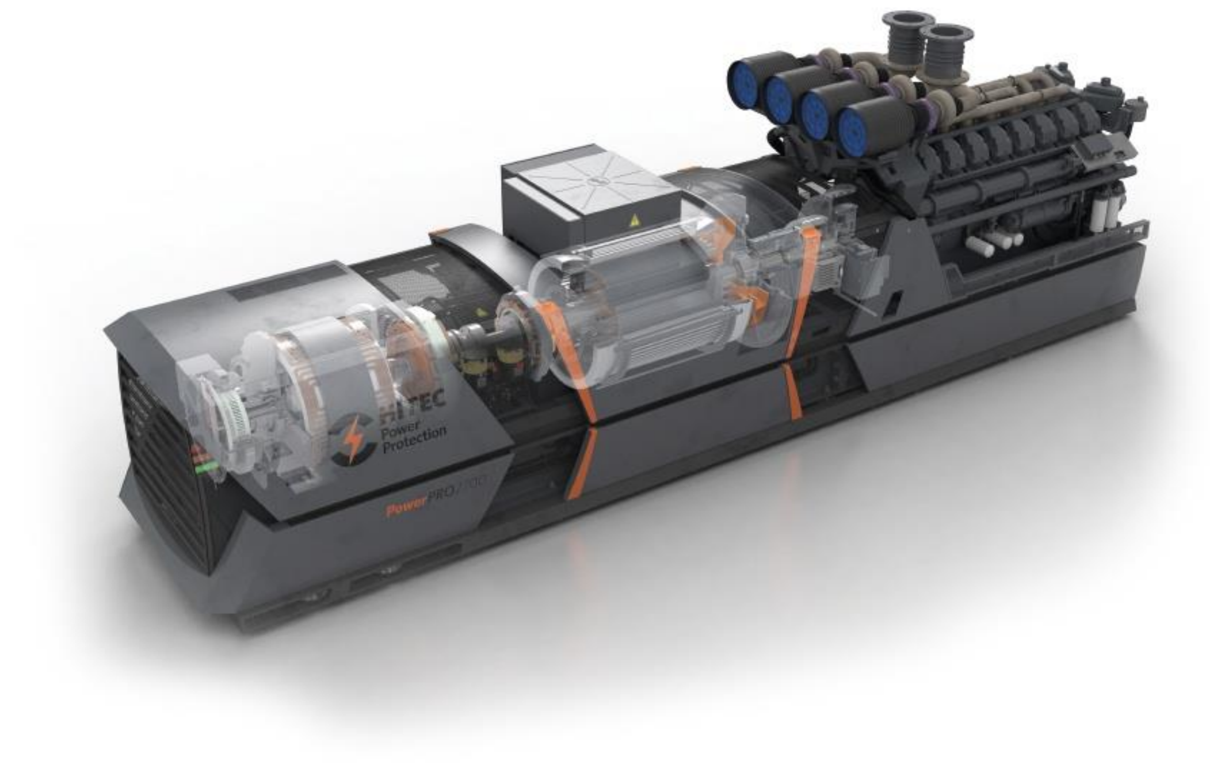
SUPPORTING THE MAINTENANCE DECISIONS OF HITEC POWER PROTECTION BY PREDICTING THE HEALTH STATE TRANSITIONS OF THE UPS SYSTEM KEM INNER BEARINGS



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Preface

This research is the master graduation assignment which marks the last step of my Industrial Engineering and Management study at the University of Twente. As many of the students in the study know, finding a fitting graduation assignment can be quite a challenge. I am very happy to have ended up working on a graduation assignment that I actually feel passionate about.

My journey towards working at HITEC, as many people already know, started at the Business Days Twente. While passing through, talking to the companies on my list, I ended up squeezed between students and stuck next to a stand of for me an unknown company. Long story short, I would like to thank Anns for being way too excited telling me all about working at HITEC, and making me feel excited about working in the company. Next, I would like to thank Kim and Jan Willem for preparing a graduation assignment for me. From the very beginning I was enthusiastic about the research and the results it can achieve. I can still say that until the last day I have enjoyed working on my graduation assignment. Even though there were some days when I struggled with getting data necessary for the research, or spending hours on writing the report. Luckily, these days were easier to get by when taking lunch walks with Loreta and Tian. At last, a most important thank you for the research execution, thank you to Jan for spending hours on exporting the research data for me.

I would also like to thank my university supervisors, Engin and Hao. You helped me shape the research into what it is now. Providing ideas and support. In general, in practise, obtaining data suitable for research as this can be quite challenging. Together we explored the capabilities and potential of the available data. Resulting in a research that provides a good basis for HITEC to build up on in the future.

Lastly, I would like to thank my family for their support during my graduation assignment. Special thank you to my parents who amongst other things gifted me a bike so I could bike 20 minutes to HITEC from the Almelo station every day. Thank you to Dennis who despite momentarily deleting my code during the validation phase of my report make the challenging days of the assignment more manageable. Thank you to all my friends. Some of them live abroad, but nevertheless we are all in this together, we're all starts, we stand hand in hand, and make our dreams come true. And thank you to all the friends I made in the Netherlands. You changed my life from just studying abroad to actually living a life abroad. Special thank you to the members of the Messed Up floorball association at the university who were the first people that I actually hung out with outside of the university.

Management summary

The research is performed at HITEC Power Protection (HPP) in Almelo. HPP designs, develops, delivers, and supports uninterruptible power supply (UPS) systems across the globe. It is HPP's mission to support critical facilities such as hospitals, airports, stock exchanges, data centres and industrial manufacturing processes by assuring safe, reliable, and conditioned power. UPS systems in industry in general have very high uptime to ensure power supply for these critical facilities. It is therefore crucial for the maintenance of UPS that the downtime, both planned and unplanned, of any part of the UPS system is minimized. The decrease of unplanned downtime currently shows higher benefit for the company. Therefore, minimizing the unplanned downtime is the focus of the research, resulting in the research objective as

Improving the HPP maintenance service by decreasing the unplanned downtime of the UPS units through implementation of a PdM policy for a selected component of HPP's UPS systems.

The research examines the implementation of a predictive maintenance (PdM) policy to support the maintenance services of HPP. A PdM policy allows for maintenance planning prior to the time when maintenance action for a given component of the UPS system is required. Allowing for an immediate carrying out of the maintenance action when it is required. Resulting in a decreased unplanned downtime for the given component of the UPS system. The PdM policy is based on a developed predictive model predicting the future health state (HS) of a component of HPP's UPS systems. First, a statistical predictive model is developed as the complexity of the relation between the data is not known prior to the research. Subsequently, a data driven predictive model is developed for comparison of model predictive ability. The better performing model is used for the development of the PdM policy.

In the research a PdM policy to support the planning of maintenance actions for the kinetic energy module (KEM) inner bearing components is developed. The policy is developed using a linear regression statistical and regression based decision tree data driven model, predicting the HS of the KEM inner bearings 6 days into the future. A 6 day prediction period is selected as it provides enough time for HPP to plan a maintenance service in advance. The statistical linear regression based model is not able to make predictions for the non-healthy HSs of the KEM inner bearings. The model predicts the future HS for every instance to be a healthy HS. Therefore, the statistical linear regression based model is depicted as a not useful predictive model for the research. The data driven regression decision three model is able to correctly predict part of the non-healthy and healthy HSs. The data driven regression decision tree model is therefore depicted as useful and is used as basis for developing a PdM policy for HPP.

The developed data driven model consists of 3 parts. Namely, data driven predictive model for predicting the KEM DE Vibration, known as Model DE. Second, data driven predictive model for predicting the KEM NDE Vibration, known as Model NDE. And last, HS prediction, where the predicted KEM DE and NDE Vibrations using Model DE and Model NDE are used to depict the associated predicted HS.

During the predictive model development of Model DE and NDE it is observed that the KEM outer bearing temperature on driving end input variable for Model DE did not provide any value to the KEM DE Vibration predictions. Removing this input variable resulted in predicting 0 instead of 2 incorrect HS predictions and decreased the prediction error key performance indicators (KPIs). Moreover, the analysis of the extracted features revealed the most valuable extracted features are standard deviation, variance, root mean square, shape factor, energy, skewness, and kurtosis. Addition of these extracted features also resulted in predicting 0 instead of 2 incorrect HS predictions and in a decrease of the prediction error KPIs. Moreover, the models revealed an

effect of the operationality of the flywheel. Model predictions that are made separately for instances when the flywheel is and is not in operation resulted in the same number of incorrect HS predictions. However, the prediction error KPIs have decreased.

The final predictive model predicting the HS of the KEM inner bearings is used as basis for the PdM policy for the KEM inner bearings. The PdM policy is defined using a safety factor α as an input variable, depicting the prediction certainty used for proposal of maintenance actions for the KEM inner bearings.

The results for the testing data are:

70% certainty prediction interval

- 1 unnecessary maintenance action predicted
- 152 (27.05%) necessary maintenance actions unpredicted
- 99.88% of maintenance actions correctly predicted

80% certainty prediction interval

- no unnecessary maintenance action predicted
- 162 (28.83%) necessary maintenance actions unpredicted
- 99.87% of maintenance actions correctly predicted

90 % certainty prediction interval

- no unnecessary maintenance action predicted
- 255 (45.37%) necessary maintenance actions unpredicted
- 99.80% of maintenance actions correctly predicted

For all prediction certainty intervals, with a penalty of 50 for predicting unnecessary maintenance action, the unplanned downtime has reduced. Assuming 50% decrease of unplanned downtime when the need for a maintenance action is known 6 days in advance. The highest reduction of unplanned downtime is associated with the 80% certainty prediction interval. Reducing the unplanned downtime by approximately 36% compared to the currently used maintenance policy. The unplanned downtime reduction for 70% certainty prediction interval is approximately 32%, and for 90% certainty prediction interval approximately 27%.

The proposed PdM policy is not successfully validated using the available validation data set. The main aspect of the inability to validate the model is related to the varied step size between measurements of the input variables. This aspect directly affects the extracted features that are significant input variables for the underlying predictive model of the PdM policy. However, valuable insights for further development of the PdM policy and its underlying predictive models are made during the research.

- First, the removal of input variables for reduction of the model input complexity is analysed. Resulting in removal of the KEM outer bearing temperature measurements. However, based on set decisions, more input variables can be removed from the model input to further reduce the complexity of model development.
- Second, the value of inclusion of extracted features from the vibration data onto the model predictions is demonstrated. In the research the minimum number of extracted features is removed from the model input. However, a different approach where less extracted features are included in the model could further reduce the model complexity and lead to more accurate predictions.

- Third, the effect of flywheel speed onto the model performance for instances when flywheel is in operation and when it is not in operation is evaluated. It is demonstrated that the instances when flywheel is in operation are better modelled by model solely developed based on instances from when the flywheel was in operation. However, it is also depicted that the operational status of the flywheel has more significant influence on the KEM inner bearings on the driving end of the KEM. Therefore, model distinction between model for the KEM inner bearings installed on the driving end (where the flywheel is installed) and on the non-driving end can be made.

Taking into account the findings of the research, the research provides a good basis for developing a PdM policy for HPP. The policy supports the maintenance service of HPP by providing insight for the customers into the upcoming HS of the KEM component. However, additional aspects for further development of the PdM policy and its underlying model should be addressed first.

- Further removal of input variables in order to decrease the number of needed sensors for the measurement of the variables. Also reducing the model robustness.
- Further analysis of the most valuable extracted features. As removal of unnecessary extracted features decreases the execution time of the model and the PdM policy. Also reducing the model robustness.
- Further analysis of the effect of the operationality state of the flywheel onto the Model DE and Model DE. Potentially improving the final HS prediction.

Following the improvements, it is important for the validation of the new underlying predictive model that the time steps between the measurements of the input variables are constant. Once the underlying model is validated the PdM policy can be implemented at the customer sites and use the direct measurements from the UPS system for HS prediction. Then through the associated PdM policy the customer obtains predicted maintenance needs for the KEM component.

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List of abbreviations

CBM	Condition based maintenance
DCBM	Dynamic condition based maintenance
DE	Driving end
DRUPS	Diesel rotary uninterruptible power supply
HPP	HITEC Power Protection
HS	Health state
KEM	Kinetic energy module
KPI	Key performance indicator
NDE	Non-driving end
PdM	Predictive maintenance
PM	Preventive maintenance
PMSMT	Performance measurement (measurement from UPS system)
PP	Prediction period
PPM	Planned preventive maintenance
RUL	Remaining useful life
SCBM	Static condition based maintenance
UPM	Unplanned preventive maintenance
UPS	Uninterruptible power supply

1 Introduction

In February 2021, Texas experienced a major power crisis. At its peak, more than 4.5 million Texas homes and businesses were without power [1]. During these days of emergency all companies who installed HITEC Power Protection's Uninterruptable Power Systems did not come into problems due to the power loss [2].

Figure 1.1: Countries with HPP UPS systems

HITEC Power Protection (HPP) delivers reliable power supply across the globe. The key markets supported by HPP are manufacturing, semiconductor, finance, telecom, data centre, and government. HPP's mission is to support the critical facilities of these markets by assuring safe, reliable and conditioned power. That is why HPP designs, develops, delivers, and supports uninterruptible power supply (UPS) systems. The company currently serves and supports over 500 customers in 60 countries. From its headquarters in Almelo (the Netherlands) and customer support locations in Europe, America, and Asia. Figure 1.1 shows overview of the countries in which HPP UPS systems are installed.

The company does not simply provide their systems to the customers. It provides a power supply service. This includes maintenance support for the customers. For their maintenance operations, HPP applies preventive maintenance (PM), carrying out maintenance operations before a failure occurs. This is so that the customers do not experience down time due to loss of power. The PM policy applied at HPP is a condition based maintenance (CBM). CBM makes use of real-time measurements to evaluate the current condition of a component and evaluates its need for repair or replacement. However, with new trends in the industry the focus shifts towards the analysis of the historical data of these measurements. Shifting from PM towards predictive maintenance (PdM) policies. PdM has the same basis as CBM, however, instead of observing when a certain threshold condition is reached it is predicted. This allows for planning instead of reacting when maintenance is needed. Section 1.1 provides introduction on the basics of HPP's UPS systems and introduces the software system of the UPS systems, which is the basis for the HPP's maintenance operations. Furthermore, the section presents the current maintenance policies at HPP, and presents the specific UPS systems which will be of focus in the research. In section 1.2 the motivation of HPP for investigating the suitability of PdM for their UPS systems is presented. Section 1.3 discusses the action and core problems that are currently present at the company. The approach for carrying out the research is presented in section 1.4.

1.1 HPP UPS systems

HPP manufactures diesel rotary UPS systems (DRUPS) to provide power supply to their customers. HPP provides power supply for both short break (SB) and no break (NB) loads. SB load is a non-essential load, for example a printer or a coffee machine. NB load is an essential load, for example air traffic control or hospital operating room. The electrical circuit of the PowerPRO2700 DRUPS system can be seen in Figure 1.2. The figure shows the DRUPS system in utility mode and in diesel mode. In diesel mode utility is not provided to the system. Utility is defined as public or general

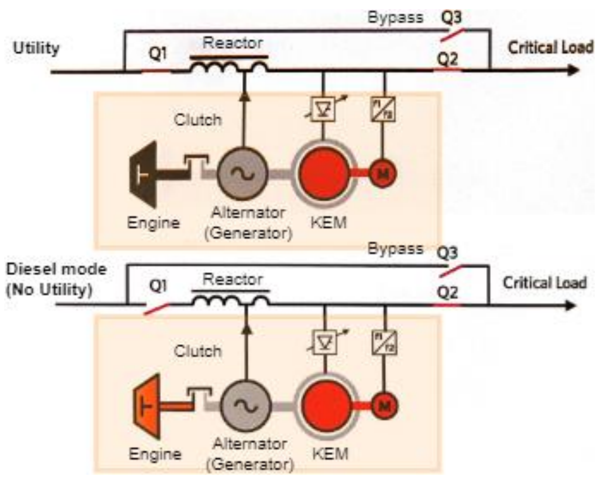

Figure 1.2: DRUPS with PowerPRO2700 unit

utility power supply, normally available to power electrical appliances. A basic DRUPS system consists of 3 circuit breakers Q1, Q2, Q3, a reactor and a unit (Figure 1.2, unit is highlighted with orange). However, multiple units can be included in a system resulting in more circuit breakers and reactors needed (Figure 1.3, 2 units system). Q1 breaker is used for (dis)connection of the utility to the unit, Q2 breaker for (dis)connection of the unit to the customer's load, Q3 breaker for (dis)connection of the utility directly to customer's load. A reactor is used to separate utility from the load and to allow the alternator to control the voltage of the load. Important components of a unit are alternator / generator, diesel / engine, freewheel clutch (FWC) and kinetic energy module (KEM). Generator can either be used as a running motor or a running generator, engine is used to provide long term energy supply, FWC is used for the (dis)engagement of the engine with the generator, and KEM is used to generate and store kinetic energy to support the system during utility loss.

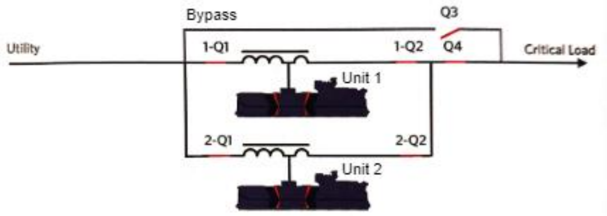

Figure 1.3: UPS system with 2 units

To demonstrate the basics of how the DRUPS system operates the transfer from utility to diesel mode consisting of 4 stages is described. Figure 1.4 shows the speed of rotary components of the DRUPS system during the different stages. Fist stage is the utility mode in which the generator is used as a running motor to provide strong pure electrical power by filtering the electrical power provided by utility and by stabilizing its voltage output. At this time KEM operates at full speed generating and storing kinetic energy. When the utility is no longer provided the DRUPS system starts the transfer to diesel operation. This is the second stage. The generator is used as running generator to generate power output. During this stage a diesel engine is starting up but cannot yet support the system. Since no interruption to the power supply can occur, in the meantime the KEM supports the system with its stored kinetic energy. Once the diesel engine is started up the system is in a full diesel operation. This is the third stage. In this stage the KEM starts to return to its full speed to generate and store energy needed to support the system during the next transfer from utility mode to full diesel operation mode. Once the utility is provided again, the system re-transfers back to utility mode. This is the fourth stage. The diesel engine disconnects from the generator, goes into cool down and the generator is used as a running motor again. It is important to note that the transfer from full diesel operation (no utility mode) to utility mode always lasts for at least 15 minutes, even if the utility outage lasts for only a few seconds. This is to provide enough time for the KEM to reach its maximum speed again, to generate and store enough energy to be ready to support the system during the next outage without any delay.

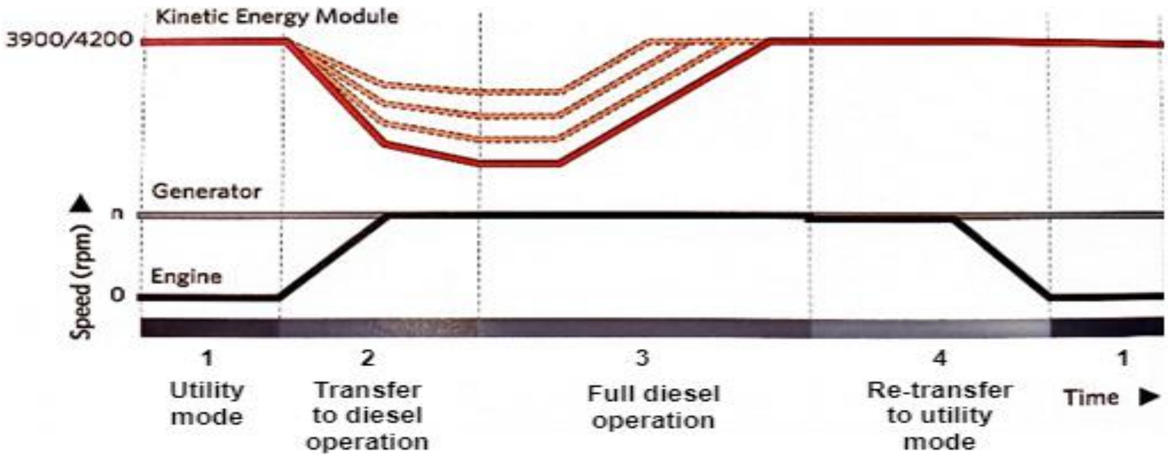

Figure 1.4: Speed of rotary components of DRUPS

When there is a failure with the DRUPS system during the utility mode the power is provided to the customer by another unit or directly from the utility through a bypass. For a system consisting of one unit, when the unit fails, the Q3 breaker is closed to provide the utility directly to the customer through a bypass. Q1 and Q2 breakers can be opened, and the unit can be disconnected from the system and undergo maintenance. Bypass is only used when no other operational unit can take over. In bypass mode the filtering of the signal and stabilizing of the voltage output are not provided, but the customer does receive power. In no utility state if there is no operational unit (when unit 1 and 2 are not operational in Figure 1.3) the customer does not receive power.

1.1.1 Software system

For maintenance purposes HPP monitors two types of performance measurements (PMSMTs) of their UPS systems. PMSMTs signify all measurements measured from the UPS system and UPS components. First, the UPS system PMSMTs are focused on the performance of the UPS system. Such as, the utility output voltage and frequency. Then, the UPS component PMSMTs focus on the health of the UPS components and the status of their environmental factors. For example, the bearing vibrations and room temperature.

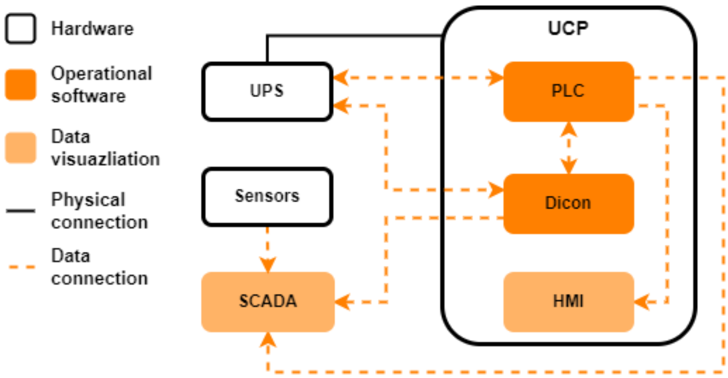

Figure 1.5: Software overview

The software system integrated with a UPS system can be seen in Figure 1.5. The UPS system is physically attached to a unit control panel (UCP) in which operational software is located. Digital controller (Dicon) monitors the performance of the UPS by measuring the UPS system PMSMTs. Dicon provides this data to programmable logic controller (PLC). Based on the received data from Dicon the PLC evaluates and operates the system. For example, if the utility voltage is 0 the PLC evaluates that there is no utility and therefore, the engine needs to be started up to generate power. The PLC commands the engine to start up.

Installed sensors on components of the UPS system measure the UPS component PMSMTs. These PMSMTs are then visualized in a Supervisory Control and Data Acquisition (SCADA) system. In addition to the UPS system PMSMTS, Dicon also contains set threshold values for all of the PMSMTs. These threshold values are used to depict the performance state of the UPS system, the health state of the UPS components, and the status of the environmental factors. These thresholds are also provided to the PLC. The PLC then based on the PMSMT values and the set thresholds evaluates the performance of the UPS system, health state of the UPS components, and the status of the environmental factors. These evaluations are then provided to Human Machine Interface (HMI) and SCADA for data visualizations for customers. HMI is a panel located on the outside of the UCP. SCADA is a control system that can be accessed remotely. In comparison to HMI, SCADA also visualizes past PMSMT data.

1.1.2 Maintenance policy

Two maintenance policies are applied at HPP. First is the planned preventive maintenance (PPM). This maintenance is carried out in form of regular prescheduled maintenance operations, where the condition of the UPS is inspected. This is a static condition based maintenance (SCBM). Second is the unplanned preventive maintenance (UPM). This maintenance makes use of the monitored PMSMT values. The UPM is a dynamic condition based maintenance (DCBM) policy. With this policy, maintenance operations are carried out whenever a PMSMT value goes out of its set threshold. When it comes to the health state of the UPS components, there are 3 health states (HS) defined by HPP: UPS component performs as intended (Healthy HS), UPS component performs with lower functionality (Degraded HS), or UPS component no longer performs and has failed (Failure HS). The thresholds for depicting the HS are set before installation of a UPS system at customer's site. The UPS system thresholds are set by HPP. These thresholds are set based on the UPS customer's site requirements. The UPS component PMSMT thresholds are set based on manufacturer's requirements and experience of HPP. Figure 1.6 shows how the PMSMTs are visualized on the HMI panel and in SCADA.

When a PMSMT goes out of its threshold range this is referred to as alarm situation. Attention and warning alarm is within the degraded HS threshold (indicated by yellow in Figure 1.6). The failure alarm is within the failure HS threshold (indicated by red in Figure 1.6). The HPP health indicators in the HMI and SCADA visualizations light a yellow/orange and red light, respectively, to indicate these alarm states.

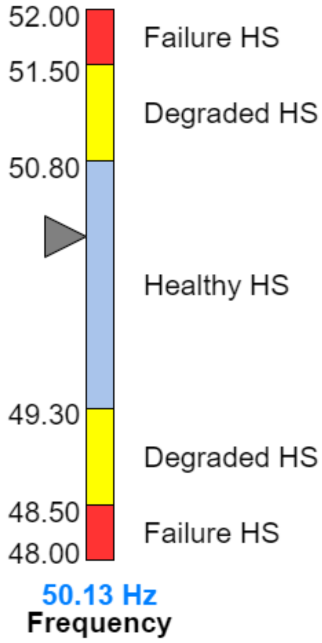

Figure 1.6: PMSMT threshold range

The red failure light turns on when a new failure appears and turns off when all the failures have been reset. It is the most important health indicator light. During failure the UPS unit is out of order and stopped. The warning alarm signifies an error that must be solved now. It is a serious error that needs action to make sure the UPS unit can operate properly. It can still operate but probably not according to its specifications. The next indicator is the yellow attention light. This is used for a minor error. Similarly, as with warning, the UPS unit can still operate but probably not according to its specifications. However, the distinction between attention and warning alarm is fading and the company is transferring to combining them into one alarm category. The last health indicator is a green operational light. It flashes during the startup of the UPS unit and is continuously on when the UPS unit is fully operational. This health indicator is not considered an alarm.

1.1.3 PowerPRO3600 and PowerPRO2700

PowerPRO3600 (PP3600) and PowerPRO2700 (PP2700) are the newest DRUPS systems manufactured by HPP. For 60Hz applications PP3600 can reach power up to 3600kVA and PP2700 can reach power up to 2700kVA. PP3600 creates the highest power density per square meter in the industry. PP2700 while having the greatest reliability and uptime is the most compact power solution in today's market. The focus on these UPSs is due to their relevance and data availability. From all the UPSs manufactured by HPP these are the systems with most available data. This is due to the software they are delivered with. Moreover, due to this software system, they are also the most suitable UPSs for implementation of PdM at HPP.

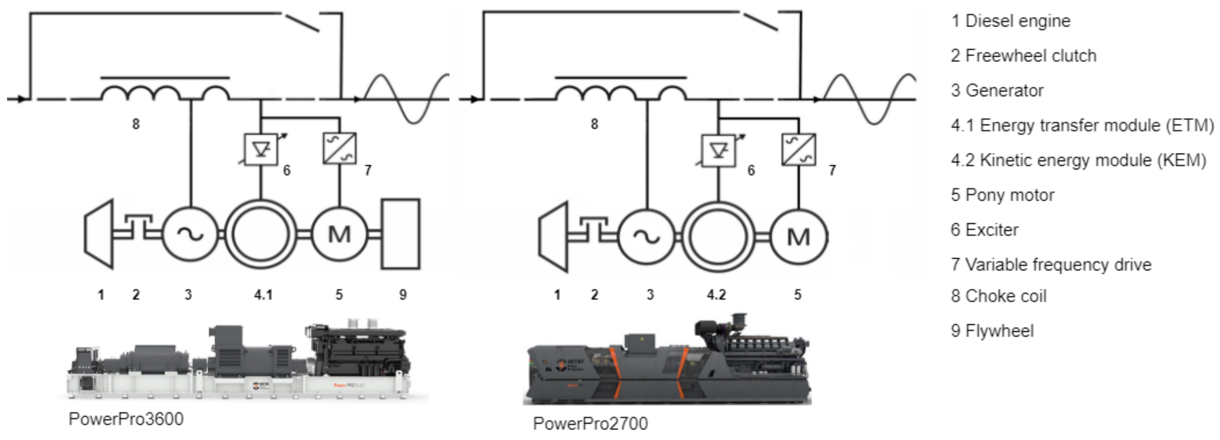

Figure 1.7: PowerPRO3600 and PowerPRO2700

The main difference between the two UPSs is the kinetic energy buffer. The PP3600 has an extra rotor combination to reach higher power.

1.2 Research motivation

'*As the population increases its reliance on communication and connectivity, urban expansion, and manufacturing and automation, the world's power grids will continue to be stretched to their limits. This power dependency creates a significant risk that can lead to dramatic utility power outages that affect business-critical facilities such as hospitals, airports, stock exchanges, data centres and industrial manufacturing processes. HITEC Power Protection's mission is to support these critical facilities by assuring safe, reliable and conditioned power*.' [3].

The motivation for HPP is to provide UPS systems to customers with a high UPS uptime. For this, the UPS systems of HPP are often provided to the customers with maintenance contracts. The related costs for HPP carrying out a maintenance service are covered by the customers. Therefore, providing revenue to HPP. At the moment these contracts include maintenance service provided by HPP, based on SCBM and DCBM policies where the PMSMTs are monitored. Due to customers' privacy reasons HPP does not have real time access to the PMSMT data for majority of the installed systems. In real time, the data is only used for visualizations of the current health state of components for the customers (as seen in Figure 1.6). Who then based on these values request a maintenance service from HPP.

With the current trends in the industry, the maintenance services and therefore also customer demands are changing. The use of data driven, machine learning approaches in the industry, and also specifically in the area of maintenance is growing. Data driven models allows for analysis of past and current PMSMT data in order to observe their development over time. This allows for developing predictive models with which the future values of the PMSMT data can be predicted.

In the coming years HPP plans to use a new platform for the visualization of the system health state for the customers. One of the new features to be included are maintenance indicators which are based on data driven analysis of the PMSMT data. Based on real time analysis of current and past PMSMT data the maintenance indicators would evaluate the health state of the system. Based on the outcome of the analysis the maintenance indicators would indicate which maintenance actions are needed to be carried out. Furthermore, the analysis can be used to predict the RUL of different components and predict when alarms for the UPS will occur. However, first, a new maintenance policy has to be implemented at HPP.

Maintenance indicators as seen nowadays in industry, and as envisioned by HPP, go hand in hand with implementation of a PdM policy. For HPP the main benefit of such policy is the potential to decrease unplanned and planned downtime for the UPS units. Resulting in a UPS system with higher uptime, which is HPP's motivation. Furthermore, customers can also benefit from a PdM policy when it comes to planning the maintenance service requested from HPP. Since the needed maintenance is known in advance, the planning can be done in a cost-effective way. For example, during a factory shutdown or together with other maintenance service.

1.3 Problem identification

As discussed in the Research motivation section, HPP provides maintenance services to their customers based on SCBM and DCBM policies. There are 3 action problems, which are defined as discrepancy between norm and reality [4], that arise from these maintenance policies at HPP.

First action problem is **increased maintenance costs**. Related to the SCBM policy, this occurs when expensive components are replaced based on their time in operation rather than based on their remaining useful life (RUL). Increased costs due to early maintenance do not affect the income of HPP. However, it has an effect on the attractiveness of the HPP UPS systems, as this extra cost affects the customer. On the other hand, related to DCBM policy, extra costs for HPP could occur. The occurrence is due to immediate planning of the service to be carried out. As an example, it is sometimes not investigated properly whether new components were installed in the system compared to the original installation and whether new replacement components taken for the service are suitable / fit in the currently installed system [5]. In case the component is not suitable, additional service visit needs to be planned to carry out the same maintenance operation. Therefore, additional costs are incurred. It cannot be easily determined how often this extra costs occur as this data is not easily available. However, it is not expected this happens often.

The norm of HPP with regard to increased maintenance costs is: Lower the maintenance costs for the customers while not lowering the income of HPP gained through provided maintenance service.

Building on the occasional need for repeated service visit for the same issue, the second action problem is defined as **increased unplanned downtime**. In situation when the unit is down, the repeated service increases the unplanned downtime period. With the current use of DCBM the planning of the maintenance service takes place once an alarm occurs. Therefore, in case of failure alarm, if a unit is down, the planning time takes place during the downtime of the unit. Again, increasing the unplanned downtime period. This downtime can be further increased due to current unavailability of resources. Such as personnel or components.

The norm of HPP with regard to increased unplanned downtime is: Minimize the unplanned downtime while not decreasing the reliability of the system.

Lastly, the third action problem is defined as **increased planned downtime**. Increased planned downtime is caused by carrying out the same maintenance operations during each PPM. Narrowing down the maintenance operations to components that actually require maintenance would decrease the planned downtime.

The norm of HPP with regard to increased planned downtime is: Minimize the planned downtime while not decreasing the reliability of the system.

The problem cluster depicting the action problems can be seen in Figure 1.8. **The selected action problem is increased unplanned downtime**. Increased unplanned downtime is related to not knowing when and which maintenance actions will be needed. Knowing which maintenance actions are needed is something HPP is interested in for developing new maintenance indicators. Therefore, focusing on this action problem is in line with the goals of HPP. Two core problems are identified as contributors to increased unplanned downtime. Namely, no predictive maintenance and no differentiation between customers.

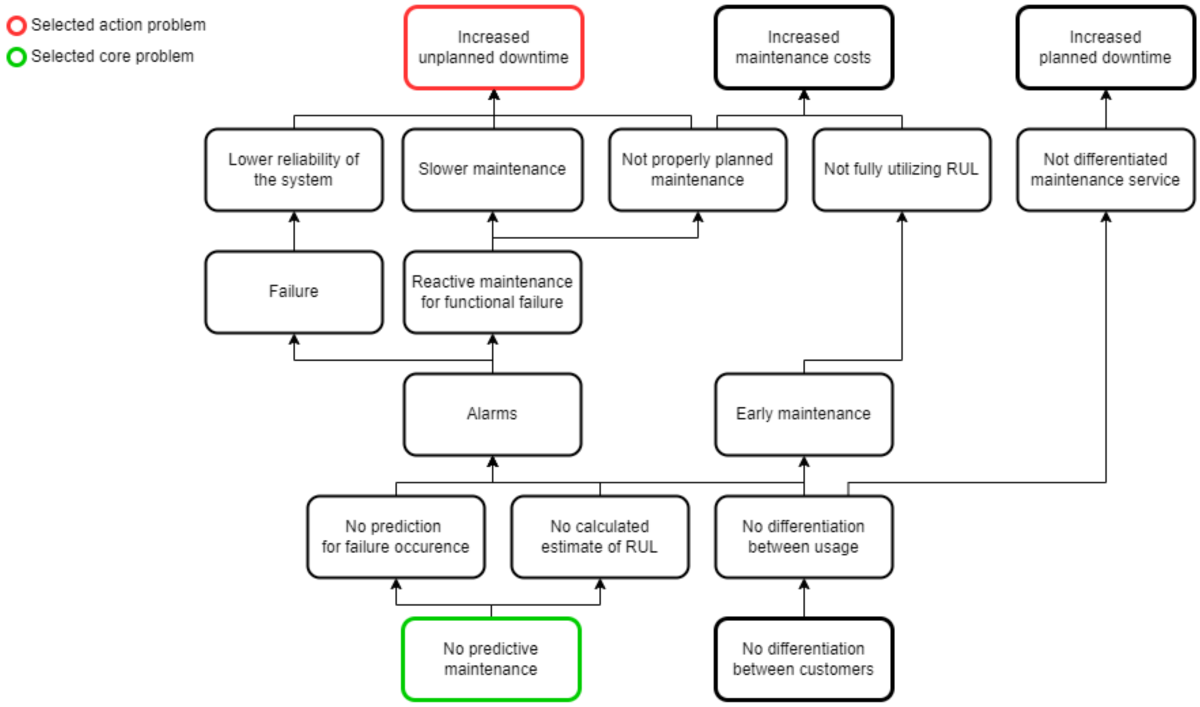

Figure 1.8: Problem cluster

The first potential core problem to be selected for the research is not using a PdM policy. As a result of not having a PdM policy, there are no predictions for failure occurrence and RUL of components. Maintenance intervals for PPM cannot be determined dynamically. This means that for each customer the maintenance visits by HPP are prescheduled independent of the condition of their system. The customers have real time access to PMSMTs of their UPS system and components. Making use of this data with a real time analysis, a more optimal maintenance intervals could be determined dynamically.

The second core problem focuses on not differentiating between the customers. And therefore, also not differentiating between the usage of the systems. Some customers are located in areas where utility is not provided more often, compared to other areas. For them the UPS system transfers to diesel mode more often. This also has an influence on the degradation of the UPS system and certain components. Therefore, a proper relation between usage and loads needs to be taken into account for the systems. Then an appropriate maintenance planning for each customer can be made.

The selected core problem for the research is **no predictive maintenance (PdM)**. This is due to the fact that to fully address the action problem, addressing core problem differentiation between customers still leaves the core problem of no PdM to be dealt with. On the other hand, addressing the core problem of no PdM can potentially address the core problem of no differentiation between customers. It provides opportunity to fully address the action problem by solving this one core problem, while eliminating the other core problem.

1.3.1 Deliverables

The main deliverable of the research for HPP is a PdM policy proposal with underlying predictive model used for predicting the health state of a selected component from the two newest HPP UPS systems. Furthermore, KPIs for evaluating the PdM policy and the underlying predictive model are provided for HPP. These can be used to further improve the PdM policy. Additionally, the research contributes to HPP by evaluating the impact of each of the used PMSMTs onto the developed predictive model. Moreover, also contributing to the industry in general, the impact of input variables and extracted features onto statistical and data driven models is evaluated.

1.3.2 Research objective

The reality of the selected action problem is that the maintenance operations are not always optimal and lead to increased unplanned downtime of the UPS units. By addressing the selected core problem, a PdM policy can be developed and implemented at HPP. Then HPP's maintenance operations can be planned in advance and carried out when needed without expected delays. For achieving this norm, the research objective for the research is defined as:

Improving the HPP maintenance service by decreasing the unplanned downtime of the UPS units through implementation of a PdM policy for a selected component of HPP's UPS systems.

1.4 Research approach

Design science research methodology (DSRM) provides a guide for approaching a research project. Four main DSRM phases have been defined for the research project (Figure 1.9). The first phase focuses on setting the problem context and introducing the current situation at HPP. The second phase presents relevant literature related to the research. During the third phase a solution for the action problem is developed. This is done through developing and demonstrating an artifact. The artifact consists of a predictive model for predicting the health state of a selected component of HPP's UPS system. Lastly, in the fourth phase the artifact is evaluated and used for implementing a PdM policy. This PdM policy is then validated using a validation data set. Afterwards, conclusions of the research are presented.

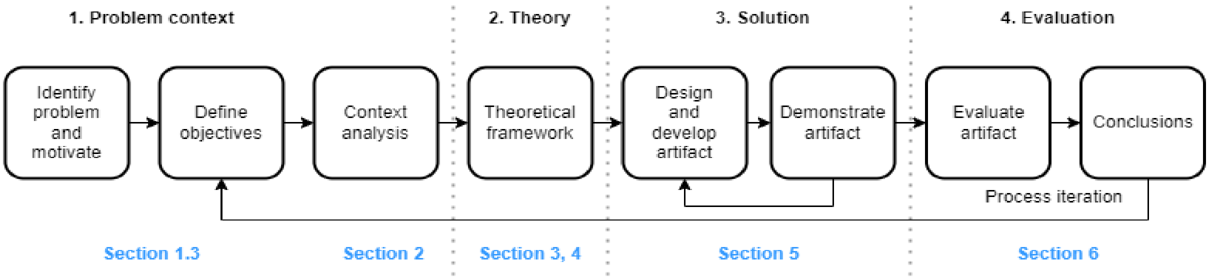

Figure 1.9: DSRM steps (adapted from [6])

For evaluating the research, the norm related to the selected core problem needs to be quantified. The norm is defined as minimizing the unplanned downtime while not decreasing the reliability of the system. With the current maintenance policy, the unplanned downtime of the UPS unit occurs when a degraded or failure HS for a component of the unit is observed. This unplanned downtime includes the planning for carrying out the necessary maintenance service. With a PdM policy the unplanned downtime occurs every time a degraded or failure time is predicted, instead of when it is observed. Therefore, this downtime does not include the planning of the necessary maintenance service. And therefore, it can be concluded that this unplanned downtime is shorter compared to the one related to the current maintenance policy applied at HPP.

Therefore, the reality and norm as quantified as follows:

$$Reality = NH_{obs} * t_c$$

$$Norm = Under * t_c + (NH_{obs} - Under) * t_n + Over * P$$

$$t_n < t_c$$

Equation 1: Core problem quantified (reality and norm)

Where NH_{obs} stands for number of observed non-healthy HSs. t_c and t_n stand for downtime related to current and new maintenance policy, respectively. Under and Over counters, introduced during predictive model development section, count the number of under and over HS predictions. P stands for penalty incurred by Over predicting a HS.

1.4.1 Research questions

An overview of research methodology approaches to answer the research questions (RQs) defined by the company, relevant to maintenance concepts, can be seen in Table 1.1. Moreover, an overview of research methodology relevant to RQs defined for the research by the author can be seen in Table 1.2. The research is exploratory, researching aspects that were not researched before. Or descriptive, reporting of already known and recorder information. All research is qualitative. The methods used to answer the RQs are either a literature study or an interview. Literature study is either based on literature or documentation of HPP. All interviews are held with the employees of the company.

Five RQs are defined by the company to gain insights into maintenance concepts:

1. *What different maintenance policies are available?*
2. *What are the new trends in PdM?*
3. *Is the right PMSMT data available?*
4. *Which assets or failures should be investigated first?*
5. *How to evaluate maintenance policies for different assets?*

Table 1.1: Research methodology approach: RQs of the company

Research questions	**1**	**2**	**3**	**4**	**5**
Exploratory			X	X	
Descriptive	X	X	X	X	X
Qualitative	X	X	X	X	X
Literature study: literature	X	X	X	X	X
Literature study: HPP docs			X		
Interview			X		
Report section	3.1	3.2	3.3	3.4	3.5

Five RQs are defined to guide the research:

6. *What are the suitable approaches to develop a predictive model for the selected component of HPP's UPS systems?*
7. *What are the suitable methods to develop a predictive model for the selected component of HPP's UPS systems?*
8. *What are the selected models for developing a predictive model for the selected component of HPP's UPS systems?*
9. *How to validate the developed predictive models?*
10. *How to develop and validate a PdM policy for HPP?*

Table 1.2: Research methodology approach: RQs defined for the research

Research questions	6	7	8	9	10
Exploratory	X	X		X	X
Descriptive	X	X	X	X	X
Qualitative	X	X	X	X	X
Literature study: literature	X	X	X	X	X
Literature study: HPP docs					
Interview					
Report section	4.2	4.3	4.4	4.6	4.9

1.4.2 Research scope and limitations

To set a realistic scope for the research the predictive model is developed for a single component of HPP's UPS systems. This is due to the set time restrictions for carrying out the research project. The development of the predictive model is also limited by the unavailability of historical data. Only currently accessible data, with history of up to 6 months, can be extracted from customers during the research. This constitutes of 7 data sets out of which 3 data sets contain limited failure data. On average, only one failure data set is available for each of the model development stages: training, testing, validation.

2 Context analysis

This section provides the context for the research by describing the current maintenance related aspects at the company. To obtain a good understanding of the maintenance operations, first the current monitoring system is presented in section 2.1. Together with the PMSMT visualization systems. Next, PPM operations and UPM operations based on the PMSMTs from the monitoring system are described in section 2.2. This section includes information about maintenance activities, data storage and maintenance contracts. Section 2.3 focuses on determining the most critical components of PP3600 and PP2700 UPS systems. Then a specific component for which predictive model is developed is selected.

2.1 Dicon

PLC is the operational system of the UPS. In order to operate the system, it needs data from the Dicon measurement device. When a new UPS system is to be delivered and installed for a customer the Dicon needs to be set up. Figure 2.1 shows an overview of the setup process. Project Configurator software is a basis for the setup. The component requirements are defined in the Project Configurator. Based on these requirements the threshold values are set for the different components. In Project Builder a new project is designed for the UPS system to be installed. This consists of defining the system requirements such as voltage output, and by specifying manufacturers of the UPS components. In addition, PMSMTs to be measured are assigned. Once the project is registered, the Dicon Tool connects the project and its parameters to the actual UPS system via physical Dicon device. Once the connection is established the Dicon Scope can be used to visualize the PMSMTs. This visualization is used during commissioning when the system is installed to make sure everything is running as intended. Moreover, service engineers can also use the Dicon Scope during maintenance operations.

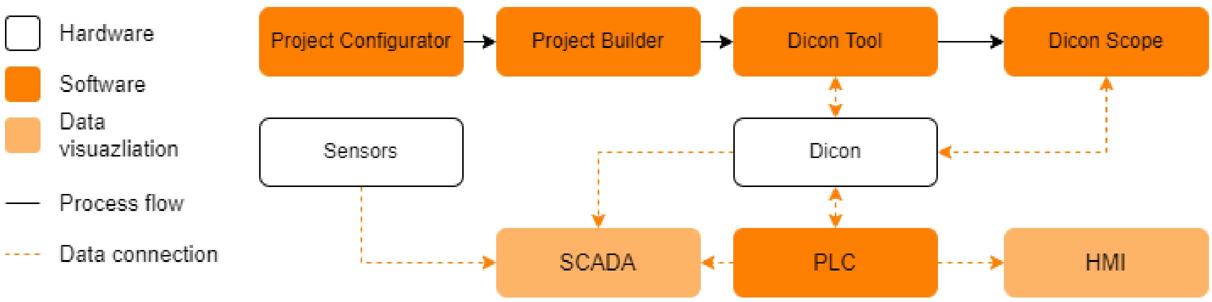

Figure 2.1: Dicon setup process

Once the setup is complete the Dicon collects the assigned PMSMTs. These are then provided to the PLC and subsequently to HMI and SCADA for visualizations. Regular PMSMTs are performed every 500ms. In case of an event, event log is recorded in SCADA and for a short period of time Dicon directly provides data to SCADA itself. This is done at a higher frequency of 10ms in order to have more detailed data for evaluating the event. What constitutes as an event is determined by the PLC. An example of an event is a certain PMSMT going out of its set threshold range.

Dicon contains around 950 PMSMTs out of which around 200 PMSMTs are direct measurements from the UPS. Other PMSMTs are general parameters, limits (threshold range), controllers, commands, status parameters, and others. In section on SCADA the important PMSMTs visualized for the customers, affecting the operationality of the system, are presented.

