MASTER

A data-driven condition monitoring approach for the main bearings of a marine diesel engine

Heek, D.A.

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Department of Industrial Engineering & Innovation Sciences
Operations, Planning, Accounting and Control Group

A data-driven condition monitoring approach for the main bearings of a marine diesel engine

Student:	D.A. Heek	
Student no.:	1388703	
Supervisors:	Dr. A.E. Akçay	TU/e, OPAC
	Prof. Dr. Ir. G.J.J.A.N. van Houtum	TU/e, OPAC
	R.J. Van Dongen	Koninklijke Marine, TGP
	KLTZ(TD) bd B.A.M. Pollmann	Koninklijke Marine, DvO
	Dr. W.W. Tiddens	Koninklijke Marine, DvO
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I. Preface

Four years ago, I finished my Bachelor of Mechanical Engineering at the HU University of Applied Sciences Utrecht. On the day of graduation, I decided to continue and get a master's degree. This report finalises that master study Operations Management and Logistics at the Eindhoven University of Technology. And with that, my time as a student also ends.

First of all, I would like to thank my supervisors and colleagues at the RNLN. Despite the limited number of days in Den Helder, I had a great internship in an unique environment where I have learned a lot. Ruud and Jacco, thank you both for introducing the maintenance process at the RNLN and the conversations we had about my research and many other things. Bart, for the weekly (early) updates, interesting discussions, passionate stories and anecdotes from your operational experience. Wieger, originally not intended as supervisor, nevertheless spoke for many hours in the often-long sessions. It could also have been faster. These meetings did help me on my sail in the domain of predictive maintenance.

Secondly, my supervisors from the TU/e. Thanks to the supervisors who helped me get the results sharp and give me the opportunity to present my work within various consortiums. First, Alp Akçay, for introducing me to this great internship at the RNLN and the valuable weekly updates in which you helped steering the research into this final direction. Second, Geert-Jan Van Houtum, as the second supervisor, may have been a little less involved in the project, but the sessions we had were to the point, which ensured that we got the most out of it.

Of course, also friends and fellow students for always having time to brainstorm and keeping each other focussed, but also helped to relax from time to time. The first weeks at the navy with the other students at Data voor Onderhoud were really pleasant, not only on the navy base. Special remark for Arno, although the busy schedules, the weekly bike rides on Saturday morning provided the necessary relaxation and constructive discussions to overcome any difficulties.

At last, I want to thank my parents and siblings for all their support, giving me the opportunities to achieve what I have achieved so far. And a special thanks to my girlfriend, Katrin, for your patience and help during the finalisation of my thesis. As well as distracting me from the stress involved in the project.

Derek Heek
Montfoort, April 2021

II. Executive summary

Project background

The Royal Netherland Navy (RNLN) explores data-driven maintenance opportunities as part of the Sailplan 2030 and Defence Vision 2035. Part of that exploration is performing different case studies, in which IPMS data of the Holland class is analysed. This research focuses on the early detection of defective main bearings of the main diesel engines. This creates opportunities to make maintenance decisions that prevent failures, resulting in an increased reliability.

The main bearings are located in the main diesel engine and support the crankshaft and rotate with minimal friction. Literature and expert knowledge are utilised to determine the failure mode and underlaying failure mechanisms. The most important failure mechanisms found are cavitation and abrasive wear. In the IPMS data, the only measurements directly related to the bearings are temperature measurements. These individual temperature readings could be used to detect degradation. The current maintenance policy of main bearings is an usage-based policy with inspection and preventive replacements. Failures are self announcing and detected by the safety system of the main diesel engine.

Proposed monitoring approach

The data-driven defect detection model that is used to detect the increased bearing temperature, consists of different steps, see Figure 1. Data preparation is necessary to transform the high-resolution data into useful data for the monitoring model. As operational circumstances influence the bearing temperature, the measurements must be removed from its contextual anomalies. This is performed by a multiple linear regression model (MLR). MLR is selected based on four criteria: understandable, domain knowledge, suitable with data, implementation. These criteria are selected to build a model that could be used as proof of concepts and convince maintenance engineers who are not familiar with artificial intelligence.

The next step is trend analysis on the residuals, the difference between the measured and the estimated bearing temperature. This is performed based on statistical process control (SPC) in the form of EWMA control charts. This method is able to detect small progressive mean changes in the process. Indicating the change of the physical process, which could be due to deterioration of the main bearings. Based on these warnings maintenance decisions could be made.

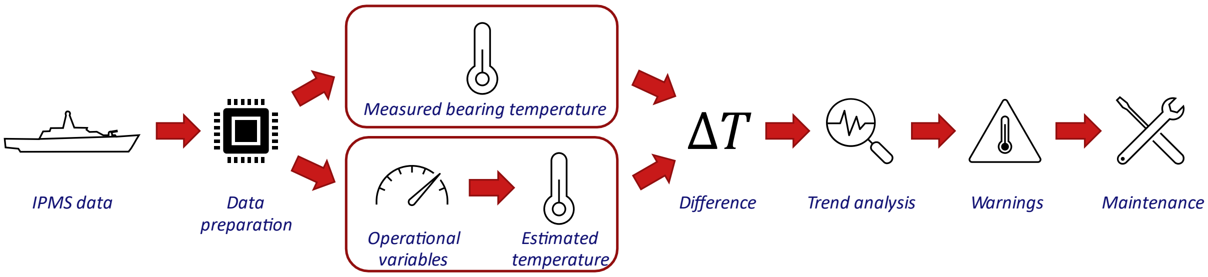


Figure 1: Flowchart of the proposed monitoring approach

Result

With the developed data-driven defect detection model, warnings could be generated when a positive temperature shift is found. Three cases are monitored in the research, of which one is shown in Figure 2. In this case, the model is learned and set in the initialising period of 800 hours. Several hundreds of hours before the failure, at the end of the timeline, the warnings arrive, indicated by the vertical red lines. In the second case, it is seen that maintenance disrupts the monitoring process, changing the statistics suddenly. Shortly after maintenance, the bearings are failed. In a third case, another maintenance scenario is analysed, here it is demonstrated that after relearning, the model behaves as expected.

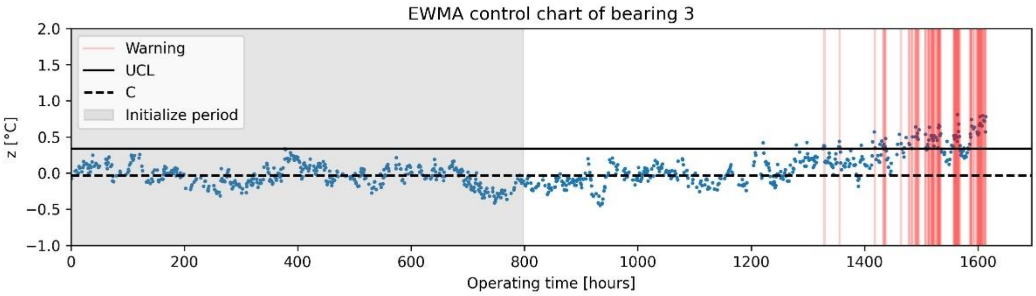


Figure 2: EWMA control chart detecting defect, failure is at the end

Since the first warnings are not sufficiently decisive and could be caused by other events such as maintenance, it is recommended to implement a validation step into the current maintenance policy to validate the additional warnings. The proposed extension of the maintenance policy is schematically shown in Figure 3. During the validation, the engine is under enhanced supervision. An action that could be taken for validating the warnings is data analytics or additional oil sampling. These actions could be performed without interrupting the operations of the vessel.

The advantage of adding this to the current policy is that the reliability increases because the probability of sudden failures decreases. Alternatively, when preferring to keep the reliability identical, the inspection interval could be extended. Because there is limited information available to approximate a mathematical distribution, exact numbers for the improvements are not determined.

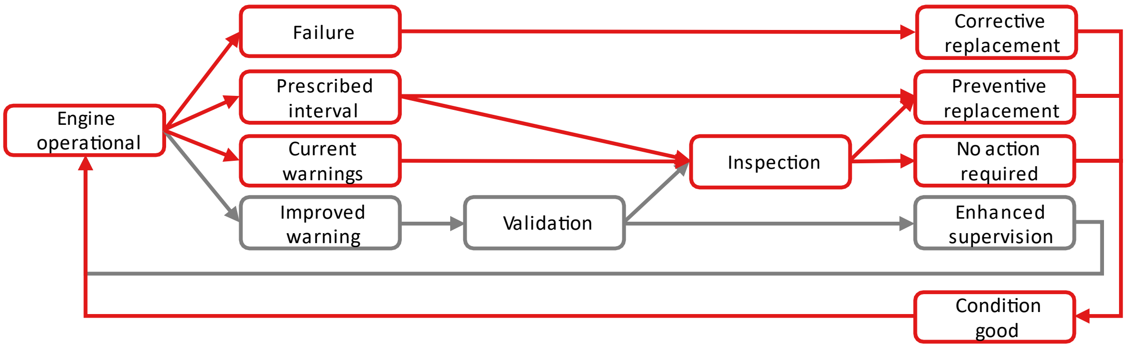


Figure 3: Schematical overview of maintenance policy, in grey the additional procedure for warnings

Conclusion, discussion, recommendations

It can be concluded that by making use of the proposed monitoring approach, it is possible to detect defects with the available sensors, as shown in the presented case, in the operating hours before the failure warnings are generated. The warnings generated with the data-driven defect detection model could be used to plan preventive maintenance action to increase reliability.

The developed model is built as a proof of concept. Therefore several discussion points could be addressed. The user should understand the model's capabilities, it is made to detect an increasing temperature trend caused by the found failure mechanisms. Other failure mechanisms that develop differently will not be detected. The model is also built to be able to handle non-stable operations. The consequence of this is that long constant operations, such as ocean crossings are not monitored. The model as build in this research is not ready for implementation in practice yet. Several issues must be solved, such as automatization of data acquisition, initialising of models and effect of maintenance action should be further investigated.

In future research at the RNLN on this subject, three topics should be addressed. First, converting this proof of concept towards a pilot project. Second, apply this method to other components to create more insights into the model's performance. Third, improve the quality of the different steps taken in the defect detection model, including the data preparation, regression model and control chart.

Contents

III. List of Figures

IV. List of Tables

V. Acronyms

Acronym	Explanation
AM	Assisted Maintenance
aNN	Artificial Neural Network
BO	‘Benoemd Onderhoud’, English: Assigned Maintenance
CBM	Condition Based Maintenance
CUSUM	Cumulative sum
DLM	Depot level maintenance
DMI	‘Directie Materiale Instandhouding’, English: material conservation department
DvO	‘Data voor Onderhoud’, English: Data for Maintenance
EWMA	Exponentially weighted Moving Average
FMECA	Failure Mode Effect & Criticality Analysis
HLMNS	His (Her) Netherlands Majesty’s Ship
HVAC	Heating, Ventilation and Airconditioning
ILM	Intermediate Level Maintenance
IPMS	Integrated Platform Management System
JSS	Joint Support Ship
MARCONI	Maritime Remote Control Tower for Service Logistics Innovation
OEM	Original Equipment Manufacturer
OLM	Organic Level Maintenance
OLS	Ordinary Least Squares
OPV	Oceangoing Patrol Vessel
RFR	Random Forest Regression
RMSE	Root mean squared error
RNLN	Royal Netherlands Navy
RPM	Rotations per minute
SPC	Statistical process control
TC	Turbocharger
TGP	‘Techniek Groep Platform’, English: Technology group platform
UCL	Upper control limit

1. Introduction

Back in 1896, Guglielmo Marconi created the basics for long-distance radio transmission (Bondyopadhyay, 1995). Nowadays, data exchange with vessels around the world is an ordinary subject. The digitalization of systems is often described as industry 4.0, which could change the domain of maintenance (Tiddens, 2018). The MARCONI project focuses on using digitalization developments to optimise the service logistics chain. This thesis, conducted at the Royal Netherlands Navy, goes into the phenomenon of data-driven maintenance. Performing adequate maintenance is essential for the Royal Netherlands Navy to keep its fleet of vessels operational.

In this chapter, the background of the project will be explained. The case that will be used during the project is introduced in the second chapter. The actual procedure of data-driven maintenance is explained in chapter three, after which it is worked out in chapters 4 to 6. In chapter 7, there is attention to the implementation of data-driven maintenance in the current policy. Completing the thesis with a conclusion, discussion and recommendations in chapter 8.

1.1. Organisation Royal Netherlands Navy

The Royal Netherlands navy (RNLN) is the maritime department of the Netherlands Ministry of Defence, the military organization of the Netherlands. Besides the RNLN there are six other organizational elements, as shown in Figure 4. The four-armed forces, of which the RNLN is part, are headed by the Chief of Defence, General Eichelsheim. The Defence Materiel Organisation (DMO) is the department engaged throughout the entire life cycle of material, from procurement to sale. It supports the armed forces with logistics supports, administrative and coordination of equipment.

The goal of the Ministry of Defence is 'protecting what we value'. In a world of turmoil, it is necessary to protect all that we as a nation cherish. This could be summarised in the following three main tasks (Ministerie van Defensie, 2020):

- Defending national territory and that of our allies.
- Enforcing the national and international rule of law.
- Providing assistance during disasters and crises.

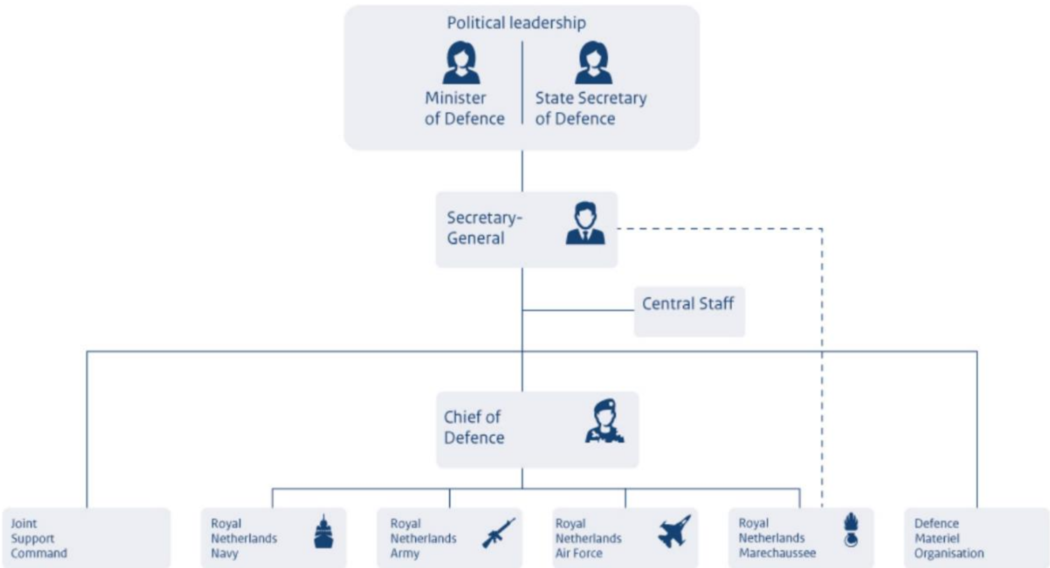


Figure 4: Organization chart of the Ministry of Defence (Ministerie van Defensie, 2020)

The RNLN supports these three main tasks at sea and from the sea. Understanding these tasks is important throughout this thesis because the RNLN is not driven by financial profit, instead, it is about the ability to act when necessary, to ensure safety. The Dutch government is responsible for the decision which mission will be performed, influenced by international allies (The NATO). The RNLN has, at its disposal, a fleet of 29 navy vessels, consisting out of frigates, submarines, patrol vessels, minehunters, Landing Platform Docks (LPDs) and a Joint Support Ship (JSS). Besides these major vessels, there are multiple tugboats, training vessels and supporting vessels (Karremann, 2020).

The organization of the RNLN (Figure 5) is lead by vice-admiral Kramer, who is responsible for ensuring that the navy units are mission ready. The commander of the RNLN also holds the position of Admiral Benelux, which implies supervising the close cooperation with the Belgian navy. The division which has a leading role in this thesis is, the Directie Materiele Instandhouding (DMI).

DMI is responsible for maintaining vessels, submarines and other systems to provide reliable equipment for the users. This involves systems like power supplies, electronics and weapon systems. Besides maintaining assets of the RNLN, assets of other defence departments are maintained as well as for international partners. Interestingly, the DMI employs several civilians who contribute with their technical background to the operations. This thesis is conducted at two departments within DMI, DvO ('Data voor Onderhoud', English: Data for maintenance) and TGP ('Techniek groep platform', English: 'technology group platform').

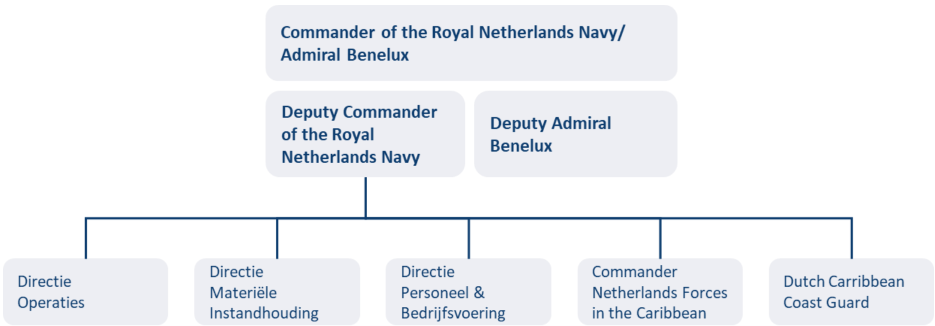


Figure 5: Organization chart of the Royal Netherlands Navy (Ministerie van Defensie, 2020)

Data voor Onderhoud

Data voor Onderhoud (DvO) is a relatively new department that focuses on the transition to smart maintenance within RNLN. With different projects, they are exploring the opportunities and focus on the involvement of the different operational departments to get them ready for the future. This is done by different topics, such as data acquisition, infrastructure, governance, data analytics and asset management. Examples of different projects are improving the maintenance process for future vessels and analyses for the CO_2 race for seafarers from OceansX program that focuses on social value and sustainable impact.

The data that DvO uses is primarily gathered from the Holland-class, consisting out of four identical oceangoing patrol vessels (OPV). Part of the Holland-class is the HLNMS Groningen, which is equipped with multiple extra sensors that are logged for further analyses as part of a pilot in data-driven maintenance. The tasks of these OPV's differ between defence operations, border patrol, and rescue missions. They operate in areas with a lower violence spectrum, such as the Caribbean. The vessels are operative since 2012/2013 and are expected to last for 25 to 30 years.

As part of their strategy, DvO collaborates with various consortiums, such as the MARCONI project (Maritime Remote Control Tower for Service Logistics Innovation). This project is a collaboration between universities and businesses within the maritime industry. The goal is to build a 'control tower' to improve service logistics in a maritime setting involving multiple stakeholders. Therefore, the processes of operations, maintenance and resource planning should be synchronised.

Techniek Group Platform

The Techniek Groep Platform (TGP) is responsible for the major maintenance tasks of the different mechanical installations on board the different vessels, such as the engines, freshwater maker and HVAC. The strength of this department is the amount of expertise they have and the capabilities to repair almost all the equipment that is on board the vessels. They normally operate from their workshop 'Marine Bedrijf' in Den Helder, The Netherlands. But in case of urgency, they travel around the world to support the crew on board with specific maintenance actions. TGP is one of the departments that is involved in the exploration of smart maintenance in the form of providing cases that could be explored by DvO.

1.2. Problem definition

Interest to invest in data

In the Defence Vision 2035 of the ministry of defence and more specific the Sailplan 2030 of the RNLN, the importance of innovation in the field of data use is underlined. In those plans, the opportunities given by big data are mentioned for improving current processes. The department DvO is working on this first exploration of data to implement in future vessels. This is done using the current sensors and additionally installed sensors, part of the regular process control, to generate data for maintenance.

Another change mentioned in the Sailplan 2030 is the test with alternating crews and smaller crews onboard. Currently, there is a pilot study in which crews rotate between different Oceangoing Patrol Vessels (OPV), which improves the balance between activities and gives more perspective and space to perform the tasks for the employees. Besides that, crews are getting smaller due to scarcity of employees and technological evolution. However, the consequence is that more responsibility is shifted towards the engineers located in Den Helder. As a result of this, online services and diagnostics from ashore are increasing in value.

Current maintenance situation

Currently, maintenance is planned based on the determined intervals by the OEM. Due to the specific use pattern of the RNLN, this method is not always successful. Vessels are used on their limits and compared to commercial operated vessels, relatively low number of operating hours. This causes irregular deterioration of their assets which is hardly possible to incorporate in predetermined maintenance intervals. Yet, for the RNLN, it is important to have reliable equipment to carry out missions at any time.

Challenge to transform data into decision making

The use of IPMS (Integrated Platform Management System) data provides opportunities to increase reliability. This data is usually used for monitoring and control but not for predictive maintenance. Creating additional value from this data in the form of maintenance decisions is often seen as challenging. The engineers responsible for the maintenance do not have the knowledge and capacity to process a large amount of data. That is why a supportive decision-making model is needed to use the potential added value of data in the maintenance process.

Case: main bearings of the main diesel engine

The current state of innovation at the RNLN is exploring opportunities for data-driven maintenance by performing real case studies on different systems/components. The main journal bearings are such a component for which a decision-making model would have added value, as shown in section 2.1. The main diesel engines onboard are used irregularly depending on the current tasks. And the bearings are mission-critical components, a single failure will influence the operational unavailability of the entire vessel. In Chapter 2 the further explanations about the main bearing itself and why they were chosen as a case study are given.

Research goal

The ambitions as mentioned above lead to the following research goal*: improve the reliability of the main diesel engine by making a data-driven model such that the condition of the main bearings could be determined in order to make operational decisions*.

1.3. Research questions

The project's definition leads to the following main research question:

> *How could the available data of the main diesel engines of the oceangoing patrol vessels be used to create a defect detection of the main bearings to make maintenance decisions to increase the reliability of this critical asset?*

The following research questions (RQ) help to answer the main research question and structure the research. This structure is schematically shown in Figure 6.

1. *What are the different failure modes and mechanisms of the main bearings in the diesel engine?*
2. *What sensors are available to give insight into the condition of the main bearings?*
3. *How could the available sensor measurements be related to the condition of the bearings?*
4. *How could a defect detection of the main bearings be generated using a data-driven model?*
5. *How could the developed defect detection model of the main bearings be used to make maintenance decisions to increase reliability?*
6. *What are the advantages of implementing the developed defect detection model for the maintenance process?*

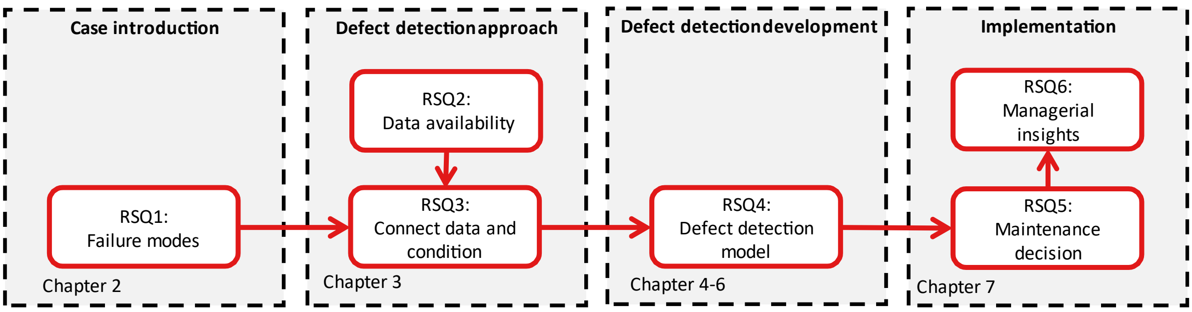


Figure 6: Setup of research and document

1.4. Methodology

The methodology that is used in the report is CRISP-DM methodology (Wirth & Hipp, 2000). As part of the business understanding, with RQ1 the important failure mechanisms of main bearings will be investigated. This is done based on literature in combination with expert knowledge within the RNLN. Data understanding is the focus of RQ2, in which the available data in the data sets is explained.

The information gathered in the first two research questions is input for RQ3, in which current monitoring of bearings is studied and the link is made between the available information and failure mode. These business and data understanding results are input for the defect detection. As part of RQ4, the data-driven defect detection model will be created based on selected studies and the earlier obtained information. This question consists of the data preparation and modelling step of the CRIPS-DM methodology, resulting in a model that can provide a warning when the process is out of control.

