develop a predictive maintenance model of an industrial applied electric gearmotor system first the state-of-the-art of the industry was analysed followed by an in depth literature research into fault detection and diagnosis. From here a hybrid diagnosis model was developed and verified and validated through data taken from SEW Eurodrive. Based on the results from the sub-questions the main research question can be answered. The model should be a hybrid model, implying that fault detection is done through a model-based solution and fault classification should be done using a data-driven algorithm. Fault detection which utilises a mathematical description of the torque of the system, this is used together with a measurement to calculate a health indication value. The fault diagnosis is done using a machine learning algorithm, namely a decision tree classifier. This solution provides a robust, accurate and reliable solution for the given problem.

Limitations and Recommendations

Limitations

Limitations of the research are: limited data VDL Nedcar and data was from 7 year old machine. Larger data set could have shown influence of seasons and of internal and external influences, e.g. temperature. Temperature has an large influence on the torque thus seeing impact would be interesting. Could not apply hybrid diagnostic model to other systems to compare accuracy and how accurate mathematical model is with different movement. Limited by the fault data. Other solutions from model-based and data-driven could have been used and tested, however limited by time.

Recommendations scientific research

The recommendation for scientific research are as followed. Even though, research into FDD and PdM have been going on for decades, the research is one sided and focuses on the technical part of PdM and FDD. There are five dimensions to PdM/FDD, such as technical, economic, environmental, social and safety and many papers focus only on the technical dimension. This can be achieved through combining knowledge from different universities or through having closer contact with industries where the technology is intended for. When researching for papers that are relevant to the literature review there were many papers that tried to use complex algorithms to find minuscule faults in components. While results were usually promising, these are difficult to use in an industrial setting. Thus, while pushing technological boundaries is good, extra focus should go towards models which add value and are simple to apply to industrial settings. Another problem is data, many models and algorithms use data that does not represent a real-life situation. Faults and failures are made in unrealistic methods (e.g. drilling large holes in bearings) which limits usage of models.

Recommendations practical research

For SEW Eurodrive the following is recommended. Further research can be done into the model and how it can be implemented into the different systems of clients. Research can also be done into how the model could run locally on a computer or be integrated into a cloud which captures data. There are many PdM and FDD algorithms in literature. All work in separate ways and have advantages and disadvantages. To effectively understand these models trail and error method would be suggested. Next recommendation would to gather as much data as possible and also gather data from different industries as well. Gathering data from different industries helps to understand where certain failures are more likely to happen, how machines behave in different environments and to work towards helping as much clients as possible. Essential is to create simple products which cater towards the needs. When working products start getting developed a focus should move towards future products and how to easily integrate DriveRadar in these. To lower the threshold for companies to adopt PdM or FDD it would be the best if these solutions would come with the products. This not only would give better reliability to the customer, it would financially help SEW Eurodrive.

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