2.1.1 HMI

The HMI panel on the UCP consists of 4 main aspects (Figure 2.2). 1: Screen selection buttons where the operator selects which data screen they want to see. 2: Selected HMI screen which shows the current PMSMT values for the selected data screen. 3: Health indicators. 4: Operation switches. The data visualizations (1 ,2) are the same as in SCADA and will be discussed in SCADA section. The health indicators (3) are explained in section 1.1.2. The operation switches (4) are used to operate the UPS system and are further explained in this section.

Figure 2.2: HMI panel layout of UCP for PP3600 (PP2700 can be found in Appendix A)

The Unit mode switches are used to start the UPS unit by selecting ON and stop the UPS unit by selecting OFF. The NB Load Mode switches put the unit into a UPS mode when Auto is selected. And put the unit into bypass mode when Bypass is selected. Similarly, the SB Load Mode puts the unit into automatic mode by selecting Auto and into utility mode by selecting Utility. Diesel mode switches are used for carrying out diesel and system tests. Auto puts the unit into automatic UPS mode, Diesel test switch stars the diesel test, and System test switch starts the system test on the UPS unit. The diesel and system test are described in section on Maintenance as they are performed during maintenance operations.

2.1.2 SCADA

SCADA visualizes the UPS performance PMSMTs based on data received from Dicon, and the UPS component PMSMTs based on sensor measurements. SCADA provides the same visualizations of current PMSMT values as are shown on the HMI screen. However, in SCADA the past PMSMT values are also visualized. There are several views that can be selected in the SCADA system. For the system as a whole a minimum of 5 views is available. For each additional (second or more) NB load a new view is added. For a unit there are 8 views that can be selected. Since a system can consist of multiple units, operator can select for which unit the data should be visualized.

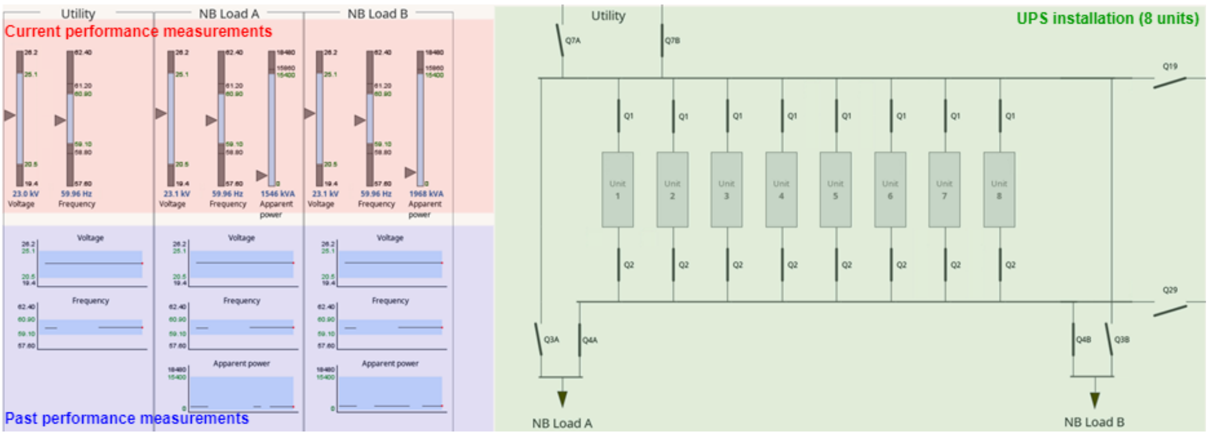

Figure 2.3: SCADA system overview

System views are overview, utility, NB load, alarms, and trending. The overview view shows what the installation of the UPS system looks like. It also shows the system PMSMTs. Both, current ones within their set thresholds and past ones for visualizing their development over time (Figure 2.3). The utility view visualizes the utility PMSMTs, and NB load view the NB load PMSMTs. The overview of these PMSMTs and SCADA maintenance counters can be seen in Figure 2.4. The alarms view shows active alarms and alarm history / event logs. These are sorted first by importance and then by time of occurrence. The trending view visualizes any selected PMSMTs on a graph with their relevant y axes and time domain x axis. An example for y axis is rpm for speed of flywheel or °C for room temperature. Again, this trending of PMSMTs is mostly looked at retrospectively when an event occurs to determine its cause.

Utility	**NB Load**	**Maintenance**
Voltage	Voltage	Switch counter Q1
Frequency	Frequency	Switch counter Q2
	Current	Engine running time
	Active power	System running time
	Apparent power	
	Reactive power	

Figure 2.4: SCADA system performance measurements

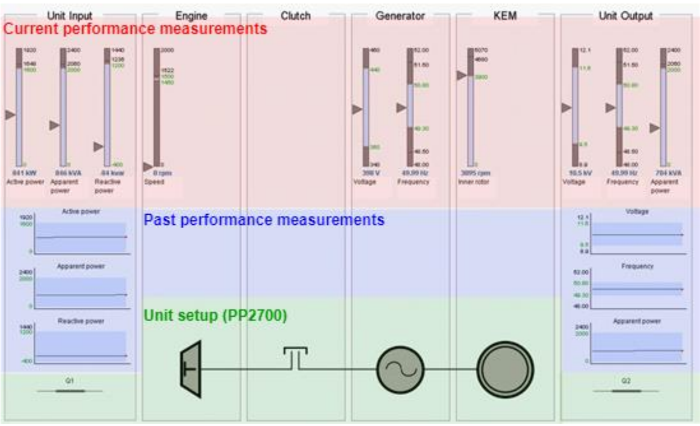

Figure 2.5: SCADA unit overview

Unit views are overview, unit input, engine, clutch, generator, KEM, unit output, and room cooling. This is the SCADA for PP2700. For PP3600, KEM view is ETM view with an additional flywheel view. Similarly to the system overview, unit overview shows the setup of the unit and the value of selected PMSMTs (Figure 2.5). Other unit views visualize their relevant PMSMTs. The PMSMTs related to each of the views can be seen in Figure 2.6.

Unit Input	**Engine**	**Clutch**	**Generator**	**KEM**	**Unit output**	**Room cooling**
Voltage	Speed	Bearings temp	Voltage	Inner rotor speed	Voltage	Status
Frequency	Oil temp	Oil temp	Frequency	Active power	Frequency	Temperature
Current	Oil pressure	Vibration	Current	Apparent power	Current	
Active power	Battery voltage		Active power	Vibration engine side	Active power	
Apparent power	Coolant temp		Apparent power	Temp engine side	Apparent power	
Reactive power			Reactive power	Vibration non driving end	Reactive power	
			Vibration engine side	Temp non driving end		
			Temp engine side			
			Vibration KEM side			
			Temp KEM side			

Figure 2.6: SCADA unit performance measurements

To demonstrate how the data is visualized, within set threshold values, the SCADA PMSMT visualization for an operational & failed generator is shown in Figure 2.7. The blue bar area depicts the values that are within the set operational threshold range and therefore do not trigger alarms. Once a measurement goes out of the blue area into the grey area it is outside of the set operational threshold range. Attention / warning and failure threshold ranges are then highlighted to show the criticality of the current value of the PMSMT. In Figure 2.7, voltage and frequency of the failed generator are within the red failure range, visualizing that this generator has failed and is no longer operational.

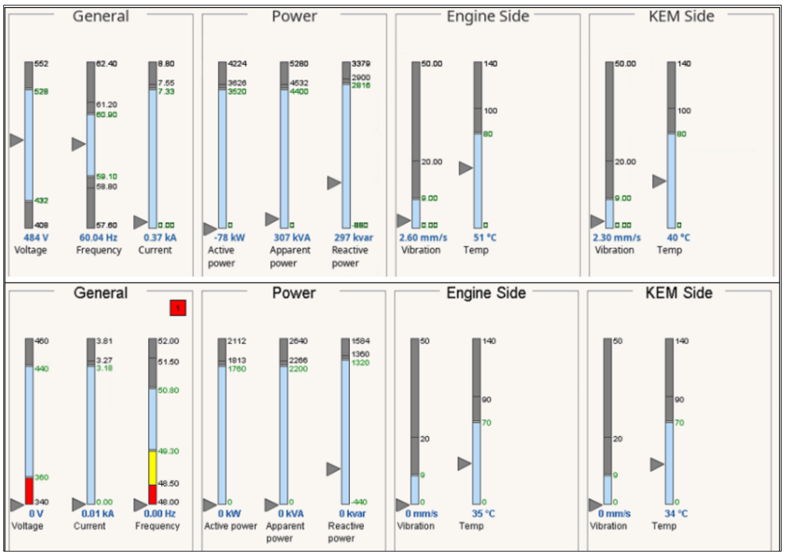

Figure 2.7: Operational(top) and failed(bottom) generator PMSMTs

2.2 Maintenance operations

Maintenance operations are a very important aspect of HPP's power supply service. This section first discusses how the PM inspections are currently determined for HPP maintenance operations (section 2.2.1). Section 2.2.2 then describes the processes of the standard PM operations. Section 2.2.3 describes the data storage process of PPM, and section 2.2.4 the data storage process of UPM. In section 2.2.5 the processes of additional maintenance operations are presented. Section 2.2.6 introduced the prio failure terminology. In section 2.2.7 the maintenance contracts contributing to HPP's revenue are discussed. Lastly, in section 2.2.8 the maintenance costs of carrying out the maintenance operations are briefly mentioned.

2.2.1 Determination of maintenance intervals

The maintenance intervals for HPP PM operations are determined both in a static way (SCBM), before the system is in operation. And in a dynamic way (DCBM), when the system is already in operation. Static intervals are defined for system and component inspections, as well as for maintenance activities. There are daily, weekly, and monthly PPM intervals for inspections. And quarterly (only for PP3600), semi-annual, annual, and additional PPM intervals for maintenance activities. The dynamic intervals are determined based on the PMSMT values. If customers do not monitor the PMSMTs and health indicators outside of the scheduled inspection, the intervals remain static for them. However, it is expected that the customers do monitor the PMSMTs in real time to ensure the reliability of their system.

2.2.2 Standard maintenance

The current maintenance policy applied at HPP is CBM. SCBM, using static intervals for inspections and maintenance activities. And DCSM using real time monitoring of current PMSMTs. For this, the company and customers monitor the UPS system and component PMSMTs of the UPS system to determine whether maintenance action is needed.

Inspection	Personnel	Warranty
Daily	Operator	✗
Weekly	Operator	✓
Monthly	Operator or HITEC	✓

Figure 2.8: Inspection overview

The requirements for the different inspections can be seen in Figure 2.8. Personnel defines who can perform the inspection and warranty signifies whether the inspection is a part of the warranty contract with the customer. If the inspection is a part of the warranty it is mandatory for the operator (customer) to have this inspection performed. Appendix B provides an extract from an inspection task list. It clearly specifies when and which components need to be inspected, and what specifically needs to be inspected for them.

The **daily inspections** are highly recommended. However, they are not included in the warranty contract. SCADA can be accessed remotely to check the system and component PSMSTs and the alarm indicators. However, a physical walk around allows to inspect for leakages and unusual indicators. That is why it is highly advised to the operators to also perform the daily inspections. For the **weekly and monthly inspections,** the operators are instructed to register the results of the maintenance tasks. For this HPP provides maintenance logbooks (Appendix C). It is also requested that the current logbook results are compared with the ones from the previous inspection to check for abnormalities. If alarms are present and cannot be solved or abnormalities are found in the logbook, the HPP regional helpdesk should be contacted.

Inspections are carried out in utility mode. However, for **monthly inspections** the system is also inspected during and after carrying out a diesel test, and during and after carrying out a system test. These tests can be started and stopped via the HMI panel. In case the utility supply stops during either of the tests, the UPS system overrules the tests and transfers to diesel mode. Diesel test is used to inspect the functionality of the diesel engine. The diesel engine will be started and run just below the specified rpm. For 50Hz application at 1450 instead of 1500 rpm, and at 60Hz application at 1750 instead of 1800 rpm. The system test is used to test the whole UPS system. Switching from utility to diesel mode by opening the utility breaker Q1 and starting up the engine.

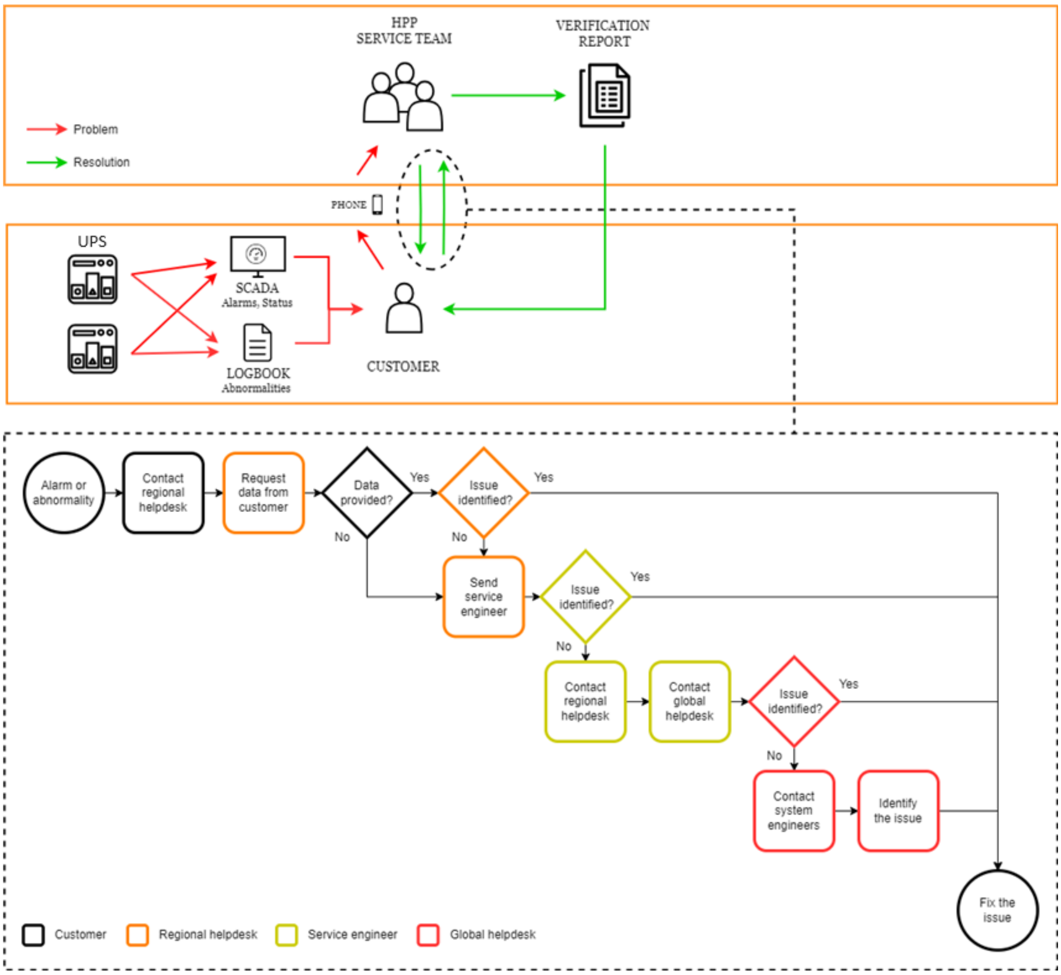

Figure 2.9: Unplanned maintenance process

Task list for quarterly (only PP3600), semi-annual, and annual **PPM operations** is provided by HPP (Appendix B). These maintenance operations can only be carried out by certified operators, HPP, or HPP's global qualified service partner. In addition, **UPM operations** take place when alarms are present and cannot be solved by operator. Or when abnormalities in logbooks are found by the operators. The process of carrying out the UPM activities can be seen in Figure 2.9.

2.2.3 Data storage of PPM

Some customers do not like to share their data due to online security issues and privacy reasons. For the customers that do not share their data due to online security reasons the aim is to receive their data during each PPM visit. VIBROTEST 60 (VT60) measurement tool is used to measure the PMSMTs of the components. These are one point entry measurements only showing the current PMSMT values. For PP2700 these measurements are carried out once per year. For PP3600 the measurements are carried out every 3 months as this system is not equipped with the SCADA system. Therefore, for PP3600 only 4 measurements are available per year.

For PP2700 continuous data from SCADA is exported onto a USB every half a year. The aim is to bring the data to HPP and use it for data analysis. For example, such data could be used for this research. However, this does not happen in reality. A potential reason is the extensive time period that is needed to export the half year data. For this research a selection of specific PMSMTs was made. However, even with this selection the export time of data was very extensive.

2.2.4 Data storage of UPM

When UPM takes place, the fault which triggered the maintenance is registered in a fault overview document. This is done by each HPP regional helpdesk (Americas, APAC, EMEA, UK) by filling out the same template fault overview document. These documents are then combined in a global faults overview documents consisting of faults from every region.

The fault overview documents are Excel documents and allow for input mistakes. Each cell is free to be entered with any format. This allows for mistyping important references, such as project number. Also due to different regions / personnel contributing to the document a proper data analysis is not easily performed. As an example, in failed component field it was entered in one instance: *suspected that faulty speed sensor*, instead of just *speed sensor*. Analysing the data quantitatively, which is an important feature nowadays, is then not possible. Another issue is not having complete data. There are 24 fields that are defined to be filled for each fault. This does not happen in reality, as will be seen in the section on Critical components.

For proper overview of a fault and its resolution, it is expected that each reported fault has properly stored data. Within the fault overview document each fault has a project reference number which links the fault to a specific customer project. Each project has its own folder in HPP storage. It is expected that for any fault, the fault relevant PMSMTs are stored in the project folder. Moreover, the maintenance report of whether and how the fault was resolved should be present. However, this is not the case. Sometimes the data is communicated through an email and never stored in the project folder. In some cases, the data was never obtained in the first place. For example, when it comes to KEM bearing faults, it happens that only a screenshot from SCADA trending view of KEM PMSMTs is obtained. The actual PMSMT data is not exported in many cases.

In general, looking for relevant information is an issue. A lot of time was spent on relating the faults in fault overview to PP3600 and PP2700 systems. Fault is related to project, and UPS system to a project. Fault's project number has to be searched for in the fault overview document. Then the project number is searched for in a project overview file. Then using these two documents it can be determined what is the installed UPS system of the registered fault. This is a timely process when evaluating all faults of a specific UPS systems.

2.2.5 Additional maintenance

'The purpose of the additional maintenance is to inspect carefully the system components and replace or repair any parts or components that show wear and tear of at least 50% of the service life and fatigue, corrosion, weather impact or aging with a risk of failure in the near future' [7].

Table 2.1: Standard additional maintenance

PP3600	PP2700
Cabinets - control panels	Cabinets - control panels
Diesel engine	Diesel engine
Freewheel clutch	Freewheel clutch
Stromag/Vulkan coupling	Stromag/Vulkan coupling
Generator	Generator
ETM	KEM
Flywheel	-
External fuel system	External fuel system
Engine cooling system	Engine cooling system
Base frame / Dampers	Base frame / Dampers
Arpex springs	Arpex springs
Exhaust system	Exhaust system
Room ventilation	Room ventilation
Load test	Load test
Copyright	Copyright

The standard additional maintenance covers but is not restricted to items shown in Table 2.1. Additional maintenance can only be carried out by HPP or their global qualified service partner. It takes place every 5 years, with overhaul every 10 years. Task list for these maintenance activities is provided by HPP.

Items that are compulsory to be replaced after 5 years of their operational life are: FWC. And after 10 years of their operational life: Stromag / Vulkan coupling, generator, ETM, and KEM. This is due to their criticality when it comes to the reliability of the UPS systems.

2.2.6 Prio failures

A prio failure signifies that a UPS unit with a faulty component has also failed. There are three levels of prio failures. Prio 1 is the most urgent failure, during which no utility is provided to the customer. At prio 2 level, the utility is delivered to the customer, however it is delivered through bypass and the quality of the electrical signal is not controlled. At prio 3 level, the utility is delivered through another unit within the UPS system. In this case, the failed unit was a redundant component and therefore this is the least urgent prio level failure.

2.2.7 Maintenance contracts

The maintenance contracts state that quarterly (only PP3600), semi-annual, annual, and corrective maintenance of the UPSs is carried out by HPP or any subcontractor assigned by HPP. The customer is not allowed to subcontract any of the work to third parties. The PPM visits are scheduled in advance with the customer. However, prior to every visit the customer needs to send a maintenance order to HPP. It might happen that in the fifth year when additional maintenance is needed, the customer is happy with their system and components are running well. They might then decide to not send an order for additional maintenance and just continue using the system as it is. Meaning that for example, the FWC is not replaced even though it is stated it needs to be replaced every 5 years (section 2.2.5). The customer then saves money on maintenance. However, the reliability of the system is affected.

The contract further defines the exclusions from the scope of maintenance provided by HPP. These protect the company from damages caused to customer outside of the warranty, as the customers are the ones responsible for maintaining the system. HPP does not lose money when a failure occurs. On the contrary, the company gains money as it performs corrective maintenance for the customer. The contracts are valid for one year and are automatically renewed each year unless terminated by either the customer or HPP. Obligations of HPP then cease 3 months after termination of contract.

2.2.8 Maintenance costs

There are 5 cost categories for carrying out maintenance operations. Travel and accommodation, working hours and travel, materials / testing equipment, diesel service, and other costs. Travel and accommodation costs are the only setup costs. The other costs are dependent on the specific maintenance operations that are performed.

2.3 Critical components

To identify the most critical component of PP3600 and PP2700, the first focus in section 2.3.1, is on the most occurring failed components of these systems. Moreover, most observed failure codes of these systems are discussed. In section 2.3.2 the selected component is presented in more detail. Together with its PMSMTs relevant for developing a predictive model for its health state.

2.3.1 Research component selection

To determine the most critical component, an initial indicator is depicted by focusing on the most failing component from fault overviews. However, as mentioned before in section 2.2.4, this information is not always entered. The percentages of entries for which the failed component and failure code input are filled in can be seen in Table 2.2. This data is applicable for the first 5 months of the year 2023 (January until and including May 2023) and for the year 2022.

Table 2.2: Availability of failed component and failure code data [8] [9]

Jan - May	Failed component	Failure code
Americas	6%	100%
APAC	33%	100%
EMEA	0%	100%
UK	0%	100%
Overall	10%	100%

2022	Failed component	Failure code
Americas	0%	100%
APAC	40%	100%
EMEA	0%	100%
UK	-	-
Overall	14%	100%

The analysis focusing on failed components is limited due to unavailability of this input data. Moreover, the current way of reporting faults in fault overviews is not suitable for proper quantitative analysis. Different entries for same component input are observed: *FWC*, *freewheel clutch*, *freewheelclutch*. These are then not considered as the same component during quantitative analysis. Carrying out qualitative analysis, the highest count of entries for failed component is for FWC and KEM [9]. Interviews discussing these findings reveal that the FWC failures are related to GMN clutches which are no longer in service and only in operation for old UPS systems. The new FWC from Stieber does not have many observed failures. Therefore, FWC should not be the focus of the research. It is instead suggested to focus on the KEM of PP2700 or on flywheel of PP 3600 UPS system.

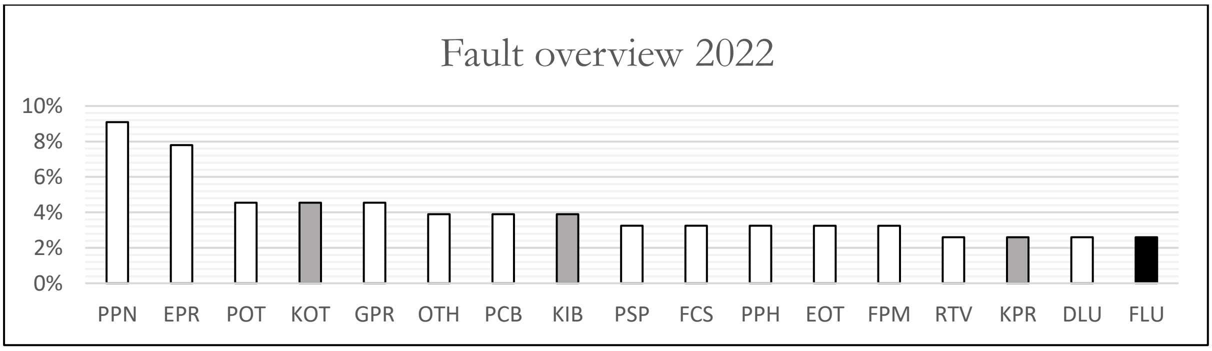

Figure 2.10: Fault overview 2022 (adapted from [9])

Prio failure analysis of 2022 reveals that PP2700 has contributed to more prio failures compared to PP3600 [10]. Therefore, it is decided to focus on the PP2700 failures. Moreover, the combined fault overview from all regions from year 2022 is consulted. Overview of all failure codes and subcodes can be found in Appendix D. In total there have been 43 failure codes registered. Contributing to 154 faults of PP3600 and PP2700 UPS systems in 2022 [9]. Figure 2.10 shows the overview of the failure codes which contributed with at least 3% (when rounded to a whole number) to the overall faults. These cover in total 70% of all faults and constitute of 17 different failure codes. Full overview of the faults from 2022 can be found in Appendix E.

The fault overview from 2022 further highlights the priority of focusing on the KEM component (Figure 2.10). 3 failure codes related to KEM (grey) and only 1 failure code related to flywheel (black) are depicted. These contribute to 11.04% and 2.60% of the 2022 faults, respectively. The KOT failure code stands for KEM other failures which are unique failures. Therefore, the KEM failure code of the most interest is KIB – KEM inner bearings failure.

2.3.2 KEM inner bearings

The KEM component is used to generate and store kinetic energy to support the UPS system during utility outage while the engine is starting up. The KEM component can be seen in Figure 2.11. To get a better idea of the size of this component, it is noted that the mass of the KEM is around 6000kg.

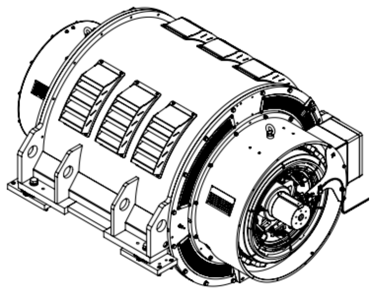

Figure 2.11: KEM drawing

There are 7 PMSMTs measured for evaluating the condition of the KEM component (Figure 2.6). Through evaluating the fault overview documents and conducting interviews, it is depicted that the KEM failures are always accompanied by the increase in vibrations. As a reminder for the reader, the UPS systems and their components do not run until failure. Failure is signified as having PMSMT value in the failure threshold region. Therefore, the selected PMSMT for developing a predictive model for KEM component faults are the KEM DE vibration and the KEM NDE vibration. Moreover, the inner bearing temperature DE and the inner bearing temperature NDE are of interest. These 4 selected PMSMTs are the most important PMSMTs to develop the predictive model for depicting the health state of the KEM. The aim of the model is therefore, to predict when the KEM inner bearings transition between the healthy (operational), degraded (warning / attention), and failure (failure) health states.

The threshold values for the healthy health state (HHS) are defined as range from lower bound (LB) to upper bound (UB). The degraded health state (DHS) has threshold LB equal to UB of HHS threshold and its own UB as UB. Failure health state (FHS) has threshold LB equal to UB of DHS threshold. It does not have an UB since there is no health state after failure. The LBs and UBs of the 4 KEM inner bearing PMSMTs are shown in Table 2.3.

Table 2.3: Selected KEM PMSMTs' thresholds

	HHS		DHS		FHS		
Measurement	**LB**	**UB**	**LB**	**UB**	**LB**	**UB**	**Unit**
KEM DE Vibration	0	9	9	20	20	-	mm/s
KEM NDE Vibration	0	9	9	20	20	-	mm/s
Inner bearing temp. DE	0	70	70	85	85	-	∘ C
Inner bearing temp. DE	0	70	70	85	85	-	∘ C

The mechanical drawing of the rotor combination, which is a crucial part of the KEM component is shown in Figure 2.12. The circled sections B and C correspond to the sections in which the KEM inner bearings are located. In section B, bearing 1 is located. This is a cylindrical bearing of type N218 (Figure 2.13, Left). The bearing has a width of 30mm, inner diameter of 90mm and outer diameter of 160mm. The inner ring rotates at 1500 rpm and the outer ring at 3900 rpm. With this input the manufacturer provides the calculation for ball pass frequency of outer race (BPFO) and ball pass frequency of inner race (BPFI). These are relevant parameters for vibrations in a frequency domain. For the N218, BPFO ≈ 288.73Hz and BPFI ≈ 391.27Hz [11].

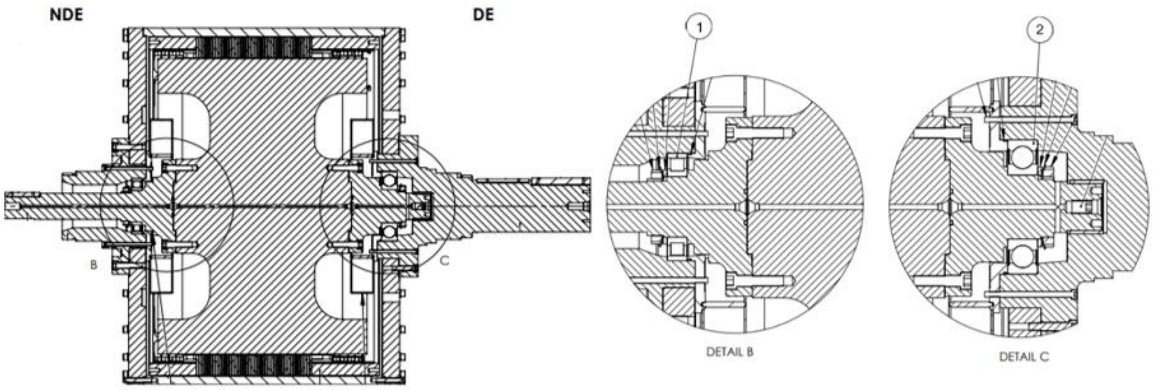

Figure 2.12: KEM rotor combination

Bearing 2 located in section C is a ball bearing 6319 (Figure 2.13, Right). The bearing has a width of 45mm, inner diameter of 95mm and outer diameter of 200mm. The manufacturer provides the calculation of the fault relevant parameters. The BPFO ≈ 123.837Hz and BPFI ≈ 196.163Hz [11].

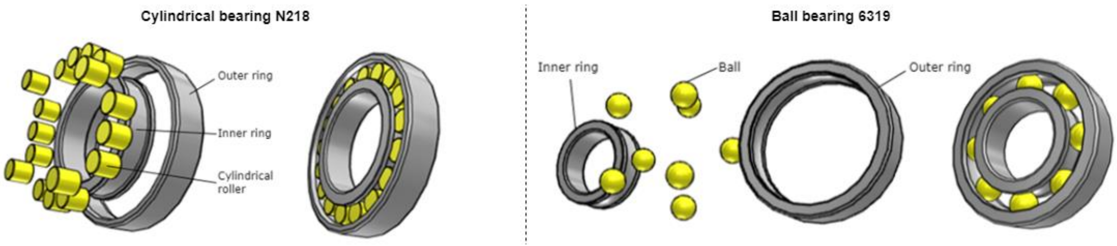

Figure 2.13: Left: Bearing N218 [12], Right: Bearing 6319 [13]

Due to the size and time needed for extracting available data for each PMSMT, a selection of PMSMTs relevant to KEM inner bearings and their condition is made. The following PMSMTs are selected for developing a predictive model for the KEM inner bearings:

- Output Frequency
- Inner Bearing Temperature DE
- Inner Bearing Temperature NDE
- Room Temperature
- Outer Bearing Temperature NDE
- Outer Bearing Temperature DE
- Q1 Actions Counter
- Flywheel Speed
- Gen DE Vibration
- Gen NDE Vibration
- KEM DE Vibration
- KEM NDE Vibration

3 Theoretical framework for HPP

This section lays down the theoretical framework related to the RQs of HPP. In section 3.1 different reliability centred maintenance policies are presented. In section 3.2 the relevant developments in predictive maintenance are discussed. Section 3.3 briefly evaluates the PMSMT data measured by HPP. In section 3.4 the guidelines for prioritizing failures and assets are presented. Lastly, section 3.5 shortly discusses the effectiveness of the current maintenance policy applied at HPP. The section also provides a formula for the evaluation of a maintenance policy.

3.1 Reliability centred maintenance

The International Organization for Standardization (ISO) defines reliability as *ability of a product to perform specified functions under specified conditions for a specified period of time without interruptions and failures* [14]. The reliability centred maintenance (RCM) is therefore concerned with maintenance strategy that is based on how long a machine can perform its intended function without a breakdown. There are 7 questions defined to guide the RCM process [15]:

1. What are the functions and associated performance standards of the asset in its present operating context?
2. In what ways does it fail to fulfil its functions?
3. What causes each functional failure?
4. What happens when each failure occurs?
5. In what way does each failure matter?
6. What can be done to predict or prevent each failure?
7. What should be done if a suitable proactive task cannot be found?

The first 5 questions are concerned with carrying out the failure mode, effects and criticality analysis (FMECA). The last two questions address the selection of a suitable maintenance policy for each defined failure mode. An overview of different RCM maintenance policies [15] and the characteristics of parts that are suitable for them [16] can be seen in Figure 3.1.

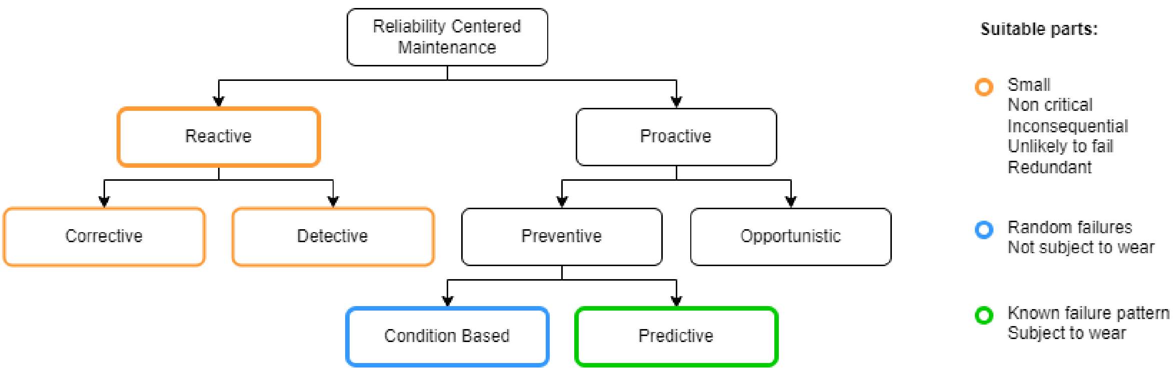

Figure 3.1: Reliability centred maintenance policies (adapted from [15] and [16])

3.1.1 FMECA

FMECA is a reliability procedure which documents all possible failures of a system and their criticality. It is a combination of failure mode and effects analysis (FMEA) and criticality analysis (CA). Within FMEA components of the system or its subsystems are defined. The potential failure modes are then listed for each of these subsystems and components. Potential failure effects of the failure modes determine the severity, potential causes the occurrence, and current controls the detection of the failure modes [17]. Failure effects can be anything having effect on the safety and environment. There are 4 possible cause categories for a failure mode. Namely, human error, load-carrying capacity, unavoidable, and avoidable load [15]. Current controls are for example, sensors monitoring the condition of component of the failure mode. The severity, occurrence, and detection scores are then combined to calculate the risk priority number (RPN) of each failure mode so they can be ranked based on associated risk. The criticality analysis also uses the RPN score to rank the failure modes, however, in addition to this quantitative input it also takes into account qualitative input for determining the overall criticality and importance of failure modes.

3.1.2 Reactive maintenance

Reactive maintenance takes place after a failure has occurred. There are two reactive maintenance policy alternatives, corrective and detective. Corrective maintenance takes place only when failure actually occurs. This is a failure that is observed during the usage of a system. Similarly, detective maintenance takes place only when failure actually occurs. However, it is discovered during a check-up when the system is not in use. The main benefit of such maintenance strategies is that the RUL of a failed component of the system is not wasted. The main disadvantage of the strategies is the downtime during which the system cannot be used. Therefore, the strategy is mostly suitable for parts that are small, non-critical, inconsequential, unlikely to fail, or redundant.

3.1.3 Proactive maintenance

Proactive maintenance is carried out before a failure occurs. Either in a preventive way or in an opportunistic way. Opportunistic maintenance is triggered by another maintenance operation. While other component of a system is being maintained, another component can be preventively maintained to make use of the fact that the system is already down due to the other maintenance. This maintenance can be applied for any parts within the same (sub)system as the maintenance needing component. Preventive maintenance can either be condition based or predictive. For condition based maintenance a planning on how and when components need to be inspected is needed. Once a certain condition threshold is reached, maintenance or replacement of the component is necessary. This type of preventive maintenance is suitable for parts which have random failures and are not subject to wear. For parts that are subject to wear and do not have random failures which means their failure pattern can be defined, PdM is the best maintenance policy.

3.2 Relevant developments in PdM

'*Recently, predictive maintenance has become prevalent in the industry due to the capability of reducing maintenance costs, unexpected downtime, and while extending the life span of equipment.*' [18]. These benefits of PdM come from the 4th industrial revolution focused on digitalization. Where technological developments took place in order to automate, integrate, and exchange real time data of systems. Due to this growing complexity of systems, model based approaches for developing algorithms for PdM are too difficult to develop. Therefore, in practise, data driven artificial intelligence (AI) approaches are used to develop PdM models. A review of "Recent advances and trends of predictive maintenance from data driven machine prognostics perspective" proposes 2 AI prognostic model categories [18]. Namely, conventional machine learning based models and deep learning (DL) models. DL is an extension of ML, which makes use of larger number of layers in its models compared to ML. DL methods show outstanding performance as the data increases in dimensionality and volume.

Four common machine learning / deep learning (ML/DL) methods are recognized [19]. First, clustering, which focuses on pattern analysis in order to group data points. Second, classification, which focuses on decision development in order to classify new data points. Third, regression, which focuses on trend analysis in order to predict values of new data points. Fourth, anomaly detection, which focuses on analysing the normal state of a system and depicting data points deviating from this normal state. Anomaly detection is a common approach for fault detection.

Three approaches for ML/DL methods are proposed [19]. First, unsupervised approach, where unlabelled data is used to develop models. This data can for example, be used to model normal behaviour of data and test how well the model describes a new set of data. Second, supervised approach, where labelled data is used to build a model. When it comes to anomaly detection for example, this data contains both healthy and anomalous data. Third, semi-supervised, where unlabelled data is available, and small data set with manually added labels is added to develop a model.

3.3 PMSMTs

This section first discusses the use of PMSMTs related to the implementation of a PdM policy at HPP, in section 3.3.1. Then, in section 3.3.2 the PMSMTs relevant for the depicting the HS of the KEM inner bearings are addressed.

3.3.1 PMSMTs at HPP

The access of HPP to the real time and historical PMSMT data at the customer sites has effect on the potential implementation of a PdM policy for their UPS systems. For developing a PdM policy it is necessary to have access to historical data from different customer sites with instances from different HSs. Currently this poses a challenge for HPP.

For majority of the customers HPP does not have access to real time PMSMT data. In some cases, it is possible to export historical data during maintenance service. This data can be used to develop a predictive model for a PdM policy. However, for this, clear guidelines on which data needs to be exported need to be made. It has been observed that the export of selected PMSMTs for a history of 2 month period can be easily exported and shared with HPP.

The real time access is not a must for a valuable PdM policy. Once a PdM policy has been implemented and validated, the policy can be setup within the operating system of the UPS system at the customer site. Using the direct PMSMTs from the UPS for PdM policy execution.

However, the current structure of storing the PMSMT data also poses challenges for the PdM policy. Different UPS system have different name sets for the same PMSMTs. Moreover, the set dead bands and band withs for PMSMT storage affect the time steps between the PMSMTs. The PMSMTs measured in real time have set constant time steps. However, the stored PMSMT values have varied time steps. This poses a challenge for the PdM policy. Especially if the PdM policy would be set up such that it further develops during its operationality, re-evaluating its performance and improving accordingly. Therefore, for HPP a set PdM policy is a suitable option.

3.3.2 PMSMTs for HS of KEM inner bearings

A review of bearing fault detection techniques presents 4 monitoring approaches for the health state of bearings. Vibration measurements, acoustic measurements, temperature measurements, and wear debris analysis [20]. At HPP all of the 3 mentioned measurements are being performed.

There are no issues with the vibration measurements at HPP.

For the temperature measurements, there is a data collection issue for some installed bases, where the inner bearing temperatures are no longer being measured. For some bases not even the room temperature was properly monitored.

For the acoustic measurements, there are 3 different acoustic measurements recorded for the KEM inner bearing DE and NDE side (together 6 different measurements). These are however not being used at HPP and are therefore also not included in the research. It should be evaluated whether these measurements are useful to measure or not. Then they can either to be used for data analysis in the future, or the relevant sensors can be removed. [21] performs a case study concluding better bearing fault identification using acoustic signals compared to vibration signals. Therefore, it is advised to perform an analysis of the usefulness of the acoustic PMSMT.

3.4 Failure and asset prioritization

A suitable maintenance policy for each asset should be selected for a cost-efficient maintenance service. Assets are categorized based on 2 aspects, cost and criticality. Based on position of an asset within these categories, different maintenance policies are suitable. A diagram of suitable maintenance policies based on this asset categorization can be seen in Figure 3.2.

Non-expensive non-critical assets do not require lot of effort to be put in when it comes to developing a maintenance policy. The operationality of system is not affected by their failure and it is cheap to simply throw them away and replace them with new ones when decided. This can either be once the asset fails or when other maintenance is being carried out on the system.

When it comes to expensive non-critical assets, maintenance is important in order to prolong the operational life of the assets. This leads to saving costs by not purchasing a new asset more often than required. This can be done by monitoring the condition of the asset or by providing maintenance for the asset during other maintenance activities.

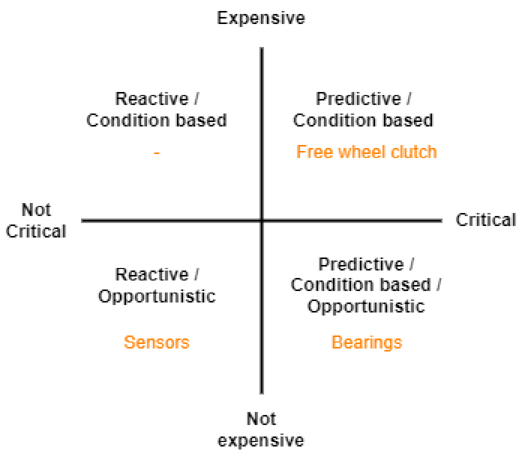

Figure 3.2: Maintenance policies suitable for different assets

On the other hand, when it comes to critical assets, a more advanced maintenance policy is required. For non-expensive critical components, condition monitoring of the asset through sensors or during other maintenance activities carried out on the system is a good option. However, if a suitable predictive maintenance is available/does not require a lot of developmental and implementational effort this is the best choice. For expensive critical assets either condition based or predictive maintenance should be used. These assets are too costly to replace before issues are observed. However, as they do affect the operationality of the system, they need to be maintained proactively.

To depict which maintenance policy is the most suitable for a given asset with a certain position in the diagram there are other aspects that can be taken into account. For example, for the bearings, which are the main focus of the research, PdM is depicted as the most suitable policy. On one hand, bearings are not expensive, and it might be said that CBM is a suitable policy choice. However, the UPS installed bases are not easily accessible for regular short interval maintenance of bearings. As the bases are located all over the world. Moreover, the bearings are located deep within the UPS system, and it is not practical to have to dismantle the system to maintain the bearings during for example every weekly check. Moreover, the frequency of failures of the asset is an important factor. Bearings in general within the industry, are components that fail the most in machinery. Therefore, in this case the bearings could be characterized as one of the most important assets.

3.5 Maintenance policy evaluation

The current maintenance policy applied at HPP is CBM. This policy is effective, with a high uptime of the HPP UPS systems. However, during maintenance service a unit from the UPS system is disconnected from the system, removing a potential redundancy. This affects the customer satisfaction. Therefore, to improve the maintenance it is important to provide more insights for the customers into the HS of the UPS system and its components. For this a PdM policy is needed.

To evaluate whether the selected maintenance policy is a suitable choice for a given asset, it is important to carry out a maintenance cost calculation. Where the following variables are used as input for the calculation:

- C_A: Cost of the asset replacement
- C_P: Cost of the preventive maintenance
- C_C: Cost of the corrective maintenance
- P_A: Probability of failure after time T
- P_B: Probability of failure before time T

The value of the maintenance policy is calculated as replacement asset value (RAV) percentage. Where the lower the percentage, the better the maintenance policy for the given asset.

$$RAV = \frac{P_A * C_C + P_B * C_P}{C_A} * 100$$

Equation 2: Replacement asset value (adapted from [22])

4 Theoretical framework for the research

This section provides the theory for development of a PdM policy for KEM inner bearings of HPP's UPS systems (Figure 4.1). In order to develop the PdM policy, predictive models for evaluating the HS of the KEM inner bearings need to be developed. The current categorization of HS of the KEM inner bearings at HPP is presented in Table 4.1. Where ∧ stands for AND operator, ∨ stands for OR operator and the unit of the numerical values is mm/s. For simplicity, the KEM DE Vibration is referred to as DE and KEM NDE Vibration as NDE.

Table 4.1: Health states split [Table 2.3]

Health state	Condition
Healthy	$(DE < 9) \wedge (NDE < 9)$
Degraded	$[(9 \le DE < 20) \wedge (NDE < 20)] \vee [(DE < 20) \wedge (9 \le NDE < 20)]$
Failure	$(20 \le DE) \vee (20 \le NDE)$

Therefore, for predicting the HS of the KEM inner bearings, two predictive models are developed. One for predicting the future value of KEM DE Vibration, and one for KEM NDE Vibration. These predictions are then used to evaluate the associated predicted HS according to Table 4.1.