Finally, based on the outcome of the data-driven defect detection model, a decision-making model will be implemented/deployed for RQ5. An expansion of the current policy will be made and mathematically worked out. By making use of numerical analyses, the advantages of the new policy can be explored to answer RQ6.

1.5. Contribution

This research is performed at the RNLN, which focuses on the exploration of data-driven maintenance. It is also part of the research consortium MARCONI. This research contributes in the form of working out theoretical models in a real application with real data. The final results of this thesis could be an important step in the path towards data-driven maintenance. By using simple 'white-box' models, the data could be transformed to obtain useful information for maintenance. Knowledge will be developed about which hurdles must be taken to handle data efficiently. As a secondary effect, employees involved in the project become familiar with the possibilities that data has. This is important for the successful implementation of data-driven maintenance at the RNLN.

1.6. Scope

In this section, the scope of the thesis is defined. The complete exploration of data-driven maintenance is broad and too complex to handle in the available time of the master thesis. Therefore, this project focuses only on the exploration of a defect detection model for a single component. And describing the maintenance policy in which the information of the defect detection model could be implemented to improve the reliability.

The RNLN has multiple vessels in their fleet, this research focuses on the Holland class. The selected component is the main bearings of the main diesel engine, as mentioned in section 1.2 and section 2.1. Although this project focuses on a specific vessel, the used techniques and generated insights should be useful to expand further for the RNLN. The expansion to other equipment and implementation of the model are excluded.

2. Case introduction

This chapter introduces the case that will be used throughout the entire thesis. Therefore, this chapter is quite dense with information and the first research question will be addressed. It starts with the justification of the selection of the main bearing for this thesis. Followed by the current policy and the mechanical explanation of the working and deterioration of the component. At the end of the chapter, the conclusion is given for the first research question.

2.1. Justification of component selection: main bearings

The component for this study has already been selected. The selection procedure that is followed consists out of multiple steps, as shown in Figure 7. First, because this thesis is a follow up of another project, the main diesel engines of the Holland class is further explored. Second, based on the available data in the data set, the candidate subsystems/component is selected. A restraining factor is the fact that there is only a limited amount of data points. Third, based on the added value of predictive maintenance for these subsystems' maintenance process, the main bearings are selected for this thesis. The entire selection procedure is captured in the research proposal (Heek, 2019). In the following paragraphs, a small summary is given.

Figure 7: Selection procedure of component (based on Tiddens, 2018)

2.1.1. Critical asset

The critical asset on which this thesis is performed are the main diesel engines. The diesel engines are part of the diesel-electric transmission system onboard. This is one of the primary functions and therefore, critical equipment on board the vessel. The main diesel engines installed are two identical MAN V12 engines delivering approximately 5460 KW, Figure 8 shows the engine that is 6.2 by 2.3 by 3.7 meters (l x w x h). The two engines are placed on port side and starboard side, which have different fire order. This leads to a different rotational direction of the propeller to prevent drifting off to one side.

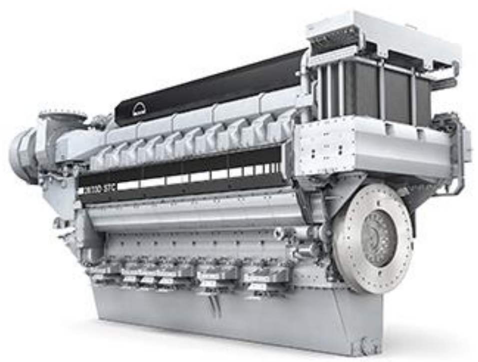


Figure 8: MAN V28-33D engine (onboard are similar V12 engines installed) (source: MAN)

2.1.2. Show stoppers

Data availability and lack of potential critical failures could be a major showstopper for a component to be selected. For the project, data is already collected over the last years and therefore limiting the opportunities. Within the available dataset, there are 60 sensors directly marked towards the main engine. Most of them are temperature sensors and pressure sensors in cooling or oil circuits. Besides that, the engine's performance could be determined based on information on fuel usage, RPM and torque. Also, a Failure Mode Effect & Criticality Analysis (FMECA) of another type of marine diesel engine is used as a guideline to obtain critical components based on their frequency of failure and subsequent impact (Tiddens, 2014). The subsystems/components in Table 1 came out through these showstopper criteria.

Table 1: Candidate sub-systems/ components

System/parts	Function and measurements
Bearings	Main bearings supporting the crankshaft, directly measured with individual temperature sensors.
Cooling	Two separate circuits (high and low temperature) cool the engine indirect with seawater. Temperature and pressures are available as measurements.
Air inlet	The air inlet system consisting out of two turbochargers and heat exchangers to cool the air back. Different temperatures and pressures are measured which could be used to determine performance.
Oil system	The oil system secures lubrication of the engine and the internal cooling. Parts are gear pump, cooling and filtering. Pressure and temperatures could give insights.
Fuel	Supply and injection of fuel into the engine for combustion. Flow, temperature and pressures are captured and available for analyses.

2.1.3. Selection framework

Selecting the right component is important for CBM, creating models for the selected component must have a positive impact on the operational process. Tiddens (2018) developed a framework for selecting suitable candidates for CBM. The criteria used are clustering of maintenance activities, technical feasibility, economic feasibility, and organisational feasibility. Applying this framework to the diesel engine case resulted in the main journal bearings as the most interesting component. Below a summary is given why the bearings pass the different conditions.

The maintenance actions of the main bearings could be executed independently of other activities, making it useful to optimise the scheduled inspections and replacement actions. From a technical point of view, considerable research has been previously performed on bearings which shows the feasibility of capturing degradation. As already covered by the showstoppers, the data for defect detection modelling is also available for the project. In the dataset, it is known that there were deprecated bearings replaced. Therefore, analysis of the deterioration process could be made.

Another criterion is economic feasibility, the developed models on bearings are beneficial to implement in the future within RNLN. The impact of bearing failure is significant on the engine, influencing the engine's availability and, therefore, the entire operations of the vessel. Lastly, organisational feasibility, the maintenance policy for the selected component must fit the work methodology of the RNLN. In the case of main bearings, there is a clear need for engineers to monitor these components thoroughly. They are open to supporting tools to improve the current maintenance process.

2.2. Maintenance process

As part of understanding the general maintenance process at RNLN and for the main bearings, multiple conversations with employees were held. They have different roles within the process from planning the maintenance moments to deciding which maintenance actions to perform during these maintenance moments. This section will explain the used maintenance policy and available maintenance opportunities for the main bearings.

Maintenance policy

Maintenance is important to keep capital goods available for the primary processes. Sufficient losses or danger could occur when navy vessels suddenly face failures, especially in the transmission system. There are multiple policies to perform maintenance, as shown in Figure 9 (Arts, 2017). Below the maintenance policy of the main bearings will be discussed and explained why that is implemented.

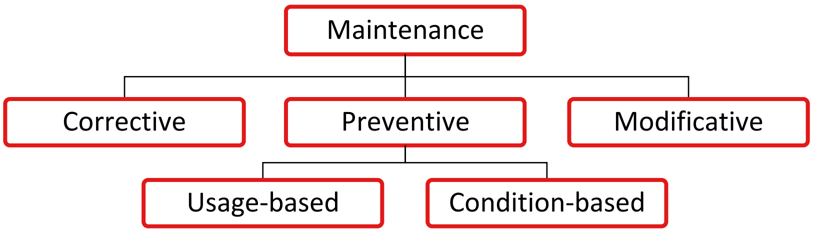


Figure 9: Overview of maintenance policies (Based on Arts, 2017)

Since the main bearings are critical components, preventive maintenance is used to prevent having unscheduled breakdowns. The maintenance actions are performed based on the usage of the main diesel engine defined in operating hours. This policy is defined by the original equipment manufacturer (OEM) but could be adapted by DMI. During the life cycle of the bearings also visual inspections are planned based on operating hours. These inspections reveal the actual condition and could be used as input to perform the maintenance action before originally planned. Periodically there are also oil samples taken, the presence of wear debris, metallic particles give valuable information of the engine wellbeing (Kumar et al., 2018).

Maintenance actions

The maintenance actions that are important for the bearings are inspections and replacements. These actions are integrated into Figure 10 with their triggering events. The inspections and preventive replacements are determined based on operating hours indicated by the OEM. These actions could be scheduled to fit the operational schedule of the vessel. Inspections could also be triggered by the currently used warnings of the safety system of the engine or wear debris monitoring based on oil samples. In case of a failure, the bearings are correctively replaced to make the vessel back operational. After the maintenance actions, the condition is good, either from the replacement or found in the inspection.

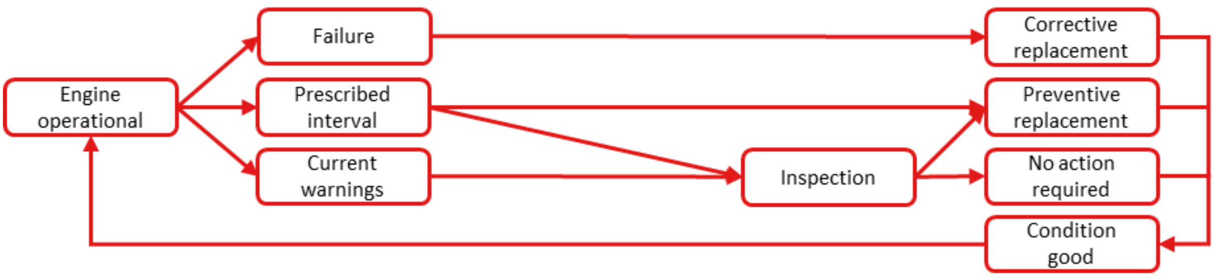


Figure 10: Overview maintenance actions

Bearings are wear parts, therefore they are replaced for identical new components in case of maintenance. The visual inspections in which a bearing is dismantled and visually inspected is also a labour-intensive procedure. Performing either of these actions takes several working days due to the complexity, difficulty to reach, size, and weight of components. These actions are performed by TGP or a contractor, which makes scheduling more important.

The deterioration of the bearings is correlated, during an inspection, only one bearing has to be visually inspected. Based on expert knowledge and experience one of the heavily loaded bearings is selected, which is expected to be representative of the group. The replacement of bearings is carried out simultaneously for the entire group. This is due to the setup costs for the maintenance moment and the correlated degradation. After maintenance, there are several assessments before releasing for operational tasks as part of the quality control.

Maintenance planning

In general, there are three levels of maintenance actions to distinguish: Organic Level Maintenance (OLM), Intermediate Level Maintenance (ILM) and Depot Level Maintenance (DLM).

First of all, OLM consists of the daily activities executed by the crew on board, also named ‘unassisted maintenance’ jobs for DMI. This consists out of small repairs, emergency repairs and regular checks of the systems. These activities are performed during the mission.

The second level is ILM, also referred to as ‘assisted maintenance’ (AM), which are maintenance tasks executed by experts of TGP. These tasks are bigger and more complex, therefore more expertise is necessary. These actions are undertaken approximately twice a year and take multiple weeks (approximately 4-6 weeks).

Finally, there is DLM, also referred to as ‘Benoemd Onderhoud’ (BO, English: ‘assigned maintenance’), after four years of service the vessel undergoes major maintenance and is for a longer time in Den Helder. This takes roughly one year, in which the vessel also will go to the dry dock. During these longer periods, it is possible to perform updates are performed to keep up with the current technology available.

Maintenance associated with the main bearings belongs to ILM, which implies that it must be planned during the predetermined scheduled downs. On rare occasions, it could also occur that during a mission a scheduled down is organized. During those maintenance actions, a vessel is for a few days off duty in any foreign harbour.

2.3. Function and working of journal bearings

The function of the seven main bearings, is to support the crankshaft and limit the amount of friction while rotating in the V12 engine block. The bearings are located around all six pairs of piston rods, see Figure 11 and Figure 12. The bearings are from the type of journal bearings. This type of bearing has a simple design without rolling elements. The bearing consists of two shells, with a diameter of approximately 300 mm. In the upper shell, there is a groove for the application of oil and the lower shell is solid for optimal support of the crankshaft. Due to the rotation of the shaft, an oil film is created, which eliminates the surface-to-surface contact between the bearing and the shell, this is called hydrodynamic lubrication.

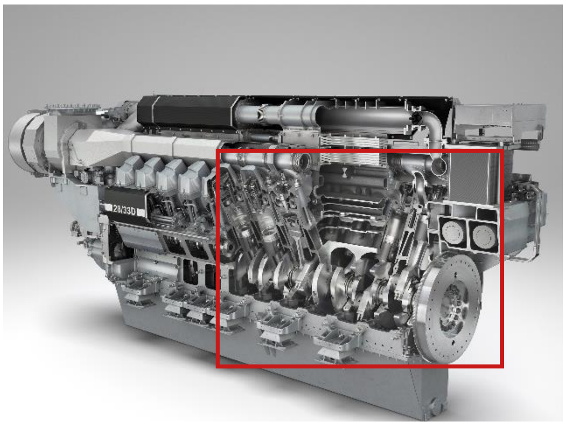


Figure 11: Cross-section view MAN 28/33D V20 (V12 is built similar) (source: MAN)

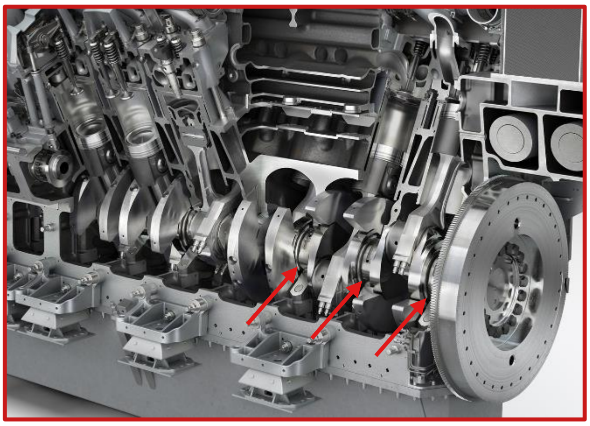


Figure 12: MAN 28/33D Zoomed in on crankshaft, pointing at main bearings (source: MAN)

The lubrication oil is actively supplied to the engine by a gear pump. The oil is drawn in from the carter and passes the heat exchanger and oil filter before being pumped back into the engine. The oil first passes the camshaft towards the free end of the engine. From this point, oil is fed towards the main bearings, supplied in the groove on the top of the bearing. The end of the groove is a smooth run out that is designed to press oil in between the bearing shell and axis. For the oil supply towards the rod and pistons, a canal inside the crankshaft is present from the main bearing journals towards the rod bearing journals. (De Schelde, 2015)

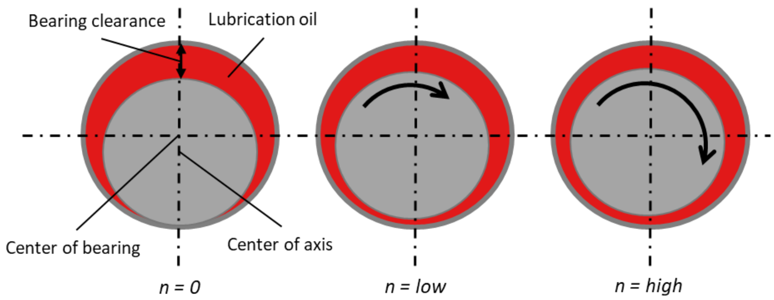


Figure 13: Position of axis in bearing in static situation (based on: (Wittel et al., 2013))

As mentioned, due to the crankshaft rotation, an oil film is created between the bearing and crankshaft. Oil is pulled along the surface of the shaft and slides in between the two surfaces. The thickness of this film depends, besides the oil properties on the angular speed, in Figure 13 this is schematically demonstrated. A higher velocity results in a thicker oil film. The crankshaft is slightly off centre compared to the bearing shell when facing a stationary force. In the diesel engine, the load is irregular due to the different cylinders' fire moment, which stand under an angle, while the principle stays the same, more vibrations will be present (Nikolic et al., 2012).

The friction of the crankshaft in the bearing is related to the rotational velocity, which the Stribeck curve could explain (Tinga, 2013), shown in Figure 14. On micro-level, material surfaces are not entirely smooth but are rough to a small extent. The minimal required height of the oil film to overcome these deviations is given by h_{min}. Low rotational velocity results in increased surface-to-surface contact, therefore the friction coefficient is high. This is a boundary lubrication condition. When there is sufficient oil, micro-level tops do not collide. The film thickness h is greater than h_{min}, there is hydrodynamic lubrication. In this stage, the friction coefficient is significantly lower, up to more than 100 times (Wittel et al., 2013). In between, there is mixed lubrication in which only part of the tops collides.

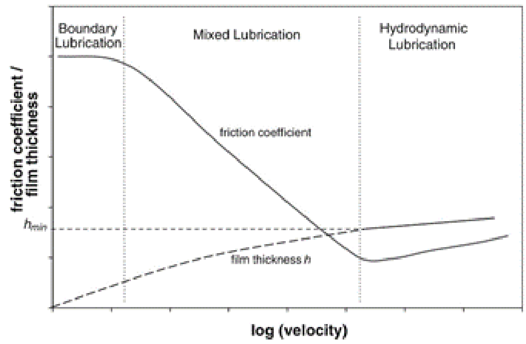


Figure 14: Schematic of Stribeck curve (Tinga, 2013)

The oil that gets in between the crankshaft and bearing provides a normal force, which represents the counterforce supporting the crankshaft. The corresponding pressure pattern that is created is shown in Figure 15. The pressure is built up from the lubrication groove due to narrowing until the location where the highest pressure is. After this pressure zone, there often is a slight under pressure (Wittel et al., 2013). Any wear or damage will affect this pressure profile (Fillon & Bouyer, 2004).

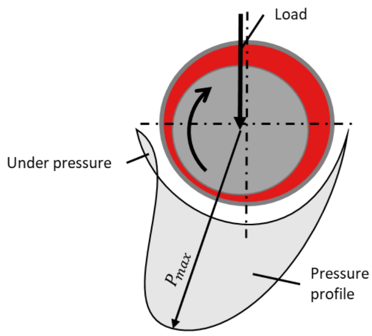


Figure 15: Lubrication oil pressure profile (based on: Wittel et al., 2013)

2.4. Failure mode and underlying mechanisms of journal bearings

Before determining the condition of the main bearings, it is important to understand the degradation process and failures of the main bearings. The failure modes, the manner in which the component fails, have to do with the overload of the surface, leading to overheating. Which result in the engine shutting down due to its safety system. There are multiple failure mechanics, physical or chemical processes that could be the cause of the failure of a bearing (Tinga, 2013).

Venci & Rac (2014) performed a field examination about failing diesel engine journal bearings. The four failure mechanisms that occurred the most in the 616 investigated cases are abrasive wear, adhesive wear, surface fatigue, and cavitation. Wear is a general term, which implies, the relative motion between elements with physical contact where movement yields a loss of material (Tinga, 2013). An overview of the four failure mechanisms leading to a failure is given in the Isikawa diagram (Figure 16). On the top of the branch, the failure mechanism is given with on the branch different causes of the failure mechanism. The maintenance engineers of the RNLN have found that abrasive wear and cavitation are the most important causes for defects, these are further explained in sections 2.4.1 and 2.4.2.

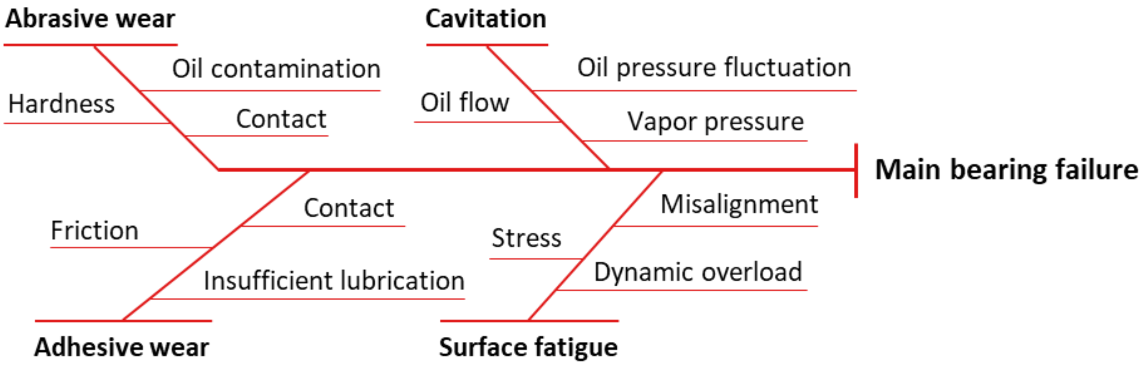


Figure 16: Isikawa diagram of selection of possible failures for journal bearings (based on: Venci & Rac, 2014)

2.4.1. Abrasive wear

Abrasive wear happens when there is surface-to-surface contact between the bearing and crankshaft. According to Tinga (2013), there are two requirements for abrasive wear, the difference in hardness and the harder material has a rough surface or when hard particles are present between the surfaces. The bearing has a softer material than the crankshaft, as these bearings are made out of a copper alloy. This design choice is made because replacing bearings is easier than replacing the crankshaft.

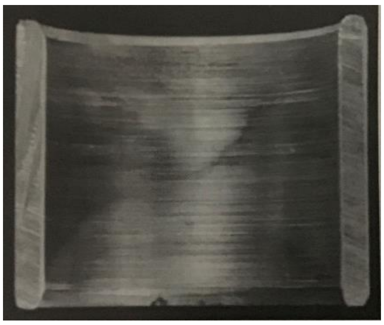


Figure 17: Example of abrasive wear (Wittel et al., 2013)

As mentioned, abrasive wear occurs when there is surface-to-surface contact, this is prevented by the lubrication oil. A temporary oil film breakdown should be avoided to have the hydrodynamic lubrication. Proper filtering is necessary to avoid third components in the form of wear particles or contamination of the oil since these particles could cause the wear (Venci & Rac, 2014).

2.4.2. Cavitation

Cavitation is a phenomenon in which vapour bubbles form in the fluid which later implodes, causing shockwaves that stress the metal surface. This overload of force results in marks on the bearing surface and the dissolving of little metal parts. This increases the risk of breaking larger parts of metal, causing potential bearing failure. Figure 18 shows the result of extensive cavitation, in this image the created holes are clearly visible.

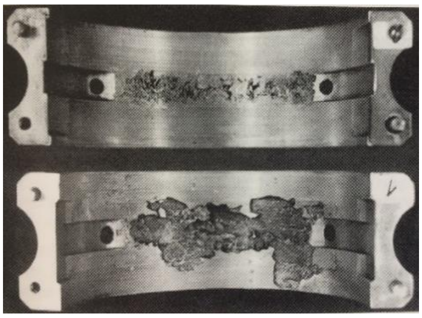


Figure 18: Example of cavitation (Wittel et al., 2013)

Important for this research is to focus on what can cause vapour bubbles and why they implode afterwards. The vapour bubbles are formed when the static pressure in the oil locally becomes below the vapour pressure of the oil at a given temperature. When these bubbles encounter high pressure, because of the fluid flows, the bubbles condense instantly and implode, causing the high local pressure waves. Repeatedly implosion at the same location can lead to 'cavitation erosion' on the bearing surface (ISO, 2008).

As shown in Figure 15, there was a slight negative pressure after the load zone. Other sources that influence the pressure are pulse pressures from the oil supply. The temperature has also an effect on the vapour pressure properties of the lubrication oil. The vapour pressure is temperature-dependent, with higher temperatures the vapour pressure drops, and more air bubbles can form. (Garner et al., 1980). As an example, this temperature effect is also visible with the boiling point of water when having different air pressure, or even getting boiling water at room temperature in a vacuum.

2.5. Conclusion RQ1

What are the different failure modes and mechanisms of the main bearings in the diesel engine?

The first research question was investigating the causes of failure for the main bearings. The different failure modes and mechanisms of the main bearings were analysed. This analysis showed that the failure mode of the main bearing is the overheating of the bearing surface that causes the safety system to shut down the engine. The common failure mechanisms that occur at the journal bearings were analysed based on literature and expert knowledge. From these analyses, abrasive wear and cavitation were marked as the most important failure mechanisms. Important to note is that these failure mechanisms do not occur during normal operations but are incidents that could happen during operations. With hydrodynamic lubrication, there is no direct surface-to-surface contact which eliminates the abrasive wear. The contamination of the oil should be avoided. Cavitation is also not a constant process that could be directly linked to operating hours.

3. Proposed data-driven monitoring approach

In this chapter, the focus is on explaining the approach of converting the data into a defect detection warning. This starts with analysing the available sensors and setting the definition of defect for this project. After that, the connection between the available data and the condition of the main bearings will be made based on literature. Finally, the approach that will be used for creating the data-driven defect detection model is demonstrated. The approach outlined in this chapter will be implemented in the following chapters.

3.1. Available sensor measurements of main diesel engine

On the main diesel engines, different sensors are already installed and logged that are available for analysis. These sensors are part of the engine control unit and are also connected to the integrated platform management system (IPMS). IPMS is used to monitor the current operating conditions of technical equipment onboard. The sensors are logged every 3 seconds before the system is updated to logging each second. There are hundreds of sensors logged in total, of which 60 are used to monitor each of the engines. Unfortunately, not all installed sensors from the motor management system are available due to the manufacturer's protection. This limits the number of sensors that could be used for analysis of the engine performance.

Table 2: Sensor measurements overview

Measurement	Unit	Range	Location
Bearing temperature	°C	45-257	Against outside of the lower bearing shell
Rotation crankshaft	RPM	0-1160	On crankshaft
Temperature of oil supply	°C	45-69	Main feedline to engine
Temperature of oil return	°C	41-77	Main return line of engine
Pressure of oil supply	Bar	0-10	Supply to the engine after filter
Temperature of cooling supply	°C	40-78	Supply to engine
Temperature of cooling return	°C	40-88	Return of engine
Fuel rack position	[%]	0-100	Valve in main fuel line to engine
Rotation turbocharger	RPM	0-36116	On shaft turbine

In Table 2, an overview of the different sensors that could be useful in this research is given with their observed range in the raw data and location of measuring. These sensors are selected in consultation with the maintenance engineers. The focus is on sensors that are related to the performance of the bearings and capturing the conditions in which the bearings operate. The positions of the sensors are schematically given in Figure 19. The seven bearings are all individually monitored, the thermocouples are placed against the bottom bearing shell, corresponding with the area that has the most load.

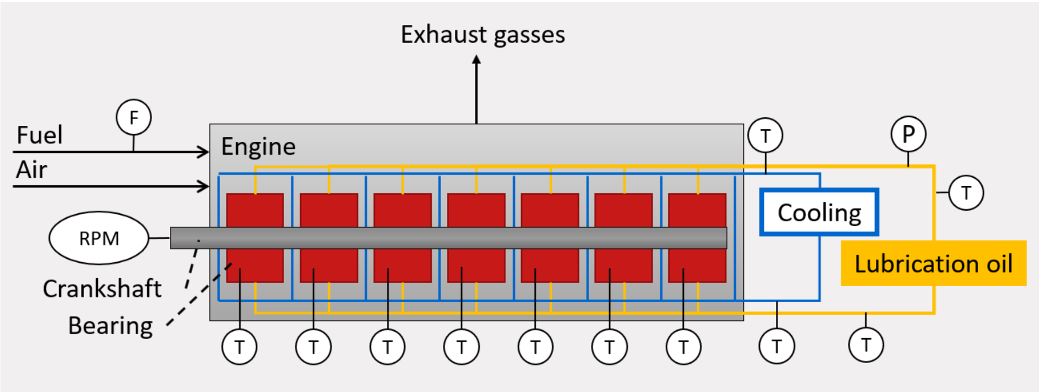


Figure 19: Overview sensors main diesel engine with focus on bearings

The rotational engine speed and turbo rotational speed are two indications of the intensity of operations. This is because the function of the crankshaft is to convert the linear movement of the pistons into the rotational movement of the shaft. Depending on the torque that is delivered, the load on the bearings varies (Gomes et al., 2018). The maintenance engineer of the diesel engines declared that the forces related to the torsion in the crankshaft result in extra friction in the main bearings. The amount of friction is related to the temperature increase of the bearing (Wittel et al., 2013).

On the other hand, there is the cooling effect from lubrication oil and conduction to the surroundings, which is cooled by the engine cooling water circuit. Measurements of these fluids are done centrally in the supply and return pipes, therefore actual temperatures or pressure at the bearings could be different. The measurements related to flow are related to the RPM because the pumps are driven by a gearbox connected to the crankshaft (De Schelde, 2015).

3.2. Discretionary the condition of main bearings

In this section, the used definition for the main bearing condition will be set. This helps with the understandability of the approach. In this thesis, three discrete stages (‘good’, ‘defect’ and ‘failed’) will be used. This distinction is often made in research (Arts, 2017). Further detailing in more stages is challenging because of the limited information available. This distinction is also approved by the engineers as a proper distinction for initial research.

Good

A bearing is defined as being in a good state if there are none to minor scratches or minor marks of cavitation. When a new bearing is mounted, the condition of the bearing is new, and therefore good, although some running in must be performed. The time of the running in is expected to be negligible compared to the expected lifetime. Bloch & Geitner (1997) stated that journal bearings would last in theory indefinitely with proper lubrication, correct design, and operating conditions.

Defect

The second stage is defect. Here the bearing is still functioning, but the wear limits are exceeded. There are scratches or cavitation marks from a certain depth, size or area are above the set limit. In an inspection, this would be the reason for preventive replacement. The development of defects are unpredictable, therefore the bearing likely to fail within a reasonable time (Kumar et al., 2018).

Failure

Failure is a state in which the main bearings can no longer perform their intended function (Tinga, 2013). The failure of a main bearing is self-announcing and revealed by the safety system on the engine. This system shuts down the engine when the threshold temperature of the main bearing (115°C) is reached. This immediately shut down is performed to keep the follow-up damage limited. This temperature will be reached when there is an increased amount of friction. This could be because of particles that are broken off or insufficient lubrication.

After failure, the engine is no longer available to run, maintenance is required before the engine is operational again. During the time from failure until the repair, the entire vessel is not able to perform its operational task. With the engine that is left, they can sail to a port where a maintenance crew must come onboard to perform the replacement.

3.3. Review of applications condition monitoring bearings

In literature, the monitoring of (journal) bearings is often performed. Nabhan et al. (2015) and Kumar et al. (2018) reviewed fault detection techniques and categorized these as either: vibration, noise, temperature or wear debris monitoring.

In this research, the focus is on investigating the possibilities of using the available IPMS data, as mentioned in section 1.2. In the IPMS data, only temperature measurements are available from the mentioned techniques mentioned by Nabhan et al. and Kumar et al.. Measurements such as vibrations and noise are not performed for the main bearings. Oil samples are taken and analysed periodically as mentioned in section 2.2, but will not be used as an input in the data-driven defect detection model.

3.3.1. Literature review

Multiple publications investigated the relationship between the condition of bearings and bearing temperature. The temperature has always been a key parameter to track for bearings to assess the condition, in the form of operational limits. Neale (2001) describes different operating limits based on temperature. These limits are based on a temperature rise of 10 °C above the normal operating temperature. The difference is seen as a more convenient indication of trouble than an absolute temperature value.

Touret et al. (2018) reviewed studies that use the thermal approach in condition monitoring. The temperature approach is based on power losses which induce temperature increase of the system. In the found studies with ball bearings most often surface defects were found. They stated that with a proper setup, the defect could be detected several months before catastrophic failure.

Fillon & Bouyer (2004) invested in a scientific lab experiment on the relation between wear and thermohydrodynamic performance of worn plain journal bearing. A 100 mm bearing was submitted to different static loads in a stationary situation. Minor defects, up to 20% of the bearing radial clearance, had little influence on the temperature, wear of 30-50% showed a significantly lower temperature, due to the tendency of the footprint. This research did not focus on the actual prediction of failures.

In case studies on the drivetrain of wind turbines by Wilkinson et al. (2014) and Kenbeek et al. (2016) the temperature sensors were used to predict upcoming failures. Statistical methods were used to detect the temperature rise compared to normal circumstances. They both used models to compensate for the external factors that influence the measurements. Wilkinson et al. were able to predict failures between one month and two years ahead. In the research of Kenbeek et al. no statistics were given of the early detection.

In the research to malfunction of a journal bearing by Antunović et al. (2018) fuzzy networks were used for temperature and vibration sensors. Different membership functions for the used fuzzy network were created, where a higher temperature (>100°C) belongs to overheated. The method was tested on a cement plant. Antunović et al. concluded that the method is reliable for the evaluation of the condition of the bearing.

A different method of using temperature data to perform defect detection is abnormality detection. In the work of Cheng et al. (2018) defective bearings of high-speed trains are detected using abnormality detection. The different identical components were compared and the defect bearings attained a higher temperature compared to the others. With this method, they were able to predict upcoming failures several days before the static operating limit was reached.

3.4. Proposed data-driven defect detection model

In section 3.3, the possibility of monitoring bearings based on temperature effects has been mentioned in the literature discussed. An objective manner is necessary to detect when the bearings are defective. Ding et al. (2020) stated that behaviour is significantly different in several stages of degradation. Using fixed thresholds for temperature monitoring has its drawback since it is not able to handle the non-stable operations of the engine. This non-stable operation significantly influences the bearing temperature, as shown in the data analyses, see Figure 30 of section 4.6. Therefore, the monitoring technique with an intermediate step has major potential as found in the research of Kenbeek et al. (2016) and Wilkinson et al. (2014).

The intermediate step is needed to take out the variability caused by the operating conditions. Chow & Willsky (1980) were one of the first to divide the monitoring process into a two-stage process. First, the residuals are generated, and second, the residuals are evaluated (Jardine et al., 2006). This procedure is integrated in Figure 20. The residuals are the temperature difference between the expected operating condition and the actual measured bearing temperature is the interesting attribute to monitor.

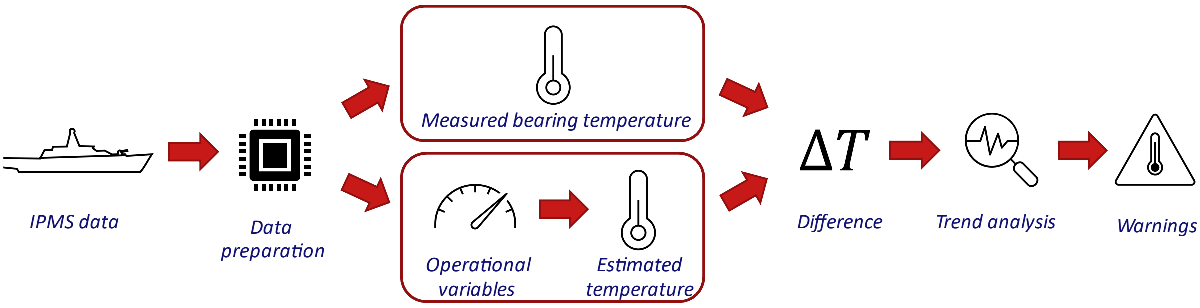


Figure 20: Flowchart of the proposed monitoring approach

Examples of implementation of this two-stage technique could be found in different studies, such as in the area of wind turbines, which are introduced in section 3.3. Similar to the case of the RNLN, condition monitoring is important due to the difficulty to reach locations and high costs of maintenance while having a low number of failures. The lesson that could be learned from Wilkinson et al. (2014) is that a physics-based model approach works the best compared to signal trending methods. Cambron et al. (2017) also used this model and explored the use of a different control chart method, namely exponential weighted moving average. With the advantage of detecting progressive variations within a process.

In the research of Kenbeek et al. (2016) this two-stage method is used on several variables, namely: nacelle temperature, generator temperature and generator vibration readings. Environmental circumstances and conditional variables are taken into account in the linear regression model. In the implementation of the two-stage model, four different steps were taken:

1) Determine a baseline period with normal operational behaviour.
2) Create a regression model for the parameter of interest for the period of step 1.
3) Determine adaptive thresholds based on the residuals of the regression model.
4) Monitor the residuals of the regression model using the set adaptive thresholds.

Based on the results of these studies, we found it promising to make use of a two-stage approach to create defect detection for the main bearings. Similar steps used in the research of Kenbeek et al. (2016) will also be used in this research. First, the data preparation is explained, after which a regression model is selected and learned to predict the bearing temperature. Finally, the generated residuals of the regression model are monitored to develop defect warnings.

3.5. Intermediate conclusions

3.5.1. Conclusion RQ2

What sensors are available to give insight into the condition of the main bearings?

This research question investigated the available sensors which will be used to create a defect detection model. The available sensors are part of the IPMS. This system is not specifically for monitoring the bearings to perform maintenance decisions. But is used to monitor the process during operations of the different platforms on board. With respect to the main bearings, the temperature is individually measured on the bottom of the bearing shell. Besides the bearing temperature, different sensors give information about the operational setting of the engine. These sensors consist of measurements from crankshaft and turbo rotation, the oil circuit, cooling circuit and fuel position. Unfortunately, not all installed sensors are available due to the protection of the manufacturer. Concluding, there are sensors available for the project that provide information on the main bearings.

3.5.2. Conclusion RQ3

How could the available sensor measurements be related to the condition of the bearings?

With the third research question, the link between the available data and the main bearing condition is made. Based on the reviewed publications, it can be concluded that there are different monitoring principles to determine the main bearing condition. From these principles only temperature monitoring is available in the situation of using IPMS data. Using fixed limits for warnings, such as in the safety system, is an indication of the condition but not as useful (Neale, 2001). The operational conditions must be taken into account since they significantly impact the bearing temperature (Kenbeek et al., 2016; Wilkinson et al., 2014). Therefore, the raise of bearing temperature compared to the normal operating temperature is seen as a sign of deterioration. By monitoring the temperature this way, defects can be found several days to months before actual failures as shown in applications build for wind turbines (Touret et al.,2018; Wilkinson et al., 2014).

4. Data preparation

In this chapter, the data is prepared before it will later be used in the modelling in chapter 5 and 6. The data preparation is an important step of the CRISP-DM methodology to ensure reliable results of the model. In Figure 21 schematically, an overview is given of the steps that are made to convert the raw data to a usable dataset.

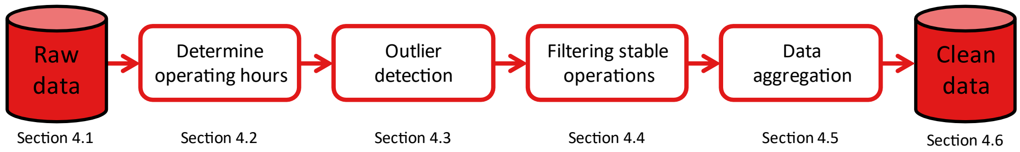


Figure 21: Schematic overview of data preparation process

4.1. Raw data

Unique about this project is the amount of real data that is available for analysis. Although DvO is still working on optimizing the process of data acquisition, there is data available for this research. The available data is recorded over a period of six years in which the vessel has performed different tasks, including deployment. In some periods, the recording of data is stopped while the vessel was in a maintenance period. An impression of the data is given in Figure 22, due to confidentiality reasons, it is not possible to provide the complete timeline of data.

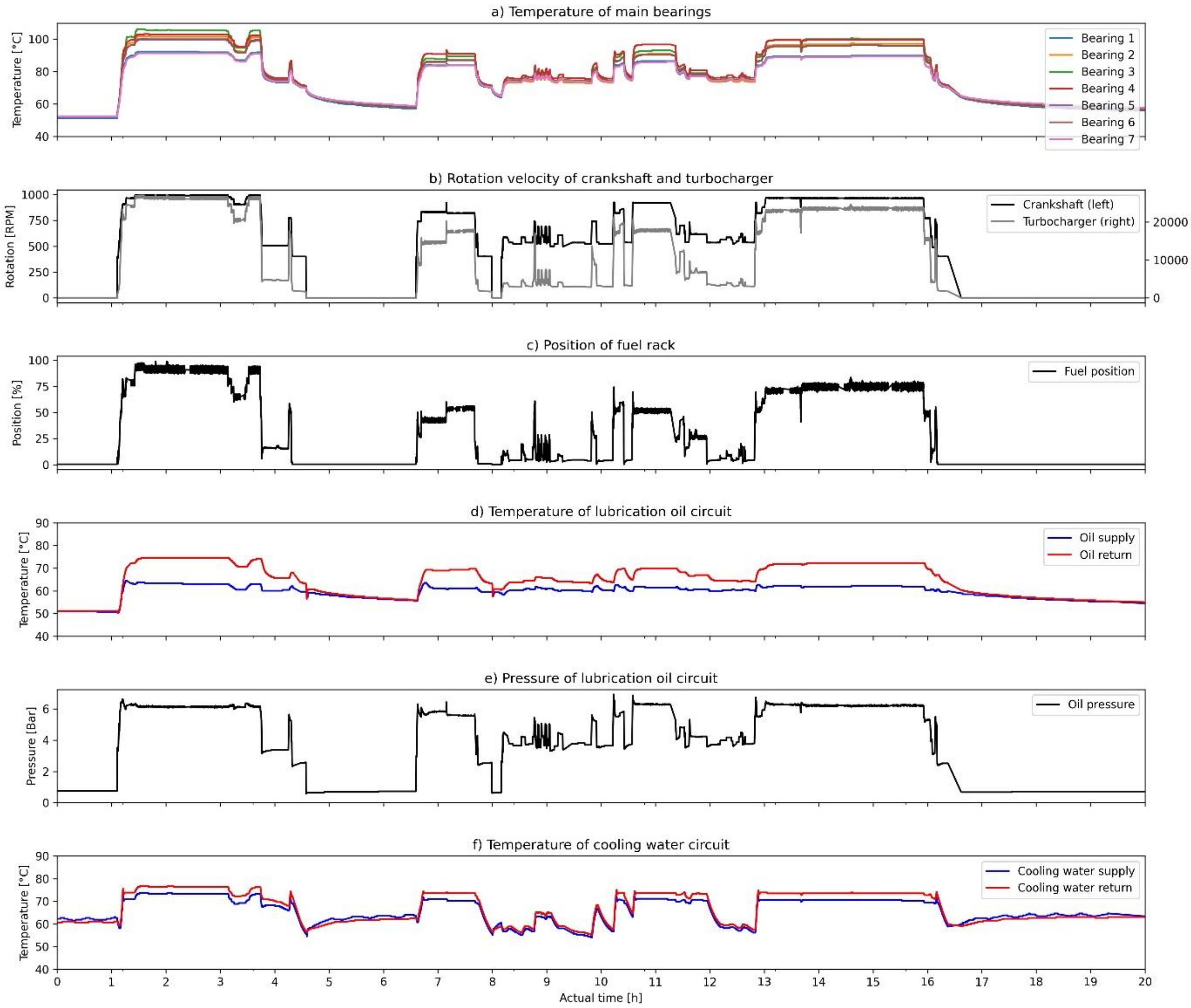


Figure 22: Extract from raw data Port side engine for 20 hours

The data of the two engines (port side and starboard side) come in separate monthly files and is collected non-stop with a sample range of 1/3 Hz, and 1 Hz after an update of the monitoring system. Combining these files results in over ten thousand operating hours of the engines combined. Each sensor is represented as a single column in these datasets. In this report, three data parts will be used which do not cover the entire lifetime of components. Two parts will have a failure in the end and are respectively 1625 and 3150 operating hours long. The third data path of 2050 operating hours does not have a failure and is added for validation of observing no changes.

4.2. Determine operating hours

The feature that must be added to the data is a record of operating hours. Operating hours are important to add to the data because the engine is used irregularly and degradation is linked to operations. Normally, the operating hours are irregularly logged by hand. This makes it important to mine operating hours from the dataset.

The engine's rotational speed is a simple indication that the engine is operational for the mining of operating hours. Therefore, the data records with a rotational speed above 400 RPM, the minimum RPM, could be seen as moments in which the engine is operating. Based on the sampling rate the elapsed time could be determined. This sample rate is increased from 1/3Hz to 1Hz in 2019, which is taken into account in the data mining.

This method has compared to the manually register operating hours a difference of 12.5%, in which there were fewer hours mined as logged. This difference is expected to have come from mistakes in the automatic recording of the sensor readings. Also, the start-up procedure of the engine and having the engine in stand-by could influence the operating hours. From this point on, the mined operating hours are used.

4.3. Outlier detection

Data quality is important for the performance of the regression model therefore, the raw data will be checked for outliers and missing values. Outliers are seen as data points that differ significantly from other data points. In the available data for this project, no outliers are found in the used raw data. The original dataset has readings from a temperature sensor in the return of cooling water, containing missing values. Based on an initial model fit, in which the period of missing values was excluded, this attribute has been found insignificant. Therefore, no measures are taken for these missing values.

4.4. Filtering out transient behaviour

The operating conditions of the engine are not constant and the engine is not always operational. Different activities lead to change in the use of the engine, for example, due to a man overboard drill. The influence of changing operational circumstances is shown in Figure 23. Here is visible that the bearing temperature depends on the RPM of the crankshaft but is disrupted when changing RPM. The bearing temperature needs time to become stable at the new setting. The process of going to that other stable point is called transient behaviour. For the analysis, this transient behaviour should be filtered out to remove bias from the physical relation. After filtering, steady operations will remain, which has a constant mean and constant variance (Dalheim & Steen, 2020). This means that warming up and cooling down behaviour after a change of rotation speed does not influence the found relation between these attributes.

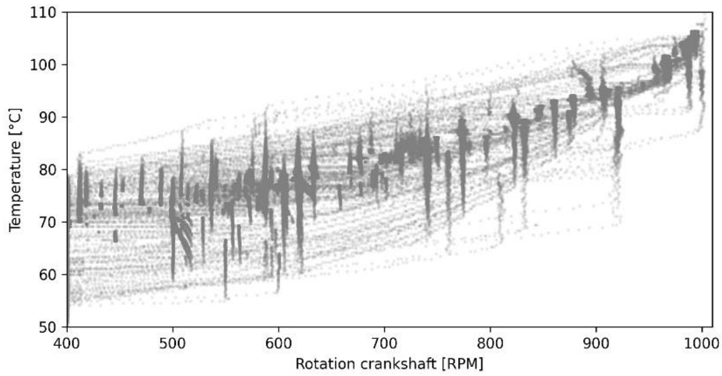


Figure 23: Transient behaviour of bearing 3

Dalheim & Steen (2020) describe a technique based on local linear trend regression to find stable points. For a moving window, the simple linear regression is established with the theory that an insignificant slope indicates stable behaviour. Unfortunately, this method is too computational-intensive to implement in this initial study. Therefore, an alternative manner will be used based on the observed variation in the moving window.

When the process is stable, the variation in the data will be limited as it is constant. Therefore, by looking at the different sensors' rolling variation, it could be determined whether the process is stable or not. This rolling variation $s_{a,t}^2$ for attribute *a* part of the set of attributes *A* for moment *t* of the entire timeline *T* could be determined for a window length of *w* observations as follows:

$$s_{a,t}^2 = \frac{\sum_{i=t}^{t+w}(x_i - \bar{x})}{w-1}, \qquad for\ all\ a \in A, t \in T \qquad \textit{Formula 1}$$

This could be performed for the different bearing temperatures and the rotation of the crankshaft. To find the stable periods there must be set a limit $\mathcal{L}_a$ to the observed variation. Time moments will only be marked stable if all attributes A meet the following criteria:

$$s_{a,t}^2 < \mathcal{L}_a, \qquad for\ all\ a \in A, t \in T \qquad \textit{Formula 2}$$

Besides the marking of stable data also the engine must be operating. An engine that is off, will have stable readings but will not provide insights into the condition of the bearings. Therefore, the last condition that must be met to detect operational stable data points is that the engine's RPM must be greater than 400. This represents the minimal RPM of the engine when running stationary.

$$x_{RPM,t} > RPM_{min} = 400 \qquad \textit{Formula 3}$$

In this project, we used a moving window (*w*) of one minute and attributes as mentioned in Table 3. These parameters are selected based on analysing the data and observing the corresponding natural variation in the sensor readings. Applying the three formulas with the selected parameters the amount of data is reduced by 82.6%. As shown in Figure 24 this technique with these settings is capable of filtering out the points in which the bearing temperature is constant.

Table 3: Used attributes to determine stable operations

Attribute	Limit ($\mathcal{L}_a$)
Temperature bearing 1	0.1
Temperature bearing 2	0.1
Temperature bearing 3	0.1
Temperature bearing 4	0.1
Temperature bearing 5	0.1
Temperature bearing 6	0.1
Temperature bearing 7	0.1
Rotation crankshaft	5

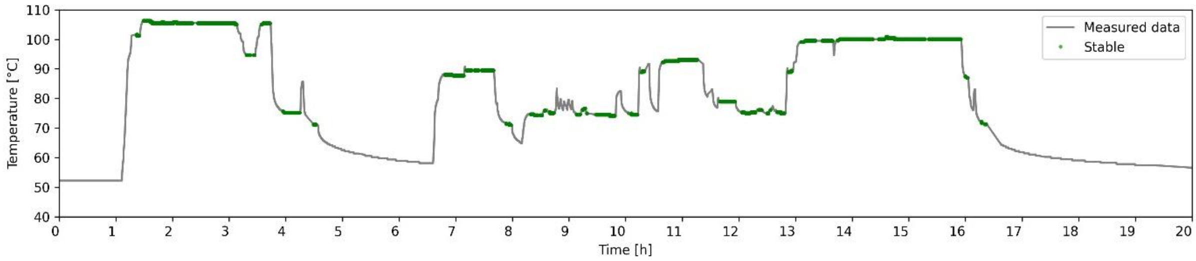


Figure 24: Example of performing filtering on stable data (green points are marked as stable)

4.5. Data aggregation

The filtered data is still of high dimension, it contains thousands of hours of data sampled with a high frequency. The sample rate of 1/3 Hz and 1Hz is compared to the degradation build up in hundreds of hours. Also, the detection should not be in several seconds before a failure but earlier in hundreds of hours. To make it computationally efficient to handle the amount of data, a single data record per operating hour will be created. This results in a sufficient amount of data to see a possible trend evolving.