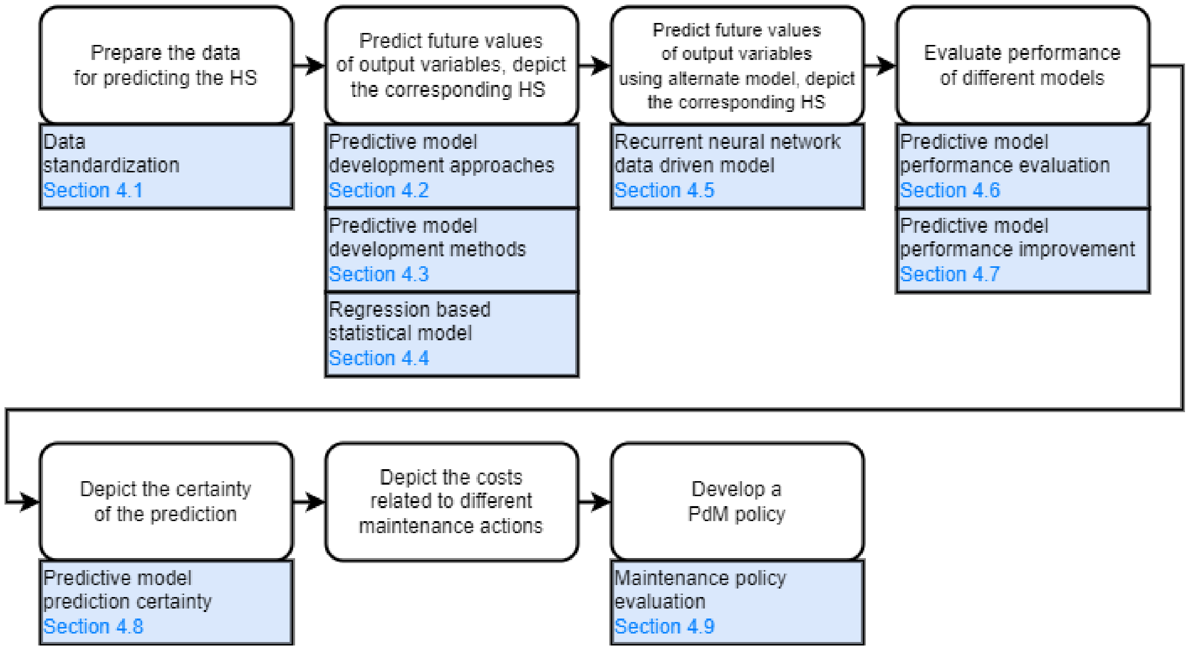

Figure 4.1: Theoretical framework: PdM policy development

Before addressing the relevant PdM policy development theories, the data used in the research is presented. 7 data sets of PMSMT data are exported for the research. Each data set corresponds to a half year of PMSMTs of one UPS unit. Since HPP does not store/have access to historical PMSMTs, the data is exported from units where the current half year history of PMSMTs could still be accessed.

There are 3 KEM inner bearing failure instances within the exported data sets. The data sets consist of time stamped PMSMTs. An overview of the exported data sets and their split for different stages of model development can be seen in Table 4.2. Train, Test, and Valid show the % of each data set included in training, testing, and validation data set, respectively. The split is randomized, but for reconstructive purposes seeds are used. With a set seed the same random numbers are drawn every time. As a remark, the validation set is used when the PdM policy is already developed to validate the PdM policy. It is not used to validate the predictive models themselves.

Table 4.2: Data sets overview

Data Set nr	Unit nr	Site nr	Status	Train	Test	Valid
1	1	1	Healthy	0.75	0.25	0
2	2	1	Including failure	0.75	0.25	0
3	3	1	Healthy	0.75	0.25	0
4	5	1	Healthy	0.75	0.25	0
5	3	2	Including failure	0.75	0.25	0
6	5	3	Healthy	0.75	0.25	0
7	6	3	Including failure	0	0	1

The overview of the exported PMSMTs can be found in Table 4.3. Including their relation to the predictive models that are developed. Where model DE stands for model used for predicting the value of KEM DE Vibration, and model NDE for predicting the value of KEM NDE Vibration.

Table 4.3: PMSMTs for model development

PMSMT	Description	Model DE	Model NDE
OuterBearingTempNDE	outer bearing temp. on KEM non-driving end	Input	Input
OuterBearingTempDE	outer bearing temp. on KEM driving end	Input	Input
Q1ActionsCounter	counter of switches to/from utility and diesel mode	Input	Input
FlywheelSpeed	speed of the KEM rotor	Input	Input
GenDEVibration	generator vibrations on generator driving end	Input	Input
GenNDEVibration	generator vibrations on generator non-driving end	Input	Input
KEMDEVibration	inner bearing vibrations on KEM driving end	Output	Input
KEMNDEVibration	inner bearing vibrations on KEM non-driving end	Input	Output

The rest of the section focuses on the theory relevant for the development process of the PdM policy (Figure 4.1). First, in section 4.1 the theory related to data preparation is presented. Next, in section 4.2 different approaches, and in section 4.3 different methods for developing predictive models are discussed. Suitable approaches and methods for the research are then selected. In section 4.4 the selected predictive model is introduced. In section 4.5 an alternative predictive model used for performance comparison is introduced. In order to compare the performance of the models, section 4.6 addresses different measures for evaluation of the predictive models. In section 4.7 approach for model performance improvement is introduced. The certainty of the predictions predicted using the predictive models is discussed in section 4.8. In section 4.9 the approach for evaluating the PdM policy is presented. Next, in section 4.10, the PdM policy development process for the research is presented. Lastly, in section 4.11, the integration of PdM policy within HPP is discussed.

4.1 Data preparation

First aspect of data preparation is qualitatively evaluating the data. This is done by cleaning the data from faulty measurements that would negatively affect the model performance. Moreover, for improving model development efficiency, duplicate data entries are removed.

Data normalization is another important aspect when it comes to model development efficiency. The effect of normalization or standardization of data on regression-based models is not expected [23]. However, [24] highlights the importance for data normalization when it comes to ML methods as it has a noticeable impact on the model performance. In the research a ML predictive model is also developed, therefore, data normalization is performed. The best normalization interval is subjective and therefore can be a parameter to be varied. For the research, the data is normalized using the [0,1] interval.

4.2 Predictive model development approaches

The key issue of predictive maintenance is to determine the maintenance inspection intervals. There are three criteria to take into account for this. Moment in the system life cycle at which intervals are determined, the way the system condition is assessed during the service life, and the prognostic approach that is followed [25].

Determining the intervals before the service life is a static method for determining the maintenance inspection intervals. These are usually determined during the design phase of a component and are provided by a manufacturer. On the other hand, when the intervals are determined during the service life it is a dynamic method. The dynamic method can either be corrective or proactive. With corrective approach components are replaced once they reach a certain condition threshold. With proactive approach the current condition value is used to predict the RUL of the components.

There are two possible ways to assess the condition of the components during their service life. First, using condition monitoring. For condition monitoring inspection intervals and/or sensors are used to monitor the performance of components. The second option is to develop a relation between usage and loads onto the components. Then by monitoring the usage of the component, its degradation and RUL can be estimated through the defined usage and load relation.

There are 3 prognostic approaches that can be followed for developing PM. Experience based, data driven, and model based. For condition monitoring, all three approaches can be applied. For usage and load relation, only data driven and model based approaches can be applied. The hierarchy of the prognostic approaches can be seen in Figure 4.2. The different approaches are discussed in more detail in the following sections.

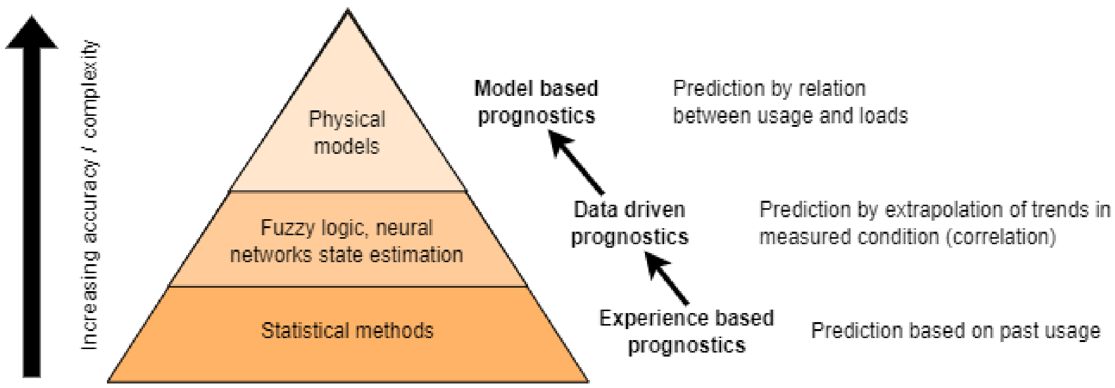

Figure 4.2: Hierarchy of prognostic approaches (adapted from [25])

4.2.1 Experience based approach

Experience based approach uses statistical methods to analyse the past usage of a system. For this historical data is required. From the historical data numerical parameters are depicted to define the failure distributions. For example, exponential or Weibull distributions are often used for failure analysis [25]. This is the simplest prognostic approach. The predictions developed are only accurate when the future usage is similar to the past / observed usage of a system. This is due to the fact that the usage and load relations are not known. The structure for applying experience based approach is shown in Figure 4.3.

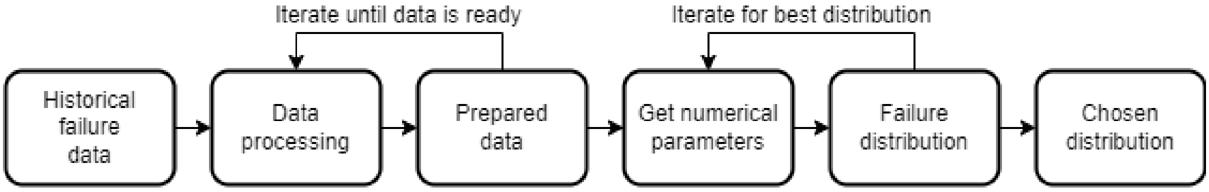

Figure 4.3: Experience based approach structure

4.2.2 Data driven approach

Data driven approach also requires availability of historical data. Advanced methods are applied to analyse the data to reveal underlying patterns, identify anomalies, and support the deterioration of components [26]. The predictions are based on correlations of performance measures and RUL. Again, the usage and load relations are not known, therefore, the accuracy of predictions is limited by the availability of historical data. Historical data sets from different usage scenarios are needed. However, when data is available, a failure model can be developed at low cost and in a short time [27]. The structure for applying the data driven approach can be seen in Figure 4.4.

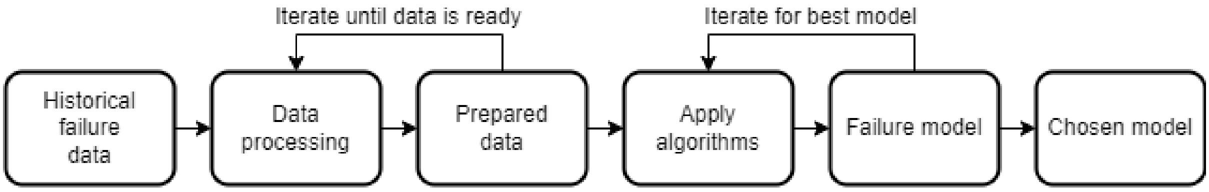

Figure 4.4: Data driven approach structure

4.2.3 Model based approach

Model based approach, also known as physics based approach, does not require historical data. Mathematical equations are used to define the relations between usage and its load onto the system. This is done in form of physical models. With these models the degradation of the system can be quantified. Therefore, predictions for RUL of systems with usage that was not observed before can be done as well. This is suitable for systems operating in variable environments [28]. However, this approach is the most complex one and requires most developmental effort [25]. The structure for applying the model based approach can be seen in Figure 4.5.

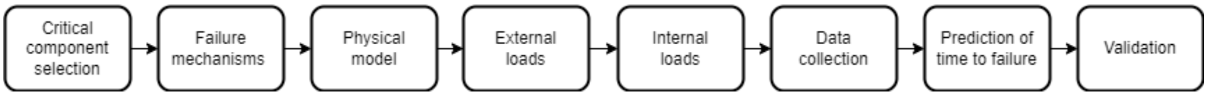

Figure 4.5: Model based approach structure (adapted from [28])

4.2.4 Selected model approach

Three approaches were presented in this section: experience based, data driven, and model based. With the complexity of the UPS systems and their units, model based approach is too complex to develop. Moreover, the complexity of the relation between the PMSMTs is difficult to determine before analysing the data. Therefore, both experience and data driven approaches are depicted as suitable. Therefore, in the research the focus is on **experience based and data driven model approaches**.

4.3 Predictive model development methods

Before diving into predictive model methods, it is important to decide on the domain in which the vibration data is analysed. There are three domains to choose from: frequency, time-frequency, and frequency domain. In time domain the x-axis represents time, and the y-axis represents the values of measurements. Creating a time series data. In frequency domain, the x-axis represents the frequency values of the measured signal consisting of several measurements, and the y-axis the count of the frequency occurrences within the signal.

For the research the time domain is selected. There are two main reasons for this selection. First, the ease of implementation into the existing systems at HPP. The measurements are recorded in time domain, and therefore no transformation to frequency domain will be necessary. Time series data is a perfect match for the research. Second, the features from time domain are more significant compared to the ones obtained from frequency domain [29].

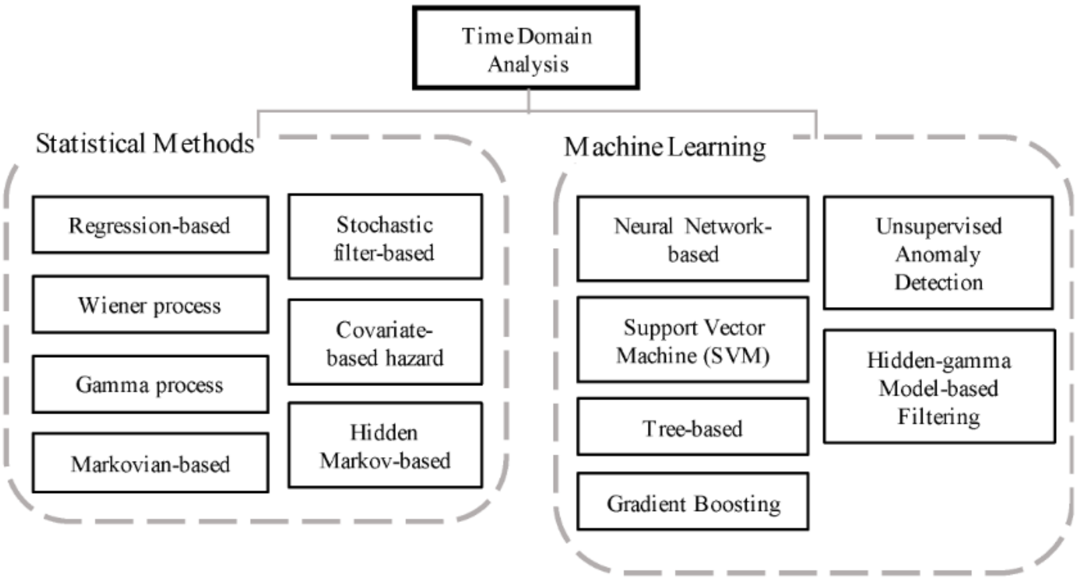

Figure 4.6: PdM model methods in time domain [29]

An overview of time domain statistical (Experience based approach) and machine learning (Data driven approach) predictive model methods can be seen in Figure 4.6 [29].

For the research, first, a statistical predictive model is developed. At this point the complexity of the relations between different PMSMTs is not known. A statistical model helps to evaluate this complexity. If the complexity is not large, the statistical model can reach a good performance and make valuable predictions. However, if the complexity is too large, the statistical model is not able to make valuable predictions. A statistical regression based model making valuable predictions is defined as a model that is able to correctly predict at least 10% of the non-healthy HSs.

Section 3.2 presents findings of ML models being the current trend in predictive maintenance. Therefore, a ML model is also developed. A simple ML model is developed to compare the model performances of these two models. To evaluate whether developing a statistical model is worth the developmental effort or a simple easily implemented ML model is enough.

The selected statistical model method is **regression-based** method. There are 2 main reasons for this selection. First, as a part of the research, the company would like to gain insights into the PMSMT data measured from their UPS systems (RQ3). The core of regression-based methods is to gain insights into the relations between the input and output variables. Second, the method fits well with the available data of the research. Data from different bearings at different unknown stages of operational life are available. Regression-based model looks at values of different variables at independent point in time. Both of these aspects are in line with the available data and the aims of the research.

The basic theory behind regression-based models is determining the relation between the input variables and the output variable. Using this learned relation the model predicts the value of the output variable based on the observed values of the input variables. However, the observed values of input variables at time $T = t$ are used to predict the output variable at time $T = t$. This is not very useful for making future predictions. An approach to deal with this issue is lagging. A lag of size L can be used to make predictions L time steps into the future. Meaning the observed values of input variables at time $T = t$ can be used to predict the value of an output variable at time $T = t + L$.

It is however important to note that vibrations do not have the same characteristics as the other PMSMTs. Temperature, for example, changes gradually and the change in its values can be easily visible. However, when it comes to vibration data it is not that simple. Vibration data changes rapidly, fluctuates, contains sudden peaks, without a visible trend. A comparison of temperature and vibration data can be seen in Figure 4.7.

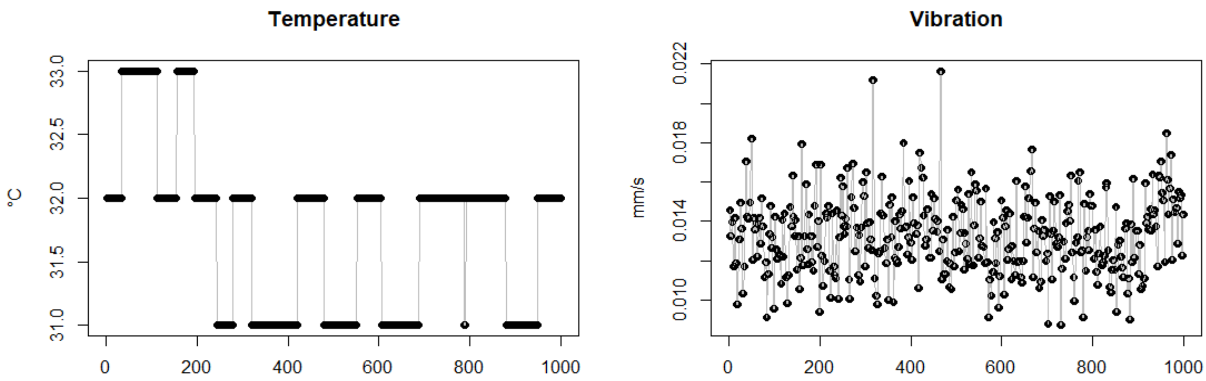

Figure 4.7: Temperature and Vibration data

Due to this nature, a regression model, which looks at individual measurements at a given point in time is likely not going to produce valuable predictions. There are two approaches to deal with this nature of vibration data for developing a regression based statistical prediction model. One is related to the frequency domain. Where vibration data is transformed to frequency domain, where after filtering processes, trends eventually become visible. However, in the research the focus is on time domain. Therefore, the other approach, which is related to time domain, is the one of interest. For depicting trends in vibration data in time domain, statistical features need to be exported from the data. These statistical features represent a certain time period consisting of consecutive measurements in time. With this approach, trends in data signifying change in health state of a component can become visible.

Extracted features can be used for regression-based models, to predict the transition between different health states. In a case study from 'Adaptive framework for bearing failure prediction' [30], regression based method is used to accurately detect health state transitions of bearings across multiple bearing failures. This approach, using extracted features with statistical regression-based models is suitable for the research. As the focus is on predicting the transition between health states of the KEM inner bearings.

A **regression-based statistical model** based on input variables **including extracted features** is developed and improved in the research. Furthermore, for a model performance comparison, a simple ML model is also developed.

The selected **ML model** is a **tree-based model**. The three-based model is selected as it is a simple ML model with which the relations between input variables and the model predictions can be easily analysed. This is due to the structure of the tree-based models, which take the form of a decision tree. In case the statistical model is able to make valid predictions, the ML model is developed using the original input variables. In case the statistical model is not able to make valid predictions, the ML model using the input variables of the improved statistical model is also developed.

4.4 Regression-based statistical model

Regression-based model is a good start for developing a model for predicting a value of an output variable. It allows an initial exploration of the relations between the output and input variables. It is very likely that a simple regression model will not be suitable to predict the output variable. Especially the sudden peaks in vibrations corresponding to the degradation HS and failure HS of the bearing. As mentioned before, this is because of the nature of the vibration data. The evolution of vibrations over time is an important factor for a predictive model. This is not an aspect covered in regression models. Therefore, the extracted features are also added to the predictive model.

The theory related to developing a statistical regression-based model first focuses on the theory evaluating the causality of the input variables used to predict the output variables. This can be found in section 4.4.1.

Then the regression-based model assumptions that need to be met for developing a valid regression-based model are addressed. There are four such assumptions. These assumptions are related to the input and output variables for which the model is built. First, concerning the output variable, is assumption of normality. Second, concerning the relation between input and output variables, is assumptions of linearity and homoscedasticity. And third, concerning the relation between the input variables, is assumption of independence of observations. The theory addressing the 4 model assumptions is presented in section 4.4.2.

For developing a regression-based model for vibration data the theory focused on the features to be extracted is presented in section 4.4.3. Moreover, the lagging theory for making predictions for the future is presented in section 4.4.4.

4.4.1 Causality between the input and output variables

Before addressing the assumptions for applying a regression-based model, a causality test between the input and output variables is performed. The test depicts whether an input variable is valuable for predicting the output variable. And what is the time period into the future for which this input variable is valuable. The outcome of the test influences the initial selection of the input variables. An input variable that does not have an effect on the output variable is not useful for predicting its value and can be removed immediately. Moreover, the outcome of the causality test depicts the period for which the input variable is useful for making predictions of the output variable.

The causality test is known as the Granger test. The test defines a null and alternative hypothesis and tests for the rejection or acceptance of the null hypothesis. The null hypothesis of the Granger test is that there is no causality between the given input and output variable. The alternative hypothesis is that there is causality between these variables. In order to reject the null hypothesis and conclude there is no significant evidence to suggest no causality between the variables, the p-value corresponding to the F statistic should be less than α. Where α is the significance level, representing the probability of wrongly rejecting the null hypothesis.

There are 3 input parameters of the Granger Causality test: the input variable measurements, their corresponding output variable measurements, and the prediction period. This test can easily be performed in R using the *grangertest* function from *lmtest* library.

$$grangertest(X \sim Y, order, data)$$

Equation 3: Granger test in R

The test checks whether variable Y Granger causes variable X. Order represents the prediction period and data the source from which the Y and X measurements are obtained.

4.4.2 Model assumptions

Normality assumption checks the distribution of the output variable. Ideally the output variable follows a normal distribution. Where the data is centred around the mean value of the distribution and 99.7% of the data lies within 3 standard deviations from the mean. However, this is not a hard assumption for applying regression.

Relation between input and output variables determines the function that fits the data. Then according to this relation it can be determined which regression model can be used. For example, if the relation between input and output variable is linear, linear regression can be applied. For this, scatter plots of the output variable versus the input variables are plotted. To see whether the data meets the **linearity** assumption.

Moreover, residual plots for linear regression model for each output and input variable pairing are developed. Then the data can be checked for **homoscedasticity.** By depicting whether the prediction errors of the linear regression model show significant changes in values.

Relation between input variables is useful when it comes to reducing the complexity of the model, by reducing the number of input variables. The input variables that are not correlated to other **input variables** are **independent** and therefore, useful for the model. Moreover, input variables that contribute the most to the increase of variability of the data are candidates for removal. The contribution to the variability can be depicted through VIF (variation inflation factor). However, in order to compute the VIF a basic regression model needs to be developed first.

4.4.3 Feature extraction

For feature extraction, the concept of a sliding window is first introduced. A window of size W contains W subsequent instances. With sliding window, every time a new instance is added, the window shifts in time. The concept of sliding window is demonstrated in Figure 4.8. The window size W represents the number of measurements from which a feature is extracted. Function f(x) indicates a formula used for extracting the features from the data. Where x stands for the measurements that are included in the window.

A window looks at a window of instances instead of looking at each instance individually, which is an important aspect for vibration data. With this concept, a regression-based approach suitable for developing a predictive model for the HSs of the bearing can be developed. The extracted features become additional input variables for a regression-based model.

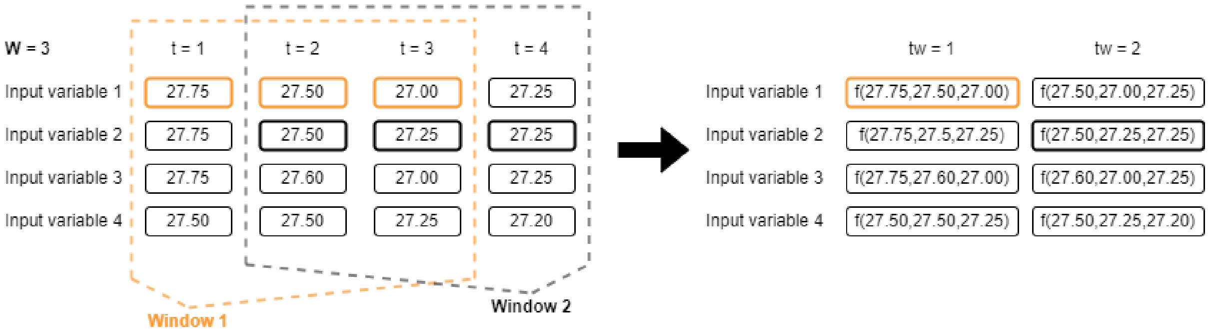

Figure 4.8: Concept of sliding window

There are several features that can characterize the degradation trend of a bearing. [31] and [32] focus on extraction of the following features: mean (Mean), standard deviation (Std), peak value (Peak), variance (Var), root mean square (RMS), shape factor (SF), margin factor (MF), energy (E), crest (Crest) kurtosis (Kurt), and skewness (Skew). However, it is stated that the features are only sensitive to a certain stage of degradation. Therefore, it might happen that the features are not able to indicate the different HSs properly. It is therefore important to evaluate whether these features are able to distinguish the differences between healthy and unhealthy measurements. The formulas for the features are show in Table 4.4. Where W stands for the window size.

Table 4.4: Feature extraction formulas

Mean	**Std**	**Peak**	**Var**
$\frac{1}{W}\sum_{i=1}^{W} x_i$ *Equation 4: Mean*	$\sqrt{\frac{\sum_{i=1}^{W}(x_i-\bar{x})^2}{W-1}}$ *Equation 5: Standard deviation*	$\frac{1}{2}[\max(x) - \min(x)]$ *Equation 6: Peak*	$\frac{\sum_{i=1}^{W}(x_i-\bar{x})^2}{W-1}$ *Equation 7: Variance*
RMS	**SF**	**MF**	**E**
$\sqrt{\frac{\sum_{i=1}^{W}\lvert x_i\rvert^2}{W}}$ *Equation 8: RMS*	$\frac{W * RMS(x)}{\sum_{i=1}^{W}\lvert x_i\rvert}$ *Equation 9: Shape factor*	$\frac{W * \max(x_i)}{\sum_{i=1}^{W}\lvert x_i\rvert^2}$ $i \in [1, W]$ *Equation 10: Margin factor*	$\sum_{i=1}^{W}\lvert x_i\rvert^2$ *Equation 11: Energy*
Crest	**Skew**	**Kurt**	
$\frac{Peak(x)}{RMS(x)}$ *Equation 12: Crest*	$\frac{\sum_{i=1}^{W}(x_i-\bar{x})^3}{W * Std(x)^3}$ *Equation 13: Skewness*	$\frac{\sum_{i=1}^{W}(x_i-\bar{x})^4}{W * Std(x)^4}$ *Equation 14: Kurtosis*	

To select the most suitable feature, the features are subject to monotonicity, trendability, and prognostability check [33]. These checks serve as indication for feature that best indicates the degradation of the component. The checks are carried out on the KEM DE and KEM NDE Vibration data containing time series from the healthy HS to the failure HS of a component. The data sets do not have the whole cycle from healthy state to failure. However, all data sets contain part of the health state degradation cycle, as the units are in operation. Therefore, based on the outcomes of the feature checks a selection of a feature that best represent the different health states is selected for the predictive model.

The equations for carrying out the feature suitability checks are presented. Where the following expressions are included in the equations:

- M: number of units / data sets
- N_i: number of windows of unit i
- x_i: the vector of all values of extracted features from unit i
- $x_i[j+1]$: the value of the extracted feature from unit i from window j+1
- $x_i[j]$: the value of the extracted feature from unit i from window j

$$Monotonicity = \frac{1}{M} * \sum_{i=1}^{M} \left| \sum_{j=1}^{N_i-1} \frac{sgn(x_i[j+1]-x_i[j])}{N_i-1} \right|$$

Equation 15: Monotonicity

$$Trendability = \min_{i,j} \left| corr(x_i, x_j) \right|$$

$$where\ i, j\ \in [1, M]$$

Equation 16: Trendability

$$Prognostability = \exp\left(-\frac{Std(x_i[N_i])}{mean|x_i[1]-x_i[N_i]|}\right)$$

Equation 17: Prognostability

4.4.4 Lagging theory

The lagging approach can be used to predict the future values of the output variable. The lagging process is demonstrated in Figure 4.9. The prediction period PP signifies the number of steps into the future for which the predictions are made. Then using input variables at time $T = t$ the aim is to predict the value of the output variable at time $T = t + PP$.

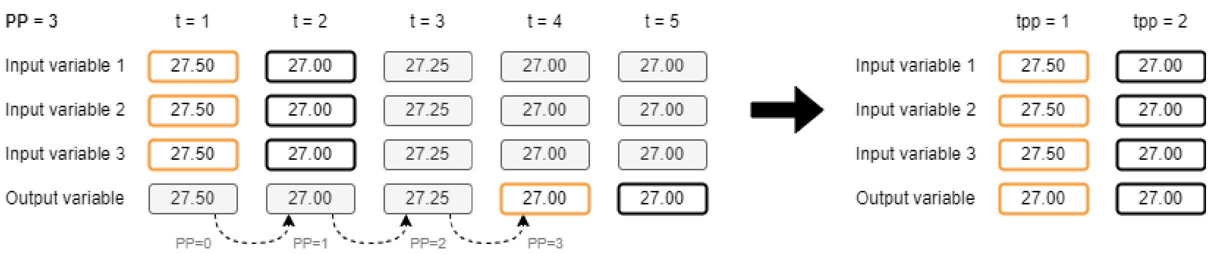

Figure 4.9: Lagging process

Using this approach, a regression model can be developed in order to predict the HS of the KEM inner bearing PP time steps into the future.

4.5 Tree-based data driven model

Tree-based ML models take a form of a decision tree. When it comes to predicting a value of a continuous output variable, a regression tree is applicable. The tree defines split criteria that lead to a certain end nodes of the tree. Based on the input variables which are evaluated using the tree splits, an end node corresponding to a certain value of output variable is reached. The main advantage of a tree-based ML model, also the reason this ML model is selected for the research, is the readability of the model. Through evaluation of the tree splits it can be clearly evaluated how which input variables contribute do the prediction of the output variable.

4.6 Predictive model performance evaluation

There are 3 KPIs to measure when it comes to evaluation of the predictive model. R^2, NRMSE, and MAPE. An overview of used expressions for their calculation is provided:

- Yobserved: observed value of output variable from training data set (data set used to build the model)
- Ypredicted: predicted value of output variable based on input variables from training data set
- Xobserved: observed value of output variable from testing data set
- Xpredicted: predicted value of output variable based on input variables from testing data set
- n: number of instances

$\boldsymbol{R^2}$ is the coefficient of determination. It determines how much the model fits the data by stating the proportion of total variance explained by the model [34]. $R^2 \in [0,1]$, where $R^2 = 1$ represents a model that is able to make prefect predictions, and $R^2 = 0$ represents a model that is not able to make predictions as the predictions (output variable values) are independent of the input variables.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Ypredicted_i - Yobserved_i)^2}{\sum_{i=1}^{n}(Yobserved_i - Avg(Yobserved))^2}$$

Equation 18: R squared

$$Avg(Yobserved) = \frac{\sum_{i=1}^{n} Yobserved_i}{n}$$

Equation 19: Average (output variable, training data)

In this case the observed values are the ones used to build the model, not ones in a testing set. The predicted values are then also based on these training set observed values. This is due to the fact that R^2 evaluates the model itself, instead of its performance when predicting new data. n is the count of the instances.

The next measure is the **NRMSE**, normalized root mean squared error (RMSE) [35]. RMSE is a common measure to estimate a prediction model performance. It represents the deviation of predicted values from their observed values.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(Xpredicted_i - Xobserved_i)^2}{n}}$$

Equation 20: RMSE

Where n is the count of values predicted. $RMSE = 0$ represents a model that predicts the output variable exactly as they are observed in testing data. There is no upper limit for RMSE. Therefore, to be able to evaluate the value of RMSE the average value (Avg) of the prediction variable is also needed.

$$Avg_{\ Xobserved} = \frac{\sum_{i=1}^{n} Xobserved_i}{n}$$

Equation 21: Average (output variable, testing data)

Where n is the count of observed values that are being predicted (same value as in RMSE formula).

The NRMSE then looks at the ratio between the RMSE and Avg. A low NRMSE signifies a good result as the RMSE is low compared to the average value of the output variable.

$$NRMSE = \frac{RMSE}{Avg_{\ Xobserved}}$$

Equation 22: NRMSE

MAPE (mean absolute percentage error) measures the accuracy of the predictions compared to their observed values.

$$MAPE = \frac{1}{n} * \sum_{i=1}^{n} \left| \frac{Xobserved_i - Xpredicted_i}{Xobserved_i} \right|$$

Equation 23: MAPE

The lower the MAPE, the more accurate the prediction model.

4.7 Predictive model performance improvement

Hyperparameter tuning is an approach for improving model performance by adjusting the training process of the model development. For linear regression statistical based models there is one such feature, set for the model development process. It is the measure to be minimized during the development process. Simple linear regression model is developed by establishing coefficients while minimizing the sum of squared residuals (RSS).

$$LinearRegression\ measure = \ RSS = \sum_{i=1}^{n} (Xobserved_i - Xpredicted_i)^{\ 2}$$

Equation 24: Linear regression measure

3 common approaches for tuning the hyperparameter are used. The approaches use cross-validation to assess how well the model performs when new independent data set is applied to the model. First approach, also known as Ridge regression, minimizes the RSS with added penalty of squared magnitude of coefficients.

$$RidgeRegression\ measure = RSS + \ \lambda \sum_{i=1}^{n} \beta j^2, \qquad \lambda \geq 0$$

Equation 25: Ridge regression measure

Second approach, also known as Lasso regression, minimizes the RSS with added penalty of absolute value of magnitude of coefficients.

$$LassoRegression\ measure = RSS + \ \lambda \sum_{i=1}^{n} |\beta j|, \qquad \lambda \geq 0$$

Equation 26: Lasso regression measure

The third approach, also known as Elastic net regression, is a combination of Ridge and Lasso regression.

$$ElasticNetRegression\ measure = RSS + \lambda\left[(1-\alpha)\sum_{i=1}^{n}\beta j^2 + \alpha\,|\beta j|\right], \qquad \lambda \geq 0$$

$$0 < \alpha < 1$$

Equation 27: Elastic net regression measure

The Ridge, Lasso, and Elastic net regression are especially applicable for model development using data where multicollinearity is present.

4.8 Prediction certainty

The implementation of the predictive model into a PdM policy requires additional output from the predictive model. Namely, the prediction probability. 2 options for evaluating the prediction probability are presented. First, evaluating the prediction probability by developing a confidence interval (CI). Second, evaluating the prediction probability by developing a prediction interval (PI). Both intervals can be easily computed in R. R provides an option where during statistical regression model prediction calculation an option to calculate the intervals can be selected.

$$predict(model, data, interval = \text{"confidence"}) \quad for\ CI\ output$$

$$predict(model, data, interval = \text{"prediction"}) \quad for\ PI\ output$$

Equation 28: Prediction probability in R

Both options have the same output format where the values for fit, lwr, and upr are obtained. Fit = the predicted value, lwr = the lower bound of the computed interval, upr = the upper bound of the computed interval. By default, 95% intervals are computed. Meaning that 95% of the predictions made, with the given input variables, have output values $Output \in [lwr, upr]$. The confidence limit can however be adjusted.

Both probability intervals are good options for evaluating the prediction probability. The CI reflects the uncertainty around the mean predictions and the PI the uncertainty around a single predicted value. Therefore, the CI will provide a narrower interval compared to PI. Which is nice. However, knowing the prediction probability of a specific prediction is more valuable. Therefore, for the research the prediction probability is evaluated by computing the PIs.

In case the statistical model provides valuable predictions the above method is used to compute the PIs. However, this is not applicable for the ML tree-based model. In order to develop the PIs for the tree-based model a quantile tree-based model needs to be developed.

4.9 Maintenance policy evaluation

In general, a maintenance policy is evaluated performing a cost calculation, such as in section 3.5. However, for HPP these costs are not directly relevant as the costs are covered by the customers. What is relevant for HPP is that the customer is aware of the HS of the UPS system and its components. The customers than have a better knowledge about needed maintenance for their system. Allowing them to plan the maintenance actions in advance, potentially lowering their costs. Making the HPP's maintenance service more attractive.

4.10 Research PdM policy development

The final PdM policy development approach adjusted following the theoretical framework is presented in Figure 4.10.

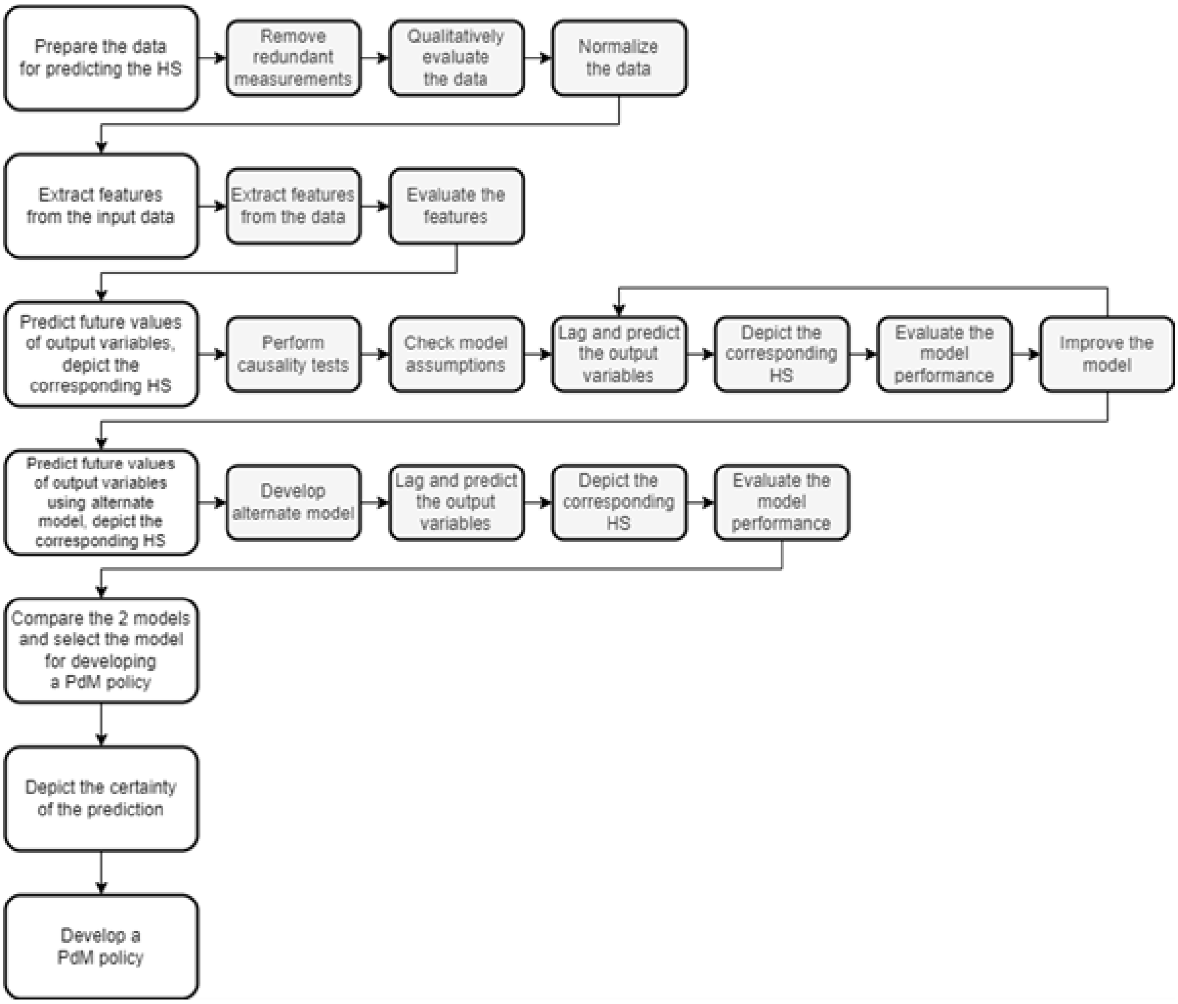

Figure 4.10: Research PdM policy development

The approach for predicting the HS of the KEM inner bearings consists of predicting the KEM DE Vibration and KEM NDE Vibration values. This is done by developing a predictive model DE and model NDE. The variables used for development of these models are shown in Table 4.5.

Table 4.5: Model DE and model NDE variables

PMSMT	Model DE	Model NDE
OuterBearingTempNDE	Input	Input
OuterBearingTempDE	Input	Input
Q1ActionsCounter	Input	Input
FlywheelSpeed	Input	Input
GenDEVibration	Input	Input
GenNDEVibration	Input	Input
KEMDEVibration	Input	Input
KEMNDEVibration	Input	Input
Unit	Input	Input
Extracted features	Input	Input
Lagged KEMDEVibration	Output	-
Lagged KEMNDEVibration	-	Output

Where Unit is defined as data set number from Table 4.2. Furthermore, the variables are split for training, testing, and validation according to Table 4.1. The prediction results of the models are then used to evaluate the associated predicted HS of the KEM inner bearings according to Table 4.1.

4.11 Implementation of PdM at HPP

The implementation of PdM at HPP requires effort when it comes to the software setup. During the installation of a UPS system at a customer site the model needs to be setup. The link between the model PMSMTs and the actual direct measurements of PMSMTs from the UPS system needs to be established. Furthermore, the outcomes of the PdM policy need to be visualized for the customers. This is to be done in the form of the proposed maintenance indicators, which initiated the research into PdM policy at HPP.

When it comes to the operational side of the PdM policy, nothing changes for HPP. The customers request maintenance service and after the request HPP plans the maintenance service. Therefore, HPP performs the same maintenance, at the same time (when requested by customer). The adjustment to the maintenance occurs at the customer site. Where the customer needs to evaluate the benefits of early maintenance. Taking into account the fact that not all HS predictions can be reliable.

This, however, also opens us a discussion for HPP on how much data to share with a customer. Especially related to the warranty aspect. If there is a prediction that in a certain prediction period a non-healthy HS will occur, the customer has a right to request a maintenance service that is les costly as a non-healthy HS is observed within a warranty period. Whereas, if the customer waits the prediction period, until when the non-healthy HS actually occurs. They might already be outside of the warranty period. Meaning, the maintenance service is more costly for the customer, and HPP earn bigger profit for their maintenance service.

5 Predictive model development

In this section the predictive model predicting the HS of the KEM inner bearings used for implementing the PdM policy is developed. First, the data used for the model development is prepared in section 5.1. Next, features from KEM DE and KEM NDE Vibration data are extracted in section 5.2. In section 5.3 the assumptions for developing a statistical predictive model are checked. In the following section, section 5.4, the statistical model is developed. The model is used to predict the HS of the KEM inner bearings. Furthermore, the model is improved within the same section. In the next section, section 5.5, the alternative data driven prediction model is developed. The model is used to make predictions for the HS of the KEM inner bearings. In section 0, the 2 models are compared and the model with better performance is selected for implementing the PdM policy.

5.1 Data preparation

The data consist of 8 PMSMTs extracted from 7 different units Table 4.2 and Table 4.3 provide overview of the extracted data. Before the data can be used for model development it needs to be processed. First, the data measurements are reduced in section 5.1.1. Then the measurements are qualitatively checked in section 5.1.2. Lastly, in section 5.1.3, the data is normalized.