Taking the average over the stable sensor reading of one hour will lead to bias in the analyses. Within one hour there could be multiple stable periods present. When there is no linear pattern, as could be observed in Figure 23 between the crankshaft rotation and bearing temperature rotation, this results in abnormalities. This is schematically shown in Figure 25, in this example, the average will have a positive difference compared to the actual relation. To overcome this problem, only the first 10 minutes will be used. This takes out the change of having multiple stable periods.

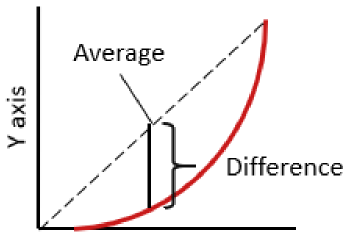


Figure 25: Example of error introduced when taking the average

In the next step, the autocorrelation should be taken into account. In the later used models, the data should be identical individual distributed, therefore correlated observations should be removed, as later explained in section 5.2. Having a constant operation of the engine results in correlated readings and therefore correlated residuals of the regression model. The research of Kenbeek et al. (2016) focused on defect predictions for wind turbines and took a single sample every four hours instead of every four minutes to reduce autocorrelation. However, using a larger fixed interval in the observations does not make sense in the application of the main diesel engine. The duration of a similar operating mode varies depending on the vessels task, for instance, ocean crossing or training on the North Sea. Therefore, it is decided to sample observations that have at least a certain difference in RPM from the last observation, represented by the limit $\mathcal{L}_{autocorrelation}$, based on the following rule:

$$\left|x_{RPM_{t-1}} - x_{RPM_t}\right| > \mathcal{L}_{\text{autocorrelation}} \qquad \textit{Formula 4}$$

With setting the minimal required difference on 50 RPM, roughly 40% of the data remains, which is selected to cover the natural variation and minor adjustments to the vessels speed. The result of this is shown in Figure 26 and Figure 27. These plots are generated later in the modelling stage but are presented to show the effectiveness of this measure. From the first lag, there is a drop visible in the autocorrelation for most bearings under 0.2. Still, there is some autocorrelation left. The possible cause is minor maintenance, as later explained in section 6.3. If the earlier mentioned uniform time interval is used to sampling records, only 8.5% of the data would have remained with similar autocorrelation results.

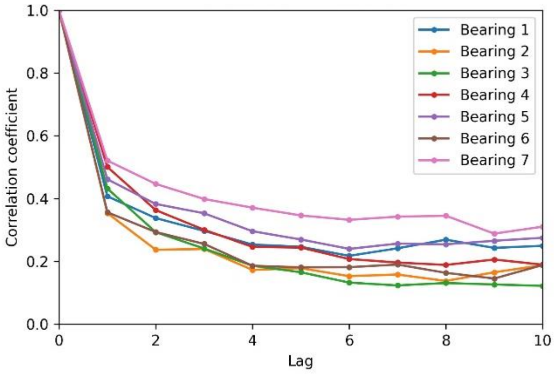


Figure 26: Autocorrelation before removing points

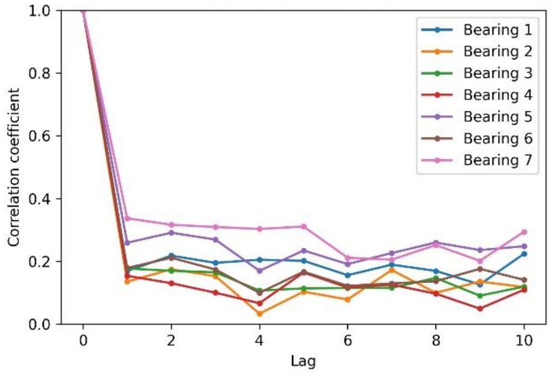


Figure 27: Autocorrelation after removing points

4.6. Result of data preparation: clean data

The data preparation step started with raw data that was recorded from the IPMS system. By taking different steps, a dataset is created that could be used to monitor the main bearings. Transient behaviour is removed from the data, which could influence the quality of detection later. The remaining data is made compact by aggregating it to a single datapoint per operating hours based on the average of the first ten minutes, making it computational possible to handle. Also, the autocorrelation in the data is limited. Due to removing several data points to limit the autocorrelation, uneven intervals are created; therefore, there will be referred to as observations from now on. In Table 4, an overview of the three different relevant data parts is given. These data parts are selected from the entire data set to show the functionality of the monitoring approach. However, this is not the entire record of the full lifetime because of data confidentially.

Table 4: Relevant data parts that are used

Case	Begin	End	Shown operating hours	Observations
I	Good	Failure	1625	889
II	Good	Failure	3150	1306
III	Good	Good	2050	1102

Data exploration

With this cleaned dataset, data analysis could be performed to understand better the data used in the defect detection model. The bearing temperature of the entire dataset is shown in Figure 28. In these boxplots, it is visible that the bearing temperature has a range in which it is operational. The bearing temperature across the seven bearings is unequal. Bearings located in the middle have a higher temperature compared to the outer bearings. Causes for this could be the heat radiation to the surroundings and the higher torsion in the crankshaft by the main bearings located in the middle (Gomes et al., 2018).

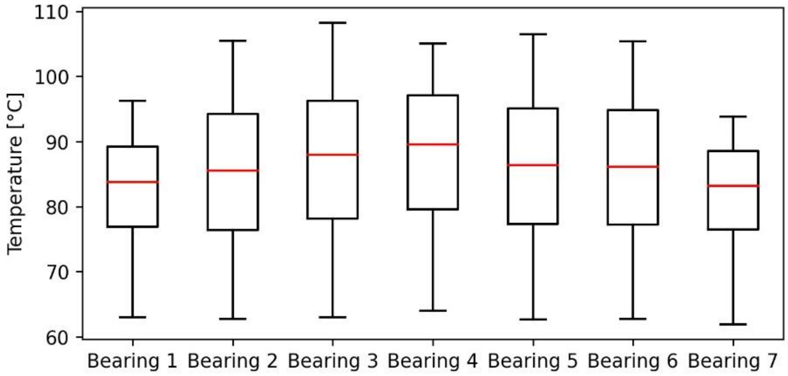


Figure 28: Boxplot of bearing temperature

In the raw data plot in Figure 22 is already visible that the different attributes are correlated to each other. The correlation matrix of the different sensors is shown in Figure 29, in which the high correlation is visible. That the different sensors are correlated does not directly mean they are causation. It is therefore important to analyse the cause of the correlation. As discussed in section 2.3, the leading factor for the bearing temperature is the rotational velocity of the crankshaft, which causes friction that is converted into heat.

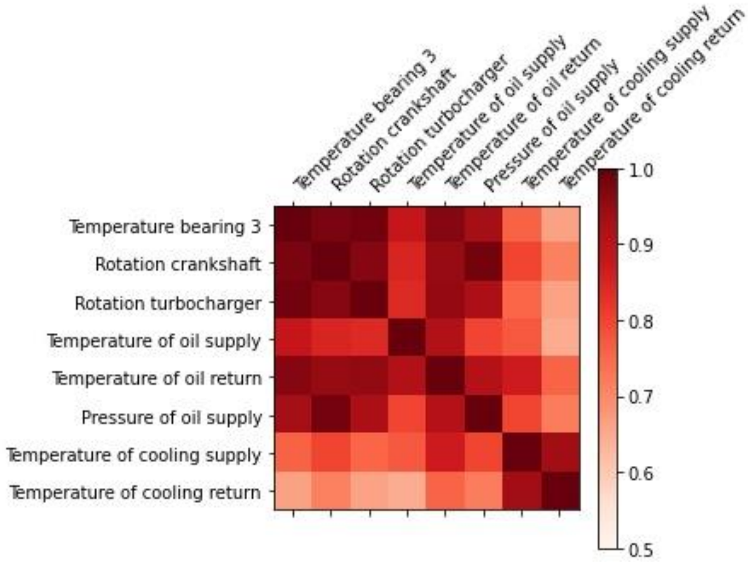


Figure 29: Correlation matrix of the explanatory variables

To show the correlation between the rotation of the crankshaft and bearing temperature, both attributes are plotted in Figure 30 for the different bearings. From these graphs, it is visible that there is a positive relationship between the two variables, although the pattern is different between the multiple bearings. This physical relation is different in the two showed cases, see the two drawn lines. This is because different bearing types were installed, which causes different physical relations.

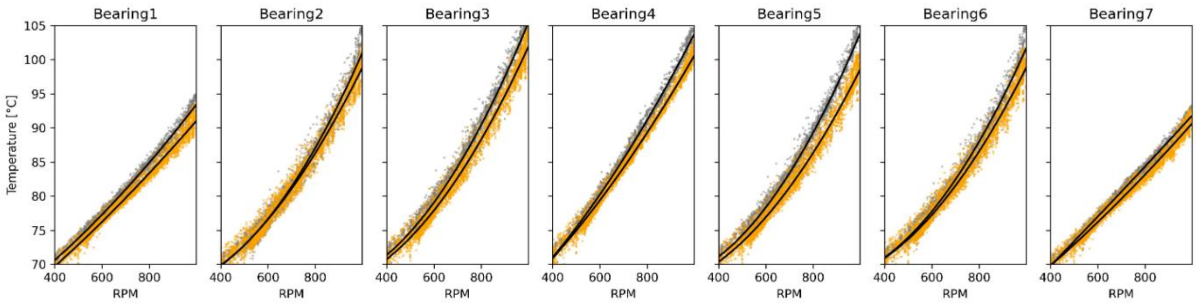


Figure 30: Scatterplots of RPM against bearing temperature of case I (orange) and case II (grey)

The initial data exploration of the lubrication oil system is shown in Figure 31. The lubrication oil pressure is generated by the gear pump that is connected to the crankshaft. In the monitored data, the gear pump is replaced by another type of pump, therefore the pressure distribution is disrupted. The temperature input towards the engine is regulated around 61 °C, the return temperature shows more variation. As can be seen in the last histogram based on the temperature difference of supply and return, the temperature increases in the engine between 2.5°C and 12.5°C. It is worth mentioning that this temperature delta is not only generated by the friction in the bearings because the oil is used to cool and lubricate also the other parts of the engine.

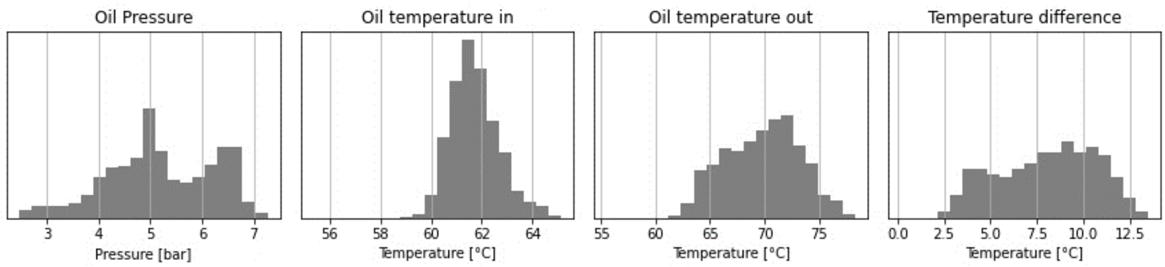


Figure 31: Descriptive plots lubrication oil

5. Modelling I – Residuals generation

In section 3.4, the monitoring approach is introduced containing out two steps, residual generation and residual evaluation. In this chapter, the residual generation is discussed and the evaluation is in chapter 6. A regression model will be developed to predict normal bearing operating temperature. The residuals of this model are the observations that are removed from their operational circumstances. The used modelling procedure is schematically shown in Figure 32. The chapter goes step by step through the development of the model, from selecting the regression model, explaining the principles, implementing and analysing the results.

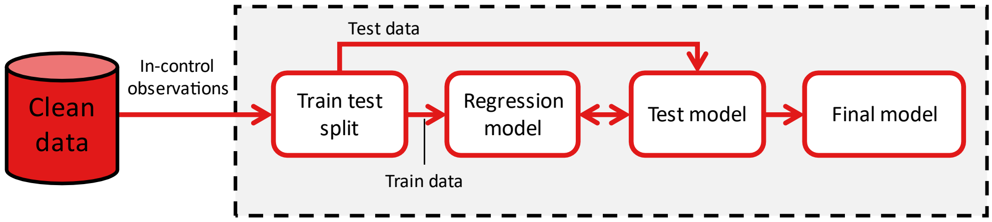


Figure 32: Schematic overview of modelling process and data handling

5.1. Selection of regression model

Various regression models could be used to determine the expected temperature. The general form of a regression model is $\hat{y}_i = f(X_i)$. In which $X_i = (x_{1,i}, x_{2,i}, \dots, x_{k,i})$ are the explanatory variables with target value $\hat{y}_i$ (bearing temperature) for observation *i*. This model should capture the physical relation between the explanatory variables and the target value. The residuals, calculated based on the observed value (y_i) subtracted with the predicted value ($r_i = y_i - \hat{y}_i$), which is defined by Chen & Patton (2012) as a 'fault indicator or an accentuating signal which reflects the faulty situation of the monitored system.' This residual will be used as an observation of the bearing condition. By monitoring this residual, the effect of different operating conditions is taken out of the data. Degradation is expected to influence the physical relation and therefore the residuals.

Design criteria regression model

Different types of regression models could be used for modelling the physical relation. The model should satisfy different factors to ensure the usefulness of the defect detection model for the RNLN. The RNLN, and especially the maintenance engineers that will be making use of the data in the future, are not familiar with artificial intelligence, therefore an understandable technique is preferable. Implementing domain knowledge of the actual situation and physical relations will further increase the trust in the model. Every engine behaves slightly different, as seen in section 4.6, therefore it should be 'easy' to transform the used method to another engine (generalization). For the model IPMS data is available, this consists of numerical values, the models should be able to handle this type of data.

These different qualitative criteria are taken into account in a multi-criteria analyse, see Table 5. The scores one, two and three correspond to good, moderate and bad, respectively. These scores are given based on experience with these models, theory (Friedman et al., 2001; Grossmann & Rinderle-Ma, 2015) and the outcome is validated with expert knowledge within the RNLN. Not all criteria are equally important, therefore a weight factor is used. The model with the lowest score is a usable model for this project. This method does not necessarily select the optimal model in terms of performance. To find an optimal model for performance, quantitative tests should be performed on the quality of the models in this situation.

Table 5: Regression model selection, good 1, moderate 2 and bad 3 points. Analysed models: Multiple linear regression (MLR), artificial Neural Network (aNN), Random Forest Regression (RFR) and k-Nearest Neighbor (k-NN)

Criteria	Weight	MLR	aNN	RFR	k-NN
Understandable	2	1	3	2	2
Domain knowledge	1	1	2	3	3
Usable with available data	2	2	1	1	2
Implementation (generalization)	1	2	2	3	3
Score		**9**	**12**	**11**	**14**

Explanation made choices
Out of the selection method the multiple linear regression (MLR) model is chosen as most useful. This model is due to the understandability of the method and knowledge that could be implemented in the model. The artificial neural network (aNN) is often seen as a black-box operation, which is why this technique scores poorly on understandability. It is capable of fitting a non-linear function but also has the danger of overfitting the data. The random forest regression (RFR) fits the data without a clear physical relation as a foundation, which makes it less understandable. A k-Nearest Neighbor (k-NN) regression model focuses on the similar points that are located around the new observation, this makes that all the training data must be stored, which could be data intensive.

5.2. Theory multiple linear regression

In multiple linear regression, multiple attributes (explanatory variables) are used to estimate a target value $\hat{y}_i$. The standard form of this MLR is given in Formula 5. In this formula, β_1 is the intercept of the model and β_a is the coefficient for attribute *a,* denoting the increase of $\hat{y}_i$ if $x_{a,i}$ increased by one and the other attributes are staying constant. Transformations of the attributes give options to add data that is by itself not linear related to the target value. Common transformations are, for example, log or square attributes. Fitting the model will be performed based on minimising ordinary least squares (OLS) over the entire observation set *N*, see Formula 6. In this approach, the coefficients are selected which minimise the sum of squares.

$$\hat{y}_i = \beta_1 + \beta_2 x_{2,\mathrm{i}} + \beta_3 x_{3,\mathrm{i}} + \cdots + \beta_k x_{k,i} \quad \textit{Formula 5}$$

$$\underset{\beta}{\operatorname{argmin}} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \quad \textit{Formula 6}$$

Mathematical assumptions
Hendry & Nielsen (2007) state the following assumptions for generating an MLR model:

1) **Independence between pairs of observations and outcome** $(X_1, y_1), (X_2, y_2), \dots, (X_n, y_n)$

The data is collected in real-time and the use of the engine could be for constant several hours. Therefore, it is likely that the observations of different sequential operations are similar. To reduce this problem data is subsampled to get rid of the constant operations, this is discussed in the data preparation see section 4.5.

2) **Identical conditional normal distributed** $(y_i|X_i) \sim N(\beta_1 + \beta_2 x_{2,i} + \cdots + \beta_k x_{k,i},\ \sigma^2)$

The model requires that the different pairs of observations are identical conditional normal distributed with the target variable. Therefore, the outcome of the model is expected to be randomly distributed, which will be later checked in section 5.5. The different bearings that will be analysed are similar but not identical to each other. In Figure 30, it is visible that each bearing is differently correlated with the RPM and that there is also a difference visible between the two presented cases. Differences between the different cases are based on bearing type, position causing different forces and rotational direction of the engine (different between portside and starboard side). Therefore, models should be individually learned for the different configurations of engines and bearing positions.

3) Exogeneity of the conditioning variables X_i, non-correlation between the exogenous variables.

This assumption goes into the independence of the different attributes. For the collected data of the main diesel engine, this assumption is violated. As shown in Figure 29, there is a correlation between the different attributes, which is logical in this kind of system which works in harmony. Having attributes that are correlated among each other does not mean the model could not get a good fit on the data (Kutner et al., 2004). In this research, the goal is to obtain precise estimates to capture the physical relation, therefore understanding the role of each independent attribute is less important. The ceteris paribus assumption, in which the coefficients β_k show the increase of y_i if $x_{k,i}$ increases by one, does not hold with the correlated data (Kutner et al., 2004).

4) Parameter space $\beta, \sigma^2 \epsilon \mathbb{R} \times \mathbb{R}_+$

The coefficients of the model should be real numbers with a standard deviation that is non-negative. This assumption is part of the formal description of the statistical model. If this assumption does not hold, there is no realistic multiple linear regression model.

5.3. Building regression model approach

For building MLR models there are different tactics to use. Because of the degree of dimensions, it is not recommended to train each different configuration. Other tactics are using forward- or backwards-stepwise selection of attributes. Hereby in each modelling step, one attribute is either added or removed until a sub-optimal model is found. In this case, forward stepwise selection will be used to be able to start with a model as simple as possible. The model generation will further explain this procedure in section 5.4 (Friedman et al., 2001).

The performance measure that will be used to determine the performance objectively is the root mean squared error (RMSE). This measure is chosen because it gives higher weights to large errors because of the squared term. Besides the performance measure, the determined coefficients will be checked for a logical sign, and the residuals plots will be examined to check if there is any pattern visible that indicates higher-order relation. If necessary, a linear transformation will be performed.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{N}} \qquad \textit{Formula 7}$$

The attributes that will be used in the model should first be standardised. Standardised attributes make it in the end easier to compare the different attributes because their ranges variate heavily. Bearing temperatures ranges are between 45°C and 257°C while the turbocharger goes up to 36116 RPM. Therefore, the corresponding coefficients are not comparable. The attributes are standardised before implementing in the model, this is done based on $x = \frac{x - \bar{x}}{s}$, in which $\bar{x}$ is the sample mean and s the sample standard deviation. This standardization comes into place when looking at the different attributes.

Data usage

Not all data will be used to learn the model, as shown in Figure 32. Because the model must capture the physical relation to a good condition of the bearing, only the in-control period is used to build the model. The in-control period is determined in consultation with the mechanical engineers based on oil analysis and an initial model with all the data. This in-control data of case I will be randomly split into two parts, 70% for training and 30 % for testing, 384 and 168 observations, respectively. The test set will check how the model behaves with unseen data and could indicate when the model is overfitting the data.

5.4. Model generation

In this section, the actual model building is performed, of which in section 5.1 and 5.2 the theory behind is explained. For the model making the package *Statsmodels* version 0.12.2 will be used in Python. This gives the options to directly check different aspects of the model such as the sign and significance of the different coefficients.

Separate models with the same formula will be learned for each bearing because, as can be seen in Figure 30, the bearings behave differently, which is also expected for the other attributes. For example, the pressure oil supply could, due to pressure loss, have a different effect on the first bearing compared to the last. In this section, there is made use of data from Case I and graphs will be given only for bearing 3, this bearing is one of the bearings with the most forces. In Appendix I, detailed information is also given for the other cases to show their similar results.

In each step of the model, different attributes are added to improve the average RMSE. The attributes that are used are explained in Table 2 of section 3.1. The bearing temperature of other bearings is excluded to ensure that correlated degradation is observed. The sequence of adding attributes is determined based on forward-stepwise selection. In each step, the attribute that has the most reduction in RMSE will be selected. In Table 6 the development of the different models is given based on the RMSE. These results are plotted in Figure 33, including the minimum and maximum over the seven different models.

Table 6: Model building, the performance measure is average RMSE

Model step	Attribute to add	Attributes	RMSE Training	RMSE Test	Accepted?
1	Basic model – rotation crankshaft	1	0.919	0.812	Yes
2	Temperature of oil return	2	0.427	0.413	Yes
3	Rotation turbocharger	3	0.268	0.262	Yes
4a	Fuel position	4	0.257	0.252	No
4b	Temperature of oil supply	4	0.257	0.251	No
4c	Pressure of oil supply	4	0.263	0.257	No
4d	Temperature of cooling supply	4	0.257	0.254	No
4e	Temperature of cooling return	4	0.268	0.261	No

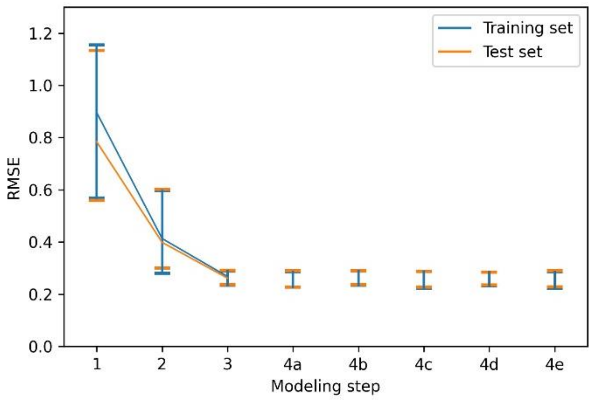


Figure 33: Model development of stepwise adding attributes

5.4.1. Model step 1 - rotation crankshaft

As a starting point, a model is made based on only the rotation of the crankshaft. This is seen as the dominant factor that drives the bearing temperature because RPM is directly linked to the operational setting of the engine. Other systems, such as oil pump and cooling water pumps, are connected to the crankshaft by the gearbox, as discussed in chapter 2, which influence the operational situation of the bearing. From Figure 30 in section 4.6, it is visible that there is no linear pattern between the RPM and temperature but more a second-order relation. The need for a quadratic term is also visible in the residuals analysis, which can be seen in Appendix IV. This results in the following formulation of the first model in which $\hat{y}_{b,i}$ is the predicted bearing temperature of bearing b:

$$\hat{y}_{b,i} = \beta_{1,b} + \beta_{2,b} * x_{RPM,i} + \beta_{3,b} * x_{RPM,i}^2, \qquad b \in \{1,..,7\}$$ *Formula 8*

5.4.2. Model step 2 - Temperature of oil return

The first attribute that is added is the return oil temperature of the engine. The function of the lubrication oil is to lubricate and cool the bearings and therefore, an important attribute when analysing the bearing temperature. Based on the first law of thermodynamics, the link could be made between the bearing temperature and the added oil temperature. The inlet temperature of oil gives a smaller improvement, this is expected because the inlet temperature is controlled to a fixed value. Over the major range of the data, there is non-linear behaviour visible between the bearing temperature and the return temperature of the lubrication oil, see Figure 34.

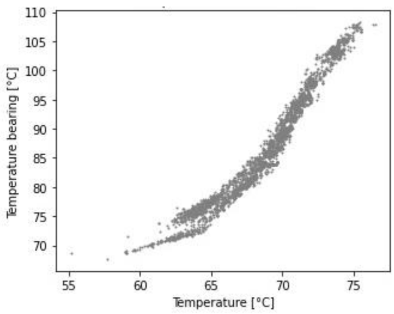


Figure 34: Temperature bearing 3 against lubrication oil temperature return

5.4.3. Model step 3 - Rotation turbocharger

As a second attribute, the rotation of the turbocharger will be added to the model. The turbo is a good indication of the intensity of the engine. Based on the amount of air input to the engine, the fuel is controlled, which is turned into the power delivered by the engine. In the scatterplot, as shown in Figure 35, it is visible that there is a non-linear pattern between the temperature and RPM of the turbocharger. Also, in the analysis of the residuals set out against the explanatory variables, there is a pattern visible. Therefore, also for the RPM of the turbocharger, a second-order transformation is added.

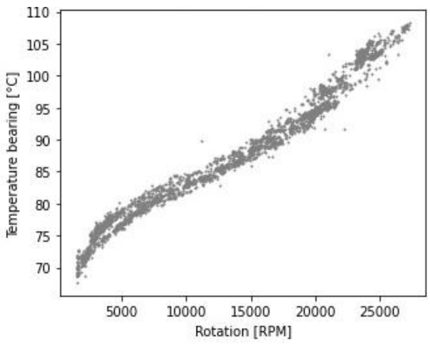


Figure 35: Temperature bearing 3 against RPM of the turbocharger

5.4.4. Model step 4 - Other elements

The other elements, the cooling system, fuel position and oil pressure measurement, do not show any substantial improvements in the RMSE and the number of insignificant coefficients increases. Therefore no additional elements are added to the model, this will only result in more bias. The different attributes are, as we saw in Section 5.2, also correlated with each other.

From a mechanical point of view, there are arguments why these attributes do not contribute. The cooling system causes more indirect cooling compared to the lubrication oil that is actively applied. The oil pressure sensor has a high correlation with RPM because the crankshaft powers the oil pump. Which variates over time is the resistance through the oil filter, which causes a pressure drop in the oil supply. This pressure drop did give a small improvement of the RMSE but bit big enough to add to the model.

5.4.5. Final model

Based on the stepwise adding of attributes, the following formula is formulated:

$$\hat{y}_{b,i} = \beta_{1,b} + \beta_{2,b} * x_{RPM,i} + \beta_{3,b} * x_{RPM,i}^2 + \beta_{4,b} * x_{Oil_{return},i} + \beta_{5,b} * x_{RPM_{TC,i}} + \beta_{6,b} * x_{RPM_{TC},i}^2, \quad b \in \{1, .., 7\}$$

Formula 9

For this formula, the coefficients are given in Table 7. In this Table, it is visible that the models have different coefficients. The corresponding p-values are all below the 0.05 margin, see appendix II. Some coefficients for the RPM and RPM TC are not positive, meaning an increase will lead to a lower bearing temperature, but these are part of the transformed attributes and present twice in the model. The sum of both standardized coefficients should be analysed to determine the positive or negative relation compared to the target value. However, we should be careful with these analysis because of the multi correlation between the attributes, as discussed by assumption 3 of the MLR model.

There is one coefficient set to zero because this one showed not to be significantly different to zero. In the parameters, we also see the symmetry come back of the system, which is also seen in Figure 28. If we look, for example, at the intercept, the outer bearings have a lower intercept compared to the more inner bearings. This comes to the forces that are different per position. Similar patterns are visible in the other attributes. When performing this stepwise selection of attributes for the other two cases, the same attributes were selected, see appendix I, but their coefficients were different. Therefore, it is concluded that only the coefficients should be learned per case.

Table 7: Fitted coefficients of the regression model for the different bearings

Final model	**Intercept**	**RPM**	**RPM^2**	**Temp. oil out**	**RPM TC**	**RPM TC^2**
B	$\beta_{1,b}$	$\beta_{2,b}$	$\beta_{3,b}$	$\beta_{4,b}$	$\beta_{5,b}$	$\beta_{6,b}$
Bearing 1	81.893	4.930	-0.018	2.166	-0.139	0.517
Bearing 2	84.308	5.051	0.535	2.957	2.315	1.027
Bearing 3	86.197	5.192	0.294	3.081	2.940	1.531
Bearing 4	87.571	7.716	0.820	2.397	0.000	0.076
Bearing 5	84.169	5.265	0.460	2.663	1.703	0.902
Bearing 6	84.423	4.848	0.349	2.887	1.749	1.002
Bearing 7	81.706	4.651	-0.003	2.408	-0.318	0.450

5.5. Regression model verification

In this section, the residuals of the final model will be explored to obtain relations and verify the results. To get a first impression of the temperature estimations, in Figure 36 the outcomes of the model are plotted in combination with the real data. In here, all hourly data points are included to give a complete image. As mentioned in section 4.5, only the first data point of a sequence of similar data points is included in the data used for monitoring. The points that are included in the model are marked with the red colour, the grey points are only for display purposes.

Based on Figure 36, we can see that the model is performing quite well. The residuals, difference between the observation and estimation must be further explored to see if the made assumptions hold. Based on assumption two from section 5.2 the residuals are expected to be white noise and normally distributed, which means that there is no correlation left in the residuals and that the model besides the unexplainable part captures all behaviour. This will be verified by making use of histograms, scatterplots, and autocorrelation graphs. In this section, the plots for bearing 3 are shown, the graphs for the other bearings are in appendix III.

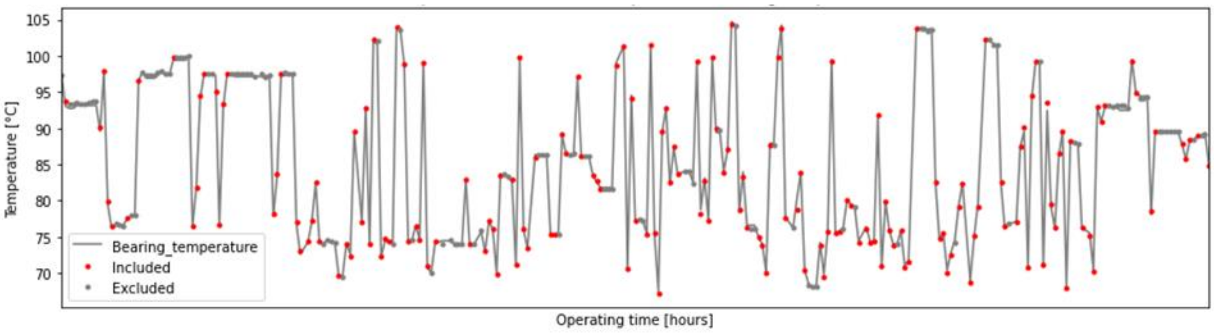


Figure 36: Estimated temperature compared with the observed temperature of bearing 3

Residuals distribution

First, we have a look at the distribution of the residuals of bearing 3 in Figure 37. Based on this graph, it is visible that the residuals seem to follow a normal distribution. The mean is centered around zero and the number of outliers from the model is limited. The cause of these outliers has to do with the data preparation, still, three data points contain the average of two stable operations. The sampling of data should be further improved in follow-up studies with investigating the generation of one data record per stable measurement period.

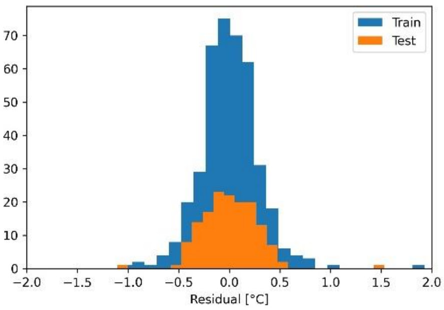


Figure 37: Histogram residuals distribution for bearing 3

Explorational variables

The spread of residuals set out against the explorational variables patterns could become visible, which would indicate some uncovered relation. In Figure 38, we see the residuals of bearing 3 plotted against the standardized explorational variables, similar graphs of the other bearings are given in Appendix III. In these plots, there does not seem to be a clear pattern. This indicates that there is no further uncaptured relation to the attributes that are added. Therefore, we can assume that there is likely no unobserved pattern and the residuals are distributed as white noise. In Appendix IV these same plots are given for the model where the x_{RPM}^2 and $x_{RPM_{TC}}^2$ terms are not included. This shows the importance of performing the quadratic transformation.

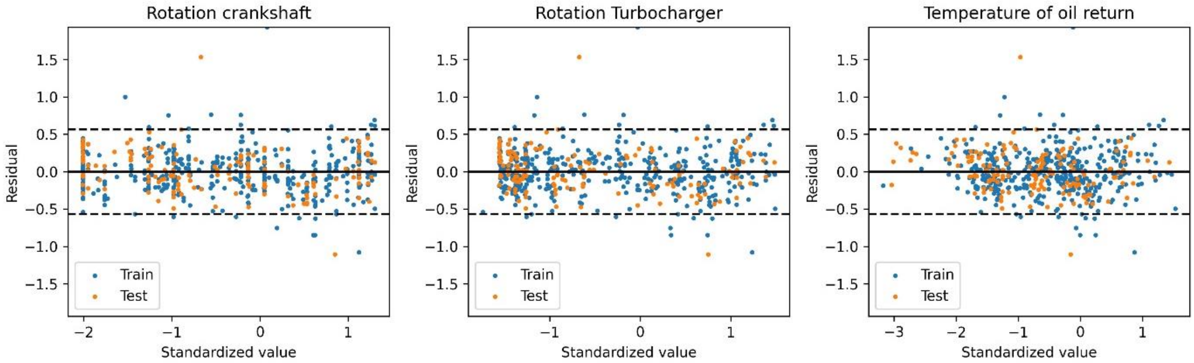


Figure 38: Residuals compared to exploration variable RPM (not standardized) of test data

Autocorrelation

At last, the correlation with respect to time is checked. The data that we have used is from a period in which the condition of the bearings was good. The correlation within the residuals of the used data should be limited. In Figure 39 the autocorrelation plot is given for the residuals of bearing 3, for the other bearings see Appendix III. From this graph, we can conclude that there is still some correlation between the residuals with respect to time. This indicates that there is an unobserved component of the physical relation, this is expected to come from minor maintenance tasks to the engine, which will be further analysed in section 6.3. The used filter, as explained in section 4.5, has ensured that the correlation has remained limited.

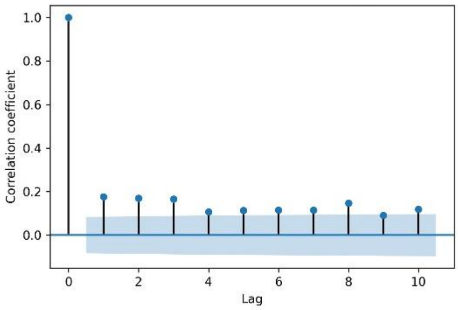


Figure 39: Autocorrelation analysis bearing 3

5.6. The result after the regression model

In this chapter, the regression model for the residual generation is explained. Based on qualitative criteria, it is concluded that an MLR model is useful. This model has understandable behaviour and domain knowledge could be used. The model is built using forward steps, ending with three different attributes: rotation crankshaft, the temperature of oil return, and rotation turbocharger. With these attributes, the MLR is able to predict with an RMSE of 0.268 °C on the training set and 0.262 °C on the test set. Adding more attributes did not result in a significant decrease in RMSE and is therefore not performed. This building is also performed on the other cases, in which the same attributes were selected, but the coefficients were different. With the MLR model, it is possible to compensate for the physical relation making use of the three attributes. The residuals are, therefore, free of their contextual anomalies. These residuals will be used in the next chapter to determine when the bearings are defect.

6. Modelling II – Residual evaluation

In the previous chapter, the residual generation is explained. This provides an attribute related to the bearing temperature that is removed from its contextual anomalies. In this chapter, the focus is on the residual evaluation, to obtain information in relation to the condition of the bearings. This information will be in the form of a warning. Which later could be used as input in the maintenance decision process.

As the first step, the generated residuals are plotted over a timeline in Figure 40. This graph shows case I, containing out the last 1625 hours before a failure. In this plot, there is some variation visible over the first 1000 hours. From hour 1200 on, there is an increase towards the end of the shown timeline. This is the first indication that defect detection could be made based on the temperature measurements. The control chart will be used to statistically determine when the process is out of control, which is expected to indicate the bearing's defect. Defect bearings stand for themselves for upcoming failures.

In this chapter, we will first go into what a control chart is and the selection of a type of control chart to use. After this general theory, we will go into how the control charts are constructed for the bearings. After that, three different cases will be worked out and analysed to see the working of this method. Further analysis of the signal and trend will be performed to get insights into the defect detection.

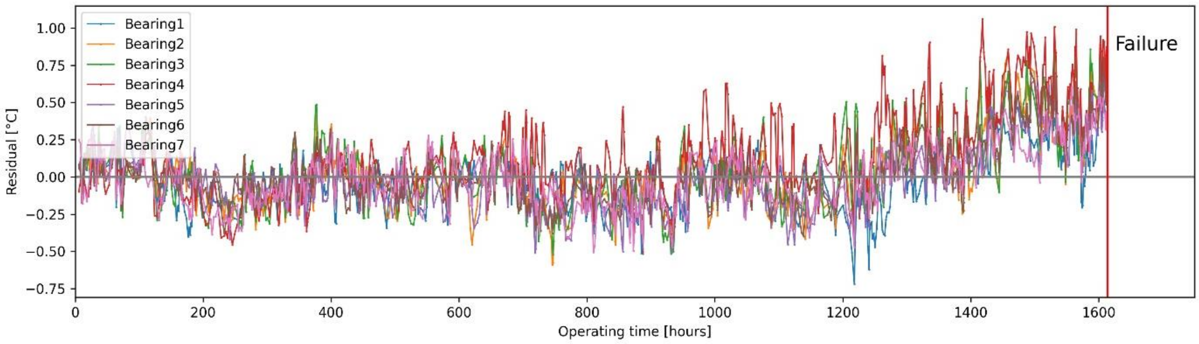


Figure 40: Residuals plotted over time of case I

6.1. Theory control chart

To find statistical changes in the residuals, the technique of control charts is used. This method is a statistical process control tool (SPC) and first introduced by Shewart back in 1924. It was designed to monitor the quality of produced goods. In normal circumstances, a certain natural amount of variation will be present in the process, but if this changes, it would come out of this normal behaviour and marked as out-of-control, which means that something happened and that the process is disturbed. Degradation could be one of the sources of variation in the process (Mehrafrooz & Noorossana, 2011).

A standard control chart consists of a few important elements, an example is given in Figure 41. There is a central line corresponding to the mean of the process and an upper and lower limit which is 3σ from the central line. The points represent observations, which should fall within the control limits with a 99.9% probability if the process is stable. This is the first phase in which the process is in-control and corresponds to having a bearing of which the condition is good. The ARL_0 is the average run length before an observation will exceed the control limits given that the process is still in control, corresponding to a false warning.

When points fall outside the limits, the process mean has likely shifted and the system is found in phase two, out of control. The cause of this difference in behaviour is expected to be from a defective bearing but could be caused by different factors that influence the physical behaviour. For the out-control phase, the ARL_1 gives the average running length until the control chart observes this change. Ideally, the system has an early detection (small ARL_1) and a low amount of false detection (high ARL_0).

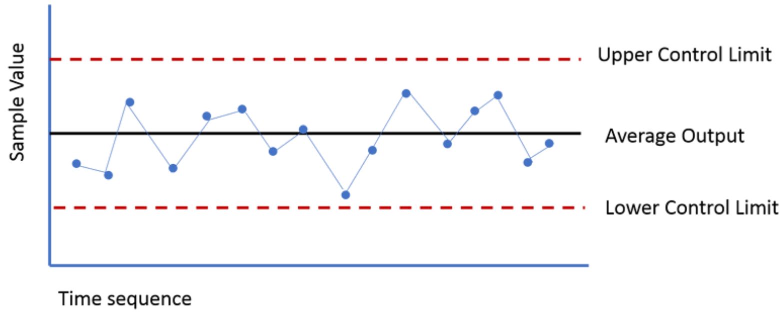


Figure 41: Example graph of Shewhart control chart

A rule for signals is having an observation outside the control limits. Besides that, there are other rules to detect not-random patterns. Statistically, these rules are set to detect activities that are unlikely to occur when the process is randomly distributed. Increasing the number of rules, however, make the control chart more sensitive. An example of such a decision rule suggested in the Western Electric Handbook (1956) is eight consecutive points located on one side of the centre line.

Different kind of control charts
As mentioned in the book *Introduction to statistical process control* by Qiu (2013), there are three traditional used SPC charts, see Table 8. All the control charts are based on the theory of Shewhart, but all with their strengths. The CUSUM (cumulative sum) is a version in which the data points are cumulatively summed to find the change point in which the process is out of control. They are useful when it takes a sufficient amount of time for trends to grow because it takes all observed data into account. The EWMA (Exponentially weighted moving average) developed by Roberts (1959) has similar capabilities but is easier to implement. In the EWMA chart and exponentially weighted moving average is taken over the past points, another advantage of taking the average is that it works as a high-frequency filter.

Table 8: Advantages of different kind of control charts (Bucchianico, 2021)

Method	Advantages
Shewhart	Easy to implement, good at detecting large changes
CUSUM	Useful for the detection of small changes, theoretical optimality in certain cases
EWMA	Easy to implement, robust against non-normality

As can be seen in the timeline in Figure 40, there is an increase of around two sigma of the mean of the process before the failure occurs. Using the standard Shewhart chart is not suitable because that model is good in detecting large changes in the process. The implementation of a CUSUM chart is relatively complicated to implement and use. That is the reason why the EWMA chart chosen to use, which has similar performance and easier to implement.

6.2. Mathematical formulation EWMA control chart

The implemented theory about the EWMA control chart is from the book *Introduction to statistical process control* by Qiu (2013). The model will be based on a stationary situation just as in the work of Cambron et al. (2016) and Kenbeek et al. (2016). Because of the relatively long period in which the degradation will develop against the number of observations that will arrive, the central line and limit will converge fast. The control chart will be learned on an initializing period, corresponding to the first part of the data per monitored case.

The observations in our two-stage model are the residuals from the MLR model because this attribute is removed from its contextual anomalies. These observations are assumed to be independent and in the in-control period normally distributed with mean μ and variance σ^2. These tests are performed in section 5.5, although the independence is violated, the control chart will be used.

$$r_i = y_i - \hat{y}_i \qquad \textit{Formula 10}$$

The EWMA chart makes use of the statistic z_i which is the exponentially weighted moving average of point *i* with the smoothing factor λ. The effect of taking a higher smoothing factor is that newer data points are taken more into account. With a lower λ factor more previous data points are weighted more. Setting λ equal to 0.3, makes it able to detect progressive drifts and to capture sudden differences (Lucas & Saccucci, 1990).

$$z_i = \lambda r_i + (1 - \lambda) z_{i-1} \qquad \textit{Formula 11}$$

The centreline (C) of the graph is based on the mean of the initial period. Because we are analysing the residuals of the MLR model, which is solved by OLS, the μ_0 will be roughly zero. As found in section 3.34.6, the increase of bearing temperature compared to normal is the indication of a degraded bearing. Therefore, the focus is only on exceeding the upper control limit of the chart. Because the upper limit normally quickly converges and we got a long observation sequence, we will take a stationary upper limit into account. Therefore, the central line and control limit could be defined as follows:

$$C = \mu_0 \qquad \textit{Formula 12}$$

$$UCL = \mu_0 + \rho \sqrt{\frac{\lambda}{2 - \lambda}} \sigma \qquad \textit{Formula 13}$$

The μ_0 and σ will be estimated based on an initial period which is the beginning of the stable period, this is not intended to be the entire stable period. The coefficient ρ is chosen to achieve a pre-specified average run length of the in-control period, ARL_0. This ρ value could be determined based on the *xewma.crit()* function in the R-package *spc* version 0.6.5. For taking an $\lambda = 0.3$ and an ARL_0 of 8000 hours corresponding to the inspection interval, $\rho = 3.728$ is given.

As a rule, to generate warnings, it is chosen to look only at the multiple data points that fall outside the upper control limit. Identical to the work of Cambron et al. (2016), three consecutive points are taken. Looking at single data points that fall above the UCL the model will respond hard to outliers. In the case of using multiple rules, such as the rules from the Western Electric Handbook, the system will only get more sensitive, which is not recommended because of the slight autocorrelation that is observed in section 5.5. Therefore, warnings are generated if the following condition holds:

$$\{z_{i-2}, z_{i-1}, z_i\} > UCL \qquad \textit{Formula 14}$$

6.3. Results implemented control chart

In this section, the results of the defined statistical process control chart will be discussed. The EWMA control chart is implemented in Python as formulated in section 6.2. This gives the option to create these charts for the different bearings. Three different cases are tested with the defect detection. The first two cases are captured on a portside engine and the third case is from a starboard engine. It must be noted that in all graphs, the operating hours are levelled to start at zero, which means that these records do not correspond with the historical engine operating hour record. Also, not the entire life span of the components is shown.

6.3.1. Case I

The first situation which we will explore is a bearing that has failed during operating. The corresponding control chart is shown in Figure 42, with the defect at the end of the timeline. In this plot the first 800 operating hours are used as the initialize period, to learn the regression model and determine the SPC settings. The dotted line represents the mean of the in-control situation, which is located near zero. The UCL is based on Formula 13 set at 0.37 °C.

By analysing the exponentially weighted moving average, the signal first oscillates around the central line and in the end drifts upwards. Around hour 1300, the first warnings are given, but this trend seems to stabilize until hour 1400. From this moment, the number of warnings increases until the moment of failure. From an actual-time perspective, these warnings from operating hour 1400 to 1500 are more than a month previous to the failure. If we have a closer look at the data, the oscillating process will be related to the autocorrelation in the residuals. Given the time perspective of this pattern, it looks like minor maintenance actions cause it.

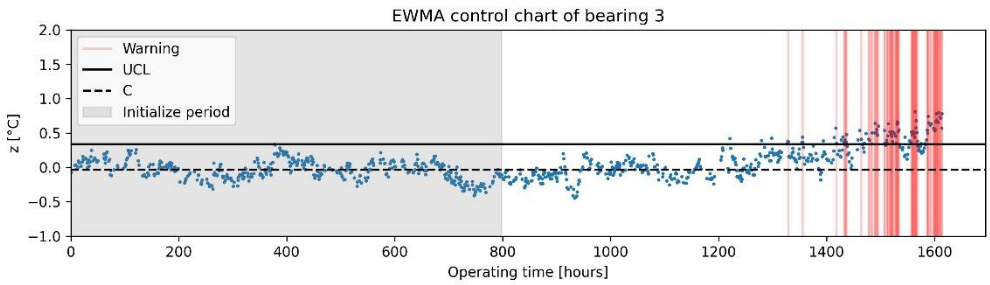


Figure 42: EWMA control chart case I, bearing 3

6.3.2. Case II

The second situation is shown in Figure 43, in this case bearing four is shown, which actually failed at operating hour 3149. Without knowing the further context, it seems that this failure could have been detected by making use of this control chart technique. Unfortunately, there is more to it than that. If we start from the beginning, again we see the data oscillating around the central line and from hour 2400 most data points above the central line. At hour 2720, there suddenly is an increase of one degree and the data points end up above the control limit.

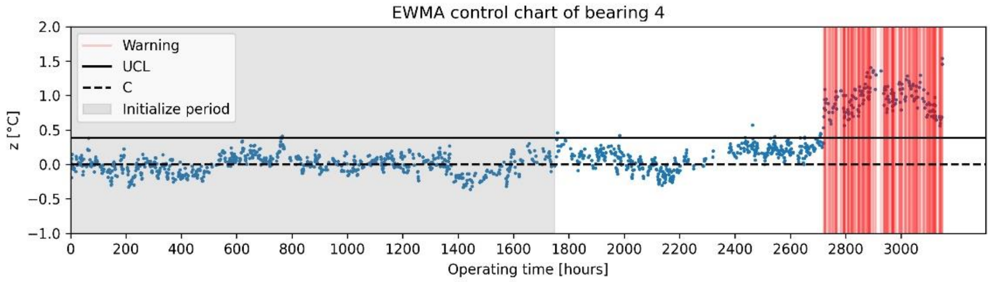


Figure 43: EWMA control chart case II, bearing 4

This sudden change did exactly happen after maintenance was performed to the engine and some parts were renewed, which had influenced the engine's performance. This has caused that under the same operational conditions, the bearing temperature becomes higher. In the first 200 hours, there is still an increasing trend visible so it could indicate the degradation of the bearing. But because of the influence of the maintenance, this is difficult to establish with certainty. To overcome this problem, the model should be continuously updated, especially after a maintenance moment.