5.1.1 Data measurement reduction

Before starting other manipulation of the data, the original data sets are reduced to adjusted data sets with only consecutive unique measurements. This helps reduce the size of the data sets while not removing any unique information. The usefulness of this adjustment can be seen in Table 5.1. Where it is stated that only 18% of the original measurements added unique information to the data sets. The following parameters are shown in the table:

- Data set : data set number (data set number is also referred to as 'unit' in the rest of the paper)

- #Original: number of instances in original data set

- #Adjusted: number of instances in adjusted data set

- Kept %: the percentage of instances from the original data set kept in adjusted data set

Table 5.1: Transformation to unique data sets

Data set	#Original	#Adjusted	Kept %
1	191 595	32 761	17 %
2	199 533	48 688	24 %
3	276 981	66 215	24 %
4	251 651	59 303	24 %
5	367 450	312 581	85 %
6	1 042 006	47 098	5 %
7	1 254 878	84 703	7 %
Total	3 584 094	651 349	18 %

5.1.2 Data quality check

Next, the data is qualitatively checked. The summary for unit 5 shows values that are out of their expected range. Temperatures of over 6000 ∘ C are recorded. Moreover, vibrations reach values of 2000 mm/s. Which is not realistic. The process of dealing with these values can be seen in Appendix F. Moreover, the summary of data of unit 5 before and after processing can be seen in Figure 5.1 and Figure 5.2, respectively . The data set for unit 5 after qualitative check shows realistic maxima for the variables. For example, for the KEM DE Vibration, the maximum value went from ≈20154 mm/s to ≈66 mm/s.

```
> summary(Unit5)
 OuterBearingTempNDE OuterBearingTempDE Q1ActionsCounter FlywheelSpeed
 Min.   :   0.00     Min.   :   0.00    Min.   : 0.00    Min.   :   0
 1st Qu.:  34.00     1st Qu.:  38.00    1st Qu.:14.00    1st Qu.:4196
 Median :  38.00     Median :  41.00    Median :14.00    Median :4196
 Mean   :  39.17     Mean   :  41.31    Mean   :34.73    Mean   :3894
 3rd Qu.:  45.00     3rd Qu.:  46.00    3rd Qu.:61.00    3rd Qu.:4197
 Max.   :6551.00     Max.   :6354.00    Max.   :65.00    Max.   :4197
 GenDEVibration     GenNDEVibration    KEMDEVibration     KEMNDEVibration
 Min.   : 0.03427   Min.   : 0.02989   Min.   :    0.031   Min.   :  0.03344
 1st Qu.: 2.25717   1st Qu.: 3.67615   1st Qu.:    1.233   1st Qu.:  2.22420
 Median : 2.36449   Median : 3.79286   Median :    1.463   Median :  2.39425
 Mean   : 2.39598   Mean   : 3.92686   Mean   :    1.713   Mean   :  2.47626
 3rd Qu.: 2.42890   3rd Qu.: 4.47557   3rd Qu.:    1.704   3rd Qu.:  2.57019
 Max.   :12.43093   Max.   :12.49402   Max.   :20154.260   Max.   :261.38641
```

Figure 5.1: Unit 5 summary

```
> summary(Unit5)
 OuterBearingTempNDE OuterBearingTempDE Q1ActionsCounter FlywheelSpeed
 Min.   :  0.00      Min.   :  0.00     Min.   : 0.00    Min.   :   0
 1st Qu.: 34.00      1st Qu.: 38.00     1st Qu.:14.00    1st Qu.:4196
 Median : 38.00      Median : 41.00     Median :14.00    Median :4196
 Mean   : 39.11      Mean   : 41.27     Mean   :34.73    Mean   :3894
 3rd Qu.: 45.00      3rd Qu.: 46.00     3rd Qu.:61.00    3rd Qu.:4197
 Max.   :100.00      Max.   :100.00     Max.   :65.00    Max.   :4197
 GenDEVibration     GenNDEVibration    KEMDEVibration     KEMNDEVibration
 Min.   : 0.03427   Min.   : 0.02989   Min.   : 0.03114   Min.   : 0.03344
 1st Qu.: 2.25717   1st Qu.: 3.67615   1st Qu.: 1.23343   1st Qu.: 2.22420
 Median : 2.36449   Median : 3.79286   Median : 1.46332   Median : 2.39425
 Mean   : 2.39603   Mean   : 3.92695   Mean   : 1.64816   Mean   : 2.47547
 3rd Qu.: 2.42890   3rd Qu.: 4.47557   3rd Qu.: 1.70416   3rd Qu.: 2.57019
 Max.   :12.43093   Max.   :12.49402   Max.   :65.93390   Max.   :77.06567
```

Figure 5.2: Unit 5 summary after processing

5.1.3 Data normalization

Next, the data is normalized. For the predictive model, the data is normalized using the [0,1] interval. The normalization is performed for all data sets jointly. The summary of the data before normalization (Data) and after normalization (Data_Normalized) for units 1 to 6 can be seen in Figure 5.3. It can be seen that the normalized data indeed has all minima equal to 0 and all maxima equal to 1. Unit 7 is normalized separately as it is a validation unit.

```
> summary(Data)
 OuterBearingTempNDE OuterBearingTempDE Q1ActionsCounter FlywheelSpeed
 Min.   :  0.00      Min.   :  0.0      Min.   :  0.00   Min.   :   0
 1st Qu.: 33.00      1st Qu.: 36.0      1st Qu.: 14.00   1st Qu.:3897
 Median : 39.00      Median : 41.0      Median : 28.00   Median :4196
 Mean   : 40.31      Mean   : 41.1      Mean   : 38.45   Mean   :3438
 3rd Qu.: 46.00      3rd Qu.: 46.0      3rd Qu.: 61.00   3rd Qu.:4196
 Max.   :100.00      Max.   :100.0      Max.   :136.00   Max.   :4197
 GenDEVibration   GenNDEVibration  KEMDEVibration   KEMNDEVibration
 Min.   : 0.000   Min.   : 0.000   Min.   : 0.000   Min.   : 0.000
 1st Qu.: 1.099   1st Qu.: 1.439   1st Qu.: 1.214   1st Qu.: 1.524
 Median : 2.240   Median : 3.578   Median : 1.539   Median : 2.286
 Mean   : 2.013   Mean   : 2.773   Mean   : 1.613   Mean   : 2.131
 3rd Qu.: 2.408   3rd Qu.: 3.837   3rd Qu.: 2.012   3rd Qu.: 2.595
 Max.   :12.431   Max.   :12.494   Max.   :65.934   Max.   :77.066
```

```
> summary(Data_Normalized)
 OuterBearingTempNDE OuterBearingTempDE Q1ActionsCounter FlywheelSpeed
 Min.   :0.0000      Min.   :0.000      Min.   :0.0000   Min.   :0.0000
 1st Qu.:0.3300      1st Qu.:0.360      1st Qu.:0.1029   1st Qu.:0.9284
 Median :0.3900      Median :0.410      Median :0.2059   Median :0.9997
 Mean   :0.4031      Mean   :0.411      Mean   :0.2827   Mean   :0.8192
 3rd Qu.:0.4600      3rd Qu.:0.460      3rd Qu.:0.4485   3rd Qu.:0.9998
 Max.   :1.0000      Max.   :1.000      Max.   :1.0000   Max.   :1.0000
  GenDEVibration     GenNDEVibration   KEMDEVibration    KEMNDEVibration
  Min.   :0.00000    Min.   :0.0000    Min.   :0.00000   Min.   :0.00000
  1st Qu.:0.08844    1st Qu.:0.1152    1st Qu.:0.01841   1st Qu.:0.01978
  Median :0.18017    Median :0.2864    Median :0.02334   Median :0.02966
  Mean   :0.16194    Mean   :0.2220    Mean   :0.02446   Mean   :0.02765
  3rd Qu.:0.19373    3rd Qu.:0.3071    3rd Qu.:0.03052   3rd Qu.:0.03368
  Max.   :1.00000    Max.   :1.0000    Max.   :1.00000   Max.   :1.00000
```

Figure 5.3: Normalization data summary

5.2 Extracted features

There are 11 features to extract from data to be analysed for suitability as HS transition indicators. Namely, Mean, Std, Peak, Var, RMS, SF, MF, E, Crest, Skew, and Kurt (Table 4.4). These features are first extracted in section 5.2.1, using a window of half a month. Subsequently, in section 5.2.2, the extracted features are checked for suitability as HS transition indicators.

5.2.1 Feature extraction

The aim of the extracted features is indicating that a component is transitioning from one HS to another. Therefore, it should be visible that the values of features change before observing a spike in the vibration data. The features are extracted using half a month windows. Therefore, for each data set $W = \frac{N_D}{12}$. Where N_D stands for number of measurements of data set D. This selection of window size is made based on the size of the data sets and the feature extraction time. However, the effect of different window sizes is evaluated later on when a predictive model is developed.

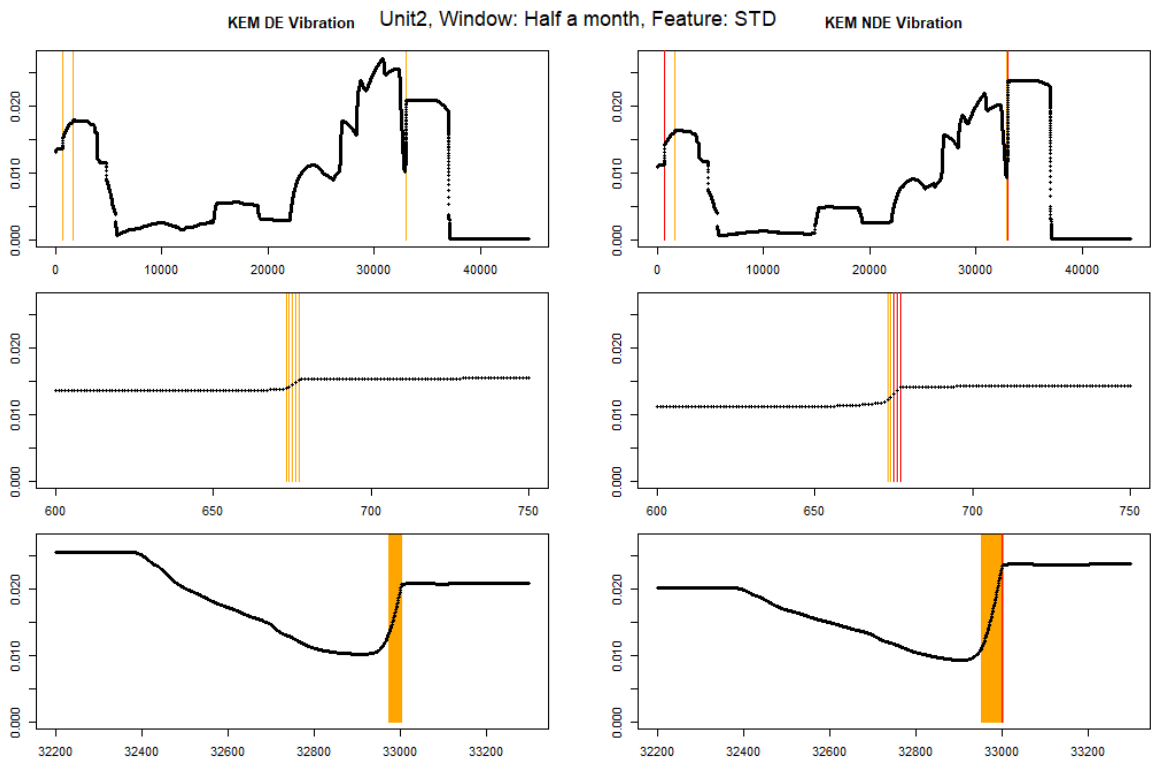

Figure 5.4: Extracted feature: Std

The extracted feature Std for data set 2 can be seen in Figure 5.4. The orange and red vertical lines represent the measurement from degraded and failure HS, respectively. The figures for the rest of the extracted features can be found in Appendix G. It can be seen in Figure 5.4 that there is an increase in the value of Std prior to and within the degradation and failure HS region. This can however be observed also within some healthy HS regions. However, there are other aspects of this extracted feature that can be distinguishable for the healthy versus degraded or failure HS region. For example, the steepness of the increase of the extracted feature value.

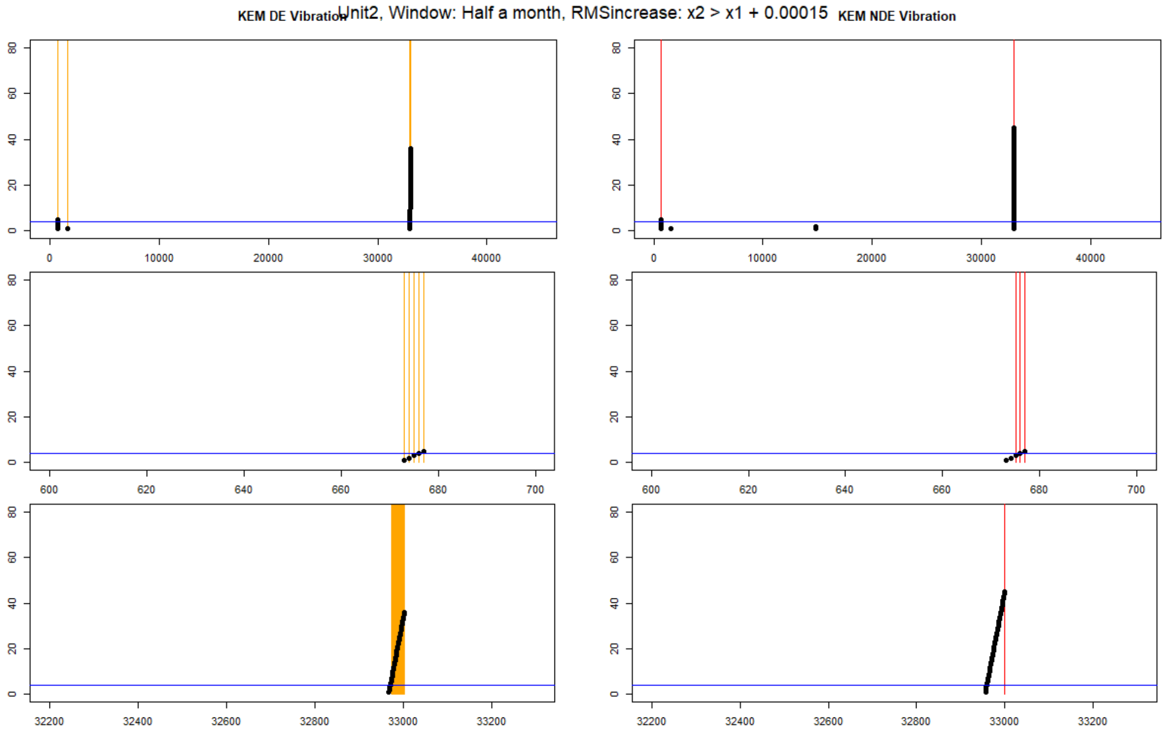

Figure 5.5: Std increase steepness

The Std increase of at least a certain increment value (Incr), in the example Incr = 0.00015, for data set 2 is visualized in Figure 5.5. To distinguish between healthy and non-healthy data it is also important to note the 'streak' for which this difference occurs. This streak count value is represented in y-axis. The x-axis stays the same and represents the time order of the measurement. The R code including the streak calculation is presented:

```
Incr <- 0.00015 #set the increment value

STDIncreaseCount <- data.frame(STD_DEVibration=Unit2_DE$STD, STD_DEIncrease=NA) #create table with Std values and an empty column for Std minimal increase streak count

STDIncreaseCount$STD_DEIncrease[1] <- 0 #start the streak count at 0

for(x in 2:nrow(STDIncreaseCount)) { #for second to last Std value

 if (STDIncreaseCount$STD_DEVibration[x]>STDIncreaseCount$STD_DEVibration[x-1]+Incr) { #check if the current Std value is more than the increment larger than previous Std value

  STDIncreaseCount$STD_DEIncrease[x] <- STDIncreaseCount$STD_DEIncrease[x-1] +1 #if yes increase the streak count by 1

 } else { #if no

  STDIncreaseCount$STD_DEIncrease[x] <- 0 #reset the streak count to 0

 } }
```

Using the streak count a cut-off horizontal line (blue line in Figure 5.5) is defined to distinguish between healthy and non-healthy data. All points below the line are disregarded and all points above the line are considered as indicators of HS transition. It can be seen from Figure 5.5 that for the KEM NDE Vibration the Std extracted feature could predict the failure region at T=33000. However, for the failure region starting around T=675 the HS transition is identified when the failure occurs and not prior to it. Moreover, a HS transition is never identified during healthy HS, which is good. This example shows that the extracted features contain useful information for indicating a HS transition. Even though it might not seem that way at first look (Figure 5.4).

5.2.2 Feature evaluation

An initial evaluation is made to check for suitability of the different extracted features when it comes to indicating the HS transitions of the KEM DE Vibration and KEM NDE Vibration. The results computed from all data sets for monotonicity, trendability, and prognostability check are shown in Figure 5.6.

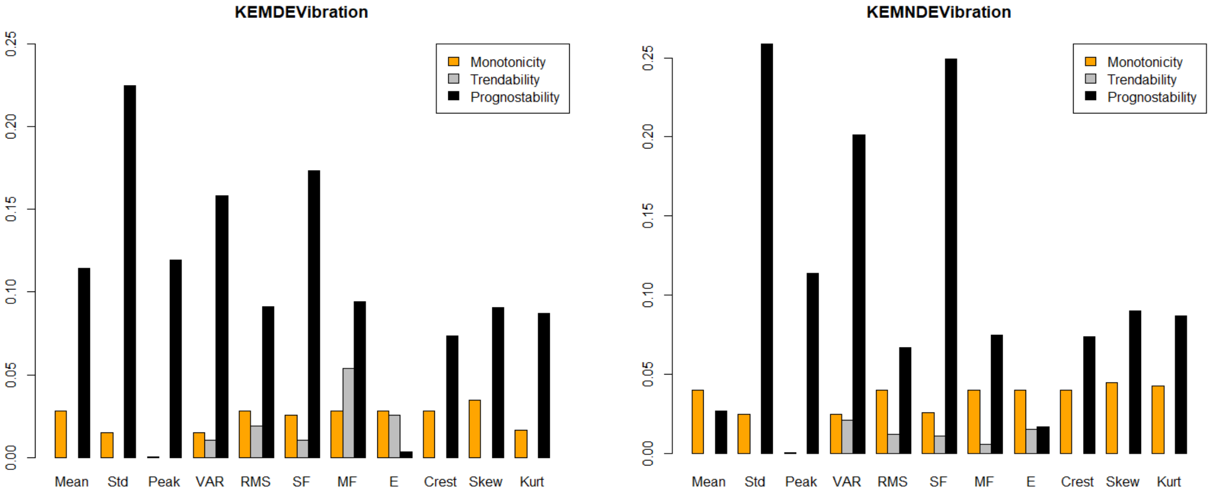

Figure 5.6: Feature suitability check

The Std, VAR, and SF features look as promising indicators of HS transitioning as the prognostability result for both KEM DE Vibration and KEM NDE Vibration are high. However, no definitive conclusions can be made at this point. All the extracted features will be further evaluated during the model development / improvement step (section 5.4).

5.3 Regression-based model assumptions

This section focuses on preparation for developing a predictive regression-based model for predicting transition between different HSs of KEM inner bearings. First, in section 5.3.1, the causality checks between input and output variables are checked. Then the regression-based model assumptions are checked. In section 5.3.2 the normality check, in section 5.3.3 the linearity check, in section 5.3.4 the homoscedasticity check, and in section 5.3.5 the independence of observations check are performed. Lastly, in section 5.3.6 a conclusion regarding the model assumptions is made.

Table 5.2: Health states count (seed: 123)

Health state	Index	#Training	#Testing
All	-	424 977	141 662
Healthy	0	423 225	141 109
Degradation	1	1 707	536
Failure	2	45	17

Before checking the regression-based model assumptions, a count of measurements for each health state is made (Table 5.2). Where index stands for the referral number for a given HS, #Training stands for the number of instances included in the training part of the data, and #Testing for the number of instances included in the testing part of the data. This provides an initial view of the number of data points coming from a non-healthy HS.

5.3.1 Causality check

For the causality test, three different prediction periods (PP) are evaluated: PP=1, PP=15, PP=30. Assuming that 1 time step corresponds to approximately 5 hours (Appendix H), the upper bound is selected as 30. This should correspond to approximately a 6 day PP (30*5hr=150hr≈6days). The p-values of the F test statistics for the different causality tests for the HS output variable can be seen in Table 5.5. These are calculated using the *grangertest* function in R (Equation 3).The light green cells correspond to values where it is concluded with 95% probability that the input variables Granger cause the output variable. Similarly, the dark green cells signify the same conclusion with a 99% probability.

A causality test for KEM DE Vibration and KEM NDE Vibration outputs are performed. The outcomes of these tests can be seen in Table 5.3 an Table 5.4, respectively.

Table 5.3: Causality test –KEM DE Vibration

Input variable \ p-value	PP=1 ($\approx 5hr$)	PP=15 ($\approx 3days$)	PP=30 ($\approx 6days$)
OuterBearingTempNDE	7.27e-29	2.27e-16	1.98e-18
OuterBearingTempDE	9.98e-34	5.67e-52	1.87e-54
Q1ActionsCounter	3.47e-37	3.17e-35	1.07e-50
FlywheelSpeed	0.00e+00	1.23e-197	3.99e-202
GenDEVibration	0.00e+00	0.00e+00	0.00e+00
GenNDEVibration	1.59e-239	0.00e+00	0.00e+00
KEMNDEVibration	0.00e+00	0.00e+00	0.00e+00
Unit	4.93e-231	1.83e-23	3.46e-13

Table 5.4: Causality test – KEM NDE Vibration

Input variable \ p-value	PP=1 ($\approx 5hr$)	PP=15 ($\approx 3days$)	PP=30 ($\approx 6days$)
OuterBearingTempNDE	4.39e-26	2.35e-189	7.86e-195
OuterBearingTempDE	5.33e-77	5.42e-130	1.97e-143
Q1ActionsCounter	1.57e-67	4.12e-126	1.58e-142
FlywheelSpeed	9.89e-241	0.00e+00	0.00e+00
GenDEVibration	3.38e-221	0.00e+00	0.00e+00
GenNDEVibration	8.96e-295	0.00e+00	0.00e+00
KEMDEVibration	0.00e+00	0.00e+00	0.00e+00
Unit	1.15e-124	1.27e-16	9.40e-12

It is concluded from the causality checks that for predicting the KEM DE Vibration and KEM NDE Vibration, all the input variables can be useful. Therefore, no input variables are removed at this stage of the research.

5.3.2 Normality assumption

The histograms for both output variables, KEM DE Vibration and KEM NDE Vibration, are shown in Figure 5.7. Initially, the data does not seem to follow a normal distribution. However, two other distributions are also fitted to assess their suitability. It is then concluded that the normal distribution fits the data the best. Therefore, it is concluded that for both models, model DE and model NDE, the normality assumption is met.

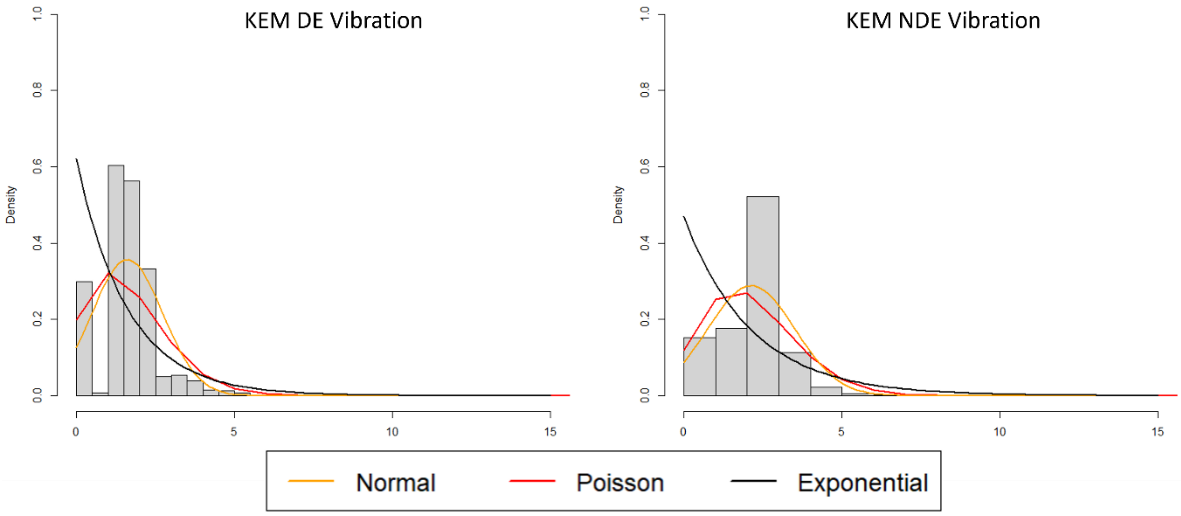

Figure 5.7: Histogram: KEM DE Vibration and KEM NDE Vibration

5.3.3 Linearity assumption

Scatterplots are developed to evaluate the relation between input and output variables. For visual evaluation the linear fit between the variables is visualized in the scatterplots. Additionally, a smooth fit between the variables is added for comparison. The results for both output variables versus the Outer Bearing Temp NDE input variable are shown in Figure 5.8. The scatterplots for the remaining input variables can be found in Appendix I.

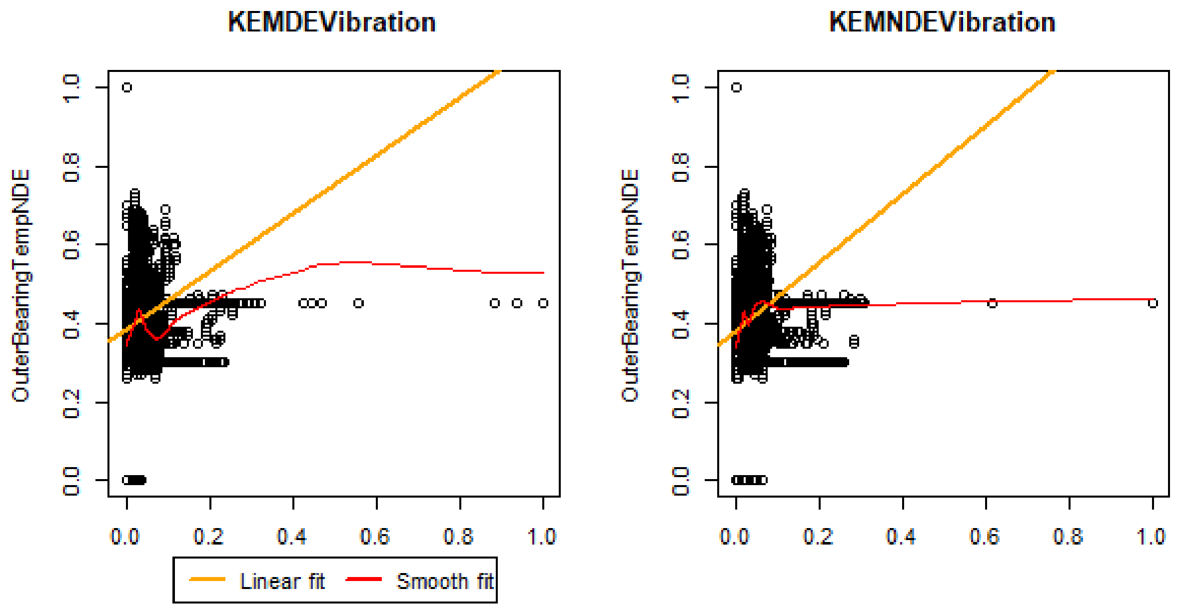

Figure 5.8: Scatterplot: OuterBearingTempNDE vs output variables

Looking at the linear and smooth fits from the scatterplots, it can be seen that for the KEM DE and KEM NDE Vibration, there are visible differences in the fits. Therefore, the linearity assumption is not met for all data. However, as seen in [30] the nonlinearity for the non-healthy part of the data set can be exploited in the model. Therefore, scatterplots for evaluating linearity for only healthy data are developed. Scatterplot between healthy KEM DE and KEM NDE Vibration output variables and Outer Bearing Temp NDE input variable can be seen in Figure 5.9. The scatterplots for the other input variables can be found in Appendix J.

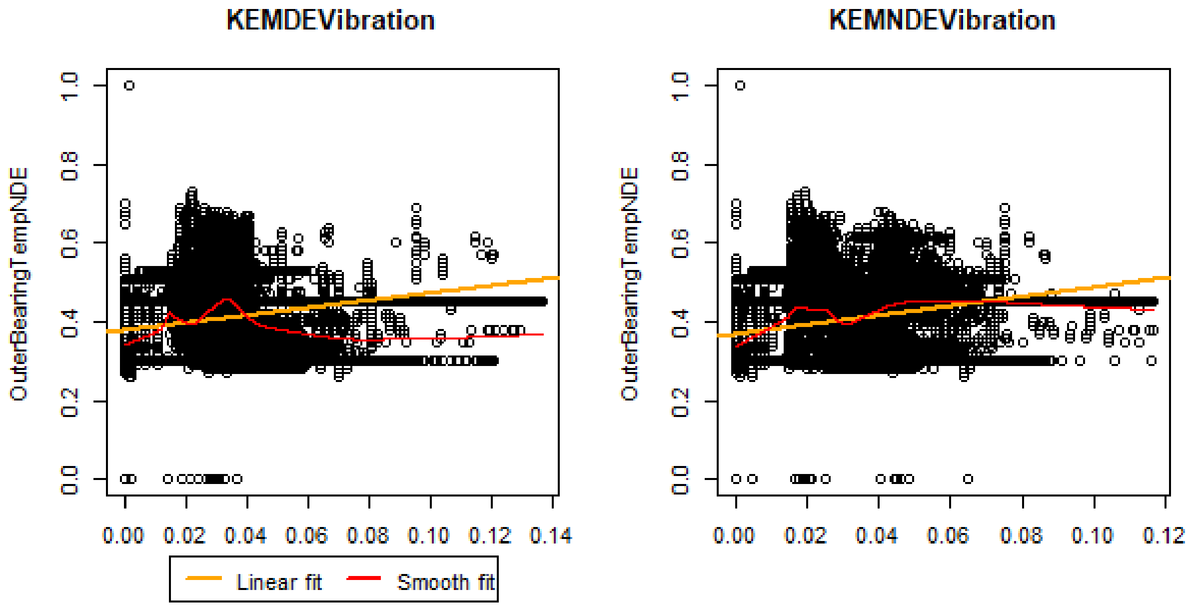

Figure 5.9: Scatterplot: OuterBearingTempNDE vs output variables – healthy data

It can be seen from the healthy data scatterplots that the linear fit does fit the data. Therefore, it is concluded that the linearity check model assumption is met.

5.3.4 Homoscedasticity assumption

Plots of residual versus fitted values of linear regression models between the input and output variables are made to evaluate the model fit. A good fit has a horizontal (red) line of fit centred around zero. This signifies no outliers. Residual plots of linear fit between the output variables and Outer Bearing Temp NDE input variable are presented in Figure 5.10. The residual plots of other input variables can be found in Appendix K.

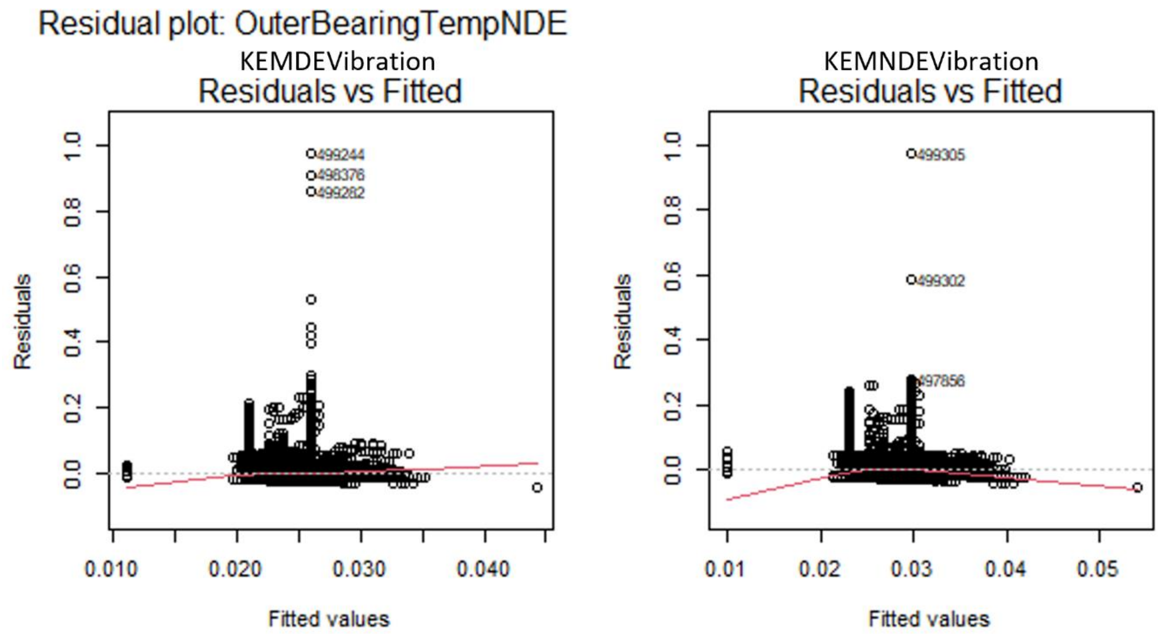

Figure 5.10: Residual plot: OuterBearingTempNDE - output variables

All scatterplots show an approximately straight line of fit centred around 0. Therefore, it is concluded for both, model DE and model NDE, that the homoscedasticity assumption is met.

5.3.5 Independence of observation assumption

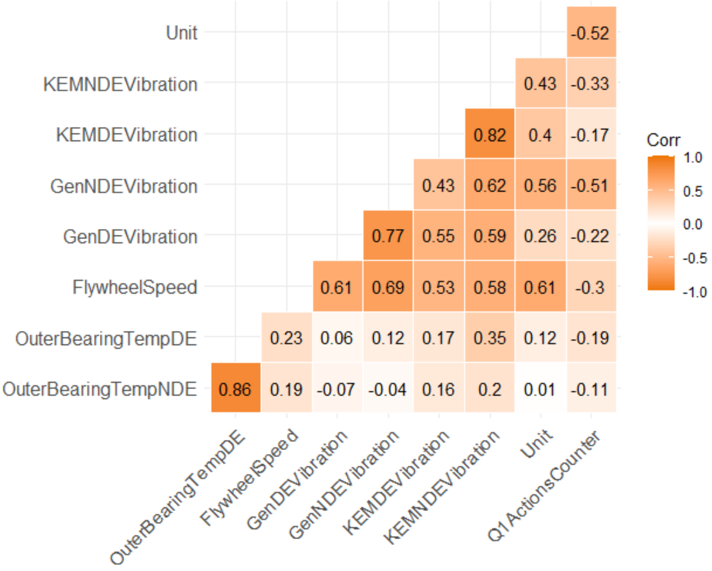

Figure 5.11: Correlation heatmap all input variables

The correlation values between all input and output variables are shown in Figure 5.11. Visualizations of correlation heat maps for the individual models can be found in Appendix L.

Highly correlated input variables can be observed within the data (Figure 5.11). However, before removing the variables from the models, a linear regression model is built. All data is used as training data to calculate the VIF values for the input variables. The VIF values for the different models can be seen in Figure 5.12.

The cut-off value of the VIF is set to 2.5. As VIF ≥ 2.5 indicates considerable collinearity [36]. To achieve this an iterative process of input variable removal is performed. In each iteration a variable with highest VIF value above 2.5 is removed from the model. The iterations are performed until model with a maximum VIF value of 2.5 is achieved. The individual iterations for each model can be found in Appendix M. After performing the iterations, the same selection of input variables for both models is observed (Figure 5.13). Flywheel Speed is removed as last.

```
> vif(LMmodel_KEMDEVibration)
OuterBearingTempNDE  OuterBearingTempDE        FlywheelSpeed       GenDEVibration      GenNDEVibration
           4.643903            4.543176             3.114363             3.401469             4.584357
    KEMNDEVibration                Unit     Q1ActionsCounter
           2.116573            2.416162             1.716243
> vif(LMmodel_KEMNDEVibration)
OuterBearingTempNDE  OuterBearingTempDE        FlywheelSpeed       GenDEVibration      GenNDEVibration
           4.800875            4.303222             3.078725             4.046083             4.690348
     KEMDEVibration                Unit     Q1ActionsCounter
           1.825895            2.674157             1.723683
```

Figure 5.12: VIF values all input variables, all models

The selected input variables for the models are therefore: Outer Bearing Temp DE, Gen DE Vibration, KEM DE Vibration (KEM NDE Vibration model), KEM NDE Vibration (KEM DE Vibration model), Unit, and Q1 Actions Counter. The final VIF values of the selected input variables are shown in Figure 5.13. It is observed that all values are below the cut-off point of 2.5.

```
> vif(LMmodel_KEMDEVibration)
OuterBearingTempDE      GenDEVibration     KEMNDEVibration               Unit     Q1ActionsCounter
          1.204380            1.583457            2.031894           1.549685             1.426178
> vif(LMmodel_KEMNDEVibration)
OuterBearingTempDE      GenDEVibration      KEMDEVibration               Unit     Q1ActionsCounter
          1.063037            1.470179            1.653942           1.608071             1.454973
```

Figure 5.13: VIF values with selected input variables only, all models

A new correlation heatmaps with only the selected input variables are made. The correlation heatmap for model DE is shown in Figure 5.14. Correlation heatmap for model NDE can be found in Appendix N. From both heatmaps, the difference between the maximum correlation values can be observed. With all input variables included in the data the maximum absolute observed correlation is equal to 0.86 (Figure 5.11). This suggests a high collinearity between the input variables. Whereas, with only the selection of input variables included in the data the maximum absolute observed correlation value is equal to 0.59 (Figure 5.14). This suggests a moderate collinearity between the variables.

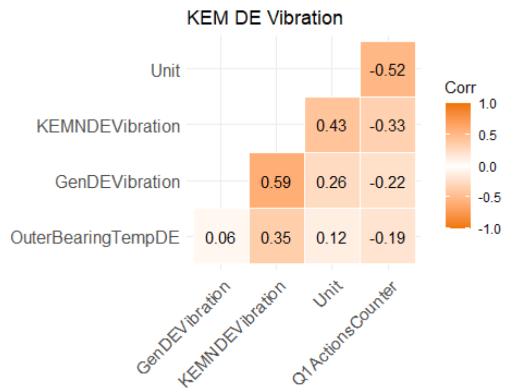

Figure 5.14: Correlation heatmap: model DE with selected input variables

Therefore, it can be concluded that the independence of observations assumption is met for both models when only the selected input variables are included in the models.

5.3.6 Conclusions of model assumption checks

For both models, model DE and model NDE, the model assumptions are met. Therefore, the predictive model for both output variables can be developed. The models are developed as linear regression models with KEM DE Vibration and KEM NDE Vibration as output variables.

5.4 Predictive regression-based model

A predictive linear regression model is build using training data and evaluated using testing data. The testing and training data split is made according to Table 4.2, using a random seed of 123. First, a basic model for predicting KEM DE and KEM NDE Vibration variable is developed. Once the model is evaluated and base performance is obtained the model improvement consisting of different aspects of focus takes place.

Due to lagging of output variables and windowing for feature extraction, the data measurements count is affected. The new count is presented in Table 5.5.

Table 5.5: Table 5.2: Health states count updated (seed: 123)

Health state	Index	#Training	#Testing
Healthy	0	373 643	124 602
Degradation	1	1 692	548
Failure	2	45	14

The section is organized as follows. In section 5.4.1, additional model KPI is introduced. This KPI is focused on the HS prediction. Then in section 5.4.2 a base model for predicting the HS of the KEM inner bearings is developed. The model is then analysed and improved, focusing of the following aspects: input variables in section 5.4.3, feature extraction window size in section 5.4.4, extracted features in section 5.4.5, flywheel speed in section 5.4.6. Next, in section 5.4.7, the improved model is developed and analysed for selection of prediction period. Afterwards, the improved model is tuned using hyperparameter tuning in section 5.4.8. Lastly, in section 0, the PdM policy based on the develop predictive model is developed.

5.4.1 Over and Under KPI

Model performance KPIs focused on the KEM DE Vibration and KEM NDE Vibration predictions are presented in section 4.6. In addition, 2 KPIs focused on evaluating the associated HS prediction are defined. Namely, Over and Under counter KPIs.

For the HS prediction KPIs, the HSs are assigned a numerical value. Healthy HS is defined as 0, degraded HS as 1, and failure HS as 2. The **Over** KPI counts how many times a higher state than the observed one is predicted. And the **Under** KPI counts how many times a lower state than the observed one is predicted. The code for calculating the Over and Under KPI is as follows:

$$\begin{array}{l} if\ (Xpredicted_i > Xobserved_i) \\ \{\,Counter = \text{"Over"}\} \\ else\ if\ (Xobserved_i > Xpredicted_i) \\ \{Counter = \text{"Under"}\} \end{array}$$

$$Over = sum(Counter = \text{"}Over\text{"})$$

$$Under = sum(Counter = \text{"}Under\text{"})$$

Equation 29: Over and under counter

Furthermore, when informative, a percentual evaluation is added to the Over and Under counters. Where the percentage is calculated as Over or Counter divided by the count of possible over and under predictions. Therefore for Over, the divisor is count of testing data from the healthy and degraded HS. And for Under, from the degraded and failure HS. With the set seed of 123 the divisor for the Over = 124602 + 548 = 125150, and for the Under = 548 +14 = 562 (Table 5.5).

5.4.2 Base predictive statistical model

Predictive model signifies that the output variables are lagged. Ideally, predictions in the research can be made with lag size of approximately 6 days. This corresponds to a lag $L = \frac{N_D}{30}$. Where N_D stands for number of measurements for data set D. The performance of this predictive linear regression model with PP≈6days using all original input variables can be seen in Table 5.6.

Table 5.6: Predictive linear regression model: all input variables

Measure	ModelDE	ModelNDE
R²	0.2889	0.2888
NRMSE	0.6133	0.5664
MAPE	0.3967	0.3466
Over	2 (00.002%)	0 (00.00%)
Under	429 (100.000%)	555 (100.00%)
Measure	**Joint prediction**	
Over	2 (00.002%)	
Under	562 (100.000%)	

5.4.3 Model improvement: input variables

First aspect to focus on in this research when improving a predictive linear regression model, is evaluating the effect of single input variable on the model. For this, model performance results for removing a single input variable from the model input are developed. The results for models with PP≈6days can be seen in Table 5.7. Where the following input variables are removed from the models, A: Outer Bearing Temp NDE, B: Outer Bearing Temp DE, C: Q1 Actions Counter, D: Flywheel Speed, E: Gen DE Vibration, F: Gen NDE Vibration, G: KEM DE Vibration, H: KEM NDE Vibration, I: Unit. For the model improvement, the input parameters are removed until no removal would result in lowering either the NRMSE KPI or MAPE KPI value, while also lowering or at least keeping the same value for the other one of these two KPIs.

Table 5.7: Model KPIs: removal of specific input variables

ModelDE	-A	-B	-C	-D	-E	-F	-G	-H	-I
R^2	0.2878	0.2889	0.2819	0.2545	0.2736	0.2352	0.2860	0.2873	0.2409
NRMSE	0.6141	0.6133	0.6160	0.6265	0.6211	0.6377	0.6139	0.6135	0.6362
MAPE	0.4097	0.3963	0.3769	0.3955	0.5095	0.4509	0.4220	0.3942	0.5642
Over	2	2	1	0	3	3	0	0	3
Under	429	429	429	429	429	429	429	429	429
ModelNDE	**-A**	**-B**	**-C**	**-D**	**-E**	**-F**	**-G**	**-H**	**-I**
R^2	0.2859	0.2729	0.2774	0.2828	0.2703	0.2659	0.2788	0.2841	0.2392
NRMSE	0.5677	0.5731	0.5710	0.6585	0.5738	0.5754	0.5703	0.5680	0.5867
MAPE	0.3774	0.3550	0.3409	0.3444	0.3778	0.3839	0.3579	0.3565	0.4208
Over	0	0	0	0	0	0	0	0	0
Under	555	555	555	555	555	555	555	555	555

Moreover, for each combination of removal of an input variable the associated HS is depicted. The joint Over and Under counter for all combinations can be found in Table 5.8 and Table 5.9, respectively. The results of the joint Under counter table at this point unfortunately do not show any difference between the different models and are all equal to 0. Meaning that all the non-healthy HSs are not predicted as correct non-healthy HSs.

Table 5.8: Joint Over counter: removal of specific input variables

\ DE NDE\	None	-A	-B	-C	-D	-E	-F	-G	-H	-I
None	2	2	2	1	0	3	3	0	0	3
-A	2	2	2	1	0	3	3	0	0	3
-B	2	2	2	1	0	3	3	0	0	3
-C	2	2	2	1	0	3	3	0	0	3
-D	2	2	2	1	0	3	3	0	0	3
-E	2	2	2	1	0	3	3	0	0	3
-F	2	2	2	1	0	3	3	0	0	3
-G	2	2	2	1	0	3	3	0	0	3
-H	2	2	2	1	0	3	3	0	0	3
-I	2	2	2	1	0	3	3	0	0	3

Table 5.9: Joint Under counter: removal of specific input variables

\ DE NDE\	None	-A	-B	-C	-D	-E	-F	-G	-H	-I
None	562	562	562	562	562	562	562	562	562	562
-A	562	562	562	562	562	562	562	562	562	562
-B	562	562	562	562	562	562	562	562	562	562
-C	562	562	562	562	562	562	562	562	562	562
-D	562	562	562	562	562	562	562	562	562	562
-E	562	562	562	562	562	562	562	562	562	562
-F	562	562	562	562	562	562	562	562	562	562
-G	562	562	562	562	562	562	562	562	562	562
-H	562	562	562	562	562	562	562	562	562	562
-I	562	562	562	562	562	562	562	562	562	562

It can be seen from the model KPIs, and joint Over counter that model DE has bigger impact on the joint HS prediction. The model DE KPIs show less accurate predictions compared to model NDE (higher NRMSE and MAPE values). Moreover, from the joint Over counter table it can be seen that the counter is dependent on the input variable removal of model DE, while no differences based on model NDE input are depicted. Therefore, model DE input variables are addressed first.

The model KPIs suggest that the removal of B: Outer Bearing Temp DE input variable from the model DE does not have large negative influence on the HS predictions. When comparing the model KPIs of the model using all input variables, and of the model where Outer Bearing Temp DE input variable is removed, the R^2 has the same value. The same applies to the NRMSE value. Moreover, the MAPE is lower for the model with removed Outer Bearing Temp DE input variable, suggesting more accurate predictions. Therefore, **Outer Bearing Temp DE is selected as first input variable to be removed from the model DE**.

The removal of further input variables for model DE is evaluated by performing the same KPI measurements for model DE with already removed Outer Bearing Temp DE input variable. These results are shown in Table 5.10. By removing any additional input variable from model DE the NRMSE KPI performs worse. Therefore, no additional input variable is removed from model DE. The decision process with clearer visualization can be found in Appendix O.

Table 5.10: Model DE: removed B input variable

ModelDE	-A	-C	-D	-E	-F	-G	-H	-I
R^2	0.2846	0.2819	0.2524	0.2725	0.2340	0.2848	0.2865	0.2366
NRMSE	0.6152	0.6161	0.6279	0.6212	0.6377	0.6145	0.6140	0.6372
MAPE	0.4192	0.3760	0.4001	0.4369	0.4535	0.4737	0.3930	0.4858
Over	2	1	2	0	3	0	0	2
Under	429	429	429	429	429	429	429	429

Next, the focus is on removal of input variables from model NDE. However, for this model any removal of an input variable results in worse NRMSE value. Therefore, no input variables are removed from model NDE. Again, the decision process with clearer visualization can be found in Appendix O.

The overview of the model KPIs built with selected input variables is shown in Table 5.11. In the end only one input variable from model DE is removed. Namely, the Outer Bearing Temp DE input variable is removed. For model DE, no input variable is removed.

Table 5.11: Predictive linear regression model: selected input variables

	Selected input variables		All input variables (original model)	
Measure	ModelDE	ModelNDE	ModelDE	ModelNDE
R^2	0.2889	0.2888	0.2889	0.2888
NRMSE	0.6133	0.5664	0.6133	0.5664
MAPE	0.3963	0.3466	0.3967	0.3466
Over	2 (00.002%)	0 (00.00%)	2 (00.002%)	0 (00.00%)
Under	429 (100.000%)	555 (100.00%)	429 (100.000%)	555 (100.00%)
Measure	Joint prediction		Joint prediction	
Over	0 (00.00%)		2 (00.002%)	
Under	562 (100.00%)		562 (100.000%)	

It should be noted that the input variable I: Unit is a very important one. Removal of the Unit input variable from either model results in the largest MAPE value increase. This means that the predictions of a given data set are sensitive to the predictions made based on models built on data from the different data sets. Therefore, in the current situation, to have a better prediction performance, for a given data set a model should be built only with the data from the given data set. However, the fact that only 2 out of 6 data sets contain no healthy HSs also influences this outcome. Therefore, for better HS prediction performance, instead of splitting the prediction models for each data set, more data should be obtained for model development.

5.4.4 Model analysis: feature extraction window size

The features for the model development are extracted using half a month window size (section 5.2.1). This is based on the feature extraction time when it comes to extracting features from all data sets with measurements form a half year time period. In this section the effect of using different window sizes for the feature extraction is analysed. For this, a simple model for data set 6 and 2 is developed. The data sets are selected as they should provide good representation of the different data sets. Data set 6 is a healthy data set and data set 2 contains all 3 HSs. The data sets come from units from different customer sites. The model is developed using all extracted features as input variables. The model KPIs using 1 week, 2 week (a half a month), and 4 week (a month) window sizes are presented in Table 5.12.