6.3.3. Case III

The third case is presented in Figure 44. The same monitoring is performed on a starboard engine where no defect or failure has occurred. In the first 1150 hours, the data points behave similarly as seen in other cases. But after this point, the mean seems to be shifted upwards. Similar to case II, there is a maintenance action performed in which several components are adjusted. This affects the physical relation that is captured by the defect detection model in the initialize period.

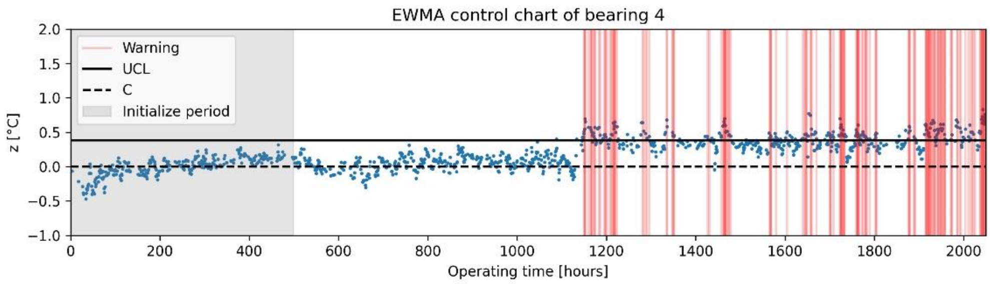


Figure 44: EWMA control chart case III, bearing 4 – maintenance causes warnings

To overcome this problem, the model must be initialized again after a maintenance action. This is performed in Figure 45, in which a second initialize period is added. After this relearning of the model, the pattern adjusts back around the central line. The outliers that were visible before are also removed. This indicates that the change in physical relation is not just a shift of the temperature upwards and therefore, the model had to be updated.

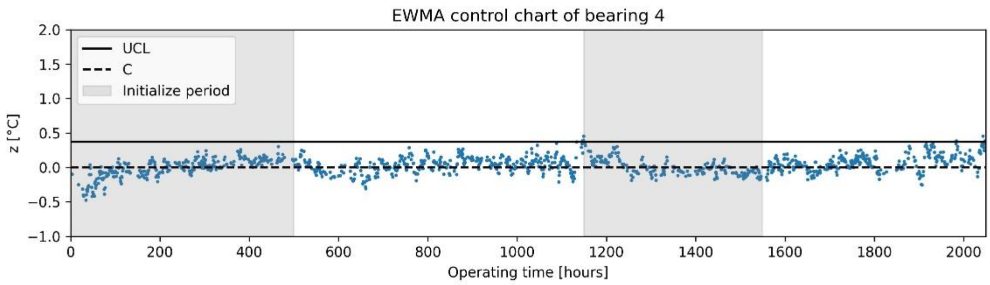


Figure 45: EWMA control chart case III, bearing 4 – after maintenance models again initialized

6.4. Analyses of the defect detection signal

In the previous section, we have seen that by making use of a control chart it is possible to detect defects. In this section, we will have a closer look at the visible trend by further analysing case I. This is performed by further analysing case I, presented in section 6.3.1. First, the signal development will be analysed. Second, we will show from this case the correlation between the defect detection of the other bearings.

6.4.1. Signal development

In Figure 46, the control chart from case I is plotted with additional markings. The first addition is the rolling mean of the EWMA residuals over a period of 200 operating hours. During the first 1200 hours, this is oscillating around the central line after which approximately linear increases starts until the moment of defect, at hour 1623. Because the trend starts around hour 1200, this is to be seen as the moment the system gets out-control. The found increase in this graph is 0.137°C per hundred hours until the inspection in which the defect is found. This means that the probability of getting a warning slowly increases. While the mean is drifting up the spread of the data points stays similar.

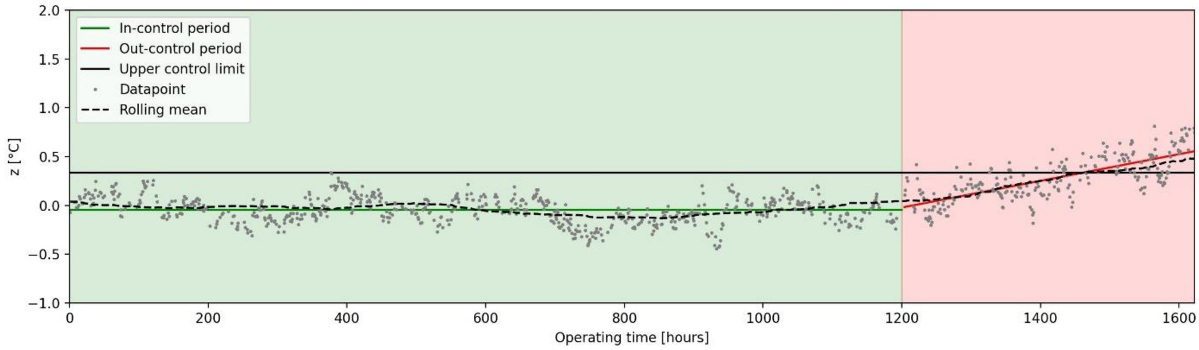


Figure 46: Annotated EWMA control chart case I, bearing 3

6.4.2. Multiple bearings

In the diesel engine, multiple main bearings are installed to support the crankshaft. These are located around the different pairs of cylinders. In this section, we investigate the correlation between the different bearings concerning defect detection. Therefore, the EWMA control charts of all bearings are shown for case I in Figure 47 until Figure 53, these plots are shown in full size in appendix V.

By analysing these graphs, we see that the increase in temperature is not only present at bearing three but on all bearings. The moment at which the first warnings are given varies over the different bearings. The bearings that face the most loads (2, 3 and 4) are the first to give warnings. This correlation shows that the degradation of these bearings is correlated with each other. In the oscillating process during the first 1200 hours, there are also some similarities visible. This indicates a part of the physical relation not encountered in the regression model, which is expected to come from the minor maintenance actions mentioned in section 6.3.1.

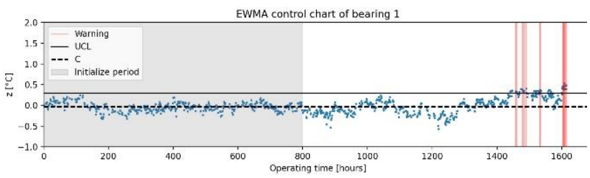


Figure 47: EWMA control chart of bearing 1

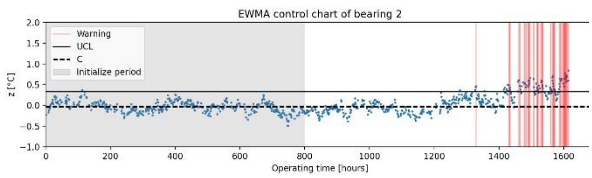


Figure 48: EWMA control chart of bearing 2

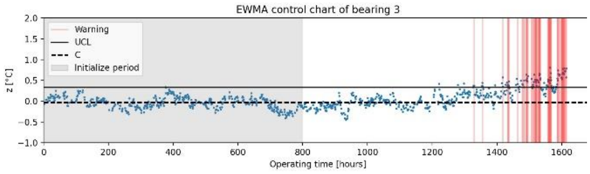


Figure 49: EWMA control chart of bearing 3

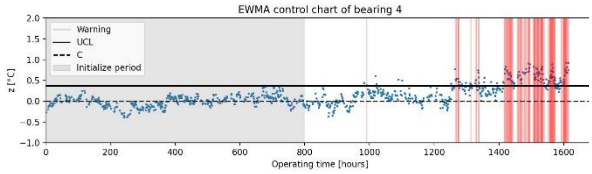


Figure 50: EWMA control chart of bearing 4

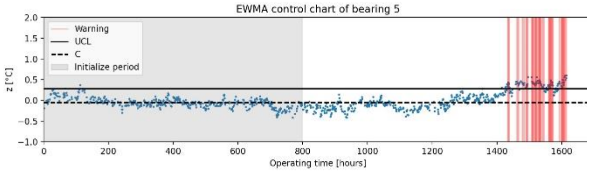


Figure 51: EWMA control chart of bearing 5

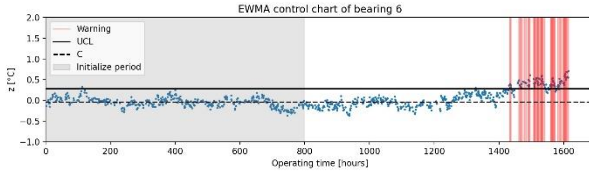


Figure 52: EWMA control chart of bearing 6

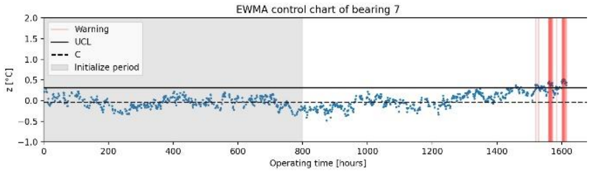


Figure 53: EWMA control chart of bearing 7

6.5. Intermediate conclusion RQ4

How could a defect detection of the main bearings be generated using a data-driven model?

This research question focuses on how the available data and acquired knowledge about the main bearings could be transformed into useful insights in the form of defect detection. In answering the previous research questions, it was found that the available temperature sensors could be used to create a defect detection. Due to the variating operating conditions, a two-stage model, as used by Chow & Willsky (1980), is convenient to use for the defect detection for the main bearings. The difference between the expected and measured temperature gives insight into the additional friction caused by the deterioration.

The MLR model, as shown in chapter 5, is able to capture the physical behaviour of the bearings. The advantage of this type of regression model is that it is understandable, making implementation within the organization feasible. The regression model residuals are a useful attribute for statistical process control because it is removed from the operational conditions. Using the EWMA control chart, the bearing temperature could be monitored, as shown in Figure 42. As expected, a raise of the residual is visible before the actual failure, corresponding to an increasing bearing temperature compared to the predicted temperature.

This model is implemented on the actual collected IPMS data of the main bearings of two different diesel engines. Based on this, we can conclude that this model is capable of detecting defects in front of actual failures. The warnings are generated approximately 200 operating hours before the actual failure, which is when constantly operating just over a week ahead. But in the actual situation, this would have been 1.5 months before failure.

7. Implementation of defect detection in the maintenance process

The focus of this chapter will be how the generated warnings could be implemented in the maintenance process with the goal to increase reliability. The imperfection of the warnings, as seen in section 6.3, must be taken into account. First, the current policy will be expanded with additional warnings from the defect detection model. Second, the potential advantage of the implementation is explored.

7.1. Putting the data-driven defect detection model into practice

Looking back at the set research goal, reliability is an important factor to improve. The definition of reliability set in ISO 8402 is: '*The ability of an item to perform a required function, under given environmental and operational conditions and for a stated period of time*' (Rausand and Hoyland, 2003). This is a general definition that implies for the main bearings did not fail, as defined in section 3.2. Missions, which take several days that should not be interrupted by sudden failures, define the duration of the period for the RNLN.

When warnings occur, different operational decisions could be made (Haddad, 2011). Before determining how these warnings should be handled, we must consider the consequences and importance of these (improved) warnings. These warnings are in favourable circumstances to predict defects hundreds of hours in advance, which we can conclude from case I, section 6.3.1. This implies that it is not possible to make decisions before the deployment of multiple months, in which the engine is used for thousands of hours.

Another question that would raise quickly is, should the engine be shut down when a warning arrives to prevent a failure. For that question, we should go into the used definition of a failure. As earlier described in section 3.2, a failure is when the safety system of the diesel engine detects a too high bearing temperature and shuts down the engine preventively. This interruption of the safety system prevents catastrophic failure. Therefore, the warnings should not be used to shut down the engine immediately.

Given the time perspective and the importance of warnings, it should not mean there is no opportunity to use this information to increase the current policy. It could be seen as an improvement of the current warnings generated by too high temperature or from oil analysis. It is possible to prevent the failure from happening during a mission and prepare the maintenance intervention in an additional maintenance moment.

The operating crew on board could be informed about the observed degradation and advised to adjust the propulsion configuration. This alternative is possible because OPVs are able to propel on multiple configurations, such as, single or both engines or using electric propulsion. This operational decision minimizes the operational hours, which extends the period before maintenance must be performed. This prevents failure so that both engines could still be used if necessary.

7.2. Implications on the current maintenance policy

The current state of research of data-driven maintenance at RNLN is still at the exploration phase, as explained in section 1.2. Therefore, for implementation to be successful, it should be applied besides the current usage-based policy. The current policy, as introduced in section 2.2, is therefore expanded with the improved warnings shown in grey, see Figure 54. This procedure consists of validating the warning before taking maintenance decisions because of the expected imperfection. This is, for example, visible in Figure 50, in which a single warning is generated before the actual trend started. This validation could be a task for a 'control tower,' as often referred to in the MARCONI project, which currently could be coordinated by the operational engineering.

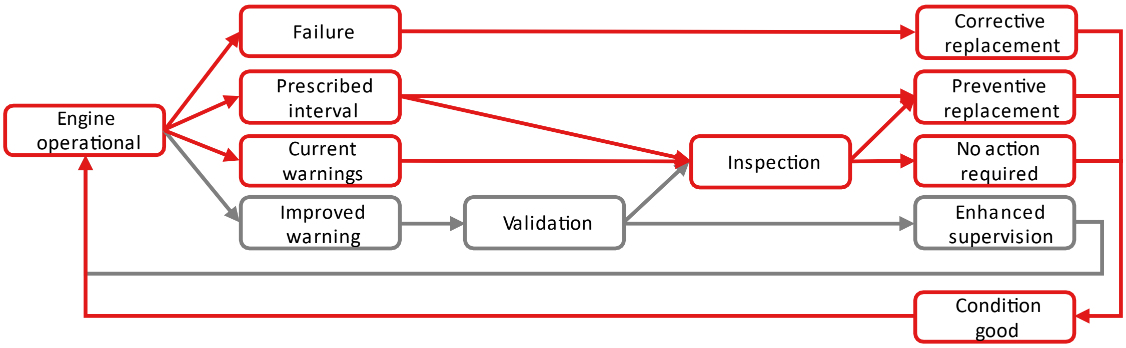


Figure 54: Expansion of maintenance policy with in grey the additional procedure for warnings

Control tower - Validation process

Experts in the control tower should validate warnings by performing actions that could be done without interrupting the operational tasks of the vessel, for instance, analysing the data or taking additional oil samples. The data could be analysed on outliers in the measurements online. Also, lubrication oil monsters for additional debris monitoring could be taken without the need to go to a harbour and to open the engine.

After an initial warning, the equipment could be taken under enhanced supervision by the control tower and involved specialists. During this period, the crew on board could be advised about the engine usage and involved in the enhanced supervision. Because of the increasing trend, as determined in case I in section 6.4.1, the first warnings will not be conclusive. The advantage of the initial validation is that it could be performed without affecting the current operations of the vessel. Also, the costs of these actions are lower as performing a full visual inspection. Which validation action should take depends on the moment in which the warnings arrive. Before a deployment, actions will be taken more quickly than during the deployment.

Performance

The situations that should be avoided are false negative and false positive warnings. In the situation of a false negative, there is no warning given while the actual condition of the bearing is defect. Because actions are only taken after a warning, this will not be captured by the defect detection model. For the defect detection performance, this is not favourable, but the current policy always has a worse performance because there is no monitoring system. As we saw in section 6.4.1, the mean temperature difference compared to the normal situation increased slowly. This indicates that the probability of getting no warnings while the bearing is defective decreases over time.

False positives are warnings that are raised while the actual condition of the bearings is good. When a simple outlier causes this, it is straightforward to validate that there is nothing. When there is an actual increasing trend visible, more validation must be performed. It can never be excluded that after validation, unjustified inspections are still carried out. Concerning reliability, this is no factor, but it will result in higher costs and decrease trust in the system, as Berrade et al. (2015) mention.

7.3. Advantage of the proposed maintenance policy

In the previous section is explained how the warnings could be implemented in the current policy. In this section, the aim is to give insight into the benefits related to the reliability of implementing the described policy. To be able to perform these analyses, the degradation process is captured in a mathematical model. This allows comparing the current policy with the just-explained expansion addition of warnings. Different assumptions are taken to capture the degradation process in a mathematical model to be able to indicate the advantages of the model. These simplifications are elaborated in appendix VI.

In principle, the degradation process for all bearings is captured in one delay-time model making uses of the three states as defined in section 3.2. While there is a limited amount of failure data available, the parameter estimation of this model is difficult. It is chosen to fit the parameters of the different distributions used in the delay-time model based on the current maintenance policy. The performance of the warnings in combination with the validation is captured in a general factor (*n*), corresponding to the number of defects that would have been successfully detected before the actual failure.

The delay-time model is implemented in a Python script to analyse two different situations. Firstly, the current policy, which will lead as the reference case. Secondly, the situation in which there are successful defect detections implemented. With this second situation, the impact on reliability could be found.

7.3.1. Reference situation – current policy

The result of the reference situation with the current policy is given in Figure 55. The graph shows the expected cycle-end given a certain inspection interval (τ). The probabilities of the different cycle-ends are stacked on top of each other to give a complete view. The different outcomes are shown in different colours. With green and orange, the bearings reached the inspection and are found in good and defect condition, respectively. A failure, shown in red, means that before the inspection, the bearings failed. These are the events that the RNLN would like to avoid. The dotted lines give the maximum inspection interval while having reliability of 95%.

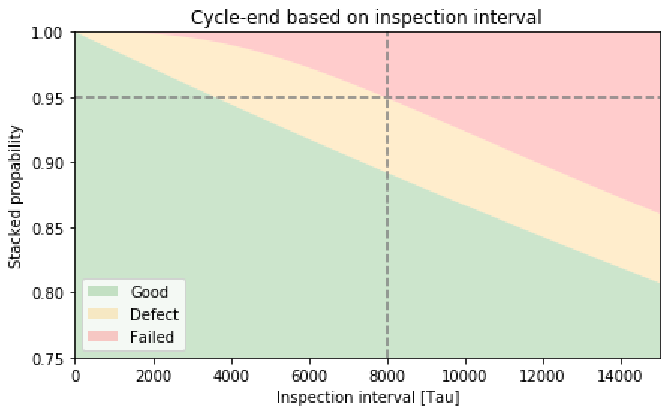


Figure 55: Results of reference situation

7.3.2. Improved policy including warnings

In Figure 56, the influence of the warnings is added to the analyses. The defects that are found making use of the improved warnings are shown in blue. This corresponds to inspections before the pre-described inspection moment, where the defects are discovered. The black dotted lines give the increase in reliability or the increased inspection interval. One of the first things to notice is that there is no change in the probability of 'Good.' This makes sense because the defect detection model does not influence the degradation process of the main bearings.

When analysing what the improvements are of the defect detection model, there are two things to conclude. First, when keeping the same inspection interval, the expectation of a failure will decrease by 50%. Before the failure happens, the defect detection model has interrupted the cycle. Second, when sticking to the same reliability level, the inspection interval could be extended from a reliability perspective. The increase in this situation will be roughly 4000 hours. The defect detection model captures defects, so the change of a facing a failure decreases. It must be noted that the size of the improvements found depends on the mathematical formulation of the problem and the parameters used. Therefore, one should be careful with the interpretation and more focus on the general insight.

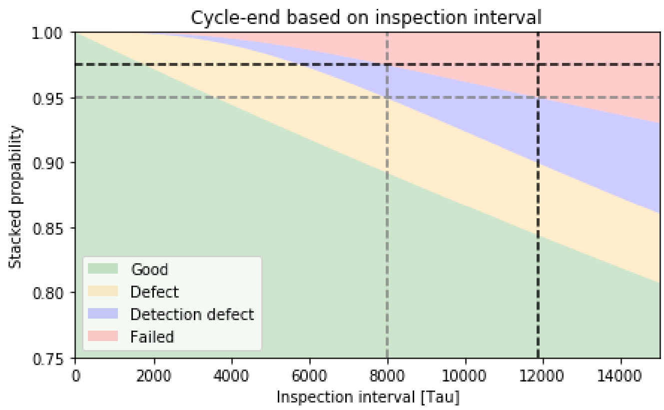


Figure 56: Results with improved policy

7.4. Intermediate conclusion

7.4.1. Conclusion RQ5

How could the developed defect detection model of the main bearings be used to make maintenance decisions to increase reliability?

The developed defect detection model is able to detect defects reliable hundred to two hundred hours in advance of failures. This relatively short before a failure compared to the duration of deployment determines that prediction in front of deployment is not possible. Additionally, the created defect detection model is sensitive to other maintenance activities. Therefore, it is concluded that a validation step must be performed before acting on the warnings. This validation and coordination of enhanced supervision could be performed from a control tower. The warnings and data could be further analysed by data analytics or additional oil samples. Both are actions in which the operational process of the main diesel engine is not restricted. Another action for the control tower is to advise the crew onboard to limit the usage of the engine to gain time for analyses and scheduling of the maintenance activity.

7.4.2. Conclusion RQ6

What are the advantages of implementing the developed defect detection model for the maintenance process?

To determine the advantage of the implementation of the developed defect detection model, the policy is captured in a delay-time model. This is used to predict the probability of having a certain condition at the inspection interval. The advantage of the developed defect detection model depends on the operational strategy. The RNLN prefers to keep the current inspection interval as described by the OEM. The benefit of this strategy is that the reliability increases because the number of sudden failures will decrease. Otherwise, it is possible to increase the inspection interval without compromising on the current reliability level. Depending on the preference finetuning between reliability and inspection interval is also possible.

8. Conclusion, discussion and recommendations

This chapter contains the conclusion of this explorative research to data-driven defect detection. Further, the research limitations are discussed, with the focus on identifying gaps for follow-up research. To extend the work further in creating added value for the maintenance process at the RNLN based on data-driven maintenance.

8.1. Conclusion

In this thesis, a data-driven defect detection model is created for the main diesel engine's main bearings. For the development of this monitoring approach, different steps are taken, captured in different research questions. In this section, these conclusions will be summarised to answer the main research question.

> *How could the available data of the main diesel engines of the oceangoing patrol vessels be used to create a defect detection of the main bearings to make maintenance decisions to increase the reliability of this critical asset?*

The main bearings in the diesel engine support the crankshaft and allow it to rotate with limited friction. A failure of a bearing results in the unavailability of the entire engine, influencing the operational availability of the vessel. The bearings are considered failed when the safety system of the engine performs an interruption and shuts the engine down. The degradation of the main bearings is limited thanks to proper lubrication, correct design and good operating conditions (Bloch & Geitner, 1997). When defective, there are marks from abrasive wear or cavitation that exceed the limit.

As stated in the main research question, the project focuses on the available data of vessels part of the Holland class. Temperature monitoring of bearings has been performed in the past (Kenbeek et al., 2016; Neale, 2001; Touret et al., 2018; Wilkinson et al., 2014). In the data collected from the IPMS, it is found that there are bearing temperature sensors that could be used. Before these sensor readings could be used to generate warnings, data preparation must be performed. The transient behaviour should be removed to get to the actual thermodynamic behaviour of the main bearings. The data should be made compact to generate useful data records for analysis.

With the defect detection model, the moment that bearings are defect must be captured. Because the operational condition of the main diesel engines varies, it is chosen to use a two-stage strategy. First, residuals generation is performed in which the temperature observations will be removed from the contextual anomalies. With a regression model, the expected temperature could be predicted based on explanatory variables, $\hat{y}_i = f(X_i)$. The difference between measured and predicted temperature is the residual that will be further used. Second, the residuals analyses which is used to detect a shift in residuals. SPC is a method that could be used to determine when the bearing temperature significantly is increased, indicating a defect.

This method is implemented on the available data making use of MLR to predict the bearing temperature and EWMA control charts to monitor the residuals. From the analysed cases, it can be concluded that this method is able to detect a defect in front of failure. The increasing temperature is visible and the signal is well developed 200 hours before failure. It is also found that the model is sensitive to maintenance actions. These actions influence the physical relation of the main diesel engine.

In the strategy towards data-driven maintenance, the created defect detection model should first be deployed beside the current policy. To cope with the imperfection for making maintenance decisions, the warnings should first be validated. This is managed by a 'control tower.' Validation consists of data analyses and could be extended with additional oil samples. When keeping the same inspection interval, the probability of sudden failure will decrease because the monitoring system could foresee them.

To summarize, the available IPMS data could be used in the defect detection model to detect increasing bearing temperature, which indicates degradation. Because other causes could influence this signal, validation of the warnings is important. At the possible detection of defects, maintenance actions could be undertaken to perform inspection and when necessary, preventive maintenance to prevent failures.

8.2. Discussion and direction future research

This research answers how the available data could be used to monitor the condition of the bearings. The used approach has potential but is a proof of concept. This brings several limitations concerning implementing the model in the maintenance process of the RNLN. In this section, the different aspects of the developed data-driven defect detection model will be reviewed and options for future research are given.

Capabilities of the defect detection model

The user of the developed defect detection model should understand the model's capabilities. The model is built to detect the increasing temperature trend. Prediction is not included because the underlying physical relation can not be determined with the limited amount of failure data. In case other failure mechanisms occur in the future with a different failure mode, the model might not be able to detect the defects. The developed model covers only the bearings. To detect defects of other components, separate models should be built. A failure of these other components could cause consequential damage, for example, when the oil supply is inefficient due to a defective oil pump.

The model is also built the be able to handle non-stable operations. Due to the filter limiting the autocorrelation as introduced in section 4.5, long constant operations are not monitored. This happens, for example, during a long ocean crossing in which the engine is used constantly. This design choice is made to monitor the varying operations that represent most of the usage of the engine. Another fundamental note must be made about the number of defects and failures that will occur. Because the model does not influence the degradation of the main bearings, the number of defects will not decrease. Only failures could be prevented by early detection. For decreasing the number of defects, preventive actions must be taken to prevent the cause of degradation.

Validation of the monitoring approach

For the validation of the monitoring approach is a limited amount of failure data available. The individual parts (regression and control chart) are known models which could be validated as, for example, performed in section 5.5 for the regression model. For the entire defect detection model, the observed pattern over the complete timeline is analysed with maintenance engineers. In this analysis, the model is verified by linking the visible pattern to expected changes after real-world actions are performed to the engine. An example is the graduate temperature decrease after installing new bearings, which correspond to break-in wear.

Takeaways of the project

The developed models are made to show the potential there is in the available IPMS data. The currently developed models are not built for direct implementation. Several aspects must be improved to make it functional. This starts with the data acquisition, the data gathering from the vessel to the analyses must be automated, without the delay of three months because of confidential reasons.

The models are made based on a specific selected initialize period which was the stable period. When deploying the models, it is impossible to determine the learning periods as in this research. From bearings, it is known that after installation, break-in wear occurs in which the temperature decreases (Bloch & Geitner, 1997). This makes the learning of the model challenging because the first operating hours will not directly be the stable period used to learn the model now.

The effect observed of maintenance actions on the physical relation needs extra attention. During the maintenance action, the defect could have been initiated. When comparing cases II and III in section 6.3, the scale of shift is different, in which case II had a bigger shift and is soon failed. This magnitude of shift could be an indication of whether the maintenance causes the defect. More maintenance actions should be analysed in future research to determine what could be classified as a typical shift and where potentially a defect has been introduced.

Used models

In this thesis, monitoring is performed individually per main bearing, using MLR for the residual generation and the residuals evaluation with EWMA control charts. These models are both selected based on qualitative considerations. They have proven to be capable of detecting the defect before the failure and therefore show that the monitoring approach has potential. However, these models are not necessarily optimal. Within the used models, improvements could be made in future research, such as using non-linear transformations for input attributes in the MLR and multi-variate control charts could be explored to improve the results.

Correlated residuals

The assumption of (identical) independently distributed residuals is made for the MLR and EWMA control chart. As Qiu (2013) stated, correlation among the observed data at different time points would have a substantial impact on the performance of the EWMA control chart. A part of the correlation is successfully removed by filtering on the operations, as explained in section 4.5. As seen in the residuals analyses in section 5.5, the assumption is still violated. Nevertheless, the models are created and used. The remaining correlation is expected to be caused by minor maintenance actions because the maintenance interval is in accordance with the found pattern.

Discretization of condition

In the thesis, the bearing condition is set to three discrete states. The degradation evolves actually on a continuous scale. In the analysed case in section 6.4.1, the increasing temperature started around 600 hours before the failure. Because the bearings are not inspected regularly during the installation, it is unknown how the degradation development happened. With the monitoring approach, only the moment in which the bearing temperature is increased, is detected. Therefore, it is not possible to prove whether this point is equal to the moment in which the bearing exceeded the wear limits.

Managerial insights

The goal of created analytics was to give a visual impression of the impact of defect detections. The specific advantages of implementing the defect detection model are difficult to describe. Distributions are unknown and the complete policy is complex to model. The use of mathematical formulation gives just limited insights because the distributions are unknown. With the multiple assumptions made, different aspects are not included, for example, having false positives and early detection of defects are not included.

8.3. Recommendations

In the previous section, the limitations of the research are discussed. Three major recommendations arise from this research and are described in this section. This contains the three paths that should be performed in follow-up studies at the RNLN.

Implementation

In this research, it is shown that the presented monitoring approach is capable of detecting defective main bearings of the main diesel engine. The next steps should be taken towards implementation. Having specific applications are important in the exploration of data-driven maintenance. Therefore, work should be carried out to translate the results into a pilot project. This pilot needs to focus on making the analyses dynamic and the interface that is needed to make it understandable. Moreover, maintenance engineers must be involved because they are responsible for making the maintenance decision.

Increase the number of assets monitored

This research focuses on the main diesel engines of the Holland class. In future research, the same technique should be implemented for other vessels at the RNLN. This is possible because the sensors that are used are also installed on other engines. But in a new situation, the best attributes to be used should be explored again. Expanding the amount of performed analyses will give a better understanding of the model performance. The same approach could also be used to monitor other (plain) bearings that are, for example, placed to support the propellor shaft.

Improve quality

As mentioned in the discussion, multiple aspects could be further improved to optimise the defect detection model. It is recommended to improve these actions in future studies to improve the quality of the defect detection model. In the current build model, techniques are used that were understandable. This shows the principles of the monitoring approach. Future models may be more complex and considered black-box models but could be verified using understandable white-box models. The specific steps that could be improved include the data sampling, type of regression model and exploring the use of multivariate control charts.

References

Antunović, R., Halep, A., Bučko, M., Perić, S., & Vučetić, N. (2018). Vibration and Temperature Measurement Based Indicator of Journal Bearing Malfunction. Tehnički vjesnik, 25(4), 991-996.

Berrade, M. D., Scarf, P. A., & Cavalcante, C. A. (2015). Some insights into the effect of maintenance quality for a protection system. *IEEE Transactions on Reliability*, *64*(2), 661-672.

Bloch, H. P., & Geitner, F. K. (1997). Practical Machinery Management for Process Plants: Volume 2: Machinery Failure Analysis and Troubleshooting. Elsevier.

Bondyopadhyay, P. K. (1995, September). Guglielmo Marconi-The father of long distance radio communication-An engineer's tribute. In *1995 25th European Microwave Conference* (Vol. 2, pp. 879-885). IEEE.

Cambron, P., Tahan, A., Masson, C., & Pelletier, F. (2017). Bearing temperature monitoring of a Wind Turbine using physics-based model*. Journal of Quality in Maintenance Engineering*.

Chen, J., & Patton, R. J. (2012). Robust model-based fault diagnosis for dynamic systems (Vol. 3). Springer Science & Business Media.

Cheng, Y., Wang, Z., & Zhang, W. (2018). A novel condition-monitoring method for axle-box bearings of high-speed trains using temperature sensor signals. *IEEE Sensors Journal*, 19(1), 205-213.

Chow, E. Y., & Willsky, A. S. (1980). Issues in the development of a general design algorithm for reliable failure detection.

Dalheim, Ø. Ø., & Steen, S. (2020). Preparation of in-service measurement data for ship operation and performance analysis. *Ocean Engineering*, 212, 107730

De Schelde (2015) *Technisch Handboek Propulsion Diesel Engines Part 1* (Internal document, unpublished)

Di Bucchianico, A. (2021) *Statistical Process Control and Predictive Maintenance* Slides colloquium Primavera-project https://primavera-project.com/wp-content/uploads/2021/02/PrimaVeraColloquiumSPC_DiBucchianico.pdf

Ding, N., Li, H., Yin, Z., Zhong, N., & Zhang, L. (2020). Journal bearing seizure degradation assessment and remaining useful life prediction based on long short-term memory neural network. Measurement, 166, 108215.

Fillon, M., & Bouyer, J. (2004). Thermohydrodynamic analysis of a worn plain journal bearing. Tribology international, 37(2), 129-136.

Friedman, J., Hastie, T., & Tibshirani, R. (2001). *The elements of statistical learning* (Vol. 1, No. 10). New York: Springer series in statistics.

Frost, J. D. (n.d.). *Multicollinearity in Regression Analysis: Problems, Detection, and Solutions.* reviewed on 9 februari 2021, Retrieved from https://statisticsbyjim.com/regression/multicollinearity-in-regression-analysis/

Garner, D. R., James, R. D., & Warriner, J. F. (1980). Cavitation erosion damage in engine bearings: theory and practice.

Gomes, J., Gaivota, N., Martins, R. F., & Silva, P. P. (2018). Failure analysis of crankshafts used in maritime V12 diesel engines. Engineering Failure Analysis, 92, 466-479.

Grossmann, W., & Rinderle-Ma, S. (2015). Fundamentals of business intelligence. Springer.

Haddad, G. (2011). *An Options Approach to Quantify the Value of Decisions After Prognostic Indication* (Doctoral dissertation).

Heek, D.A. (2019) Research proposal (unpublished)

Hendry, D. F., & Nielsen, B. (2007). Econometric modeling: a likelihood approach. Princeton University Press.

International Organization for Standardization [ISO] (2008) Plain bearings - Appearance and characterization of damage to metallic hydrodynamic bearings - Part 2: Cavitation erosion and its countermeasures (ISO/DIS Standard No. 7146-2)

Jardine, A. K., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical systems and signal processing*, *20*(7), 1483-1510.

Karremann, J. (2020). Marineschepen van de Koninklijke Marine. Retrieved from https://marineschepen.nl/schepen/marineschepen-nederland.html

Kenbeek, T., Kapodistria, S., & Di Bucchianico, A. (2019, March). Data-driven online monitoring of wind turbines. In Proceedings of the 12th EAI International Conference on Performance Evaluation Methodologies and Tools (pp. 143-150).

Kumar, S., Goyal, D., Dang, R. K., Dhami, S. S., & Pabla, B. S. (2018). Condition based maintenance of bearings and gears for fault detection–A review. Materials Today: Proceedings, 5(2), 6128-6137.

Kutner, M. H., Neter, J., Nachtsheim, C. J., & Wasserman, W. (2004). *Applied linear statistical models (int'l ed)* (4th ed.). Maidenhead, England: McGraw Hill Higher Education.

Mehrafrooz, Z., & Noorossana, R. (2011). An integrated model based on statistical process control and maintenance. *Computers & Industrial Engineering*, *61*(4), 1245-1255.

Ministerie van Defensie (2020) Ministerie van Defensie – Defensie.nl. Retrieved from https://www.defensie.nl

Nabhan, A., Ghazaly, N., Samy, A., & Mousa, M. O. (2015). Bearing fault detection techniques-a review. Turkish Journal of Engineering, Sciences and Technology, 3(2).

Neale, M. J. (Ed.). (2001). Lubrication and reliability handbook Chapter 3. Newnes.

Nikolic, N., Torovic, T., & Antonic, Z. (2012). A procedure for constructing a theoretical wear diagram of IC engine crankshaft main bearings. Mechanism and Machine Theory, 58, 120-136.

Qiu, P. (2013). *Introduction to statistical process control.* CRC press.

Rausand, M., & Hoyland, A. (2003). *System reliability theory: models, statistical methods, and applications* (Vol. 396). John Wiley & Sons.

Roberts, H. V. (1959). Stock-market' patterns' and financial analysis: methodological suggestions. *The Journal of Finance*, *14*(1), 1-10.

Shewhart, W. A. (1931). *Economic control of quality of manufactured product*. Macmillan And Co Ltd, London.

Tapiero, C. (2012). *The management of quality and its control*. Springer Science & Business Media.

Tiddens, W. W. (2018). Setting sail towards predictive maintenance: developing tools to conquer difficulties in the implementation of maintenance analytics. Enschede: University of Twente. https://doi.org/10.3990/1.9789036546034

Tiddens, W.W., (2014) FMECA worksheet Pon CAT v3, Internal Royal Netherlands Navy (unpublished)

Tinga, T. (2013). Principles of loads and failure mechanisms. Applications in maintenance, reliability and design. (Springer Series in Reliability Engineering). London: Springer. https://doi.org/10.1007/978-1-4471-4917-0

Touret, T., Changenet, C., Ville, F., Lalmi, M., & Becquerelle, S. (2018). On the use of temperature for online condition monitoring of geared systems–A review. *Mechanical Systems and Signal Processing*, *101*, 197-210.

Vencl, A., & Rac, A. (2014). Diesel engine crankshaft journal bearings failures: case study. Engineering failure analysis, 44, 217-228.

Western Electric , *Statistical Quality Control Handbook,* AT&T , Chicago , IL , 1956

Wilkinson, M., Darnell, B., Van Delft, T., & Harman, K. (2014). Comparison of methods for wind turbine condition monitoring with SCADA data. IET Renewable Power Generation, 8(4), 390-397.

Wirth, R., & Hipp, J. (2000, April). CRISP-DM: Towards a standard process model for data mining. In Proceedings of the 4th international conference on the practical applications of knowledge discovery and data mining (pp. 29-39). London, UK: Springer-Verlag.

Wittel, H., Muhs, D., Jannasch, D., Voßiek, J. (2013) . Roloff/Matek Machineonderdelen: Theorieboek. BIM Media B.V. (Original work published 1993)

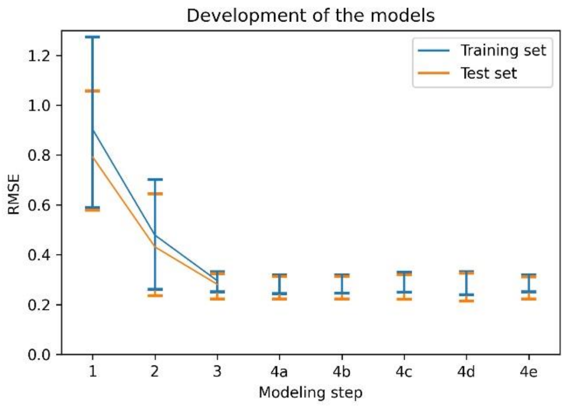
Appendix

I. Stepwise selection of attributes

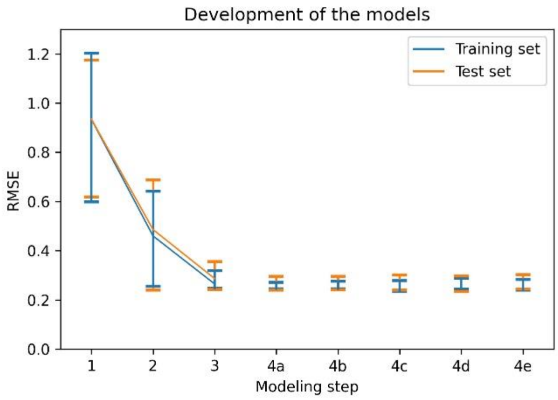
Attributes first step	Case I Train RMSE	Case I Test RMSE	Case II Train RMSE	Case II Test RMSE	Case III Train RMSE	Case III Test RMSE
x_{RPM}, x_{RPM}^2	0.9194	0.8117	0.9364	0.8187	0.9638	0.9817
$x_{RPM}, x_{RPM}^2, x_{fuel\ rack}$	0.6729	0.5695	0.5475	0.4965	0.5893	0.5737
$x_{RPM}, x_{RPM}^2, x_{oil_{return}}$	0.4265	0.4127	0.5003	0.4533	0.4810	0.5349
$x_{RPM}, x_{RPM}^2, x_{RPM\ TC}, x_{RPM\ TC}^2$	0.6798	0.5973	0.5889	0.5974	0.6423	0.6869
$x_{RPM}, x_{RPM}^2, x_{oil_{pressure}}$	0.7269	0.6342	0.6295	0.5643	0.6830	0.8136
$x_{RPM}, x_{RPM}^2, x_{oil_{supply}}$	0.7200	0.6551	0.7115	0.5971	0.9074	0.9090
$x_{RPM}, x_{RPM}^2, x_{HT_{supply}}$	0.7782	0.6666	0.8121	0.6748	0.8152	0.8127
$x_{RPM}, x_{RPM}^2, x_{HT_{return}}$	0.9167	0.8075	0.8234	0.6851	0.8460	0.8360

Attributes second step	Case I Train RMSE	Case I Test RMSE	Case II Train RMSE	Case II Test RMSE	Case III Train RMSE	Case III Test RMSE
x_{RPM}, x_{RPM}^2	0.9194	0.8117	0.9364	0.8187	0.9638	0.9817
$x_{RPM}, x_{RPM}^2, x_{oil_{return}}$	0.4265	0.4127	0.5003	0.4533	0.4810	0.5349
$x_{RPM}, x_{RPM}^2, x_{oil_{return}}, x_{fuel\ rack}$	0.3980	0.3825	0.4597	0.4075	0.3995	0.3827
$x_{RPM}, x_{RPM}^2, x_{oil_{return}}, x_{RPM\ TC}, x_{RPM\ TC}^2$	0.2682	0.2622	0.2972	0.2844	0.2657	0.2910
$x_{RPM}, x_{RPM}^2, x_{oil_{return}}, x_{oil_{pressure}}$	0.4208	0.4076	0.4948	0.4504	0.4603	0.5610
$x_{RPM}, x_{RPM}^2, x_{oil_{return}}, x_{oil_{supply}}$	0.4197	0.4055	0.4898	0.4452	0.4738	0.4994
$x_{RPM}, x_{RPM}^2, x_{oil_{return}}, x_{HT_{supply}}$	0.3578	0.3489	0.4289	0.4156	0.4343	0.4993
$x_{RPM}, x_{RPM}^2, x_{oil_{return}}, x_{HT_{return}}$	0.4237	0.4080	0.4320	0.4168	0.4401	0.4955

Attributes third step	Case I Train RMSE	Case I Test RMSE	Case II Train RMSE	Case II Test RMSE	Case III Train RMSE	Case III Test RMSE
x_{RPM}, x_{RPM}^2	0.9194	0.8117	0.9364	0.8187	0.9638	0.9817
$x_{RPM}, x_{RPM}^2, x_{oil_{return}}$	0.4265	0.4127	0.5003	0.4533	0.4810	0.5349
$x_{RPM}, x_{RPM}^2, x_{oil_{return}}, x_{RPM\ TC}, x_{RPM\ TC}^2$	0.2682	0.2622	0.2972	0.2844	0.2657	0.2910
$x_{RPM}, x_{RPM}^2, x_{oil_{return}}, x_{RPM\ TC}, x_{RPM\ TC}^2, x_{fuel\ rack}$	0.2569	0.2520	0.2894	0.2769	0.2545	0.2752
$x_{RPM}, x_{RPM}^2, x_{oil_{return}}, x_{RPM\ TC}, x_{RPM\ TC}^2, x_{oil_{pressure}}$	0.2567	0.2513	0.2939	0.2792	0.2525	0.2812
$x_{RPM}, x_{RPM}^2, x_{oil_{return}}, x_{RPM\ TC}, x_{RPM\ TC}^2, x_{oil_{supply}}$	0.2635	0.2570	0.2883	0.2760	0.2589	0.2790
$x_{RPM}, x_{RPM}^2, x_{oil_{return}}, x_{RPM\ TC}, x_{RPM\ TC}^2, x_{HT_{supply}}$	0.2568	0.2542	0.2864	0.2760	0.2570	0.2767
$x_{RPM}, x_{RPM}^2, x_{oil_{return}}, x_{RPM\ TC}, x_{RPM\ TC}^2, x_{HT_{return}}$	0.2678	0.2614	0.2869	0.2763	0.2579	0.2778



Development model Case II



Development model Case III

Resulting performance per bearing with final formula

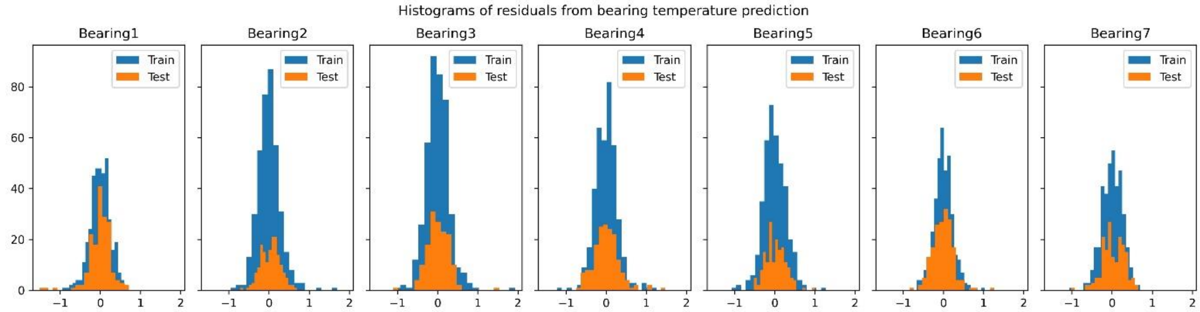
	Case I		Case II		Case III	
Model	**Train RMSE**	**Test RMSE**	**Train RMSE**	**Test RMSE**	**Train RMSE**	**Test RMSE**
Bearing1	0.2513	0.2504	0.3066	0.2906	0.3179	0.3555
Bearing2	0.2853	0.2408	0.3316	0.3129	0.2707	0.2843
Bearing3	0.2889	0.2886	0.3316	0.3246	0.2482	0.2763
Bearing4	0.2711	0.2907	0.2512	0.2223	0.2545	0.2424
Bearing5	0.2865	0.2659	0.2716	0.2388	0.2518	0.2769
Bearing6	0.2339	0.2366	0.3226	0.3023	0.2462	0.2958
Bearing7	0.2549	0.2570	0.2564	0.2774	0.2632	0.2742

II. P values of learned model

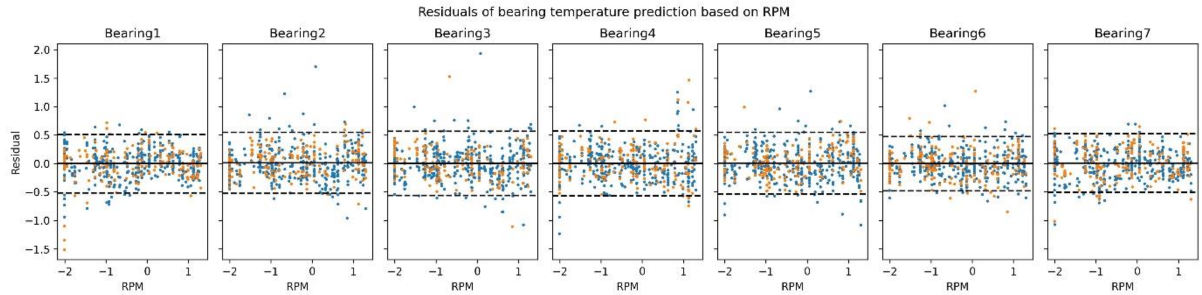
Final model	Intercept	RPM	RPM^2	Temp. oil out	RPM TC	RPM TC^2
B	$\beta_{1,b}$	$\beta_{2,b}$	$\beta_{3,b}$	$\beta_{4,b}$	$\beta_{5,b}$	$\beta_{6,b}$
Bearing1	0.00E+00	8.75E-220	1.02E-01	1.15E-111	3.92E-06	4.75E-47
Bearing2	0.00E+00	2.66E-200	3.55E-33	1.14E-117	1.60E-38	6.76E-81
Bearing3	0.00E+00	2.39E-219	9.22E-10	2.85E-125	2.35E-70	3.80E-101
Bearing4	0.00E+00	0.00E+00	1.17E-98	8.19E-163	NaN	7.98E-04
Bearing5	0.00E+00	1.93E-294	2.47E-72	4.33E-156	6.60E-21	4.64E-103
Bearing6	0.00E+00	1.71E-230	7.38E-27	4.80E-144	4.89E-24	1.21E-95
Bearing7	0.00E+00	1.14E-246	3.56E-08	1.62E-116	1.90E-07	2.18E-31