Table 5.12: Statistical model: varied window size for feature extraction

	Window size (W)		
ModelNDE	**1 week**	**2 weeks**	**4 weeks**
R^2	0.5564	0.6312	0.6601
NRMSE	0.4600	0.4149	0.4134
MAPE	-	-	-
Over	0	0	0
Under	11	9	9
ModelNDE	**1 week**	**2 weeks**	**4 weeks**
R^2	0.5160	0.5999	0.6293
NRMSE	0.5213	0.4698	0.4701
MAPE	-	-	-
Over	0	0	0
Under	19	17	17
Joint	**1 week**	**2 weeks**	**4 weeks**
Over	0	0	0
Under	19	17	17

The statistical regression-based model results show that an increase in window size improves the model performance. The model better understands the data (increase in R^2) and predicts the output variable with smaller average error (lower NRMSE). The increase of window size from 1 to 2+ week furthermore decreases the Over and Under counters. Therefore, for the statistical regression based model, selecting a larger window size (W=4 weeks) than the one used in the research (W=2 weeks) could improve the model performance. Nevertheless, due to the extraction time needed to extract features, the 2 week window size for the model development is kept.

5.4.5 Model improvement: extracted features

The model performance of model built using all input variables with addition of extracted features as input variables is evaluated. All original input variables are included. Therefore, the model performance is compared to the one obtained in Table 5.6. First, a model with adding all extracted features is developed. The results of this model alongside the result of the original model can be seen in Table 5.13. The results for the model with all added extracted features performs better for all KPIs except for MAPE. The value of MAPE is too high. Therefore, same approach as with input variables is applied next, removing the least useful extracted feature from the model one by one, until all KPIs perform better than the ones of the original model.

Table 5.13: Predictive linear regression model: all extracted features

	All extracted features		No extracted features (original model)	
Measure	**ModelDE**	**ModelNDE**	**ModelDE**	**ModelNDE**
R^2	0.3140	0.3344	0.2889	0.2888
NRMSE	0.6015	0.5465	0.6133	0.5664
MAPE	0.4029	0.9263	0.3963	0.3466
Over	0 (00.00%)	0 (00.00%)	2 (00.002%)	0 (00.00%)
Under	429 (100.00%)	555 (100.00%)	429 (100.000%)	555 (100.00%)
Measure	**Joint prediction**		**Joint prediction**	
Over	0 (00.00%)		2 (00.002%)	
Under	562 (100.00%)		562 (100.000%)	

The model DE and model NDE performance KPIs when single extracted feature is removed as an input variable are presented in Table 5.14 and Table 5.15, respectively. Furthermore, the joint Over and Under counters for the associated HS prediction are presented in Table 5.16.

Table 5.14: Model DE: addition of specific extracted features

ModelDE	**-Mean**	**-Std**	**-Peak**	**-Var**	**-RMS**	**-SF**
R^2	0.3140	0.3133	0.3140	0.3138	0.3139	0.3117
NRMSE	0.6015	0.6019	0.6015	0.6016	0.6015	0.6024
MAPE	0.3910	0.3873	0.3924	0.4176	0.3965	0.3878
Over	0	0	0	0	0	0
Under	429	429	429	429	429	429
ModelDE	**-MF**	**-E**	**-Crest**	**-Skew**	**-Kurt**	
R^2	0.3140	0.3079	0.3140	0.3119	0.3115	
NRMSE	0.6015	0.6043	0.6015	0.6024	0.6025	
MAPE	0.3911	0.3997	0.4094	0.4552	0.4047	
Over	0	0	0	0	0	
Under	429	429	429	429	429	

Table 5.15: Model NDE: addition of specific extracted features

ModelNDE	**-Mean**	**-Std**	**-Peak**	**-Var**	**-RMS**	**-SF**
R^2	0.3318	0.3338	0.3311	0.3328	0.3318	0.3321
NRMSE	0.5476	0.5467	0.5480	0.5471	0.5476	0.5473
MAPE	0.5295	0.5074	0.5400	0.7330	0.4697	0.4750
Over	0	0	0	0	0	0
Under	555	555	555	555	555	555
ModelNDE	**-MF**	**-E**	**-Crest**	**-Skew**	**-Kurt**	
R^2	0.3344	0.3282	0.3340	0.3318	0.3330	
NRMSE	0.5465	0.5494	0.5465	0.5476	0.5471	
MAPE	0.7010	0.4582	0.6619	0.4692	0.5352	
Over	0	0	0	0	0	
Under	555	555	555	555	555	

Table 5.16: Joint Over and Under counter: addition of specific extracted feature

Measure	-Mean	-Std	-Peak	-Var	-RMS	-SF
Over	0	0	0	0	0	0
Under	562	562	562	562	562	562
Measure	**-MF**	**-E**	**-Crest**	**-Skew**	**-Kurt**	
Over	0	0	0	0	0	
Under	562	562	562	562	562	

The results from the different models unfortunately still show the inability to predict the non-healthy HSs. This is depicted by the individual and joint Under counters being equal to 100% of the possible under predictions. Therefore, the choice of feature of removal is focused on the model KPIs and joint Over counters.

The **first extracted feature to be removed as input variable from the models is MF**. This decision is made based on the KPI results. When removing MF from both model DE and NDE, the R^2 is the same as before, and the value of NRMSE and MAPE is either the same or lower. Therefore, no KPI shows worse performance, and some KPIs do show improvement.

To depict whether additional extracted feature should be removed from the models, the same KPIs are developed for models with already removed MF extracted feature. These results and removal selection process can be seen in Appendix P. In the end, **4 extracted features are removed** as input variables: **MF, Mean, Crest, and Peak.** The KPIs of models with these extracted features removed as input variables, alongside the original models KPIs can be seen in Table 5.17.

Table 5.17: Predictive linear regression model: selected extracted features

	Selected extracted features		No extracted features (original model)	
Measure	**ModelDE**	**ModelNDE**	**ModelDE**	**ModelNDE**
R^2	0.3138	0.3285	0.2889	0.2888
NRMSE	0.6016	0.5490	0.6133	0.5664
MAPE	0.3900	0.3403	0.3967	0.3466
Over	0 (00.00%)	0 (00.00%)	2 (00.002%)	0 (00.00%)
Under	429 (100.000%)	555 (100.00%)	429 (100.000%)	555 (100.00%)
Measure	**Joint prediction**		**Joint prediction**	
Over	0 (00.00%)		2 (00.002%)	
Under	562 (100.00%)		562 (100.000%)	

5.4.6 Model improvement: flywheel speed

Another aspect to focus on is the Flywheel Speed input variable. It has been noted for a reason during the VIF input variable iterative process that Flywheel Speed is the last removed input variable. The Flywheel Speed has either value of 0, or operates at ~ 4000 rpm. With this huge difference, the changes in speed during operation might become negligible. Therefore, model performance for data during time when Flywheel is in operation (FWS>0) and when Flywheel is not in operation (FWS=0) are evaluated. These results are presented in Table 5.18.

Table 5.18: Model DE and NDE: flywheel in and not in operation

Measure	FWS>0		FWS=0		No split (Original)	
	ModelDE	ModelNDE	ModelDE	ModelNDE	ModelDE	ModelNDE
R^2	0.1513	0.1540	0.3603	0.4635	0.2889	0.2888
NRMSE	0.5604	0.5083	1.3871	1.1725	0.6133	0.5664
MAPE	0.2918	0.2276	3.0390	0.9913	0.3967	0.3466
Over	0 (00.00%)	0 (00.00%)	0 (00.00%)	1 (00.005%)	2 (0.002%)	0 (00.00%)
Under	429 (100.00%)	537 (100.00%)	10 (100.00%)	18 (100.000%)	429 (100.000%)	555 (100.005)

It can be seen that for FWS>0 the model has low R^2, however makes more accurate predictions compared to the model with no split of FWS. On the other hand, for FWS=0 model, the R^2 value is higher, however the prediction are less accurate. It is therefore proposed to develop a model where for FWS>0 predictions based on model developed for FWS>0 model are made. And for FWS=0, predictions based on no split (original) model are developed. The KPIs of the FWS split model, alongside the original model with no FWS split, are shown in Table 5.17.

Table 5.19: Predictive linear regression model: FWS split

	FWS split		No FWS spit (original model)	
Measure	ModelDE	ModelNDE	ModelDE	ModelNDE
R^2	0.2907	0.2953	0.2889	0.2888
NRMSE	0.6126	0.5639	0.6133	0.5664
MAPE	0.3946	0.3437	0.3967	0.3466
Over	2 (00.002%)	0 (00.00%)	2 (00.002%)	0 (00.00%)
Under	429 (100.000%)	555 (100.00%)	429 (100.000%)	555 (100.00%)
Measure	Joint prediction		Joint prediction	
Over	2 (00.002%)		2 (00.002%)	
Under	562 (100.000%)		562 (100.000%)	

The KPIs of model with separate model for FWS > 0 and for FWS = 0 measurements outperforms the original model where no FWS split is made. Where FWS split model uses input data from FWS > 0 measurements to make predictions for when flywheel is in operation (FWS>0), and data from all measurements to make predictions for when flywheel is not in operation (FWS=0).

5.4.7 Model analysis: prediction period

Until now the prediction of non-healthy HSs has not been successful. Therefore, the selection of PP is analysed. The larger the PP, the further into future the predictions are made. The predictions are then also less accurate. The current selection of PP is approximately equal to 6 days. The model performance results for PP≈6 days, PP≈3 days, PP≈1 days are shown in Table 5.20.

Table 5.20: Predictive linear regression model: prediction period

ModelDE	PP≈6days	PP≈3 days	PP≈1day
R^2	0.3155	0.3457	0.4277
NRMSE	0.6013	0.5840	0.5433
MAPE	0.3873	0.4470	0.3981
Over	1 (00.0008%)	2 (00.002%)	4 (00.003%)
Under	429 (100.0000%)	434 (100.000%)	379 (100.000%)

ModelNDE	PP≈6days	PP≈3 days	PP≈1day
R^2	0.3333	0.3569	0.4510
NRMSE	0.5471	0.5448	0.4952
MAPE	0.3368	0.3584	0.3464
Over	0 (00.00%)	0 (00.00%)	5 (00.004%)
Under	555 (100.00%)	571 (100.00%)	533 (100.000%)
Joint	**PP≈6days**	**PP≈3 days**	**PP≈1day**
Over	1 (00.0008%)	2 (00.002%)	6 (00.005%)
Under	562 (100.0000%)	575 (100.00%)	541 (100.000%)

When it comes to the model KPIs, the model with PP≈1 day shows the best performance (highest R^2, low NRMSE and MAPE). However, when it comes to actually predicting the HS of the KEM inner bearings, the model with PP≈3 days shows the best results. For the research the PP≈6 days is kept. This is due to the fact that this time period provides enough time for maintenance planning. However, HPP should consider whether for selected customer sites or components a shorter PP, PP≈3 days, could be suitable for their maintenance planning.

5.4.8 Model improvement: hyperparameter tuning

The Ridge, Lasso, and Elastic net regressions models are developed. The models are developed using the improved model input variables. Using the standard varied fold size of the k-fold cross-validation = 10. The model results for the different regression models in comparison to the improved linear regression model can be seen in Table 5.21.

Table 5.21: Predictive linear regression model: ridge regression

ModelDE	Linear regression	Ridge regression	Lasso regression	Elastic net 0.5 Ridge, 0.5 Lasso
R^2	0.3155	0.3107	0.3155	0.3155
NRMSE	0.6013	0.6032	0.6013	0.6013
MAPE	0.3873	0.3933	0.3901	0.3918
Over	1	0	1	1
Under	429	429	429	429
ModelNDE		**Ridge**	**Lasso**	**Elastic net**
R^2	0.3333	0.3244	0.3331	0.3330
NRMSE	0.5471	0.5510	0.5473	0.5473
MAPE	0.3368	0.3301	0.3356	0.3357
Over	0	0	0	0
Under	555	555	555	555
Joint		**Ridge**	**Lasso**	**Elastic net**
Over	1	0	1	1
Under	562	562	562	562

Unfortunately, only the MAPE KPI for model NDE is a visible improvement. For the Ridge regression, also the Over counter reduces. However, in general the different regression models do not show better model performance. Therefore, ordinary linear regression is selected for the final predictive model.

5.4.9 Final predictive statistical model

The final predictive statistical model is developed by applying the improvements depicted during the improvement sections. The overview of the final model development is visualized in Figure

5.15. Moreover, the KPIs of the final model in comparison to the KPIs of the original model can be seen in Table 5.22.

Table 5.22: Improved predictive linear regression model KPIs

	All improvements		Original model	
Measure	**ModelDE**	**ModelNDE**	**ModelDE**	**ModelNDE**
R^2	0.3155	0.3333	0.2889	0.2888
NRMSE	0.6013	0.5471	0.6133	0.5664
MAPE	0.3873	0.3368	0.3967	0.3466
Over	1 (00.0008%)	0 (00.00%)	2 (00.002%)	0 (00.00%)
Under	429 (100.0000%)	555 (100.00%)	429 (100.000%)	555 (100.00%)
Measure	**Joint prediction**		**Joint prediction**	
Over	1 (00.0008%)		2 (00.002%)	
Under	562 (100.0000%)		562 (100.000%)	

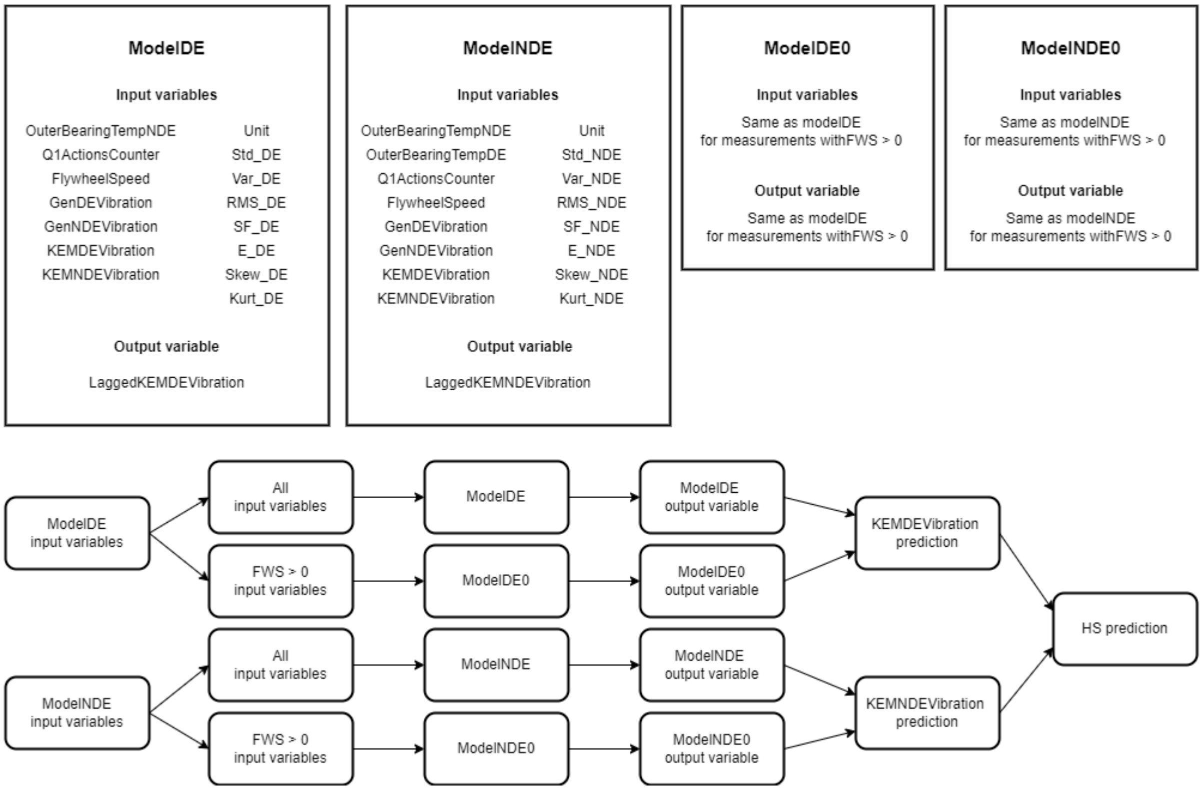

Figure 5.15: Improved predictive linear regression statistical model

It can be concluded that the final model outperforms the original model in all the model KPIs. However, the joint prediction of the KEM inner bearing HS only improves by predicting 1 less Over prediction. While all possible Under predictions are still under predicted. Meaning the model is not able to predict the non-healthy HSs.

5.5 Tree-based data driven model

Unfortunately, the statistical regression based model is not able to make valid HS predictions. A ML thee-based model is developed in this section. First, using the original input variables, and second, the improved input variables. The KPIs of these models alongside the KPIs of the statistical models are presented in Table 5.23.

Table 5.23: Predictive tree-based ML model

ModelDE	Statistical Original	Statistical Improved	ML Original	ML Improved
R^2	0.2889	0.3155	0.7568	0.9534
NRMSE	0.6133	0.6013	0.4078	0.1749
MAPE	0.3967	0.3873	-	-
Over	2 (00.002%)	1 (00.0008%)	59 (00.05%)	10 (00.01%)
Under	429 (100.000%)	429 (100.0000%)	278 (64.80%)	27 (06.29%)
ModelNDE				
R^2	0.2888	0.3333	0.7485	0.9708
NRMSE	0.5664	0.5471	0.3814	0.1249
MAPE	0.3466	0.3368	-	-
Over	0 (00.00%)	0 (00.00%)	195 (00.16%)	43 (00.03%)
Under	555 (100.00%)	555 (100.00%)	218 (39.28%)	21 (03.78%)
Joint				
Over	2 (00.002%)	1 (00.0008%)	229 (00.18%)	47 (00.03%)
Under	562 (100.000%)	562 (100.0000%)	191 (33.99%)	24 (04.27%)

The model performance KPIs for the ML models outperform the results of the statistical models. The ML models are able to make valid HS predictions. The number of Over predictions has increased compared to the statistical models. However, the number of Under predictions has finally decreased. Namely, approximately 95% of the non-healthy HSs are correctly predicted. While only 0.03% of the healthy or degraded HSs are over predicted. The tree-based model for model DE for FWS = 0 can be seen in Figure 5.16.

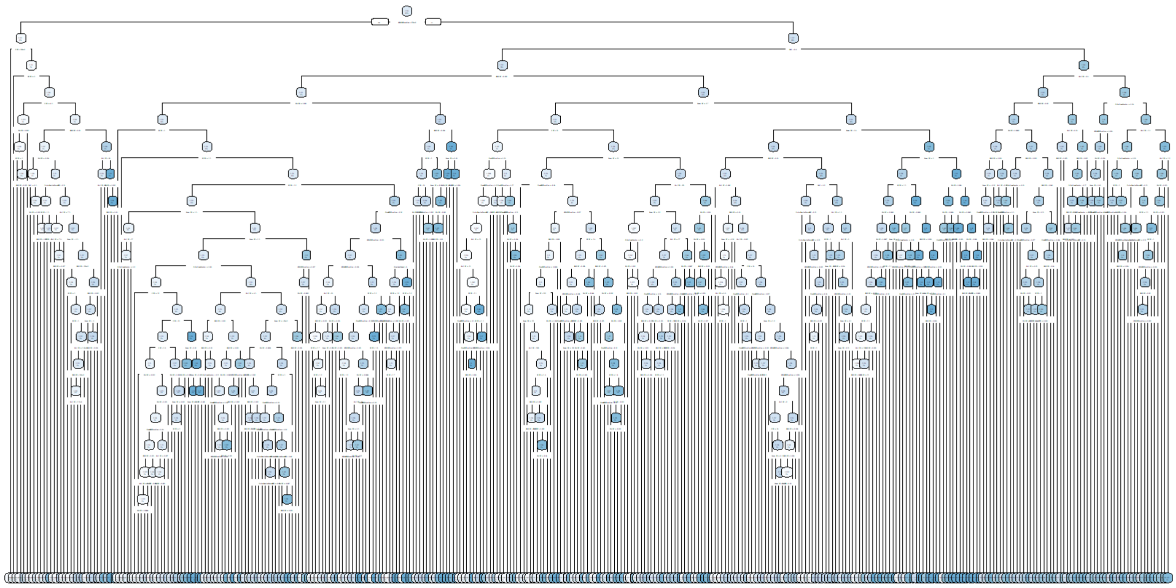

Figure 5.16: Tree-based model DE for FWS=0

Unfortunately, due to the size of the tree, the tree splits are not readable in the figure. Moreover, due to the size of the tree, the corresponding tree splits are not analysed in the research. The visualized model DE, FWS=0 has 346 terminal nodes. The variable importance for each model is depicted in Figure 5.17.

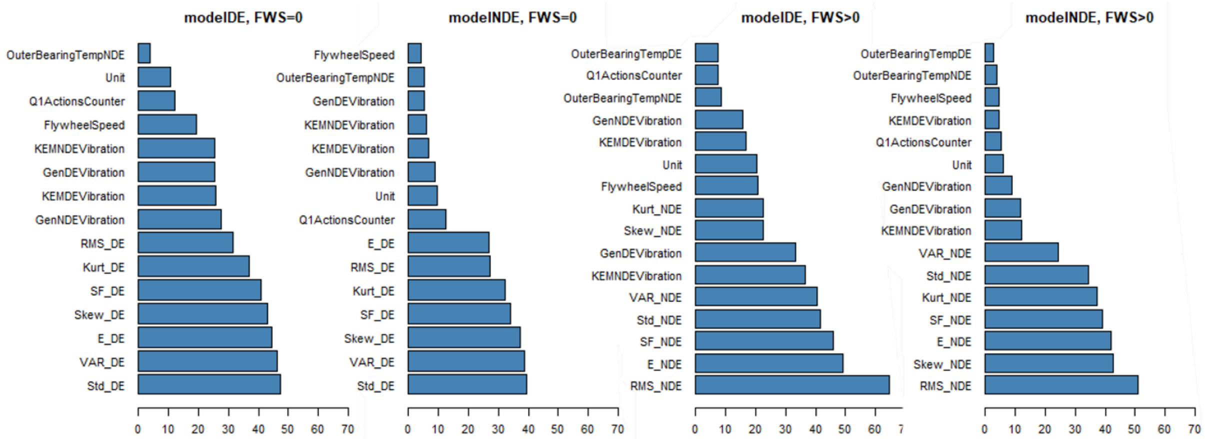

Figure 5.17: Tree-based model: variable importance

It can be seen from the variance importance for each model that the extracted features are the most important input variables. Moreover, for each model, the Outer Bearing Temp DE and Outer Bearing Temp NDE (for NDE models) input variables are within 3 least important variables. The Flywheel Speed input variable is more important for the FWS>0 models. Moreover, it can be seen that the Flywheel Speed input variable is more important for the DE models. These observations suggest that the statistical model improvements have had a valuable impact on the final HS predictive model.

To further analyse the data driven tree-based predictive model, the same aspects of analysis as were applied to the statistical model are evaluated. Namely, in section 5.5.1 the feature extraction window size is analysed. In section 5.5.2, the prediction period is analysed.

5.5.1 Model analysis: feature extraction window size

The same window size for feature extraction analysis as the one for the statistical model is performed. Therefore, the analysis is performed for data sets 6 and 2. For window sizes of 1 week, 2 weeks (half a month), and 4 weeks (a month). The model results of these models are shown in Table 5.24.

Table 5.24: Data driven model: varied window size for feature extraction

	Window size (W)		
ModelNDE	**1 week**	**2 weeks**	**4 weeks**
R^2	0.9737	0.9806	0.9730
NRMSE	0.1418	0.1017	0.1470
MAPE	-	-	-
Over	0	1	4
Under	3	0	4
ModelNDE	**1 week**	**2 weeks**	**4 weeks**
R^2	0.9678	0.9775	0.9611
NRMSE	0.1624	0.1238	0.1872
MAPE	-	-	-
Over	5	0	2
Under	2	7	9
Joint	**1 week**	**2 weeks**	**4 weeks**
Over	5	0	5
Under	2	7	7

The data driven model results show the best performance for the window size of 2 weeks. The 2 week window size model understands the data the best from the 3 models (highest R^2). Moreover, it shows the lowest average prediction error (lowest NRMSE). Similarly, it shows the best performance when it comes to the Over and Under counters. Compared to the 4 week window size model, the Under counter shows the same result. However, the Over counter decreases. Compared to the 1 week window size model the count of Over and Under counters together is the same. However, the 2 week window size model shows lower number of Over counter, which is a more important aspect. This is due to the fact that providing maintenance for components when they are not in a need for maintenance is not desirable.

5.5.2 Model analysis: prediction period

The same prediction period analysis as the one for the statistical model is performed. Therefore, the analysis is performed on the fully developed data driven model. Using prediction periods of approximately 6 days, 3 days, and 1 day. The results from the 3 models are show in Table 5.25.

Table 5.25: Predictive tree based model: prediction period

ModelDE	**PP≈6days**	**PP≈3 days**	**PP≈1day**
R^2	0.9534	0.9521	0.9503
NRMSE	0.1749	0.1723	0.1880
MAPE	-	-	-
Over	10 (00.01%)	20 (00.02%)	28 (00.02%)
Under	27 (06.29%)	21 (04.84%)	29 (07.65%)
ModelNDE	**PP≈6days**	**PP≈3 days**	**PP≈1day**
R^2	0.9708	0.9750	0.9766
NRMSE	0.1249	0.1378	0.1591
MAPE	-	-	-
Over	43 (00.03%)	17 (00.01%)	30 (00.02%)
Under	21 (03.78%)	57 (09.98%)	34 (06.38%)
Joint	**PP≈6days**	**PP≈3 days**	**PP≈1day**
Over	47 (00.03%)	23 (00.02%)	42 (00.03%)
Under	24 (04.27%)	59 (10.26%)	28 (05.18%)

It can be seen from the results that none of the 3 PP models clearly outperforms the other models. For easier depiction of performance comparison, for each KPI the best result is shown with a green cell. The model with PP≈1day does not show the best performing KPIs except for one KPI. For the PP≈6 days and PP≈ 3 days it cannot be concluded which model performs better. Model comparison

The statistical predictive model has been compared to the ML predictive model in the previous section. The KPIs for both models using original and improved input variables are presented in Table 5.23. The ML model with improved input variables is able to make valid HS predictions. With overestimating 0.03% of HSs and underestimating 4.27% of the HSs. This model is selected as the final predictive model used as basis for the PdM policy implementation for HPP's UPS system's KEM inner bearings.

6 PdM policy

In this section the PdM policy is defined. The PdM policy HS predictions are defined as follows. Given a selected significance level α, a prediction is final when its lower bound (LB) and upper bound (UB) predictions result in the same HS prediction. Otherwise, it cannot be concluded with the given certainty what the HS prediction is. In that case, the lowest HS prediction is selected as the final prediction. To demonstrate, the HS predictions for a section of testing data, with selected significance level of α=0.1 (90%PI), are visualized in Figure 6.1.

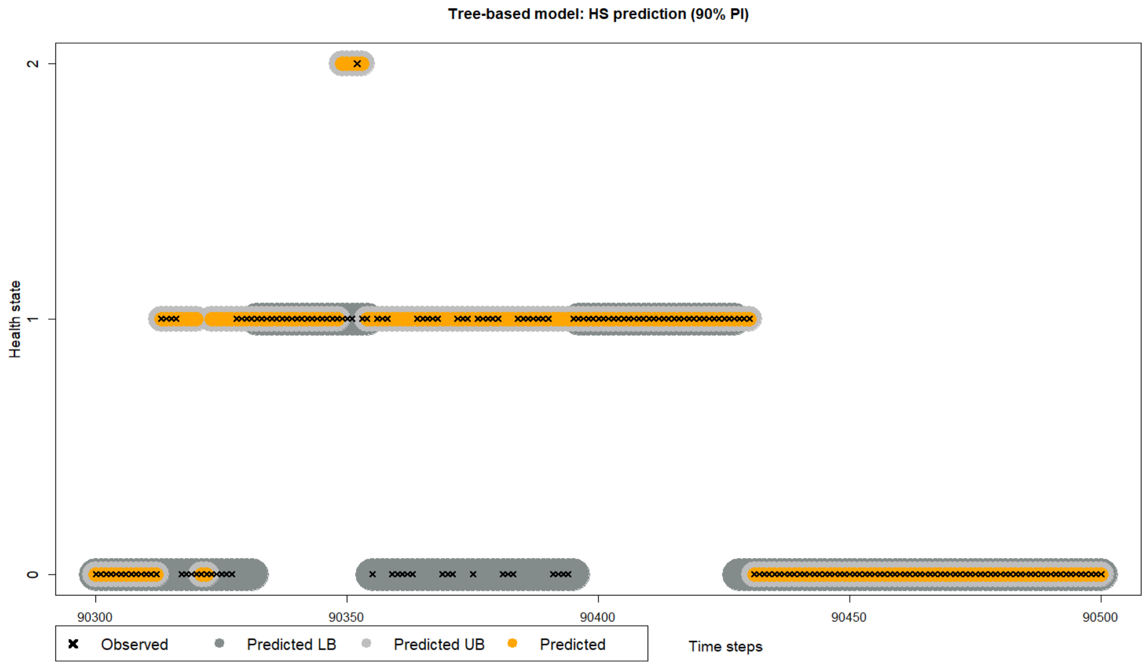

Figure 6.1: PdM policy 90% PI [90300:90500]

The measurements for which the dark grey, grey, and orange colours overlap signify the same HS prediction for LB, UB, and direct HS prediction. This HS prediction is then the final HS prediction. The measurements where all 3 of the predictions don't overlap result in the LB HS prediction (dark grey colour).

The PdM policy is then defined as follows. When final prediction is a healthy HS, no maintenance action is taken. When final prediction is a degraded HS, a maintenance plan for KEM inner bearing repair is made. When final prediction is a failure HS, a maintenance plan for KEM inner bearing replacement is made.

There is 1 input parameter for the PdM policy, the selection of significance level α. The effect of the significance level α onto the PdM policy is addresses in section 6.1. Moreover, the split according to which the different HSs are defined also affects the defined PdM policy. The effect of application of different HS splits onto the PdM policy is addressed in section 6.2.

6.1 Significance level α

The selection of α is an important input parameter for the PdM policy. With lower significance level, the certainty of the prediction is higher. However, on the other hand, it results into wider range of possible values that the prediction coming from a given terminal node can take. In some cases, it might be that the range of values ranges from healthy to failure HS, therefore, it cannot be predicted with the given certainty what the HS actually is. There are 346 terminal nodes for the model DE, FWS=0 of the selected predictive model. Selected section of terminal nodes for significance level α=0.1 (90%PI) and α=0.25 (75%PI) are visualized in Figure 6.2 and Figure 6.3, respectively.

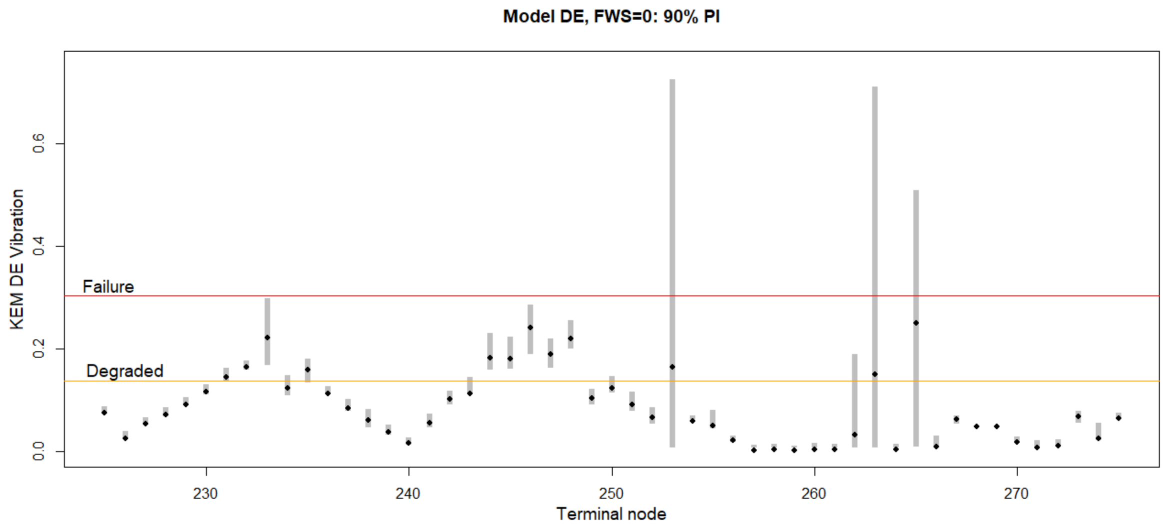

Figure 6.2: Terminal nodes: model DE, FWS=0 (90% PI)

It can be seen from the figures that with a lower prediction certainty the range of values a prediction can take in each terminal node is narrower. For example, when a prediction results in terminal node 262, with a significance level α=0.1 the prediction is with a 90% certainty either healthy or degraded HS. However, with a significance level α=0.25 the prediction is with a 75% certainty a healthy HS.

This is a trade-off that HPP needs to take into account when implementing a PdM policy for maintenance planning for their customers.

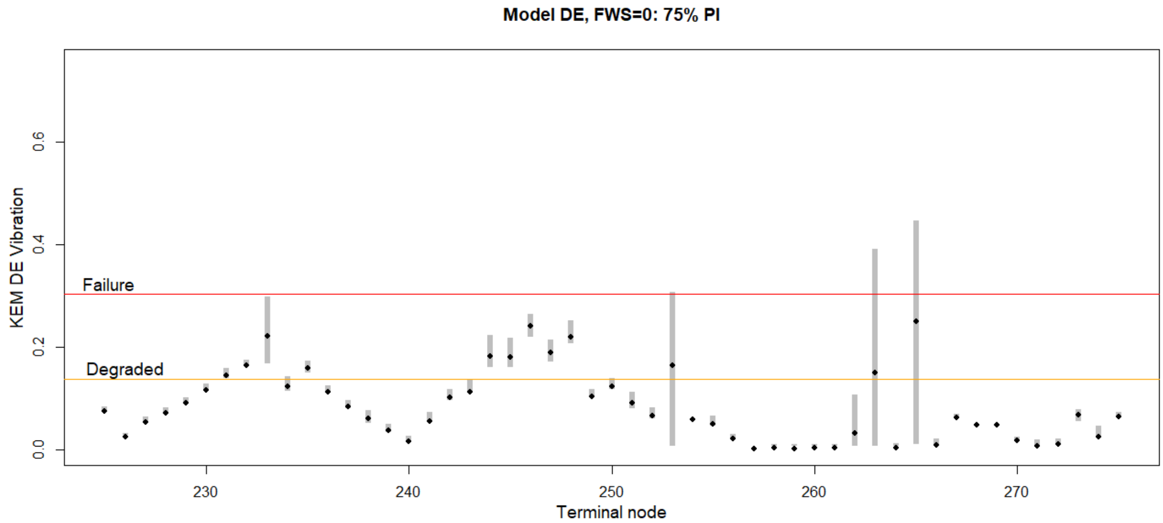

Figure 6.3: Terminal nodes: model DE, FWS=0 (75% PI)

6.2 HS splits

The split of data into healthy, degraded and failure is defined by the current policies applied at HPP. The current categorization of HS of the KEM inner bearings at HPP is presented in Table 6.1. Where ∧ stands for AND operator, ∨ stands for OR operator and the unit of the numerical values is mm/s. For simplicity, the KEM DE Vibration is referred to as DE and KEM NDE Vibration as NDE.

Table 6.1: Health states split

Health state	Split (X=9, Y=20)
Healthy	(DE < X) ⋀ (NDE < X)
Degraded	[(X ≤ DE < Y) ⋀ (NDE < Y)] ⋁ [(DE < Y) ⋀ (X ≤ NDE < Y)]
Failure	(Y ≤ DE) ⋁ (Y ≤ NDE)

The currently defined HSs are present at HPP already for a long time and are currently a standard when it comes to monitoring the condition of the KEM inner bearings. Since the bearings are replaced before actual failure it is difficult to depict whether these HS splits are representative of the condition of the bearings. However, the effect of defining different HS splits onto the PdM policy performance can be analysed.

To evaluate the effect of the HS split onto the PdM policy, different splits for the HSs are defined for the PdM policy and evaluated. The HS split for observed HSs is kept the same. However, the HS split for the predicted HSs is adjusted. The policy is evaluated using the Over and Under counter KPI. Where with an Over prediction situation it is predicted that the KEM inner bearing should be repaired when there is no need for repair or should be replaced when only repair is needed. On the other hand, with an Under prediction situation it is not predicted that the KEM inner bearing needs repair when it actually needs repair, or it is not predicted that the bearing needs replacement when it needs replacement.

The new splits are defined using the same approach, but with new set threshold values X and Y (Table 6.1). The PdM policy results for different HS splits are presented in Table 6.2. The policies are implemented using a significance level α=0.1.

Table 6.2: Predictive tree based model: varied HS split

Measure	X=9, Y=20	X=7, Y=20	X=11, Y=20	X=9, Y=18	X=9, Y=22
Over	1 (00.0008%)	147 (00.1175%)	0 (00.0000%)	1 (00.0008%)	1 (00.0008%)
Under	93 (16.5480%)	25 (4.4484%)	255 (45.3767%)	93 (16.5480%)	87 (15.4804%)
Good	125 070 (99.9249%)	124 992 (99.8626%)	124 909 (99.7963%)	125 070 (99.9249%)	125 076 (99.9297%)

It can be concluded from the results that increasing the degradation threshold (X) results in less Over predictions and more Under predictions. Overall, less correct predictions are made. However, since the number of Over predictions equals 0 this HS split for predictions actually provides better results for the PdM policy. As this new maintenance policy does not have a negative effect compared to the current policy. Only a positive effect of correctly predicting around 55% of the non-healthy HSs.

Furthermore, when it comes to the failure threshold (Y), increasing the threshold results in less Under predictions. Meaning more non-healthy HSs are correctly predicted.

Therefore, the HS split for predictions with X=11 and Y=22 is selected as the one for the final PdM policy.

7 Results

In this section the research results are presented. First, in section 7.1, the PdM policy results based on tree-based ML predictive model using the improved input variables, and adjusted HS splits, are presented. Next, in section 7.2, the PdM policy is validated using the last data set (data set 7), which has not been used before in the research. Lastly, in section 7.3, the evaluation of the PdM policy and its value for HPP are discussed.

7.1 PdM policy implementation

The PdM policy is implemented using the training data sets and evaluated using the testing data sets for 70%, 80%, and 90% PI. The overview of Over, Under, and Good counters for the different PIs can be seen in Table 7.1. The Good counter represents the number of correct maintenance action predictions.

Table 7.1: PdM policy: testing data set

Measure	70% PI	80% PI	90% PI
Over	1 (00.0008%)	0 (00.0000%)	0 (00.0000%)
Under	152 (27.0463%)	162 (28.8256%)	255 (45.3737%)
Good	125 011 (99.8778%)	125 002 (99.8706%)	124 909 (99.7963%)

It can be seen from the results that with lower prediction certainty more non-healthy HS are predicted. Which is the aim of the PdM policy. However, at some point Over predictions start to occur. This in a negative side of the proposed PdM policy as with the current maintenance policy at HPP no necessary maintenance occurs. To evaluate the best PdM policy, the norm and reality for each PI is calculated. Using $t_c = 10$, $t_n = 5$, and $P = 50$ (Equation 1). These results are shown in Table 7.2.

Table 7.2: PdM policy reality and norm results

PI	Reality	Norm
70%	10*562=5620	10*(152)+5*(562-152+1*50)=3820
80%	10*562=5620	10*(162)+5*(562-162)=3620
90%	10*562=5620	10*(255)+5*(562-255)=4085

The reality and norm represent the length of unplanned downtime. Therefore, lower number represents a better result. Therefore, for all PIs, the core problem has been solved as the norms are lower than the realities.

Further, it can be concluded that for the test data set, the 80% PI shows better PdM policy performance compared to the 90% PI. The comparison between 70% PI and 80% PI is dependent on the penalty P. However, with the strong desire to avoid Over predictions, it is decided to select a penalty such that the 80% PI show better results when it comes to the norm of the core problem.

Therefore, the overall results for best performing 80% PI PdM policy are visualized in Figure 7.1. With one zoomed in visualization shown in Figure 7.2. Visualizations for the other PIs can be found in Appendix Q. The time steps are not in order of time since the testing set consists of random split of data points.

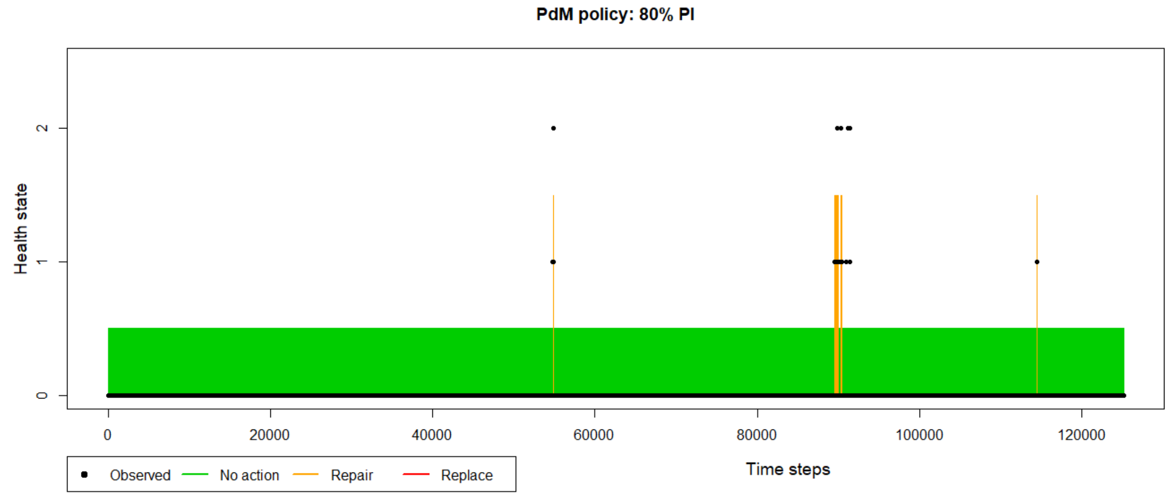

Figure 7.1: PdM policy: testing data set (80% PI)

The results show valuable predictions. Where only 28.83% of the non-healthy HSs are not correctly predicted. Meaning, the model correctly predicts 71.17% of the non-healthy HSs. Overall, 99.87% of the instances are correctly predicted. And no Over predictions are made.

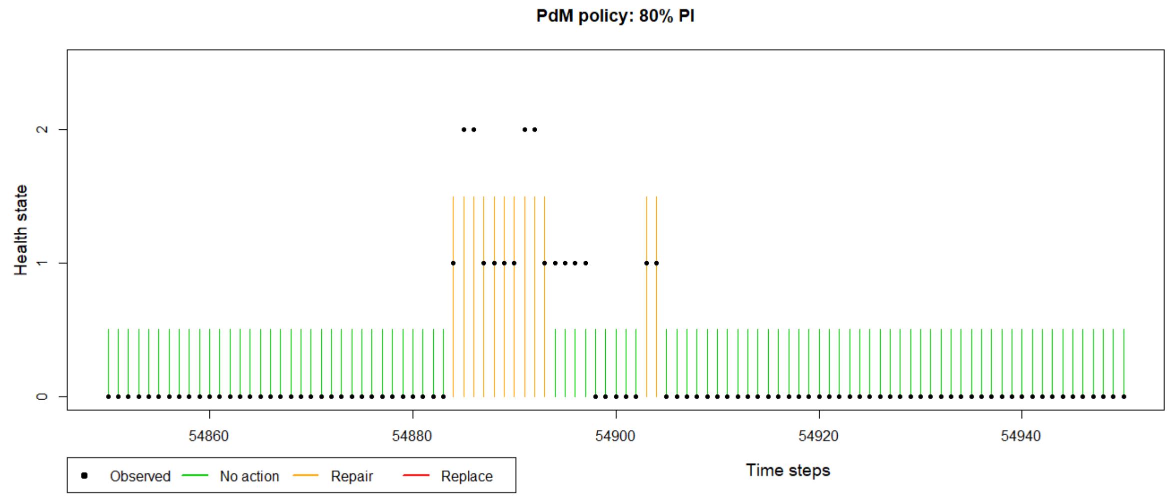

Figure 7.2: PdM policy: testing data set (80% PI) [54850,54950]

It can be seen that for each of the instances when the repair maintenance action is proposed, the observed HS is either degraded or failure HS. Therefore, the PdM policy does improve the current maintenance policy at HPP. Since several non-healthy HSs are predicted correctly, approximately 6 days in advance. Moreover, for no instances, it is predicted that a maintenance action for healthy state, or a replace maintenance action for degraded HS are predicted.

7.2 PdM policy validation

So far, the PdM policy has been evaluated on a testing data set, which has already been included during the predictive model and subsequent PdM policy development. Therefore, in order to validate the PdM policy, the validation set is used to evaluate the proposed maintenance actions. This is done by using the already developed PdM policy, based on an already developed predictive model.

The PdM policy predictions for the validation data set with a significance level of α=0.2 are visualized in Figure 7.3. The time steps are in order of time. Therefore, the figure represents a time series data for the validation data set.

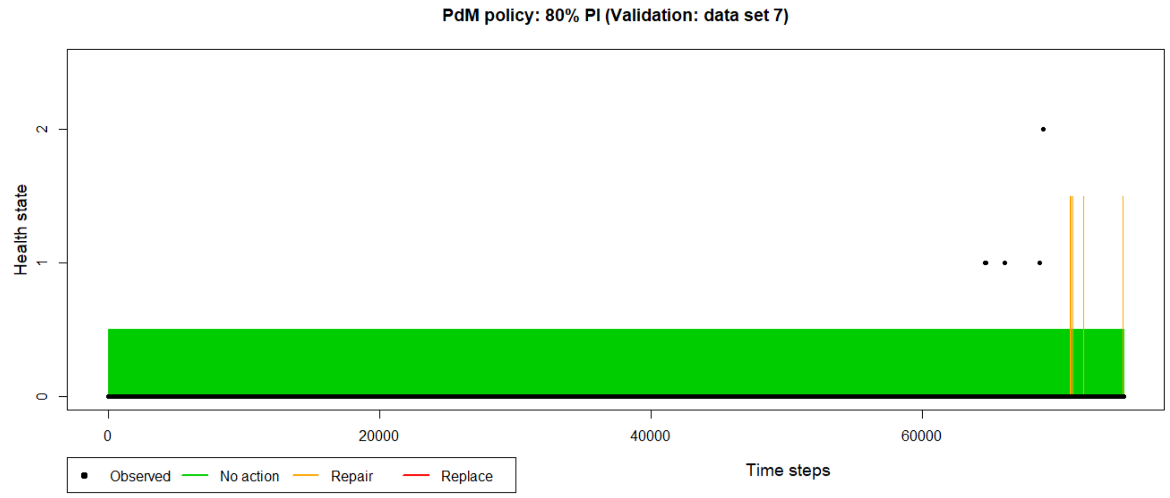

Figure 7.3: PdM policy: validation set (80% PI)

It can be seen from the figure that the PdM policy does not provide valuable predictions. For none of the non-healthy HSs a maintenance action is proposed. Maintenance actions are proposed with a certain delay. Therefore, it cannot be predicted 6 days in advance that a maintenance action is needed. The KPIs for the PdM policy for the validation data set are presented in Table 7.3.

Table 7.3: PdM policy: validation set

Measure	70% PI	80% PI	90% PI
Over	86 (00.1150%)	86 (00.1150%)	86 (00.1150%)
Under	64 (100.0000%)	64 (100.0000%)	64 (100.0000%)
Good	74 673 (99.7995%)	74 673 (99.7995%)	74 673 (99.7995%)

Unfortunately, the results support the visualization. None of the non-healthy HSs have a predicted need for a maintenance action (100% Under). This means that the proposed PdM policy based on the developed underlying predictive model cannot be validated. It is expected that the main reason for the inability to validate the PdM policy is the varied step size between PMSMTs. This aspect directly influences the extracted features, which are significant input variables used for the development of the underlying predictive model.

7.3 Value of the PdM policy for HPP

For HPP the value of the PdM policy is not monetary. The value of the PdM policy is for providing better insight for the customers into the HS of the UPS system and its components. For providing value to the customer, it is important to validate the model such that the model does not provide false non-healthy HS predictions. When the model does not provide false non-healthy HS predictions it can only be beneficial. Whenever it correctly predicts a non-healthy HS a given unplanned downtime period is reduced. To provide a high certainty of correctness of non-healthy HS prediction, the PdM policy is developed such that for a given certainty prediction, both lower bound and upper bound of the prediction result in the same HS prediction. Ensuring the customer does not need to plan maintenance for a maintenance action that would not be necessary.

8 Conclusion

The trends in industry show that companies are shifting towards implementation of data driven AI algorithms to guide their maintenance processes. However, implementation of such algorithms is not always straightforward. The proposed PdM policy in the research is a good basis for a future development of a PdM policy at HPP. Although the developed predictive model used as a basis for the proposed PdM policy was not successfully validated, it serves as a good basis for further development of such predictive model.

The research highlights the importance of development of statistical models. Prior to the implementation of more advanced, in this case, data driven ML methods, for development of predictive models. Through the development of the statistical model the effect of individual input variables onto the model prediction performance was evaluated. In the research it was concluded to only remove one such input variable due to the decision of not allowing for removal when decrease in NRMSE KPI was observed.

Moreover, the research provides valuable insights into developing prediction models for predicting the future HS of components based on vibration data. It was clearly demonstrated that in order to gain valuable information for developing either statistical or data driven predictive models using vibration data, feature extraction is a critical aspect.

Another interesting finding was the effect of the flywheel speed on the prediction model performance. It was demonstrated that for the instances when flywheel was operational the input data without instances when flywheel was not operation provided better model results. Therefore, it was decided to only use data when flywheel was in operation to develop a model for making predictions for instances when flywheel is in operation. However, it was also later noted that for the KEM inner bearings on the driving end, the changes in the speed of the flywheel have a bigger impact on the prediction value. Whereas for the KEM inner bearings on the non-driving end the difference was not that significant.

9 Discussion and further work

The PdM policy in the research was not validated. The main aspect to focus on for further development, which is expected to have a large effect onto the underlying model performance is step size between PMSMTs. In the research the step size is taken as equal along the 6 month period of PMSMTs. However, this is far from reality. The adjustment of PMSMTs into ones with constant equal time steps has not been implemented in the research. The time period for the research did not allow for such adjustment for all the data used in the research. It is strongly believed that this adjustment will have a large impact on the performance of the underlying predictive model, and subsequently also on the proposed PdM policy.

The conclusions of the research open up areas for further work towards developing a suitable predictive models and PdM policy for predicting the KEM inner bearings at HPP. First, related to the input variables. The number of input variables affects the number of sensors / measurements needed to be monitored on the UPS system. Therefore, it is proposed for further work to look into further removal of the input variables. Similarly, the computation of extracted features affects the software ability of evaluating the PdM policy. Therefore, it is proposed for future development of the predictive model to further look into the value of different extracted features. Both of these future work improvements can result in a less robust underlying predictive model. Moreover, with regard to the effect of operationality of the flywheel, for the future it is proposed to further look into the difference between the Model DE and Model NDE.

Furthermore, the PdM policy is implemented based on 6 day prediction period model with a given certainty. In a future more robust model with different prediction periods could be developed. Where a maintenance action with prediction period of 6 days is made and either revoked or further validated with prediction period of 3 days.

Following the proposed future work improvements, the improved PdM policy should be validated. Following a successful validation, the PdM policy can be implemented in the UPS software at the customer sites. The PdM policy can be executed using the direct PMSMTs from the UPS. The PdM policy can be implemented for any UPS system with adjustments made based on varied PMSMT name sets. Then the PdM policy proposed maintenance actions can be used to improve the maintenance service of HPP and reduce the unplanned downtime of the UPS units.

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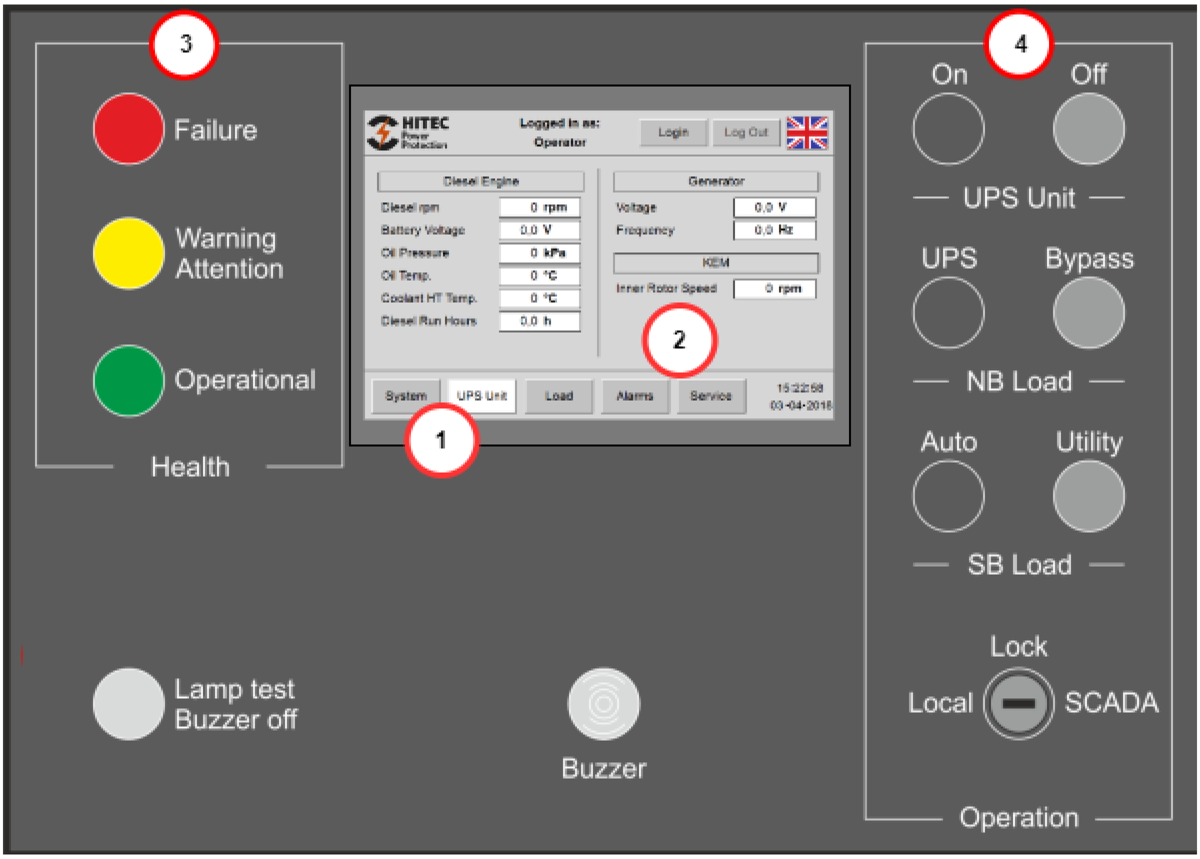
12 Appendices

Appendix A HMI panel layout of UPC for PP2700



The UPS Unit switches are used to start the UPS unit by selecting ON and stop the UPS unit by selecting OFF. The NB Load switches put the unit into a UPS mode when UPS is selected. And put the unit into bypass mode when Bypass is selected. Similarly, the SB Load puts the unit into automatic mode by selecting Auto and into utility mode by selecting Utility. For P2600 the diesel and system test switches are located on the service screen tab. Auto puts the unit into automatic UPS mode, Diesel test stars the diesel test, and System test switch starts the system test on the UPS unit.

Appendix B Maintenance activities

Following figures show extract from list of tasks that need to be carried out during the scheduled maintenance intervals and a list of remarks that are included for some of the maintenance tasks.

ITEM	Maintenance		REMARKS (see section 8)
	semi-annually	annually	
3. Kinetic Energy Module			
3.1 Check of insulation resistance driving motor, main rotor and exciter		X	3)
3.2 Check of air flow restrictions	X	X	
3.3 Inspection of driving motor		X	
3.4 Inspection of connections		X	
3.5 Inspection of earthing brush	X	X	
3.6 Inspection brushless exciter		X	
3.7 Check of running noise	X	X	
3.8 Check of bearing temperature	X	X	
3.9 Replacement of earthing brush		X	
3.10 Check Re-lubrication system	X	X	
3.11 Replace rotary joint relube system		X	
3.12 Check inner rotor speed	X	X	
4. Generator			
4.1 Check insulation resistance		X	3)
4.2 Check air flow restrictions	X	X	
4.3 Inspection of connections		X	
4.4 Inspection of earthing brush	X	X	
4.5 Replacement of earthing brushes		X	
4.6 Check running noise	X	X	
4.7 Check bearing temperature	X	X	
4.8 Re-lubrication	X	X	4)
4.9 Check Re-lubrication system	X	X	6)
4.10 Check Electrical Fan external cooling	X	X	

1) D = check during diesel test; S = check during system test
2) Depending on number of running hours
3) Depending on environmental conditions / contact helpdesk if required
4) Re-lubrication intervals may differ from this schedule depending on the applicable mains frequency and/or type of machines used.
Re-lubrication intervals must always be in accordance with the re-lubrication plate on the machine
5) Depending on the type of battery
6) Only applicable if re-lubrication system is mounted on the generator

Appendix C Maintenance logbook

The following figures show the front page and extracts from the logbook for recording the results of the weekly and monthly checks..

HITEC Power Protection	Distribution level: 5	CP 9803-01 A

Logbook Weekly and Monthly maintenance *Power PRO2700*

Customer	:			
System	:			
Location	:			
Project number	:			
Unit number	:			
Unit power rating	: NB	SB		kVA
Voltage	:	V		
Frequency	:	Hz		

This logbook will help you to carry out the "Weekly & monthly Maintenance Instructions" per *PowerPRO2700* unit, in accordance with the "User Guide" and the "Service Handbook" in an efficient and logical sequence, viz.:

- utility mode
- diesel test
- system test

Please bear in mind that you are working on an unit which is significant to your company. Therefore, before starting checks and/or maintenance, read the "User Guide" or the "Service Manual".
Pay special attention to chapter "Safe and correct use of the diesel UPS system".

Attention:
If measured values are not within the range as stated in the "User Guide" or the "Service Handbook" please contact your local service provider.

References:
CP 9803 Standard Maintenance Schedule *PowerPRO2700* Installations

Utility mode - single *Power PRO2700*

Unit no.:	*Year:*	*Week*					
1. Electrical panels							
No alarms/messages *(Fill-in remarks below if not OK)*		ok					
Utility measurement							
Utility voltage		V					
Utility current		A					
Utility frequency		Hz					
NB load measurement							
Output voltage		V					
Output current		A					
Output frequency		Hz					
NB output load (real)		kW					
NB output load (reactive)		kvar					
NB output load (apparent)		kVA					
SB load measurement (if applicable)							
SB output load (real)		kW					
SB output load (apparent)		kVA					
UPS measurement							
Generator voltage		V					
Generator current		A					
Generator frequency		Hz					

Diesel test - single *Power PRO2700*

Unit no.:	*Year:*	*Month*					
1. Electrical panels							
No alarms/messages *(Fill-in remarks below if not OK)*		ok					
When not ok, return operation mode to "AUTO" and solve problem first							
2. Diesel engine							
Lube oil leakage		ok					
Fuel leakage		ok					
Coolant leakage		ok					
Diesel engine speed		rpm					
Coolant temperature LT	(if applicable)	°C					
Coolant temperature HT	(if applicable)	°C					
Lube oil temperature	(if applicable)	°C					
Lube oil pressure		bar					

Appendix D Failure Codes

The following figures show the overview of the failure codes and sub failure codes. The failure codes highlighted with green are the ones that also contain failure sub codes.

Part	Code	Definition
Diesel Engine	DBA	Diesel engine start batteries
	DBE	Diesel engine bearings
	DCO	Diesel engine cooling system
	DCS	Diesel engine control system
	DFU	Diesel engine fuel supply system
	DHE	Diesel engine preheating system
	DLU	Diesel engine prelubrication
	DOL	Diesel engine oil leak
	DOT	Diesel engine others
	DPR	Diesel engine protection
	DST	Diesel engine start system
FWC	FLE	FWC type GMN leakage
	FTR	FWC type GMN transmission
	FSL	FWC type Stieber leakage
	FCS	FWC type Stieber transmission
	FPR	FWC protection / measurement
	TFL	Transmission flex coupling
	TLU	Transmission lubrication system
Generator	GBE	Generator DE bearing
	GBN	Generator NDE bearing
	GBR	Generator brushes
	GOT	Generator others
	GPR	Generator protection / measurement
	GSL	Generator sliprings
	GVO	Generator voltage control
	GWI	Generator windings
Induction Coupling	IBD	IC outer bearing diesel side
	IBG	IC outer bearing generator side
	IBR	IC brushes
	IEX	IC brushless exiter
	IIB	IC inner bearing
	IIS	IC isolators
	IOC	IC overcurrent avarage
	IOT	IC others
	IPR	IC protection / measurement
	ISL	IC sliprings
	IWI	IC winding
Non - PI	NOF	Nothing found/ extra measurement
	QMS	QMS problem
	RRL	Reverse reactive load
	RTE	Ride through electrical
	RTM	Ride through mechanical
	RTV	Room temperature / ventilator
	SWI	Switching fault by Customer/ Hitec
	NSA	Genset failure general
	OTH	Others
	BNB	Battery no-break failure
	MTR	Maintenance required
	FWA	General fire warning

Part	Code	Definition
Controls /Panels	DIC	Dicon / bus 500
	PAP	Panels advantys PLC
	PBA	Panels batteries
	PBB	Panels bus bar system
	PCB	Panel Circuit Breakers
	PCC	Panel choke coil
	PFR	Panels frequency control unit
	POT	Panels others
	PPH	Panels PLC hardware
	PPM	Panels PLC modem/monitoring
	PPN	Panels PLC network error
	PPR	Panels protection devices
	PPS	Panels PLC software
	PRE	Panels relays failure
	PSP	Panel supply power
	PSS	Panels SCADA system
	PTS	Panels HMI touch screen
	PWI	Panels wiring
ETM	EBE	ETM outer bearing diesel side
	EBN	ETM outer bearing generator side
	EEX	ETM brushless exiter
	EIB	ETM inner bearing
	EIS	ETM isolators
	EOC	ETM overcurrent average
	EOT	ETM others
	EPR	ETM protection / measurement
	EWI	ETM winding
KEM	KBE	KEM outer bearing diesel side
	KBN	KEM outer bearing generator side
	KIB	KEM inner bearing
	KEX	KEM brushless exiter
	KPM	KEM Pony Motor
	KIS	KEM isolators
	KOC	KEM overcurrent avarage
	KOT	KEM others
	KPR	KEM protection/ measurement
	KWI	KEM winding
FLY-WHEEL	FBE	Flywheel Bearing Driven end
	FBN	Flywheel Bearing Non-Driven end
	FLU	Flywheel Lubrication
	FPM	Flywheel protection/ measurement
	FSP	Flywheel Shear pin

DCO	Description
WIRE	Loose Wire
LEAKP	Leakage Piping
LEAKE	Leakage Engine
LEAKR	Leakage Radiator
LOW-P	Low Pressure
CNTRL	Control/Panels
SENS	Sensor Defect
Other	Other

DCS	Description
WIRE	Loose Wire
212RQ	212RQ
ACT	Actuator
116DE	116DE Regulator
PU	Pickup Sensor
Other	Other

DST	Description
WIRE	Loose Wire
BATT	Starting Batteries
FUSE	Fuse
VALVE	Valve
START M.	Start motor
SENSOR	Sensor
RESET	Reset
Other	Other

DIC	Description
DIC1	Dicon 1
DIC2	Dicon 2

FPR	Description
WIRE	Loose Wire
PT100	PT100 Sensor
Press	oil press.
KIT	Temp. wire kit
RESET	Reset
Other	Other

GPR	Description
WIRE	Loose Wire
PT100	PT100 Sensor
RESET	Reset
VIBR	Vibration system
FUSE	Fuse
Other	Other

GVO	Description
WIRE	Loose Wire
SETT	Settings
FUSE	Fuse
AVR	AVR
DIOD	Diode
RESET	Reset
Other	Other

GWI	Description
GEN	Generator
Other	Other

IPR	Description
WIRE	Loose Wire
PT100	PT100 Sensor
SPM	SPM Unit
RESET	Reset
Other	Other

PAP	Description
AIM	Analog Input Module
AOM	Analog Output Module
DDI	Digital Input Module
DDO	Digital Output Module
NMP2212	Network Modbus +
TIO	TIO Module
PDM	PDT 3100 Power Distribution Module
PT100	PT100 module
Other	Other

PCB	Description
WIRE	Loose Wire
CC	Closing Coil
OC	Opening Coil
UVT	Undervoltage Trip
MAINT	Maintenance
Other	Other

PPH	Description
CPU	Processor Module
CPS	Power Supply Module
NOM	Network Option Module
DDI	Digital Input Module
DDO	Digital Output Module
ANALOG	Analog Input module
TIO	TIO
Other	Other

PPN	Description
WIRE	Bad Connection
DEC	Decentral Network fault
CEN	Central Network fault
DIC	Dicon network fault.
EMC	Electromagnetic Compliance
SET	Settings
RS2000	RS2000 or RS4000
RESET	Reset
Other	Other

PSP	Description
WIRE	Loose Wire
PULS QT	PULS QT
PULS SL	PULS SL
PULS CD	PULS CD
SCHN	PLC Power Supply
POLY	Polyamp PSC 240
SIEM	Siemens SITOP DC-USV
MCB	Defective MCB

RTV	Description
AMB	Ambient temp high
LOUV	Louvre Motor
CNTRL	Controller

Appendix E Fault overview 2022

The following table shows the complete list of failure codes registered in the fault overview of 2022 for PP3600 and PP2700 UPS systems.

Failure code	Count	Contribution	Cummulative	Unit failure count	Unit failure contribution
PPN	14	9%	9%	10	71%
EPR	12	8%	17%	4	33%
POT	7	5%	21%	1	14%
KOT	7	5%	26%	1	14%
GPR	7	5%	31%	2	29%
OTH	6	4%	34%	1	17%
PCB	6	4%	38%	0	0%
KIB	6	4%	42%	4	67%
PSP	5	3%	45%	2	40%
FCS	5	3%	49%	1	20%
PPH	5	3%	52%	4	80%
EOT	5	3%	55%	1	20%
FPM	5	3%	58%	0	0%
RTV	4	3%	61%	0	0%
KPR	4	3%	64%	3	75%
DLU	4	3%	66%	0	0%
FLU	4	3%	69%	0	0%
PTS	3	2%	71%	0	0%
DCO	3	2%	73%	1	33%
DIC	3	2%	75%	3	100%
DCS	3	2%	77%	3	100%
PFR	3	2%	79%	0	0%
GOT	3	2%	81%	0	0%
PRE	3	2%	82%	0	0%
PWI	2	1%	84%	0	0%
SWI	2	1%	85%	2	100%
DST	2	1%	86%	1	50%
FPR	2	1%	88%	1	50%
PPS	2	1%	89%	0	0%
DBA	2	1%	90%	1	50%
FBE	2	1%	92%	0	0%
KBN	2	1%	93%	2	100%
GVO	1	1%	94%	1	100%
PPR	1	1%	94%	1	100%
DHE	1	1%	95%	0	0%
DOT	1	1%	95%	0	0%
GBE	1	1%	96%	1	100%
FBN	1	1%	97%	0	0%
EBE	1	1%	97%	0	0%
NOF	1	1%	98%	1	100%
KPM	1	1%	99%	1	100%
PPM	1	1%	99%	0	0%
PBB	1	1%	100%	1	100%
43	**154**	**100%**		**54**	

Appendix F Data quality check

The first issue

	OuterBearingTempNDE	OuterBearingTempDE	Q1ActionsCounter	FlywheelSpeed	GenDEVibration	GenNDEVibration	KEMDEVibration	KEMNDEVibration	tdiff
293100	45	46	14	0	0.178915	0.139414	0.115462	0.116143	2303619
293101	45	46	14	0	0.178915	0.139414	0.099796	0.116143	2303628
293102	45	46	14	0	0.178915	0.139414	0.450392	0.116143	2303628
293103	45	46	14	0	0.178915	0.139414	1.963316	0.116143	2303646
293104	45	46	14	0	0.178915	0.139414	0.193144	0.116143	2303665
293105	45	46	14	0	0.178915	0.139414	0.195597	0.116143	2303668
293106	45	46	14	0	0.178915	0.139414	20154.259766	0.116143	2303669
293107	45	46	14	0	0.178915	0.139414	0.057479	0.116143	2303687
293108	45	46	14	0	0.081842	0.139414	0.057479	0.116143	2303690
293109	45	46	14	0	0.081842	0.139414	0.070700	0.116143	2303701
293110	45	46	14	0	0.081842	0.139414	20.447325	0.116143	2303702
293111	45	46	14	0	0.081842	0.139414	0.263487	0.116143	2303719
293112	45	46	14	0	0.081842	0.106301	0.263487	0.116143	2303720
293113	45	46	14	0	0.081842	0.106301	0.198253	0.116143	2303726
293114	45	46	14	0	0.081842	0.106301	0.314378	0.116143	2303733
293115	45	46	14	0	0.081842	0.106301	0.185555	0.116143	2303764

Just remove

	OuterBearingTempNDE	OuterBearingTempDE	Q1ActionsCounter	FlywheelSpeed	GenDEVibration	GenNDEVibration	KEMDEVibration	KEMNDEVibration	tdiff
290895	45	46	14	0	0.096442	0.173003	0.085102	0.135080	2277973
290896	45	46	14	0	0.096442	0.173003	0.099512	0.135080	2277974
290897	45	46	14	0	0.096442	0.173003	0.071307	0.135080	2277977
290898	45	46	14	0	0.096442	0.173003	1.426208	0.135080	2277978
290899	45	46	14	0	0.096442	0.173003	0.157814	0.135080	2277995
290900	45	46	14	0	0.096442	0.173003	0.157814	0.221602	2278000
290901	45	46	14	0	0.096442	0.173003	0.157814	261.386414	2278000
290902	45	46	14	0	0.096442	0.173003	0.157814	0.081935	2278018
290903	45	46	14	0	0.096442	0.173003	0.147898	0.081935	2278090
290904	45	46	14	0	0.096442	0.173003	2.846381	0.081935	2278090
290905	45	46	14	0	0.096442	0.173003	0.081909	0.081935	2278108
290906	45	46	14	0	0.096442	0.173003	0.081909	0.238461	2278143
290907	45	46	14	0	0.096442	0.173003	0.081909	0.870858	2278143
290908	45	46	14	0	0.096442	0.173003	0.081909	0.087729	2278161
290909	45	46	14	0	0.096442	0.069941	0.081909	0.087729	2278163
290910	45	46	14	0	0.096442	0.069941	0.081909	0.096336	2278166

Just remove

	OuterBearingTempNDE	OuterBearingTempDE	Q1ActionsCounter	FlywheelSpeed	GenDEVibration	GenNDEVibration	KEMDEVibration	KEMNDEVibration	tdiff
141950	100	100	65	0	0.095793	0.092964	0.083729	0.094532	870019.3
141951	6354	100	65	0	0.095793	0.092964	0.083729	0.094532	870030.8
141952	100	100	65	0	0.095793	0.092964	0.083729	0.094532	870033.8
141953	100	49	65	0	0.095793	0.092964	0.083729	0.094532	870034.9
141954	100	33	65	0	0.095793	0.092964	0.083729	0.094532	870036.4
141955	100	28	65	0	0.095793	0.092964	0.083729	0.094532	870037.9
141956	6551	28	65	0	0.095793	0.092964	0.083729	0.094532	870068.0
141957	29	28	65	0	0.095793	0.092964	0.083729	0.094532	870070.0
141958	28	28	65	0	0.095793	0.092964	0.083729	0.094532	870075.0
141959	29	28	65	0	0.095793	0.092964	0.083729	0.094532	870076.5
141960	28	28	65	0	0.095793	0.092964	0.083729	0.094532	870078.0
141961	29	28	65	0	0.095793	0.092964	0.083729	0.094532	870083.0
141962	28	28	65	0	0.095793	0.092964	0.083729	0.094532	870084.5

First one ➔ 100

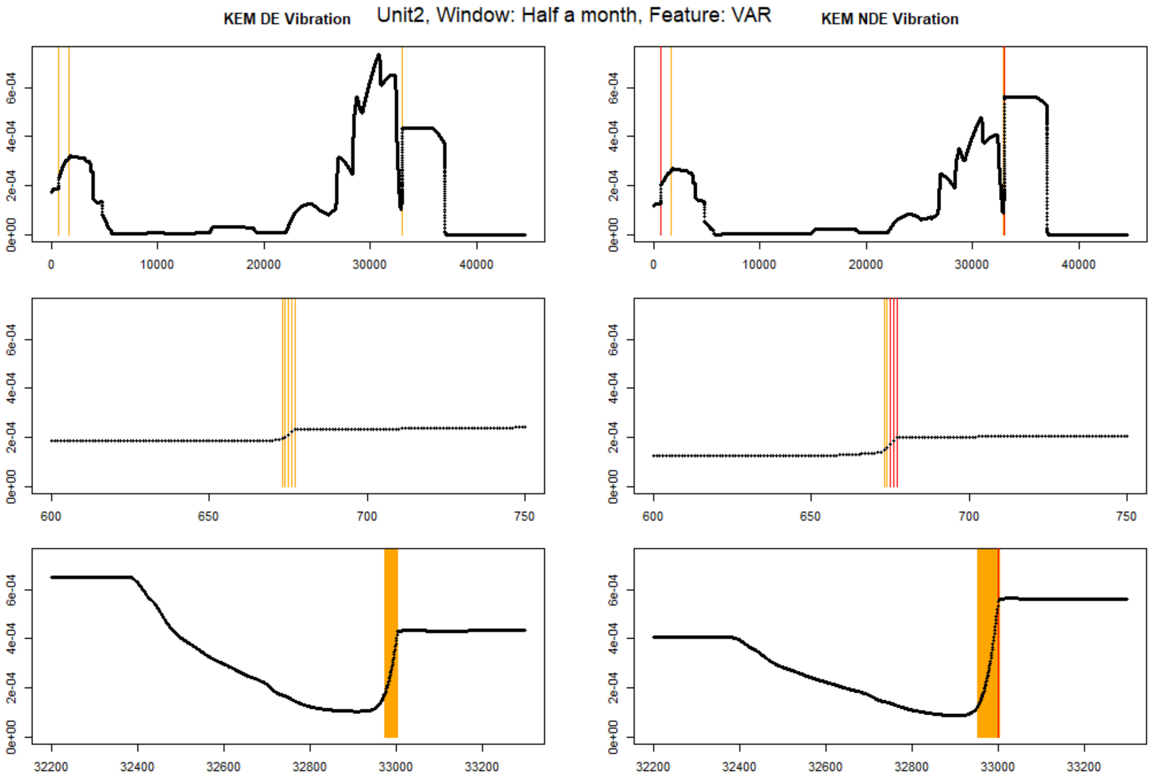
Second ➔ 29

Both remove because otherwise not unique , so no value to keep

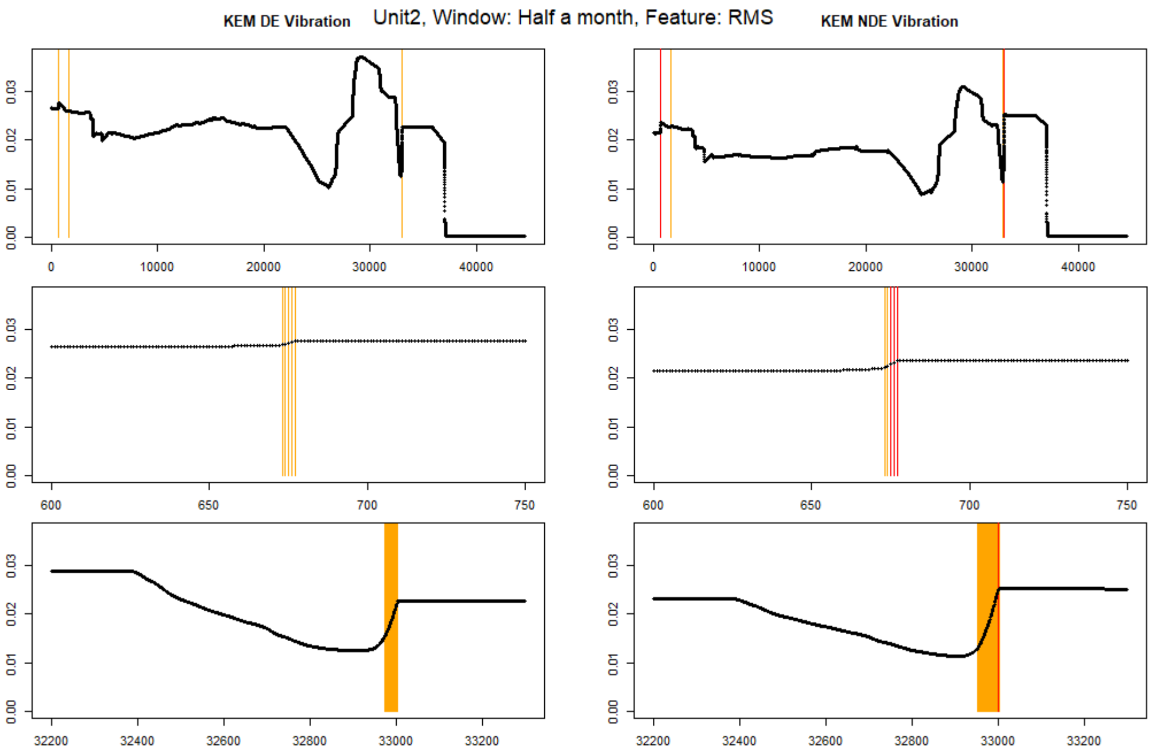
	OuterBearingTempNDE	OuterBearingTempDE	Q1ActionsCounter	FlywheelSpeed	GenDEVibration	GenNDEVibration	KEMDEVibration	KEMNDEVibration	tdiff
141941	28	29	65	0	0.095793	0.092964	0.083729	0.094532	861775.8
141942	28	28	65	0	0.095793	0.092964	0.083729	0.094532	861779.4
141943	28	100	65	0	0.095793	0.092964	0.083729	0.094532	861869.2
141944	28	6354	65	0	0.095793	0.092964	0.083729	0.094532	861871.1
141945	28	100	65	0	0.095793	0.092964	0.083729	0.094532	861874.6
141946	100	100	65	0	0.095793	0.092964	0.083729	0.094532	861881.6
141947	100	6354	65	0	0.095793	0.092964	0.083729	0.094532	861905.7
141948	100	100	65	0	0.095793	0.092964	0.083729	0.094532	861908.7
141949	6354	100	65	0	0.095793	0.092964	0.083729	0.094532	870015.8
141950	100	100	65	0	0.095793	0.092964	0.083729	0.094532	870019.3
141952	100	100	65	0	0.095793	0.092964	0.083729	0.094532	870033.8
141953	100	49	65	0	0.095793	0.092964	0.083729	0.094532	870034.9
141954	100	33	65	0	0.095793	0.092964	0.083729	0.094532	870036.4
141955	100	28	65	0	0.095793	0.092964	0.083729	0.094532	870037.9
141957	29	28	65	0	0.095793	0.092964	0.083729	0.094532	870070.0

Appendix G Extracted features

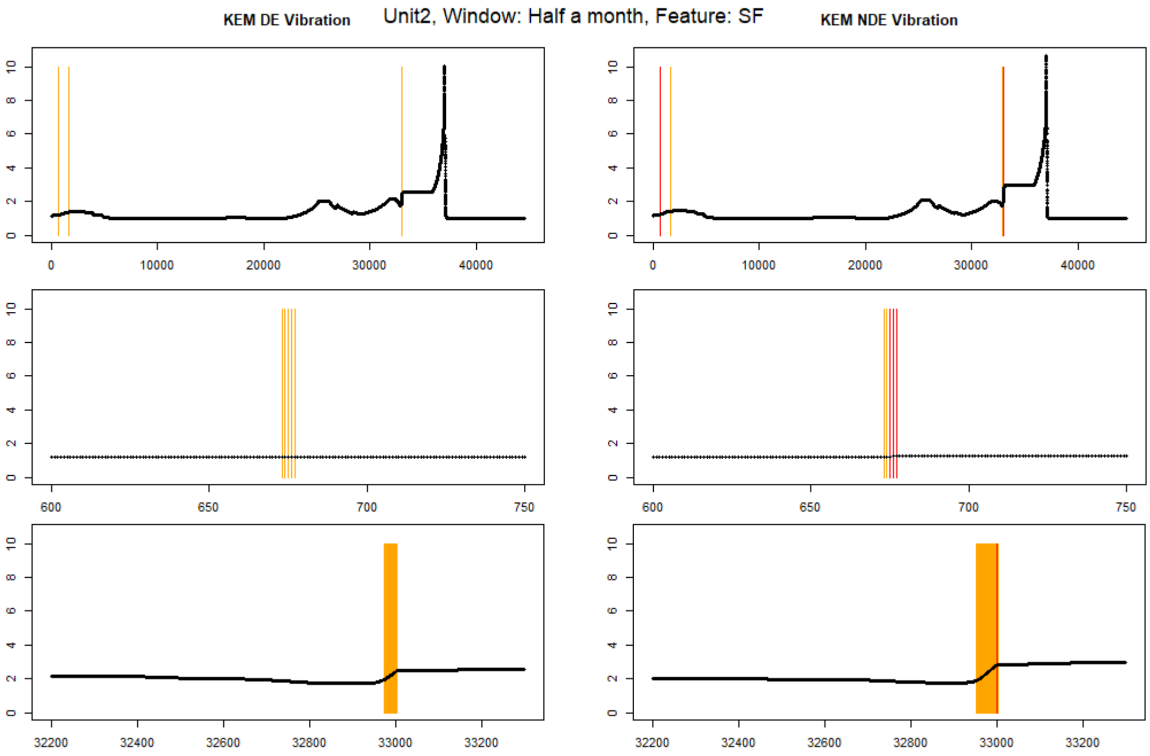
VAR



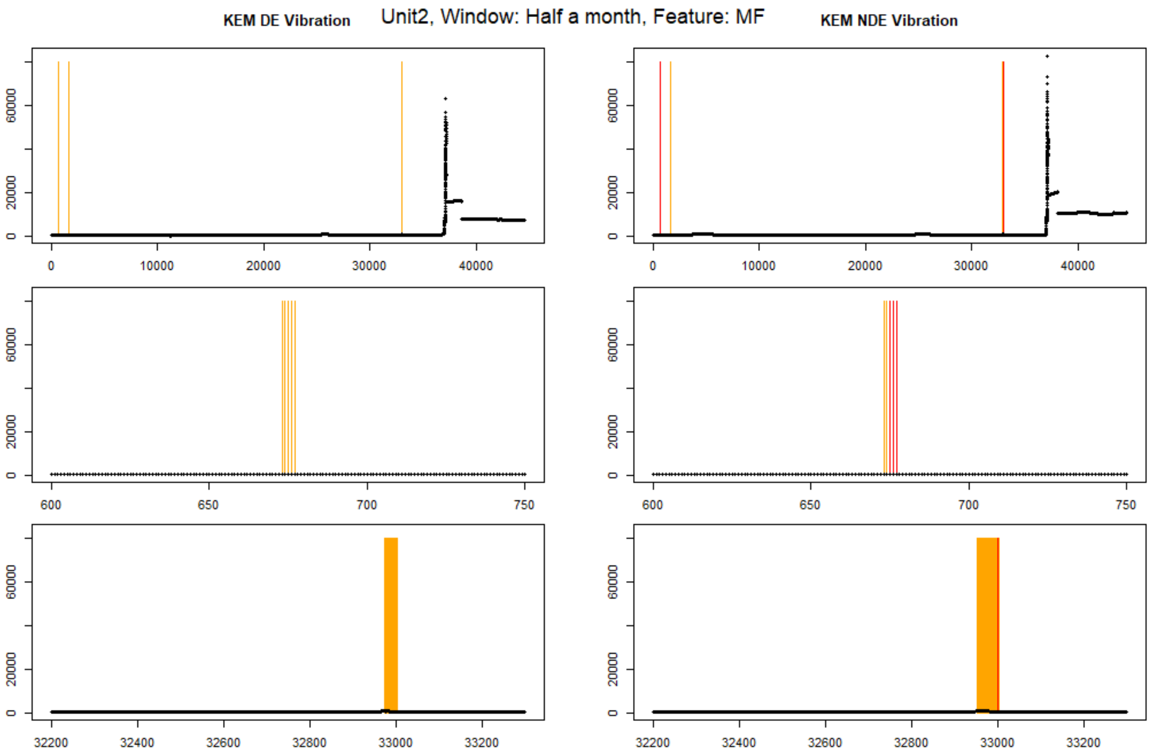
RMS



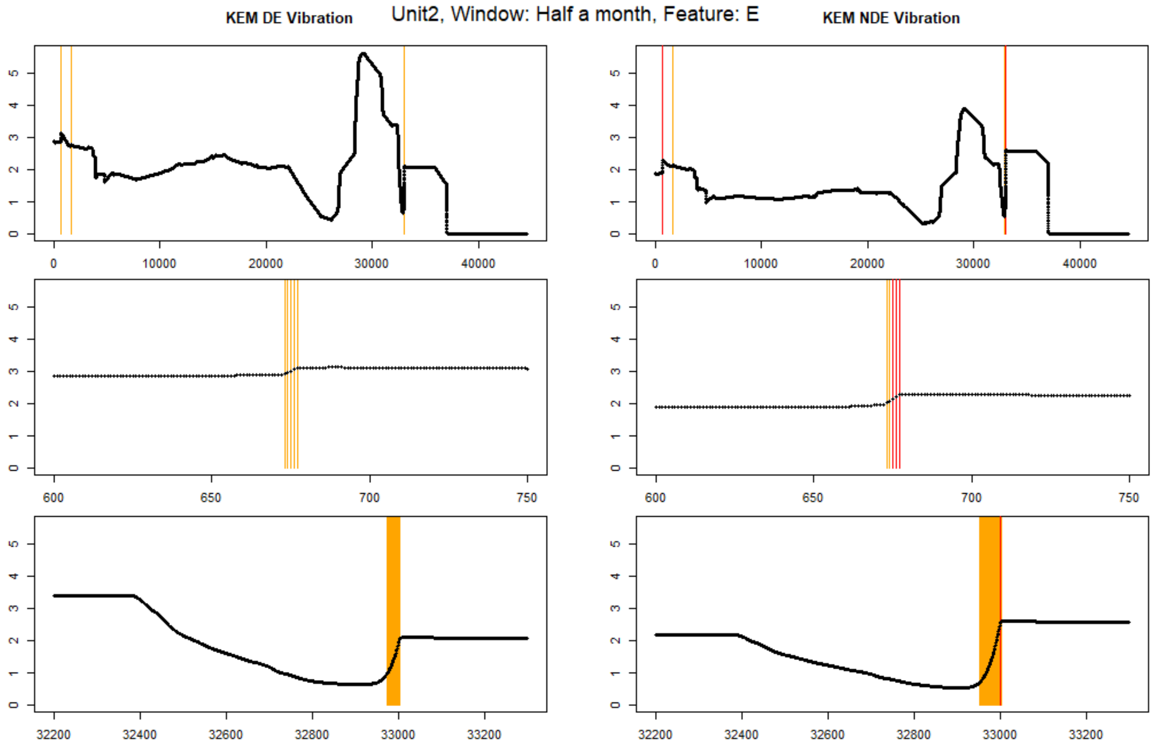
SF


KEM DE Vibration
Unit2, Window: Half a month, Feature: SF
KEM NDE Vibration
0
2
4
6
8
10
0
10000
20000
30000
40000
600
650
700
750
32200
32400
32600
32800
33000
33200

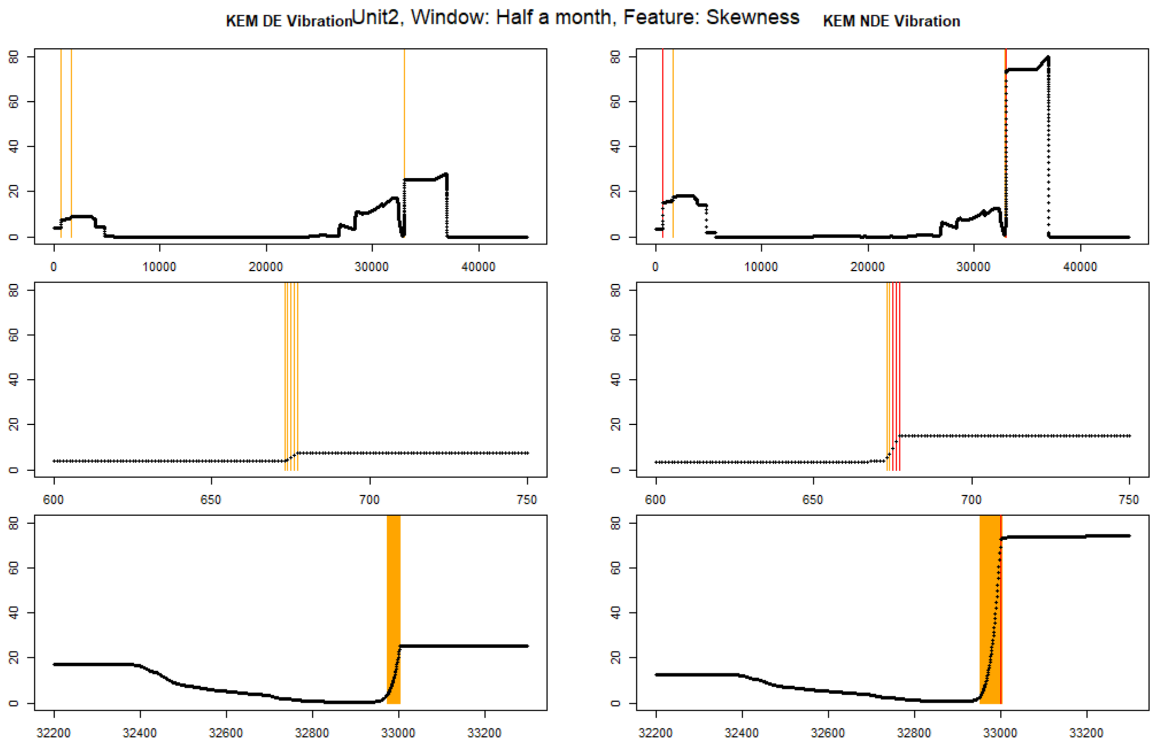
MF


KEM DE Vibration
Unit2, Window: Half a month, Feature: MF
KEM NDE Vibration
0
20000
60000
0
10000
20000
30000
40000
600
650
700
750
32200
32400
32600
32800
33000
33200

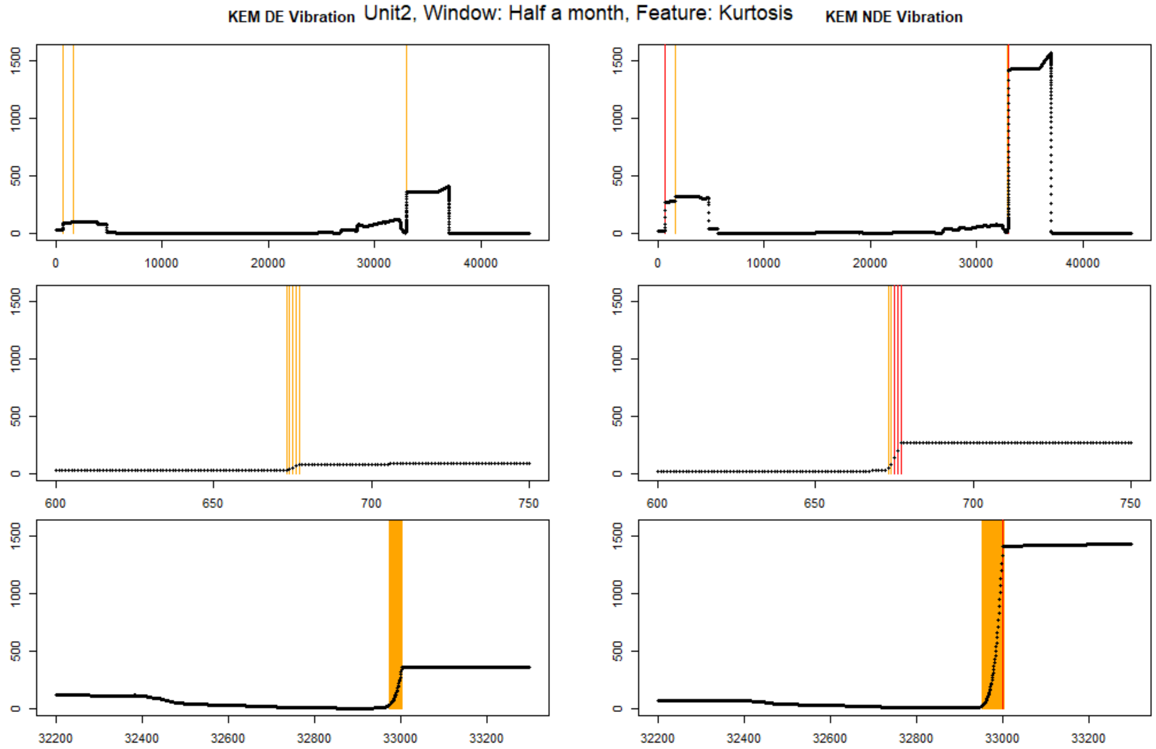
E


KEM DE Vibration
Unit2, Window: Half a month, Feature: E
KEM NDE Vibration

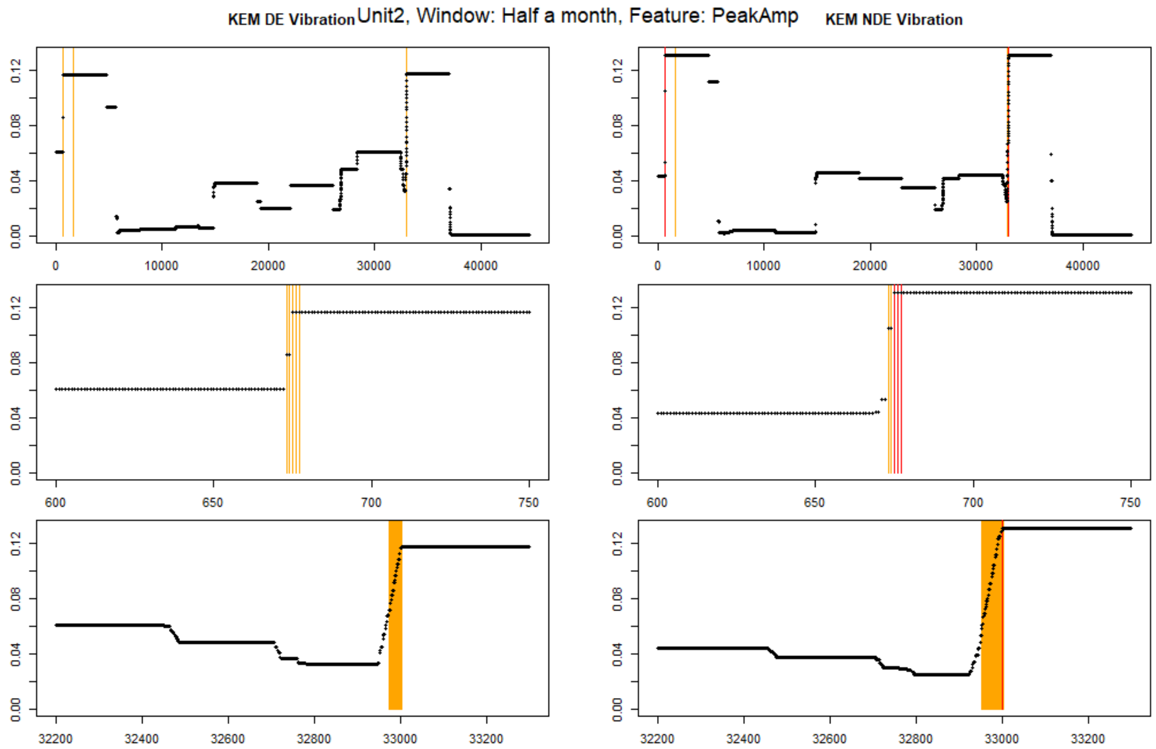
Skewness


KEM DE Vibration
Unit2, Window: Half a month, Feature: Skewness
KEM NDE Vibration