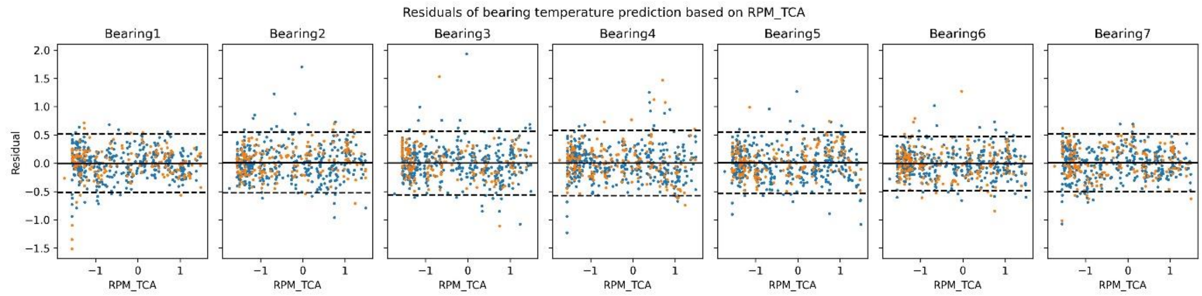
III. Graphs residuals of all explanatory variables

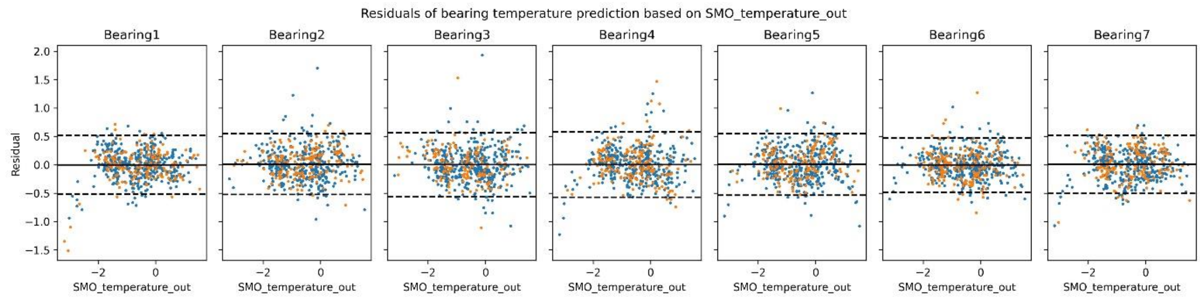
Residual distribution



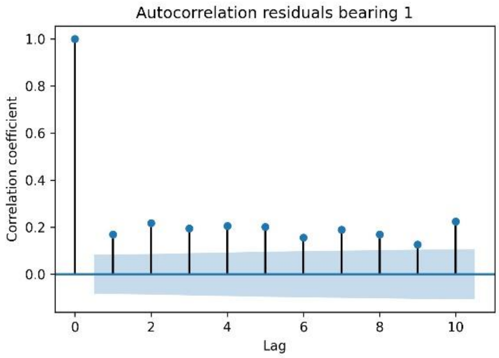
Explorational variables

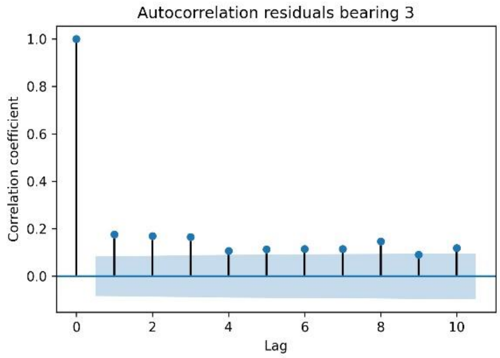


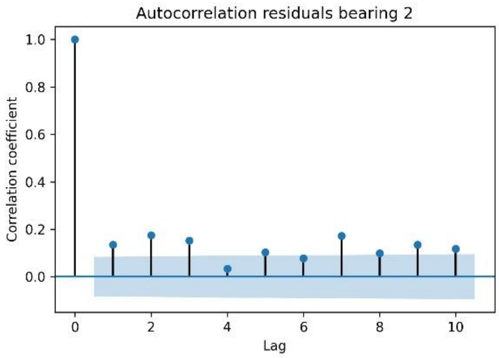


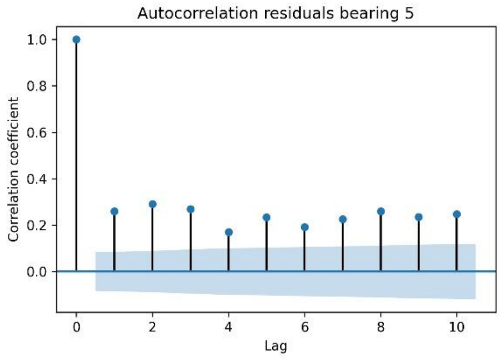


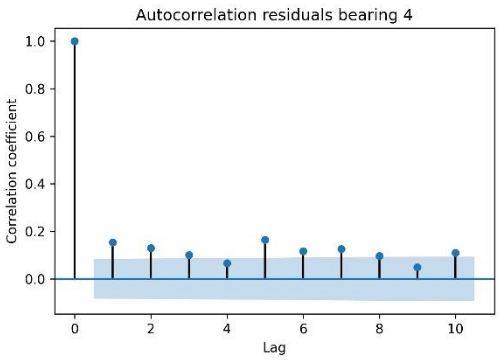
Auto Correlation Function plots

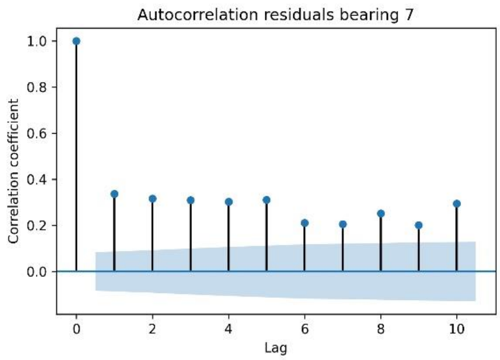


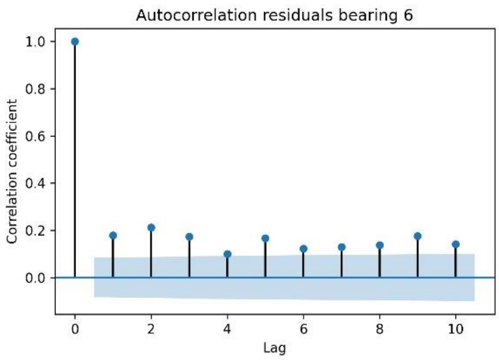






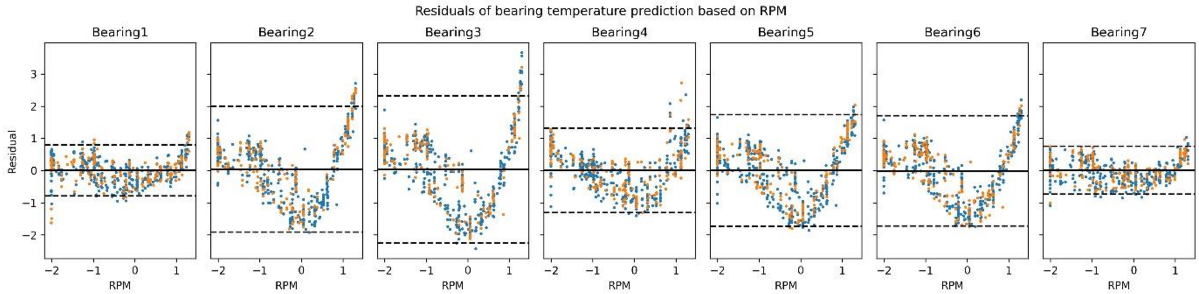


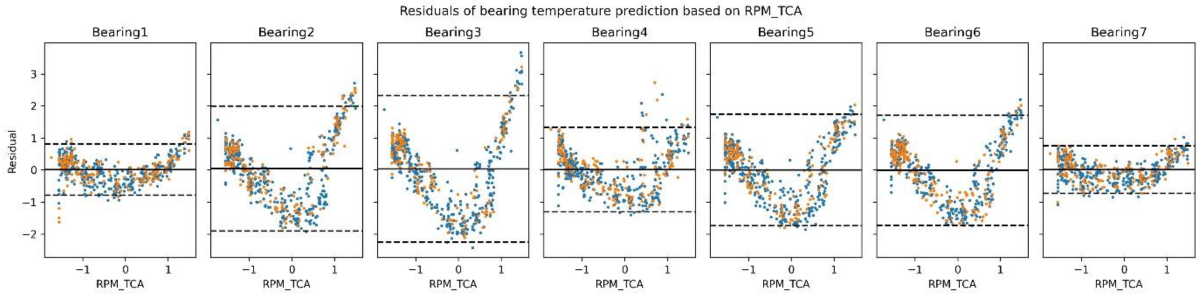


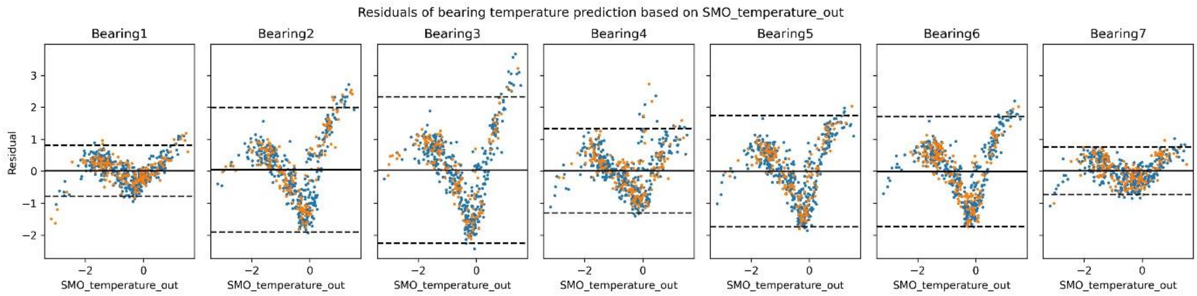


IV. Importance quadratic term

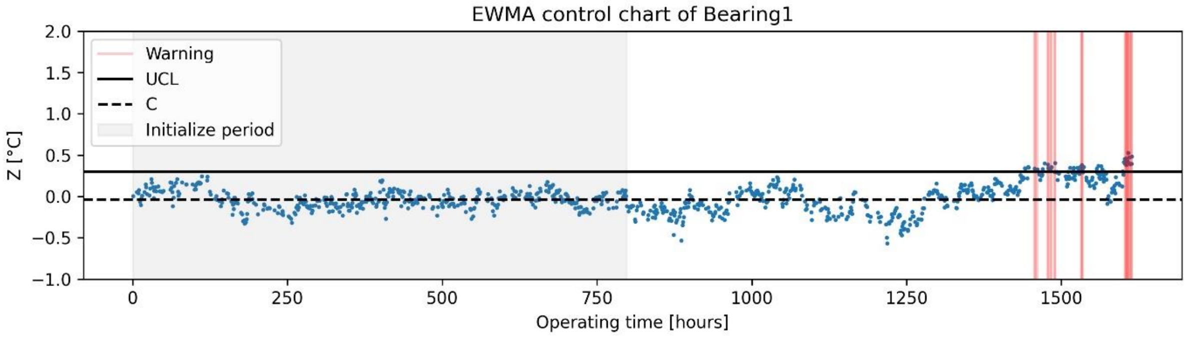
In the following plots the residuals are plotted for a model in which the quadratic terms are excluded. In these plots it is clearly visible that there is still a clear relation between the residuals and the explanatory variables. Therefore it can be concluded that the quadratic terms have added value.

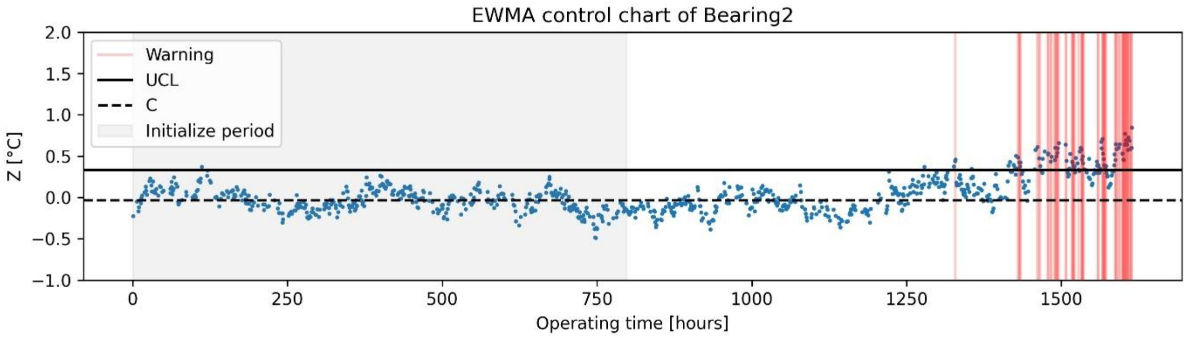


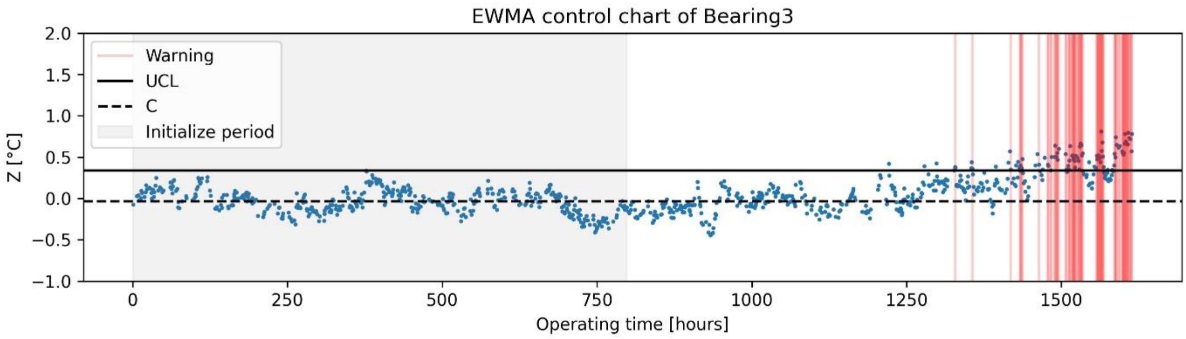


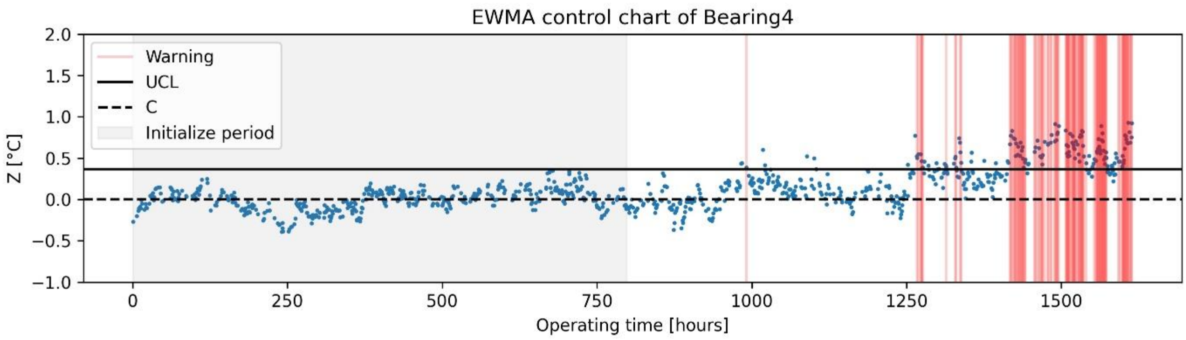


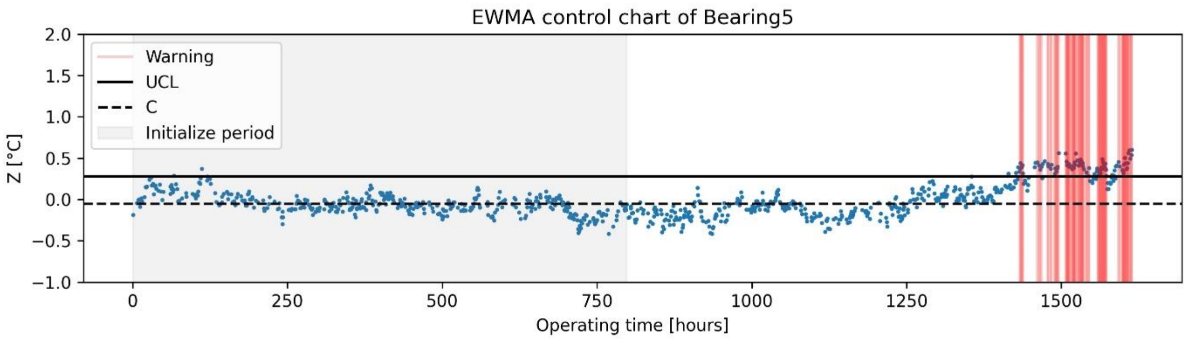
V. Plots case I all bearings

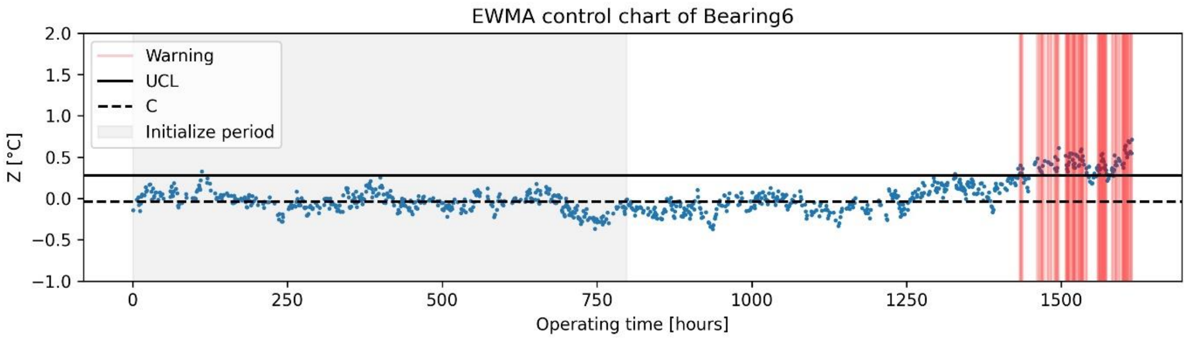


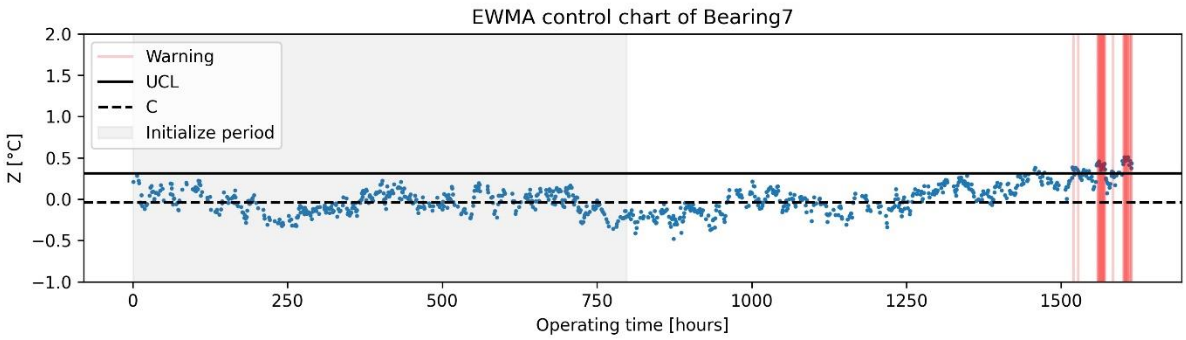







EWMA control chart of Bearing5
Warning
UCL
C
Initialize period
Z [°C]
Operating time [hours]
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
0
250
500
750
1000
1250
1500


EWMA control chart of Bearing6
Warning
UCL
C
Initialize period
Z [°C]
Operating time [hours]
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
0
250
500
750
1000
1250
1500


EWMA control chart of Bearing7
Warning
UCL
C
Initialize period
Z [°C]
Operating time [hours]
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
0
250
500
750
1000
1250
1500

VI. Formulation of the delay-time model

i. Assumptions/ simplifications

Different assumptions and simplifications are necessary to create a mathematical model of the degradation and maintenance process at the RNLN. In this appendix, these assumptions and simplifications are explained. It starts with the analytical model that is used to model the degradation process and follows by more detailed assumptions regarding the system and imperfection in the warnings and validation.

Analytical model

The degradation process will be modelled as a Markov process in the form of a delay-time model (Arts, 2017). This is different from the created defect detection model that is data-driven and does not rely on general lifetime distributions. The model has three sequential states, as shown in the Figure below, these correspond to the set definition in section 3.2. The lifetime (T) is the sum of the time to defect (X) and time to failure (Y). Based on the analysis in section 3.2 the time distributions are determined, exponential and Weibull respectively for time to defect and time to failure. This combination of distributions implies that defects occur randomly in time, but the defect development has time dependence. Analysing this policy based on the different cycle-end with the decision-making model gives insight into the performance.

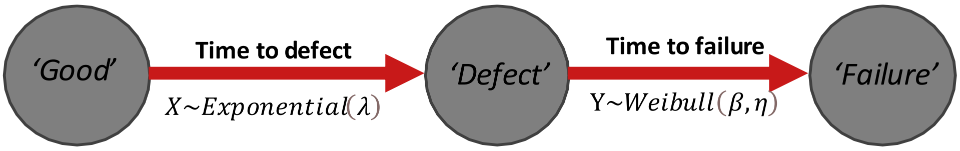


Figure: Schematically view of the delay-time model

Converting to one system

The seven main bearings in the diesel engine are in large degree correlated to each other. From the analysis in section 6.4.2, we saw that the increase in bearing temperature was visible for multiple bearings concomitantly. The bearings are also replaced in a group in the last maintenance actions, as mentioned in chapter 2. Therefore, as a simplification, the bearings are considered as one system with an identical time to defect and time to failure.

The imperfection of the defect detection model and validation process

As earlier mentioned in section 7.1, the warnings will never be able to predict all defects in advance. When simulating a signal as a condition indicator, not all imperfection of the real process could be included. The impact of the validation step is also difficult to replicate in a mathematical model. Therefore, the imperfection of the entire improved warning scenario will be implemented making use of a factor, n. Corresponding to the condition of successful detection, $w = True$. Because the temperature increase is just visible several hundred hours in advance and the defects are expected to be visible earlier, it is assumed that the moment of defect detection is equal to the failure time.

ii. Mathematical formulation

For the generation of insights, the process will be modelled. The focus will be on analysing the reliability given a certain inspection interval (τ). In the delay-time model, there are different cycle-end scenario's possible. Four different scenarios are considered, as formulated in the Table below. These scenarios are a simplification of the scenario's shown in Figure 54. The functions $F_X(x)$ and $F_Y(x)$ are the cumulative distribution of exponential distribution for the time to failure and the Weibull distribution for the time until defect respectively. The $f_X(x)$ is the probability density function of the time to defect. The factor n is Bernoulli distributed corresponding to the probability of having a successful detection ($w = True$) of the defect before failure.

Table: Formulation of different outcome scenario's

No	Scenario	Probability
1	Good	$P(X > \tau) = 1 - F_X(\tau)$
2	Defect	$P(X < \tau \cap X + Y > \tau) = \int_{x=0}^{\tau} (1 - F_Y(\tau - x)) f_X(x) dx$
3	Detection defect	$P(X + Y < \tau \cap w = True) = n \int_{x=0}^{\tau} F_Y(\tau - x) f_X(x) dx$
4	Failure	$P(X + Y < \tau \cap w = False) = (1 - n) \int_{x=0}^{\tau} F_Y(\tau - x) f_X(x) dx$

iii. Model parameters

Determining the parameters is a difficult step for this system. There is a limited amount of data available to fit certain distributions to because failures are limited due to the low amount of assets that the navy uses with these engines. The parameters that are used, if not differently specified for the given scenario, are given in the Table below. The values with respect to the delay time models are derived from the FMECA (Tiddens, 2014) and fit to match the current inspection interval. The performance of the validation cannot be estimated based on this research, as initial performance is 50% taken.

Table: Used parameters of the mathematical model

Symbol	Value	Explanation
λ	70000	Scale parameter exponential distribution time to defect
β	2	Shape parameter Weibull distribution time to failure
η	4000	Scale parameter Weibull distribution time to failure
n	0.5	Parameter of successful detection defect