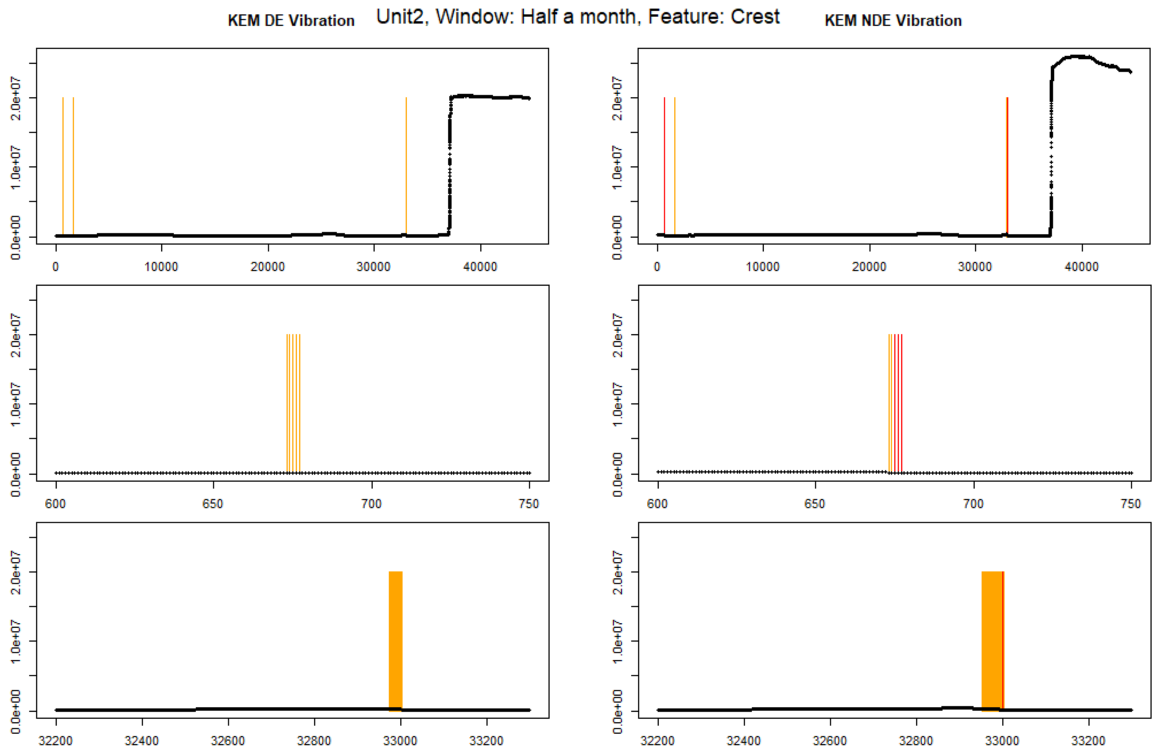
Kurtosis



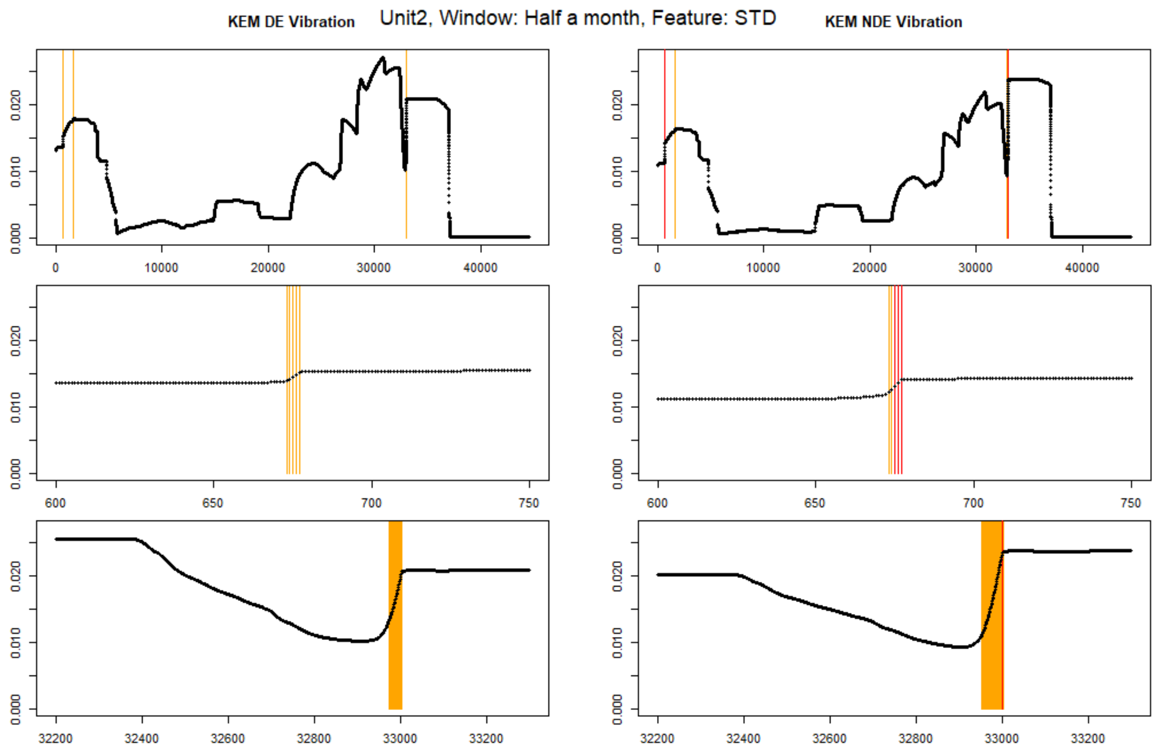
PeakAmp



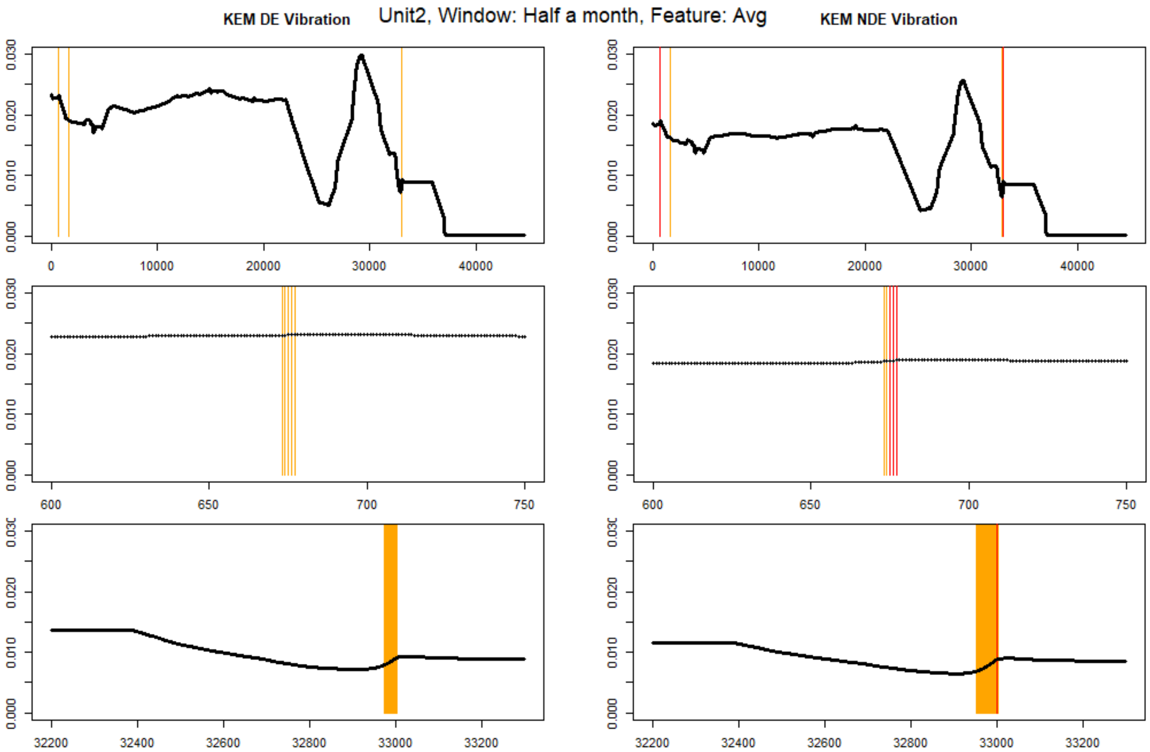
Crest


KEM DE Vibration
Unit2, Window: Half a month, Feature: Crest
KEM NDE Vibration
0.0e+00
1.0e+07
2.0e+07
0
10000
20000
30000
40000
600
650
700
750
32200
32400
32600
32800
33000
33200

Crest


KEM DE Vibration
Unit2, Window: Half a month, Feature: STD
KEM NDE Vibration
0.000
0.010
0.020
0
10000
20000
30000
40000
600
650
700
750
32200
32400
32600
32800
33000
33200

Avg



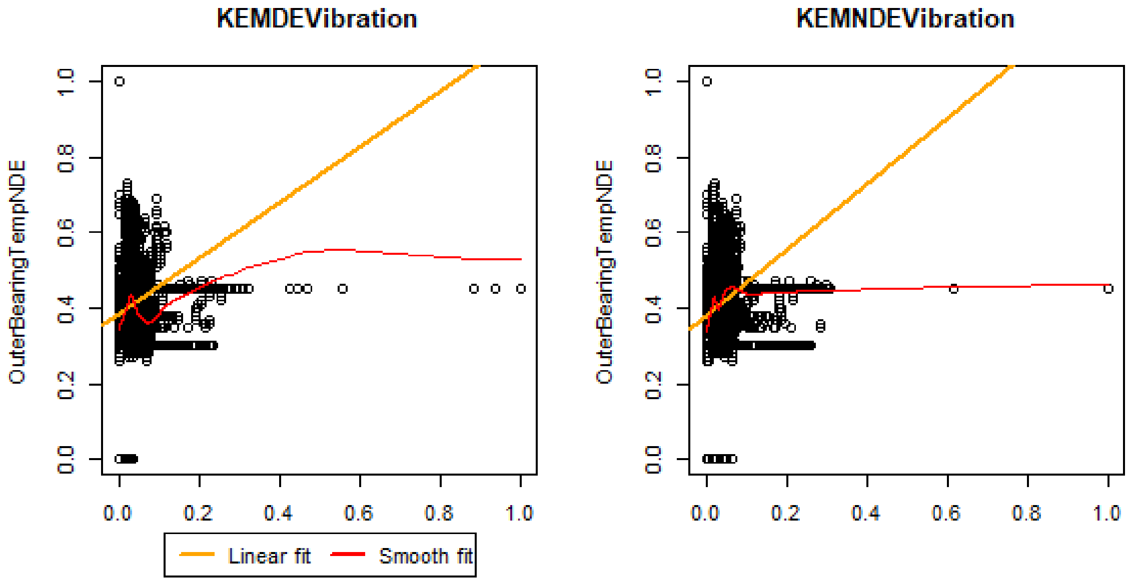
Unit2, Window: Half a month, Feature: Avg
KEM DE Vibration
KEM NDE Vibration

Appendix H Average time step

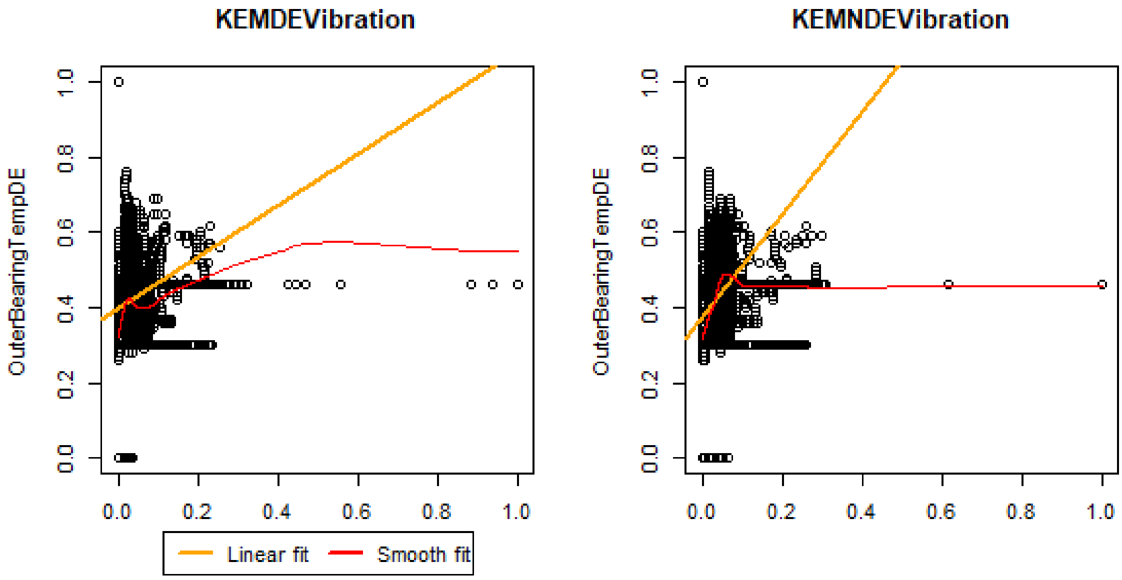
Data set	#Original	#Adjusted	Kept %	Original t_diff (min)	Adjusted t_diff (min)	Min t_diff (min)
1	191 595	32 761	17 %	4.67	1 373 501.08	1 304.85
2	199 533	48 688	24 %	5.30	1 386 789.53	519.83
3	276 981	66 215	24 %	4.59	1 761 442.43	284.79
4	251 651	59 303	24 %	4.77	1 781 471.61	58.88
5	367 450	312 581	85 %	3.01	108 774.87	1.50
6	1 042 006	47 098	5 %	10.00	5 867 503.82	0.00
7	1 254 878	84 703	7 %	10	4 925 870.59	10.00
Total	3 584 094	651 349	18 %	Mean≈ 5hours		

Appendix I Scatterplots

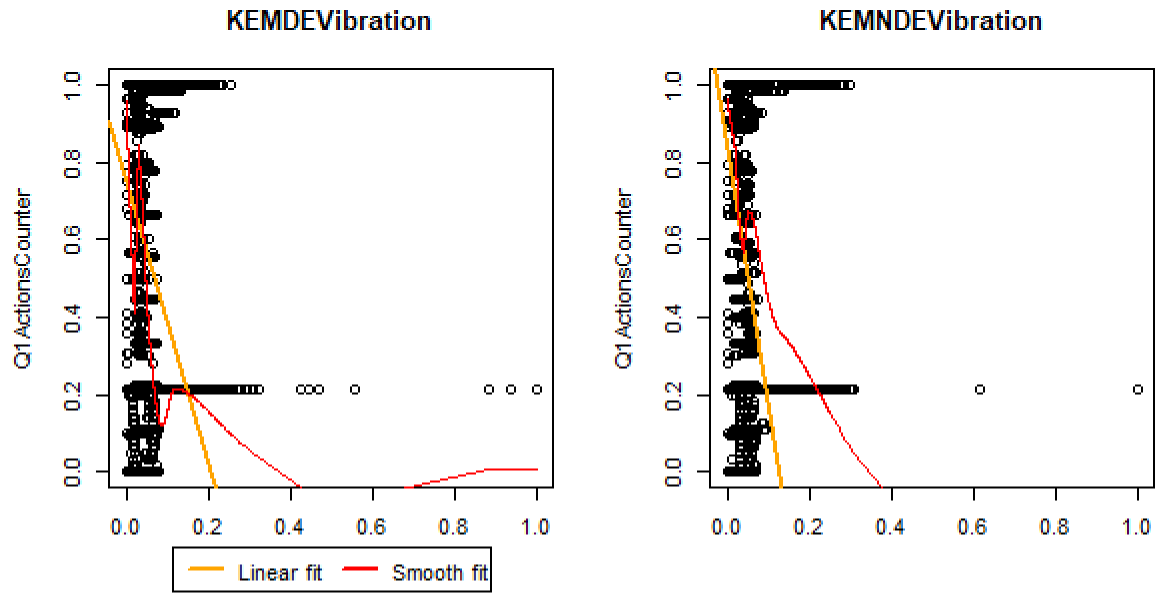
Outer Bearing Temp NDE



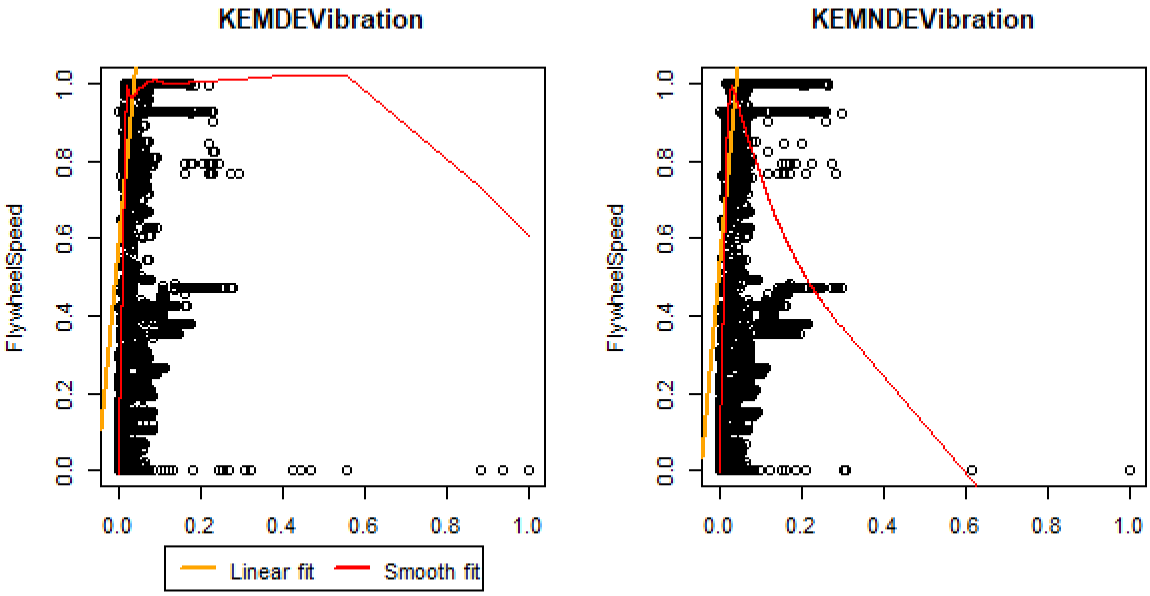
Outer Bearing Temp DE



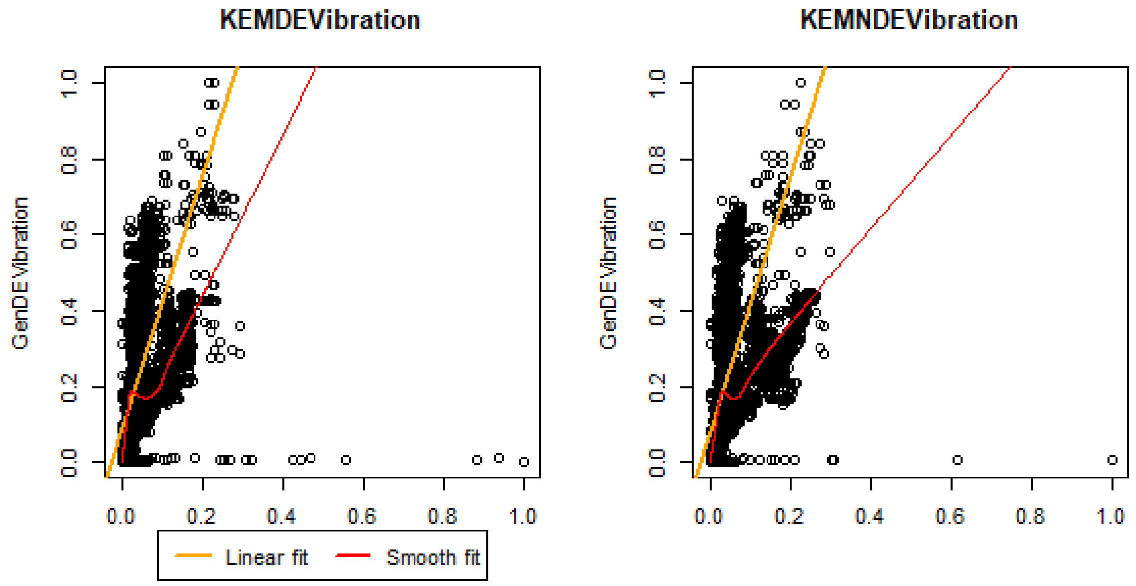
Q1 Actions Counter



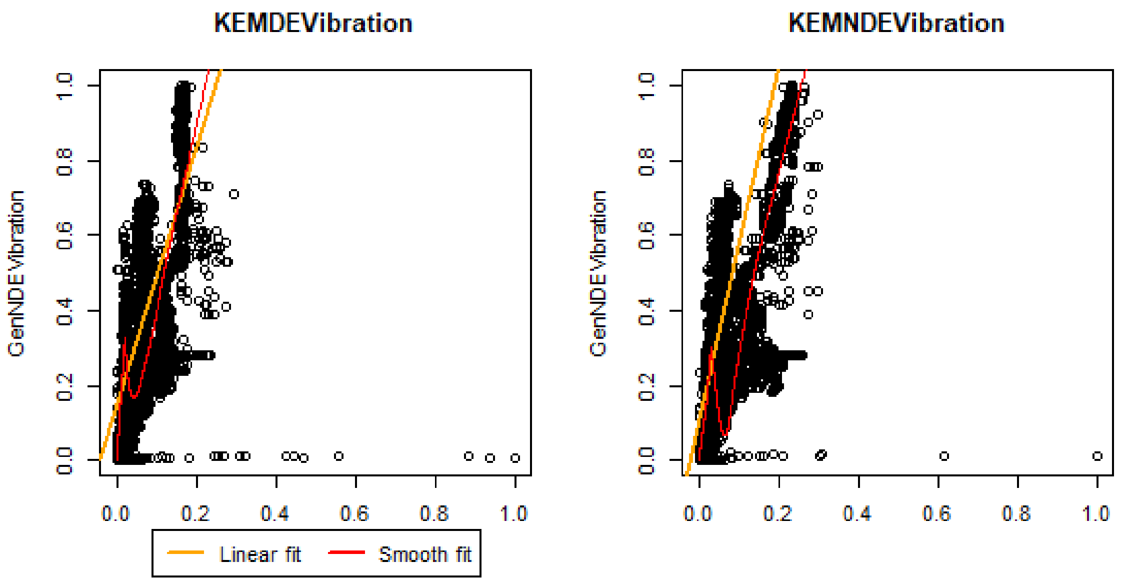
Flywheel Speed



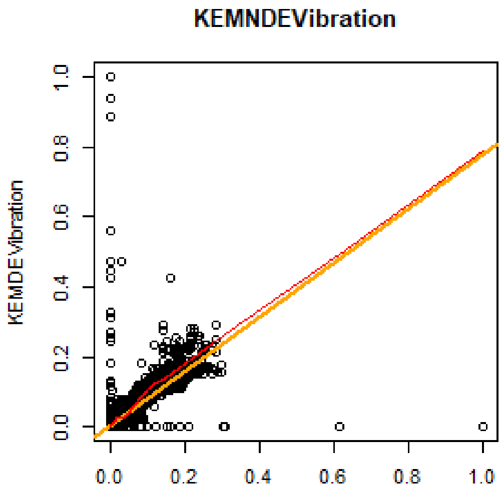
Gen DE Vibration



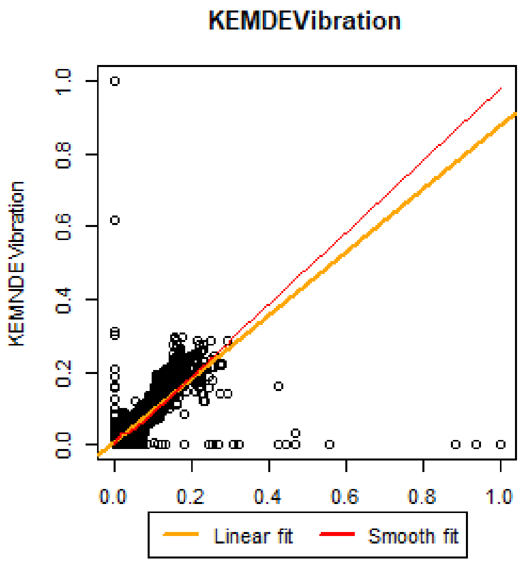
Gen NDE Vibration



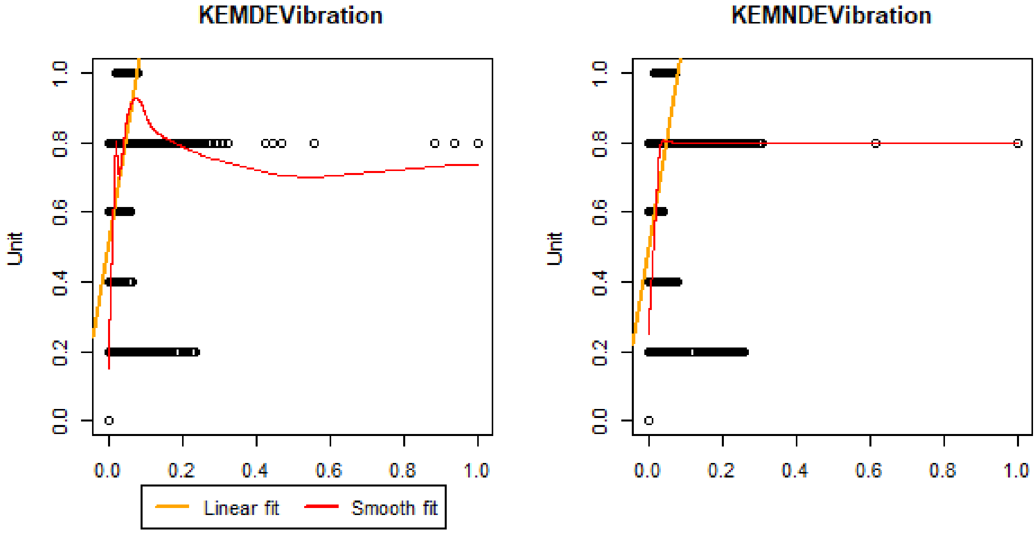
KEM DE Vibration



KEM NDE Vibration

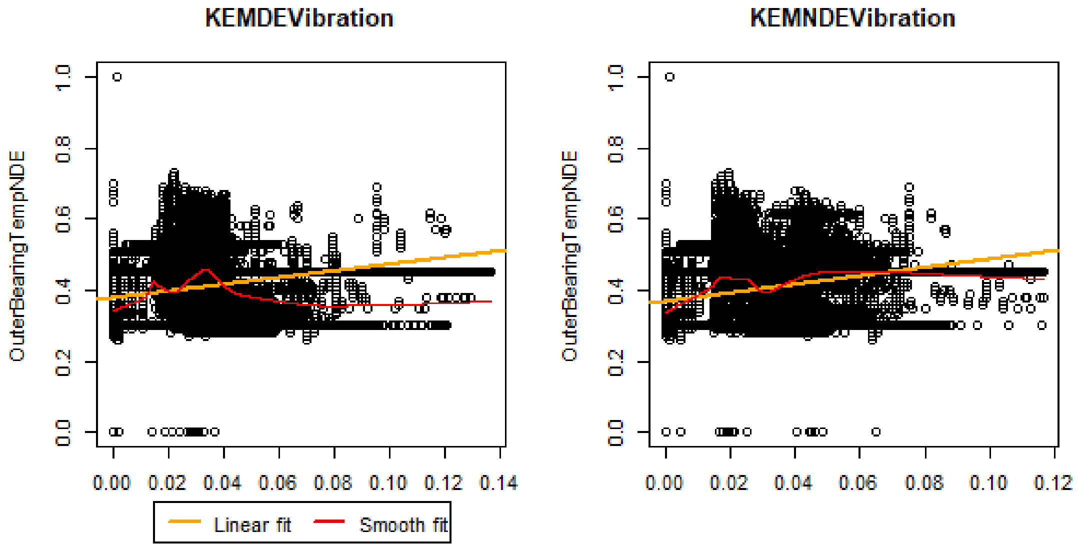


Unit

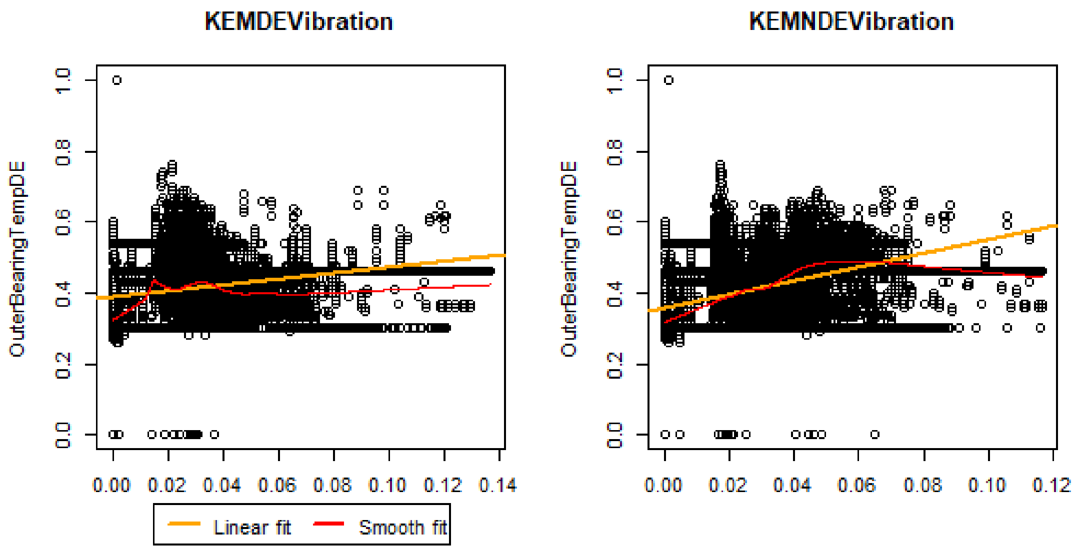

KEMDEVibration
KEMNDEVibration
Unit
0.0
0.2
0.4
0.6
0.8
1.0
Linear fit
Smooth fit

Appendix J Scatterplots – healthy data

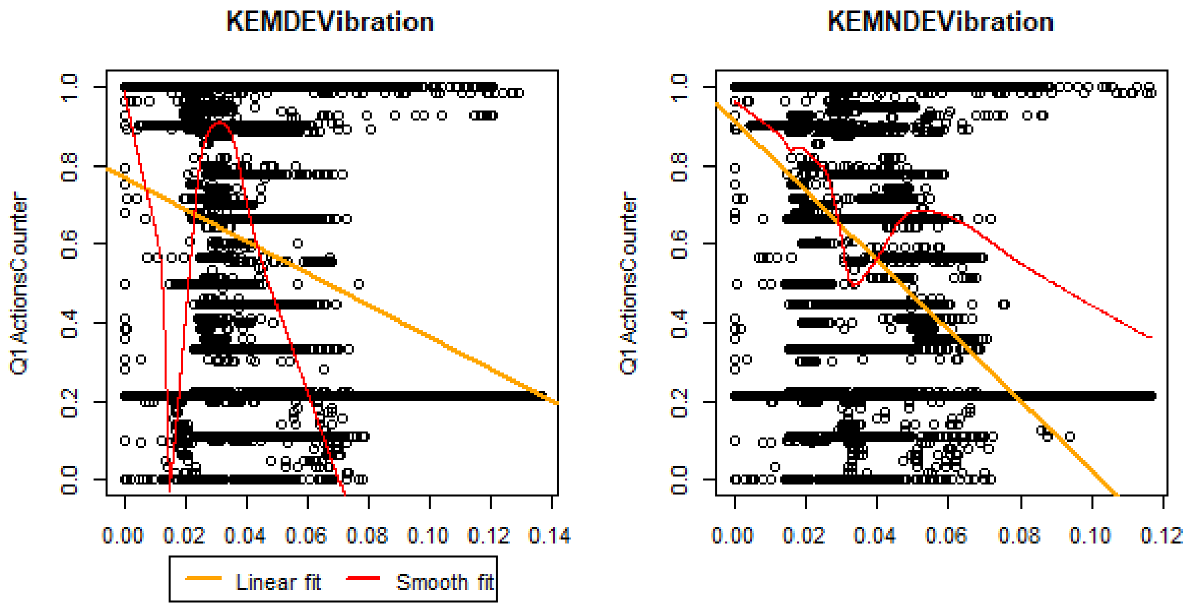
Outer Bearing Temp NDE



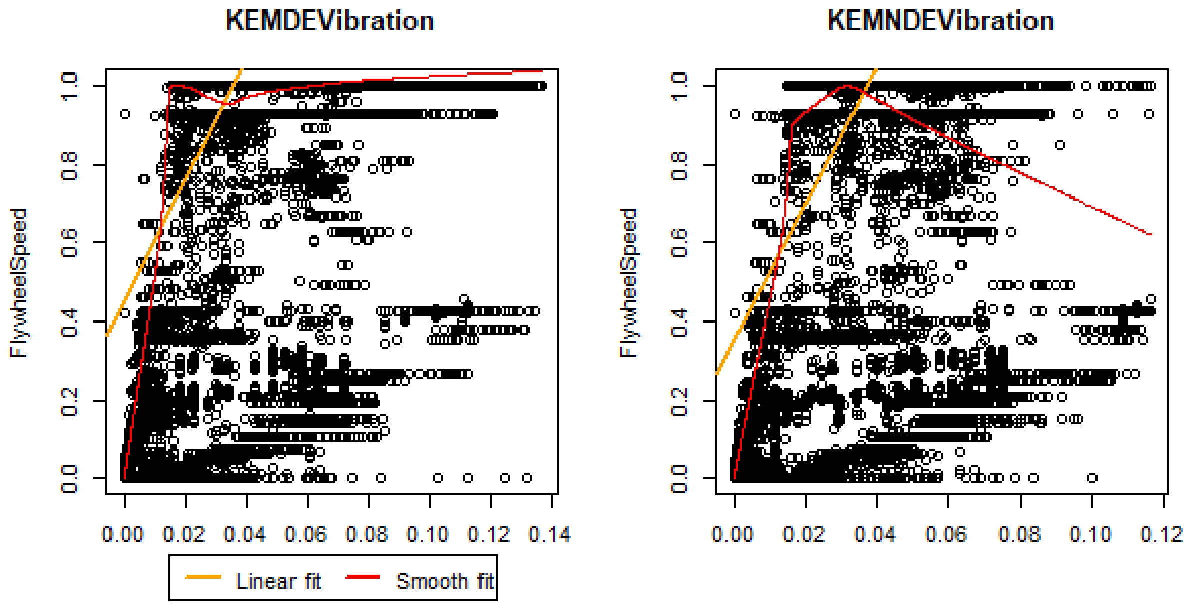
Outer Bearing Temp DE



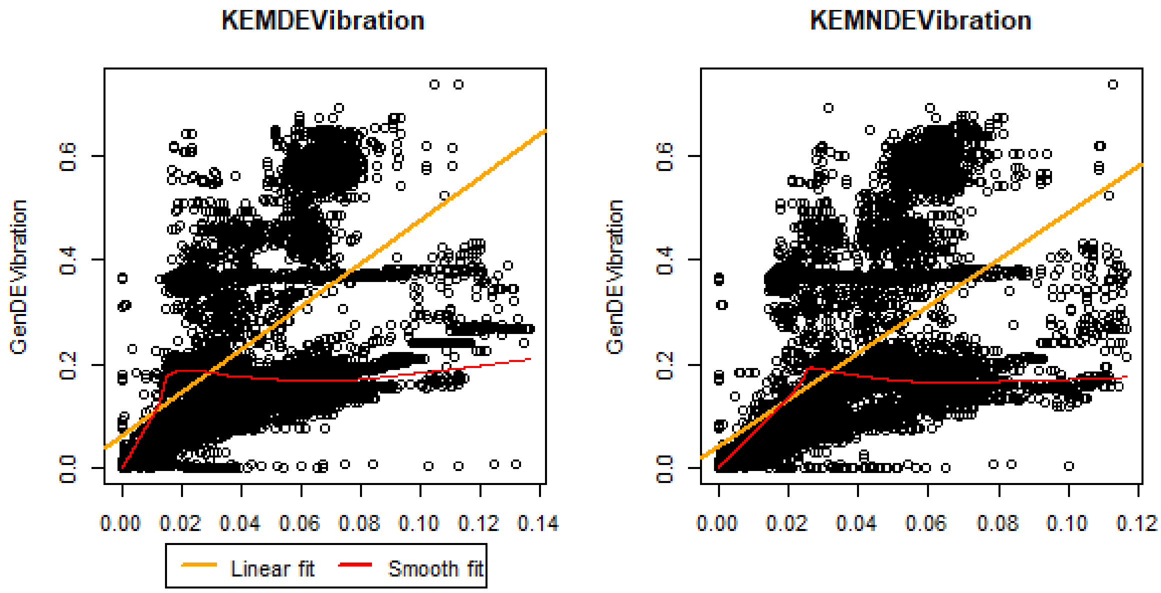
Q1 Actions Counter



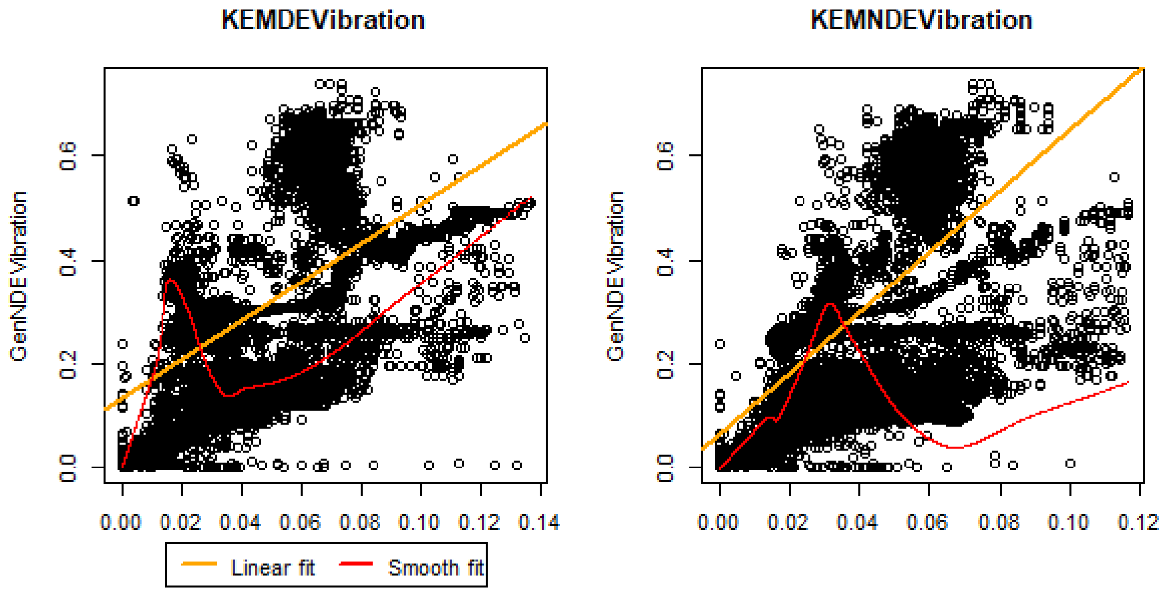
Flywheel Speed



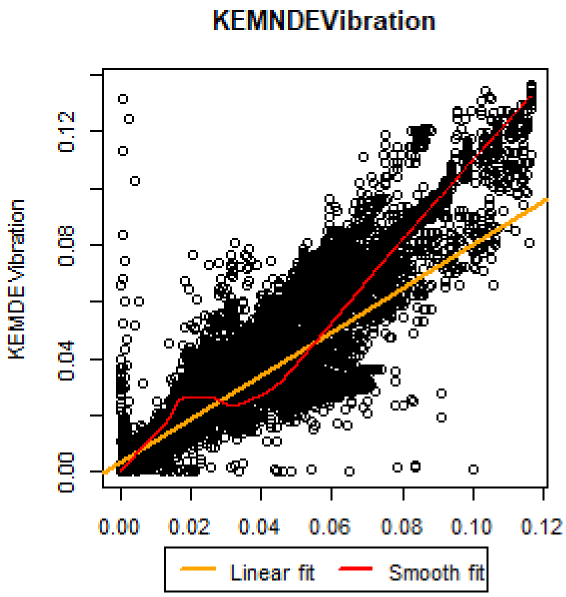
Gen DE Vibration



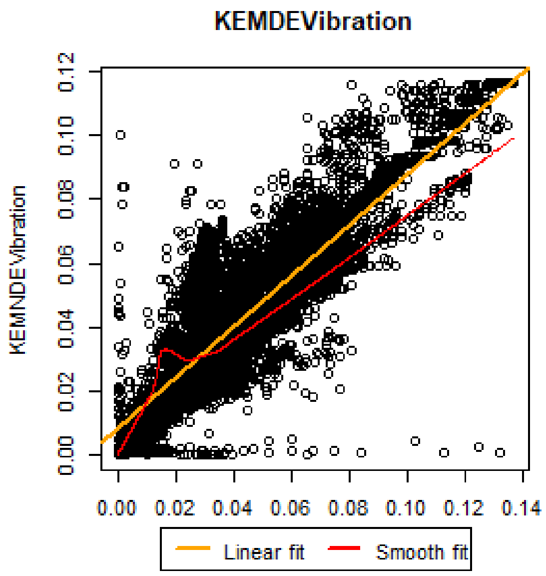
Gen NDE Vibration



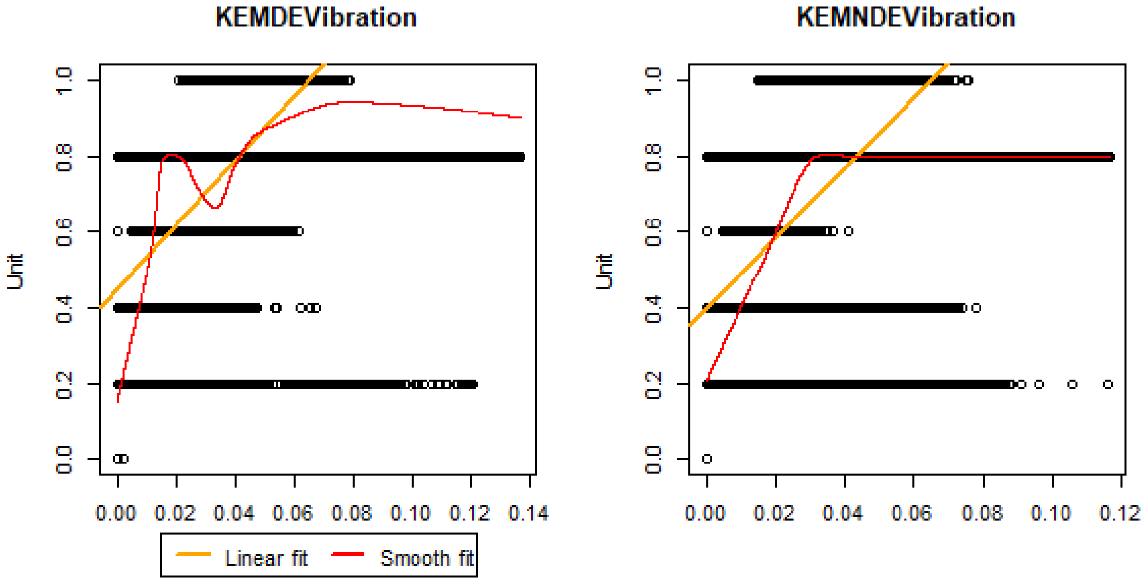
KEM DE Vibration



KEM NDE Vibration

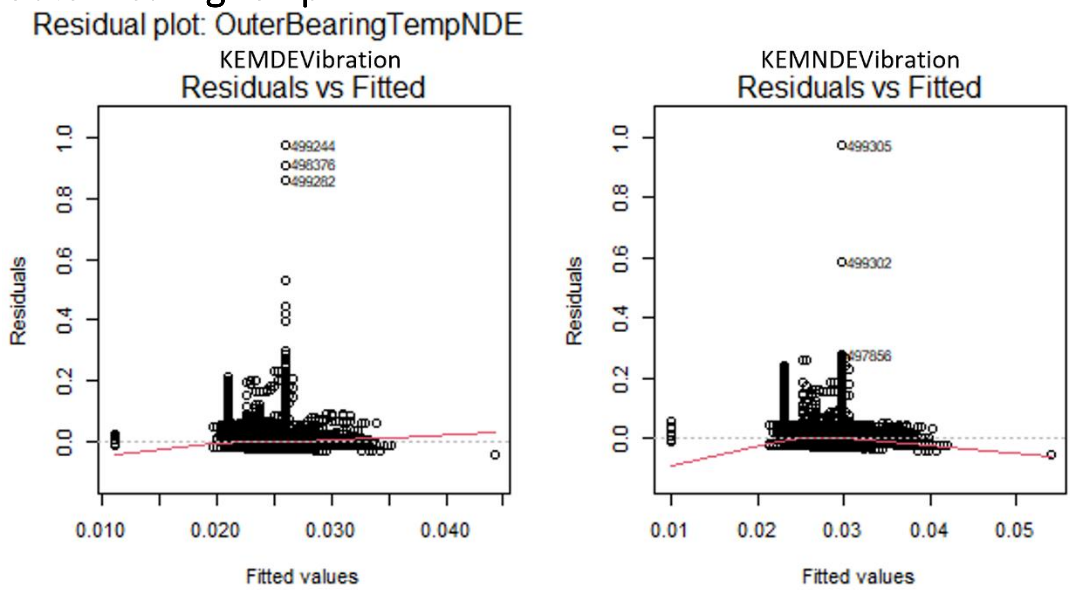


Unit

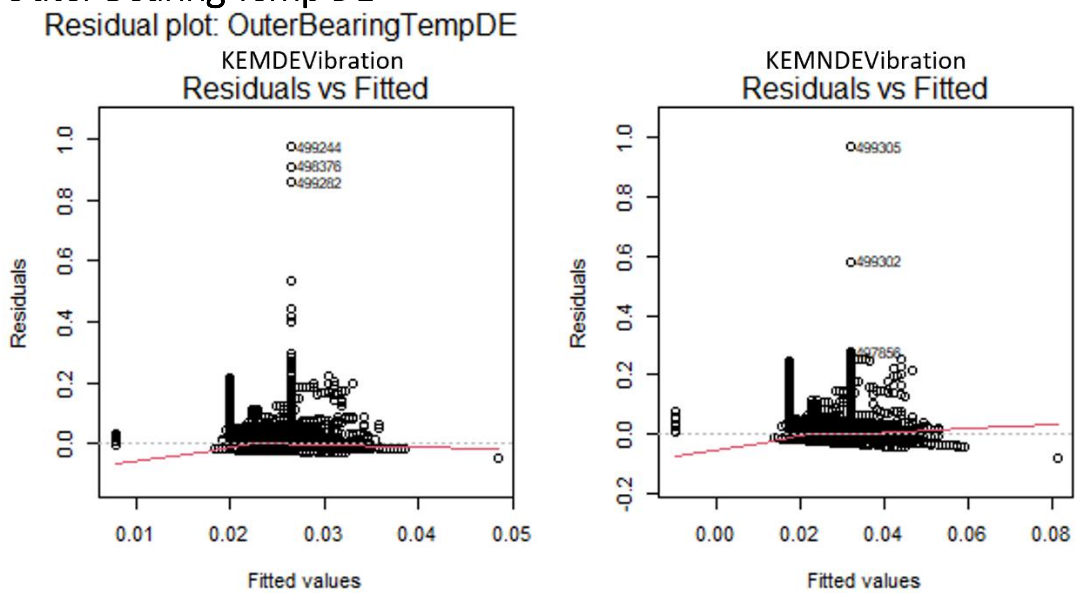

KEMDEVibration
KEMNDEVibration
Unit
Unit
0.0
0.2
0.4
0.6
0.8
1.0
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14
Linear fit
Smooth fit

Appendix K Residual plots

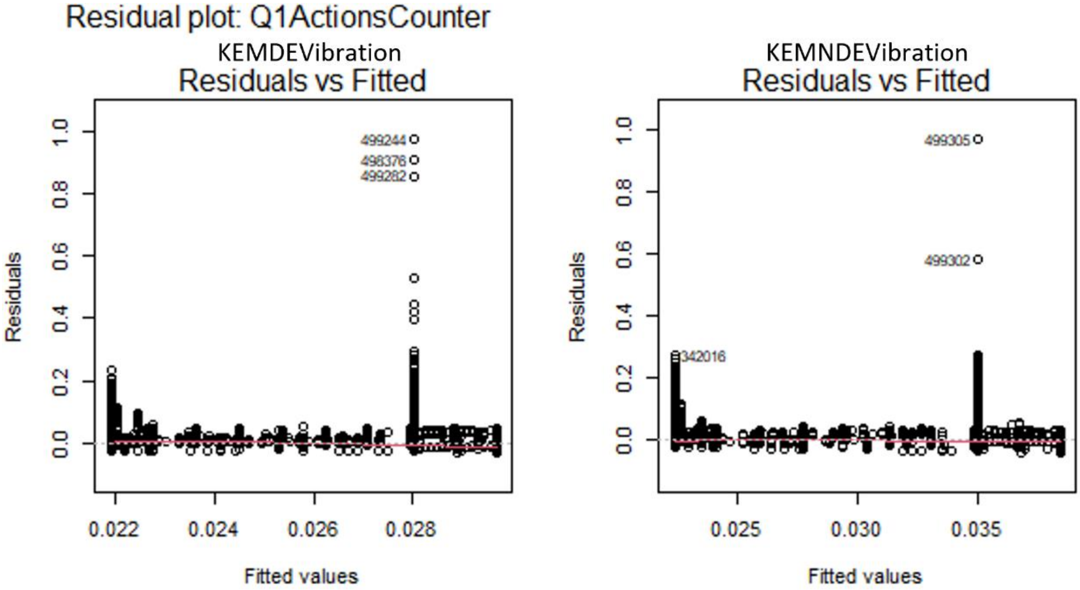
Outer Bearing Temp NDE



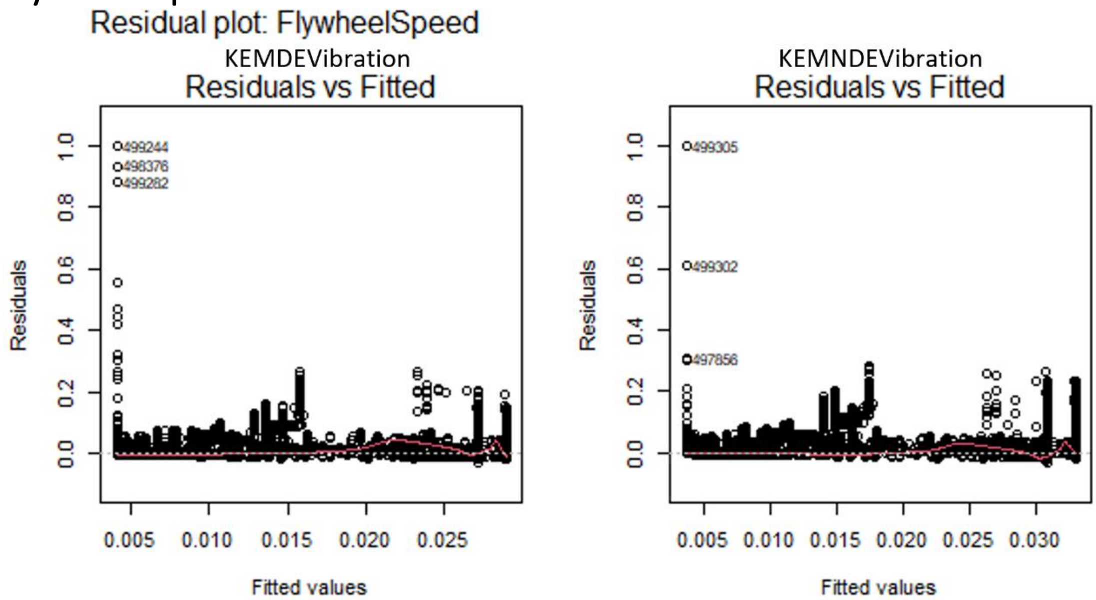
Outer Bearing Temp DE



Q1 Actions Counter



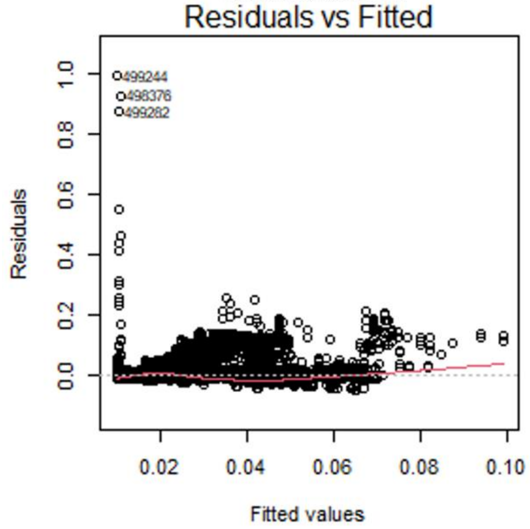
Flywheel Speed



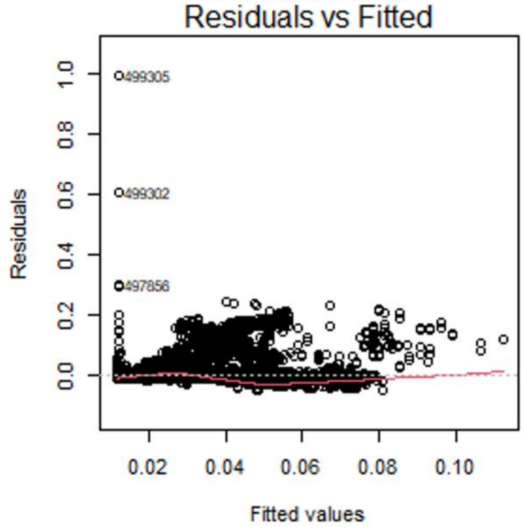
Gen DE Vibration

Residual plot: GenDEVibration

KEMDEVibration



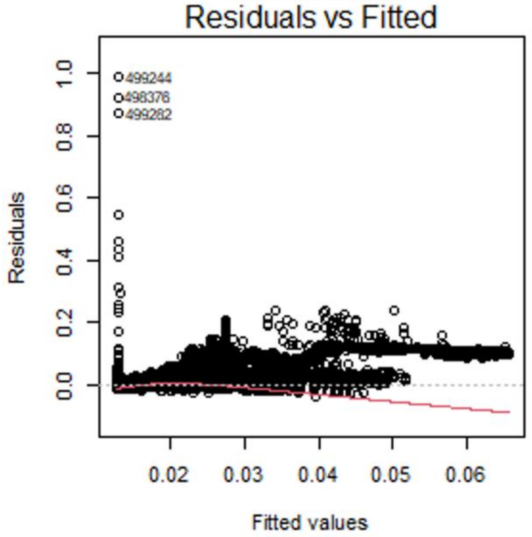
KEMNDEVibration



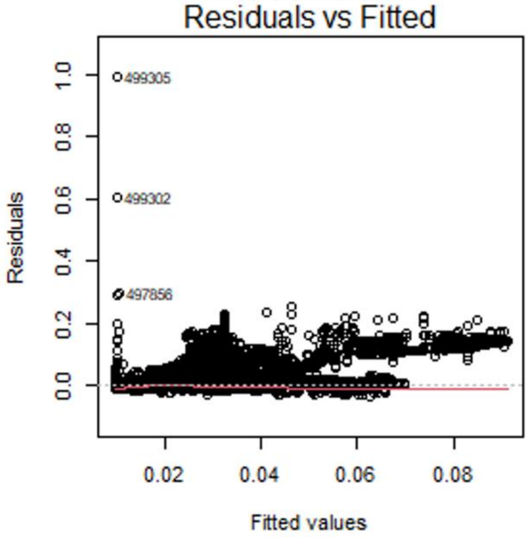
Gen NDE Vibration

Residual plot: GenNDEVibration

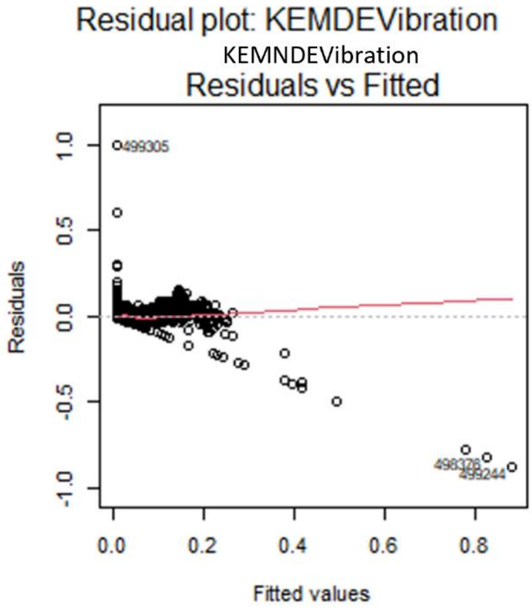
KEMDEVibration



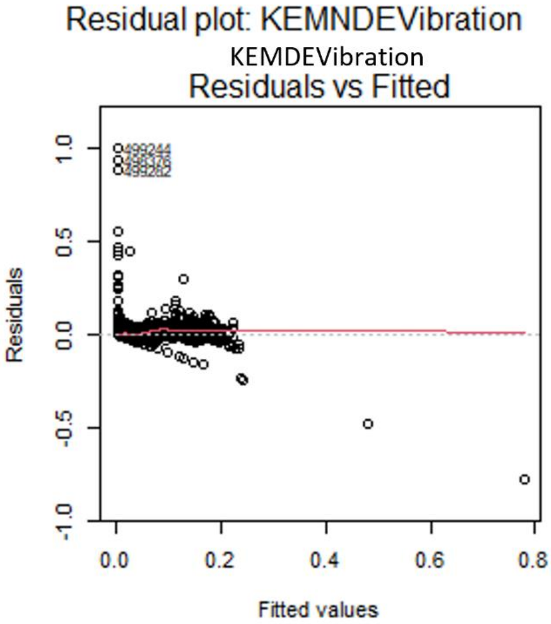
KEMNDEVibration



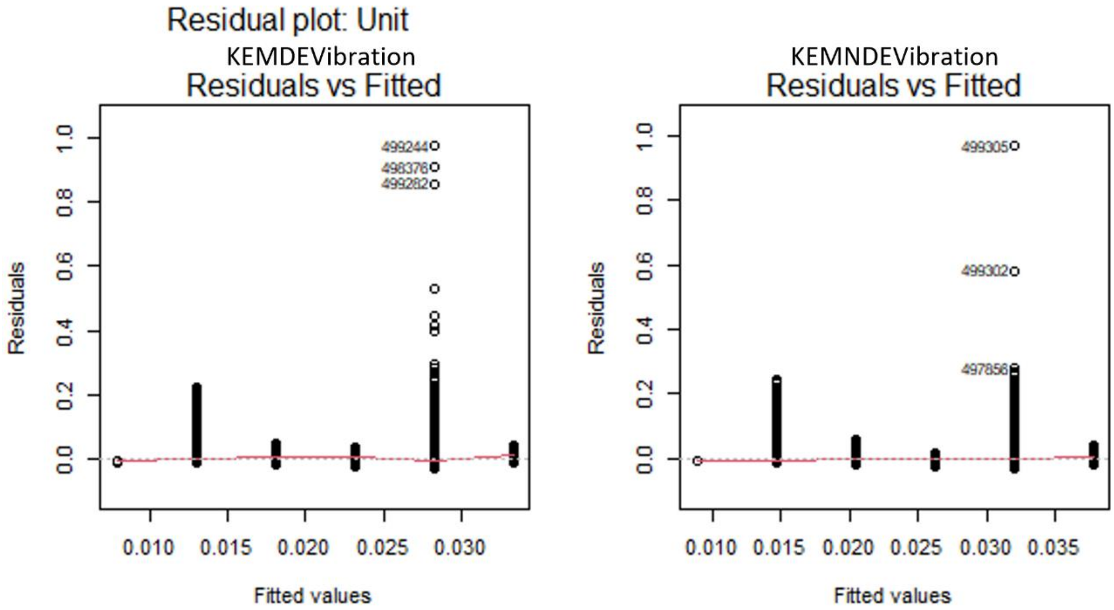
KEM DE Vibration



KEM NDE Vibration

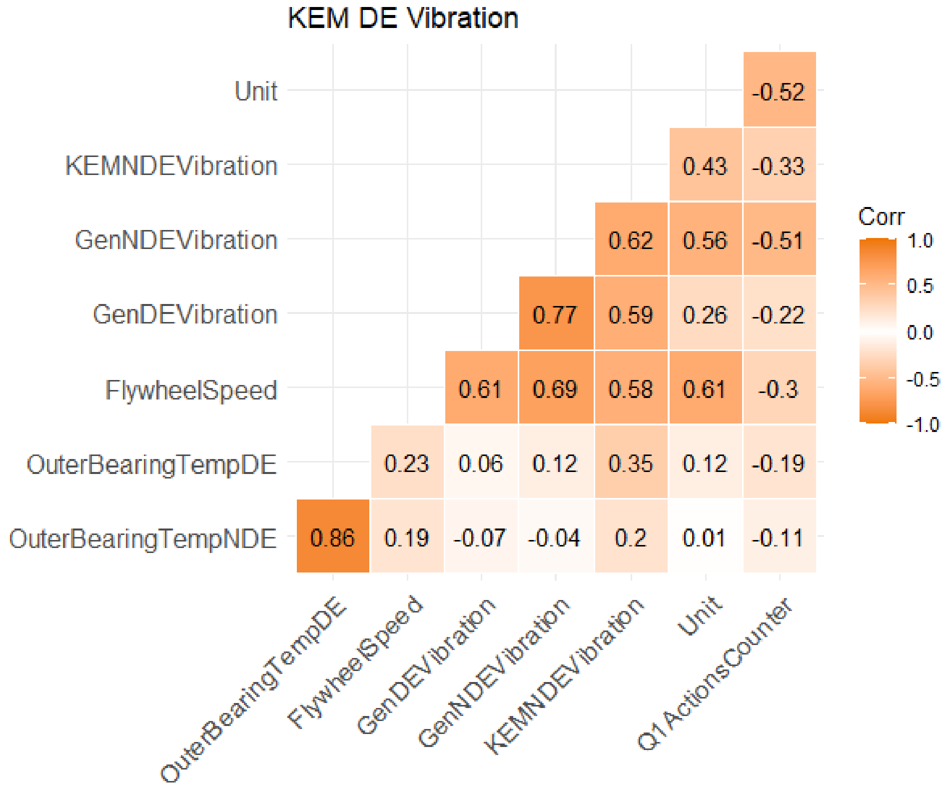


Unit

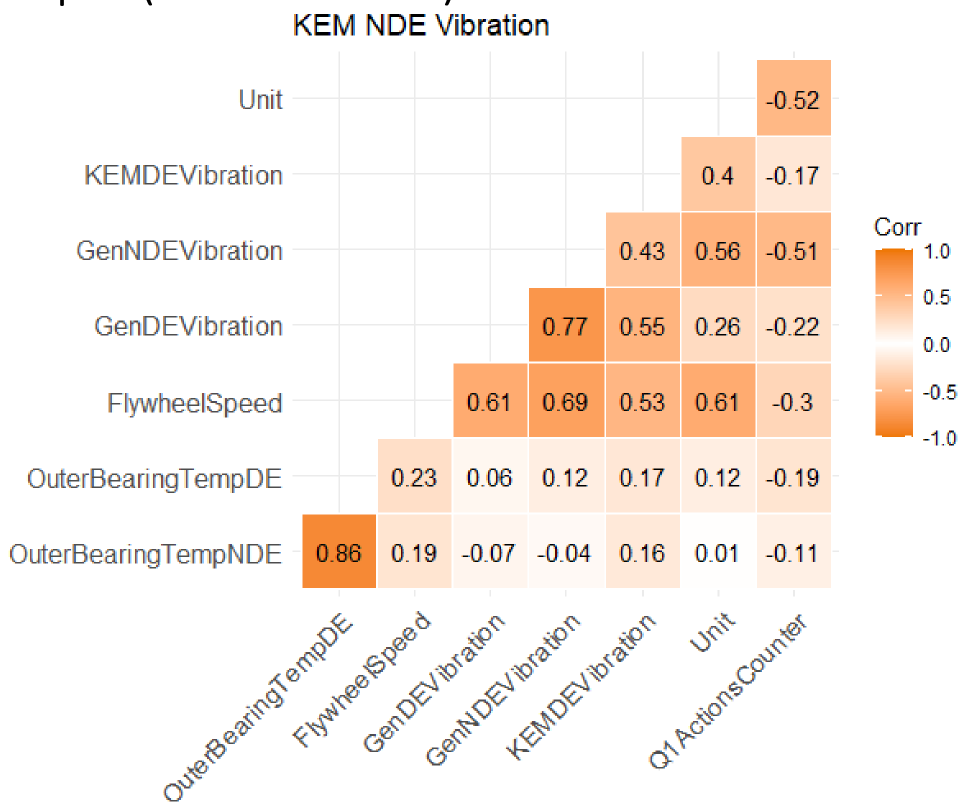

Residual plot: Unit
KEMDEVibration
Residuals vs Fitted
Residuals
Fitted values
499244
498376
499282
KEMNDEVibration
Residuals vs Fitted
Residuals
Fitted values
499305
499302
497856

Appendix L Correlation heatmaps

OutputA (KEMDEVibration)



OutputB (KEMNDEVibration)



Appendix M VIF iterations

OutputA (KEMDEVibration)

Iteration 0

```
> vif(LMmodel_KEMDEVibration)
 OuterBearingTempNDE  OuterBearingTempDE      FlywheelSpeed     GenDEVibration     GenNDEVibration
            4.643903            4.543176           3.114363           3.401469            4.584357
      KEMNDEVibration                Unit  Q1ActionsCounter
            2.116573            2.416162           1.716243
```

Iteration 1

```
> vif(LMmodel_KEMDEVibration)
OuterBearingTempDE      FlywheelSpeed     GenDEVibration    GenNDEVibration    KEMNDEVibration
          1.251051           2.724204           3.343468           4.452548           2.101352
              Unit   Q1ActionsCounter
          2.305050           1.690812
```

Iteration 2

```
> vif(LMmodel_KEMDEVibration)
OuterBearingTempDE      FlywheelSpeed     GenDEVibration    KEMNDEVibration               Unit
          1.243293           2.628993           2.073745           2.064926           2.172404
  Q1ActionsCounter
          1.456001
```

Final input

```
> vif(LMmodel_KEMDEVibration)
OuterBearingTempDE     GenDEVibration    KEMNDEVibration               Unit   Q1ActionsCounter
          1.204380           1.583457           2.031894           1.549685           1.426178
```

OutputB (KEMNDEVibration)

Iteration 0

```
> vif(LMmodel_KEMNDEVibration)
OuterBearingTempNDE  OuterBearingTempDE       FlywheelSpeed      GenDEVibration     GenNDEVibration 
           4.800875            4.303222            3.078725            4.046083            4.690348 
      KEMDEVibration                Unit    Q1ActionsCounter 
           1.825895            2.674157            1.723683 
```

Iteration 1

```
> vif(LMmodel_KEMNDEVibration)
OuterBearingTempDE       FlywheelSpeed      GenDEVibration     GenNDEVibration      KEMDEVibration 
          1.117967            2.747081            3.839080            4.602536            1.753493 
              Unit    Q1ActionsCounter 
          2.472509            1.693768 
```

Iteration 2

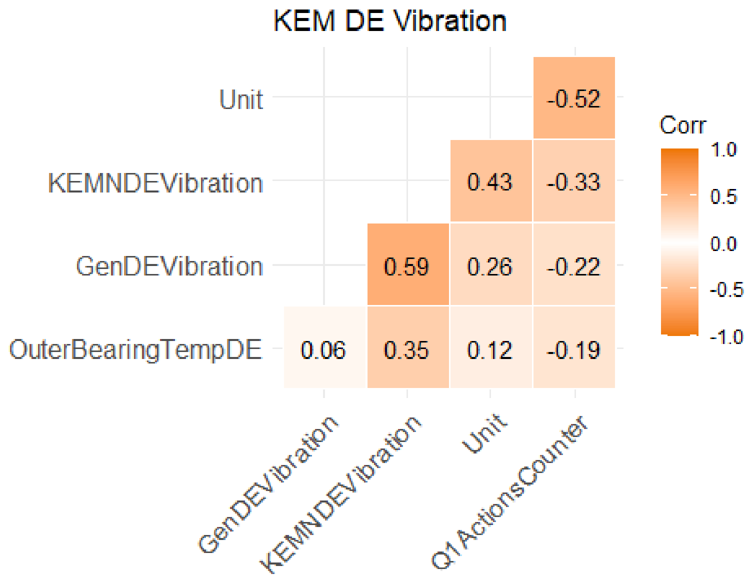
```
> vif(LMmodel_KEMNDEVibration)
OuterBearingTempDE       FlywheelSpeed      GenDEVibration      KEMDEVibration                Unit 
          1.117912            2.607276            2.005851            1.666945            2.236639 
  Q1ActionsCounter 
          1.477649 
```

Final input

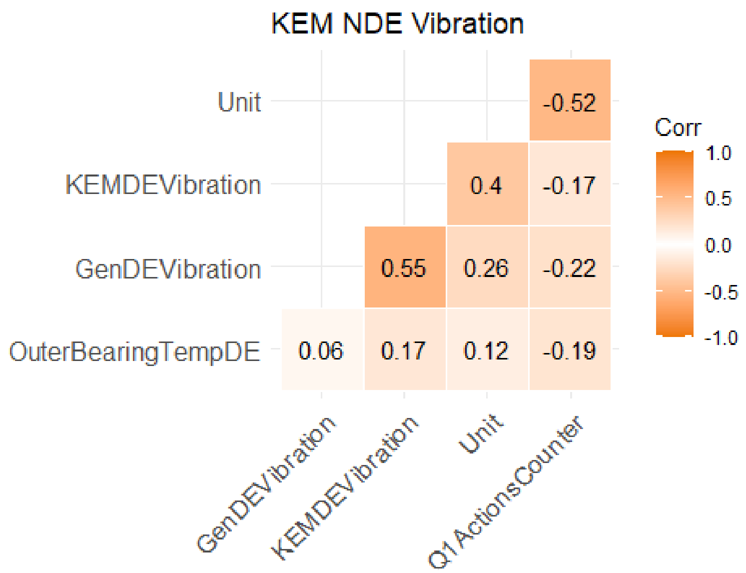
```
> vif(LMmodel_KEMNDEVibration)
OuterBearingTempDE      GenDEVibration      KEMDEVibration                Unit    Q1ActionsCounter 
          1.063037            1.470179            1.653942            1.608071            1.454973 
```

Appendix N Correlation heatmaps after VIF

OutputA (KEMDEVibration)



OutputB (KEMNDEVibration)



Appendix O Removal of input variables

Yellow cell: Same value as previous model, Green: Improved value compared to previous model. The improvement is signified by lower NRMSE or MAPE value.

Original model performance

Measure	ModelDE	ModelNDE
R^2	0.2889	0.2888
NRMSE	0.6133	0.5664
MAPE	0.3967	0.3466
Over	2 (00.002%)	0 (00.00%)
Under	429 (100.000%)	555 (100.00%)
Measure	**Joint prediction**	
Over	2 (00.002%)	
Under	562 (100.000%)	

Performance of model DE with removal of input variable

ModelDE	-A	-B	-C	-D	-E	-F	-G	-H	-I
R^2	0.2878	0.2889	0.2819	0.2545	0.2736	0.2352	0.2860	0.2873	0.2409
NRMSE	0.6141	0.6133	0.6160	0.6265	0.6211	0.6377	0.6139	0.6135	0.6362
MAPE	0.4097	0.3963	0.3769	0.3955	0.5095	0.4509	0.4220	0.3942	0.5642
Over	2	2	1	0	3	3	0	0	3
Under	429	429	429	429	429	429	429	429	429

➔ Results for -B are the only ones to have every cell yellow or green, therefore B is removed as input variable

	Removed input variable: B		All input variables	
Measure	**ModelDE**	**ModelNDE**	**ModelDE**	**ModelNDE**
R^2	0.2889	0.2888	0.2889	0.2888
NRMSE	0.6133	0.5664	0.6133	0.5664
MAPE	0.3963	0.3466	0.3967	0.3466
Over	2 (00.002%)	0 (00.00%)	2 (00.002%)	0 (00.00%)
Under	429 (100.000%)	555 (100.00%)	429 (100.000%)	555 (100.00%)
Measure	**Joint prediction**		**Joint prediction**	
Over	0 (00.00%)		2 (00.002%)	
Under	562 (100.00%)		562 (100.000%)	

➔ Improved model, can more improvement be made?

Performance of model with additional removal of input variable

ModelDE	-A	-C	-D	-E	-F	-G	-H	-I
R^2	0.2846	0.2819	0.2524	0.2725	0.2340	0.2848	0.2865	0.2366
NRMSE	0.6152	0.6161	0.6279	0.6212	0.6377	0.6145	0.6140	0.6372
MAPE	0.4192	0.3760	0.4001	0.4369	0.4535	0.4737	0.3930	0.4858
Over	2	1	2	0	3	0	0	2
Under	429	429	429	429	429	429	429	429

- ➔ No additional input variable is removed from the model. Removal of additional variable would result in worse NRMSE value. NRMSE is more sensitive to outliers, therefore, it is more important KPI than MAPE. Therefore, slight improvement in MAPE value is not good selection when NRMSE shows worse performance.

Original model performance

Measure	ModelDE	ModelNDE
R^2	0.2889	0.2888
NRMSE	0.6133	0.5664
MAPE	0.3967	0.3466
Over	2 (00.002%)	0 (00.00%)
Under	429 (100.000%)	555 (100.00%)
Measure	**Joint prediction**	
Over	2 (00.002%)	
Under	562 (100.000%)	

Performance of model NDE with removal of input variable

ModelNDE	-A	-B	-C	-D	-E	-F	-G	-H	-I
R^2	0.2859	0.2729	0.2774	0.2828	0.2703	0.2659	0.2788	0.2841	0.2392
NRMSE	0.5677	0.5731	0.5710	0.6585	0.5738	0.5754	0.5703	0.5680	0.5867
MAPE	0.3774	0.3550	0.3409	0.3444	0.3778	0.3839	0.3579	0.3565	0.4208
Over	0	0	0	0	0	0	0	0	0
Under	555	555	555	555	555	555	555	555	555

- ➔ In all cases NRMSE is worse, no input variable is removed.

Appendix P Removal of extracted features

Yellow cell: Same value as previous model (one with extracted features), Green: Improved value compared to previous model (one with features). KPIs to be improved are highlighted with red.

Original model performance

	All extracted features		No extracted features (original model)	
Measure	ModelDE	ModelNDE	ModelDE	ModelNDE
R^2	0.3140	0.3344	0.2889	0.2888
NRMSE	0.6015	0.5465	0.6133	0.5664
MAPE	0.4029	0.9263	0.3967	0.3466
Over	0 (00.00%)	0 (00.00%)	2 (00.002%)	0 (00.00%)
Under	429 (100.00%)	555 (100.00%)	429 (100.000%)	555 (100.00%)
Measure	Joint prediction		Joint prediction	
Over	0 (00.00%)		2 (00.002%)	
Under	562 (100.00%)		562 (100.000%)	

➔ Model with features not better in all KPIs, need to remove a feature

Performance of model with additional removal of extracted feature

ModelDE	-Mean	-Std	-Peak	-Var	-RMS	-SF
R^2	0.3140	0.3133	0.3140	0.3138	0.3139	0.3117
NRMSE	0.6015	0.6019	0.6015	0.6016	0.6015	0.6024
MAPE	0.3910	0.3873	0.3924	0.4176	0.3965	0.3878
Over	0	0	0	0	0	0
Under	429	429	429	429	429	429
ModelDE	**-MF**	**-E**	**-Crest**	**-Skew**	**-Kurt**	
R^2	0.3140	0.3079	0.3140	0.3119	0.3115	
NRMSE	0.6015	0.6043	0.6015	0.6024	0.6025	
MAPE	0.3911	0.3997	0.4094	0.4552	0.4047	
Over	0	0	0	0	0	
Under	429	429	429	429	429	

ModelNDE	-Mean	-Std	-Peak	-Var	-RMS	-SF
R^2	0.3318	0.3338	0.3311	0.3328	0.3318	0.3321
NRMSE	0.5476	0.5467	0.5480	0.5471	0.5476	0.5473
MAPE	0.5295	0.5074	0.5400	0.7330	0.4697	0.4750
Over	0	0	0	0	0	0
Under	555	555	555	555	555	555
ModelNDE	**-MF**	**-E**	**-Crest**	**-Skew**	**-Kurt**	
R^2	0.3344	0.3282	0.3340	0.3318	0.3330	
NRMSE	0.5465	0.5494	0.5465	0.5476	0.5471	
MAPE	0.7010	0.4582	0.6619	0.4692	0.5352	
Over	0	0	0	0	0	
Under	555	555	555	555	555	

➔ Results for -MF are the only ones to have every cell yellow or green, for both model DE and model NDE. Therefore MF is removed as input variable.

Model performance, removed extracted feature: MF

	Removed feature: MF		No extracted features (original model)	
Measure	ModelDE	ModelNDE	ModelDE	ModelNDE
R^2	0.3140	0.3344	0.2889	0.2888
NRMSE	0.6015	0.5465	0.6133	0.5664
MAPE	0.3911	0.7010	0.3967	0.3466
Over	0 (00.00%)	0 (00.00%)	2 (00.002%)	0 (00.00%)
Under	429 (100.000%)	555 (100.00%)	429 (100.000%)	555 (100.00%)
Measure	Joint prediction		Joint prediction	
Over	0 (00.00%)		2 (00.002%)	
Under	562 (100.00%)		562 (100.000%)	

➔ Model with features not better in all KPIs, need to remove a feature

Performance of model with additional removal of extracted feature

ModelDE	-Mean	-Std	-Peak	-Var	-RMS	-SF
R^2	0.3140	0.3128	0.3139	0.3134	0.3139	0.3117
NRMSE	0.6015	0.6021	0.6016	0.6019	0.6016	0.6025
MAPE	0.3905	0.3845	0.3891	0.3997	0.3928	0.3929
Over	0	0	0	0	0	0
Under	429	429	429	429	429	429

ModelDE	-E	-Crest	-Skew	-Kurt
R^2	0.3078	0.3140	0.3114	0.3115
NRMSE	0.6043	0.6015	0.6026	0.6025
MAPE	0.4245	0.3981	0.4022	0.4026
Over	0	0	0	0
Under	429	429	429	429

ModelNDE	-Mean	-Std	-Peak	-Var	-RMS	-SF
R^2	0.3317	0.3338	0.3310	0.3328	0.3318	0.3321
NRMSE	0.5477	0.5467	0.5480	0.5472	0.5476	0.5474
MAPE	0.5959	0.5033	0.8000	0.5224	0.4788	0.4873
Over	0	0	0	0	0	0
Under	555	555	555	555	555	555

ModelNDE	-E	-Crest	-Skew	-Kurt
R^2	0.3282	0.3335	0.3318	0.3330
NRMSE	0.5494	0.5468	0.5476	0.5471
MAPE	0.4490	0.4835	0.4671	0.5005
Over	0	0	0	0
Under	555	555	555	555

➔ Results for -Mean are the only ones to have every cell yellow or green, for model DE. For model NDE the amount of yellow and green cells is the maximum observed between the different model results. Therefore Mean is removed as input variable.

	Removed feature: MF, Mean		No extracted features (original model)	
Measure	ModelDE	ModelNDE	ModelDE	ModelNDE
R^2	0.3140	0.3317	0.2889	0.2888
NRMSE	0.6015	0.5477	0.6133	0.5664
MAPE	0.3905	0.5959	0.3967	0.3466
Over	0 (00.00%)	0 (00.00%)	2 (00.002%)	0 (00.00%)
Under	429 (100.000%)	555 (100.00%)	429 (100.000%)	555 (100.00%)
Measure	Joint prediction		Joint prediction	
Over	0 (00.00%)		2 (00.002%)	
Under	562 (100.00%)		562 (100.000%)	

➔ Model with features not better in all KPIs, need to remove a feature

Performance of model with additional removal of extracted feature

ModelDE	-Std	-Peak	-Var	-RMS	-SF
R^2	0.3117	0.3139	0.3134	0.3130	0.3113
NRMSE	0.6026	0.6016	0.6019	0.6022	0.6026
MAPE	0.3904	0.3895	0.3975	0.4082	0.3894
Over	0	0	0	1	0
Under	429	429	429	429	429

ModelDE	-E	-Crest	-Skew	-Kurt
R^2	0.3060	0.3140	0.3113	0.3113
NRMSE	0.6051	0.6015	0.6026	0.6026
MAPE	0.3896	0.3909	0.3973	0.4012
Over	0	0	0	0
Under	429	429	429	429

ModelNDE	-Std	-Peak	-Var	-RMS	-SF
R^2	0.3313	0.3300	0.3316	0.3317	0.3242
NRMSE	0.5479	0.5485	0.5477	0.5477	0.5508
MAPE	0.4658	0.3782	0.5403	0.5697	0.7237
Over	0	0	0	0	0
Under	555	555	555	555	555

ModelNDE	-E	-Crest	-Skew	-Kurt
R^2	0.3234	0.3304	0.3296	0.3313
NRMSE	0.5516	0.5481	0.5486	0.5479
MAPE	0.4263	0.3510	0.4401	0.5708
Over	0	0	0	0
Under	555	555	555	555

➔ Results for -RMS are the only ones to have every cell yellow or green, for model NDE. However, the -RMS results for model DE show much worse performance, with only one yellow cell. Therefore RMS is not selected as next feature for removal. Instead, we focus on -Std, -Peak, -E, and -Crest. It is decided to remove Crest as next removed additional feature. This is due to the lowest average decrease in NRMSE value. Therefore Crest is removed as input variable.

	Removed feature: MF, Mean, Crest		No extracted features (original model)	
Measure	**ModelDE**	**ModelNDE**	**ModelDE**	**ModelNDE**
R^2	0.3140	0.3304	0.2889	0.2888
NRMSE	0.6015	0.5481	0.6133	0.5664
MAPE	0.3909	0.3510	0.3967	0.3466
Over	0 (00.00%)	0 (00.00%)	2 (00.002%)	0 (00.00%)
Under	429 (100.000%)	555 (100.00%)	429 (100.000%)	555 (100.00%)
Measure	**Joint prediction**		**Joint prediction**	
Over	0 (00.00%)		2 (00.002%)	
Under	562 (100.00%)		562 (100.000%)	

➔ Model with features not better in all KPIs, need to remove a feature

Performance of model with additional removal of extracted feature

ModelDE	-Std	-Peak	-Var	-RMS	-SF
R^2	0.3116	0.3138	0.3134	0.3127	0.3108
NRMSE	0.6027	0.6016	0.6019	0.6023	0.6029
MAPE	0.4060	0.3900	0.3976	0.3992	0.3934
Over	0	0	0	1	0
Under	429	429	429	429	429

ModelDE	-E	-Skew	-Kurt
R^2	0.3057	0.3111	0.3111
NRMSE	0.6053	0.6027	0.6027
MAPE	0.3702	0.3944	0.3987
Over	0	0	0
Under	429	429	429

ModelNDE	-Std	-Peak	-Var	-RMS	-SF
R^2	0.3302	0.3285	0.3303	0.3297	0.3162
NRMSE	0.5482	0.5490	0.5482	0.5484	0.5538
MAPE	0.3610	0.3403	0.3435	0.3401	0.3383
Over	0	0	0	0	0
Under	555	555	555	555	555

ModelNDE	-E	-Skew	-Kurt
R^2	0.3223	0.3283	0.3301
NRMSE	0.5521	0.5491	0.5483
MAPE	0.3373	0.3448	0.3437
Over	0	0	0
Under	555	555	555

➔ Model DE already met the better KPIs performance compared to the original model. Removing Std, Var, RMS or Kurt would result in model DE not anymore having better KPIs than the original model. Therefore, these are not selected to be removed. The average value of NRMSE for the other extracted features is then calculated, and the feature corresponding to the lowest average NRMSE is selected.

	-Peak	-SF	-E	-Skew
NRMSE DE	0.6016	0.6029	0.6053	0.6027
NRMSE NDE	0.5490	0.5538	0.5521	0.5491
Average	0.5753	0.57835	0.5787	0.5759

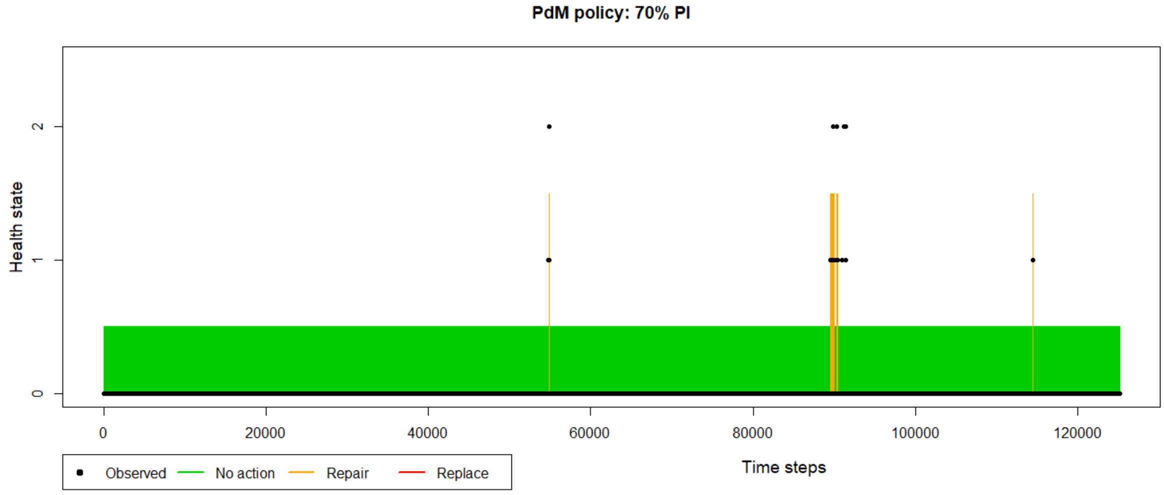
➔ The lowest average NRMSE value corresponds to the Peak feature. Therefore Peak is removed as input variable.

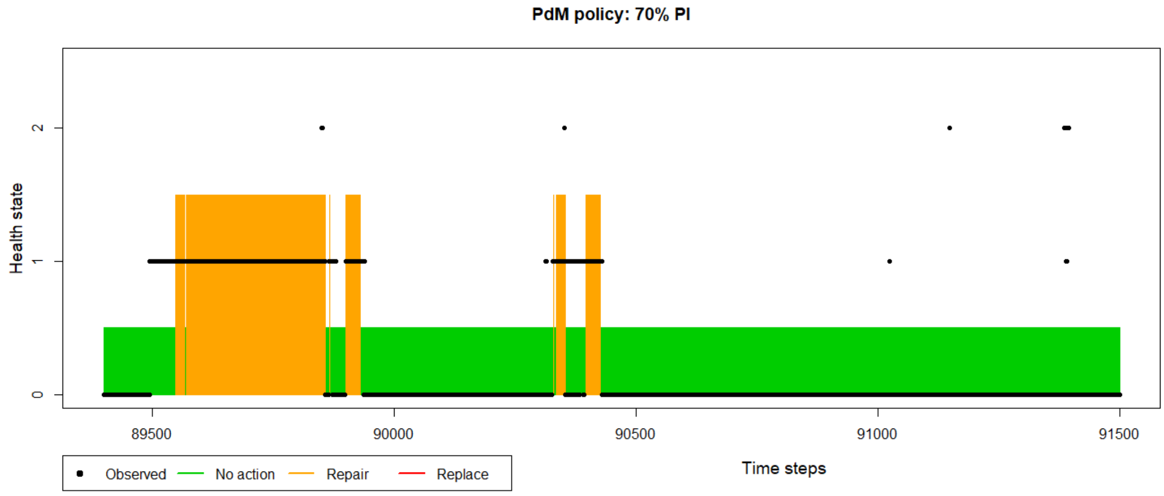
	Removed feature: MF, Mean, Crest, Peak		No extracted features (original model)	
Measure	**ModelDE**	**ModelNDE**	**ModelDE**	**ModelNDE**
R^2	0.3138	0.3285	0.2889	0.2888
NRMSE	0.6016	0.5490	0.6133	0.5664
MAPE	0.3900	0.3403	0.3967	0.3466
Over	0 (00.00%)	0 (00.00%)	2 (00.002%)	0 (00.00%)
Under	429 (100.000%)	555 (100.00%)	429 (100.000%)	555 (100.00%)
Measure	**Joint prediction**		**Joint prediction**	
Over	0 (00.00%)		2 (00.002%)	
Under	562 (100.00%)		562 (100.000%)	

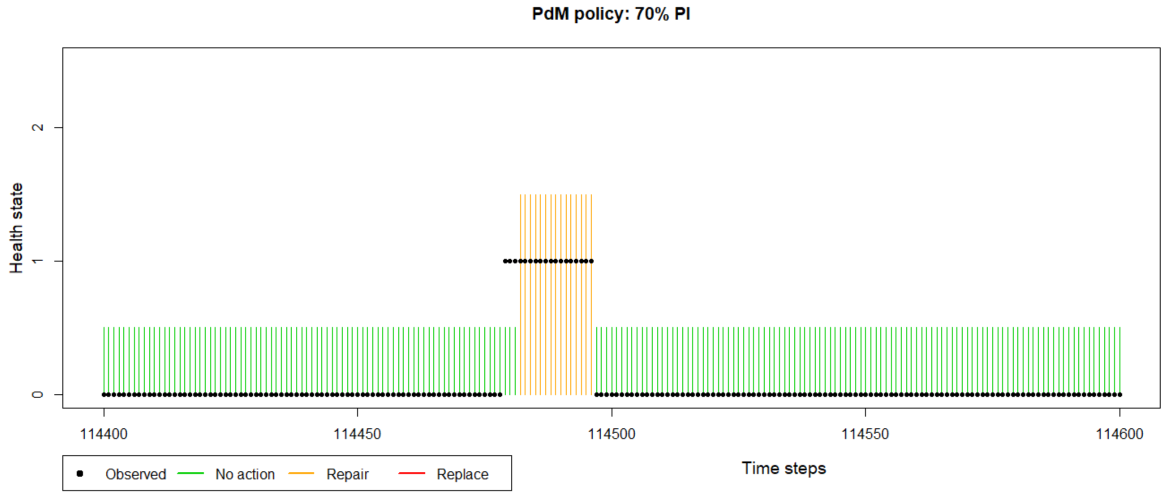
➔ Model with features better in all KPIs, no more extracted features are removed.

Appendix Q PdM policy plots

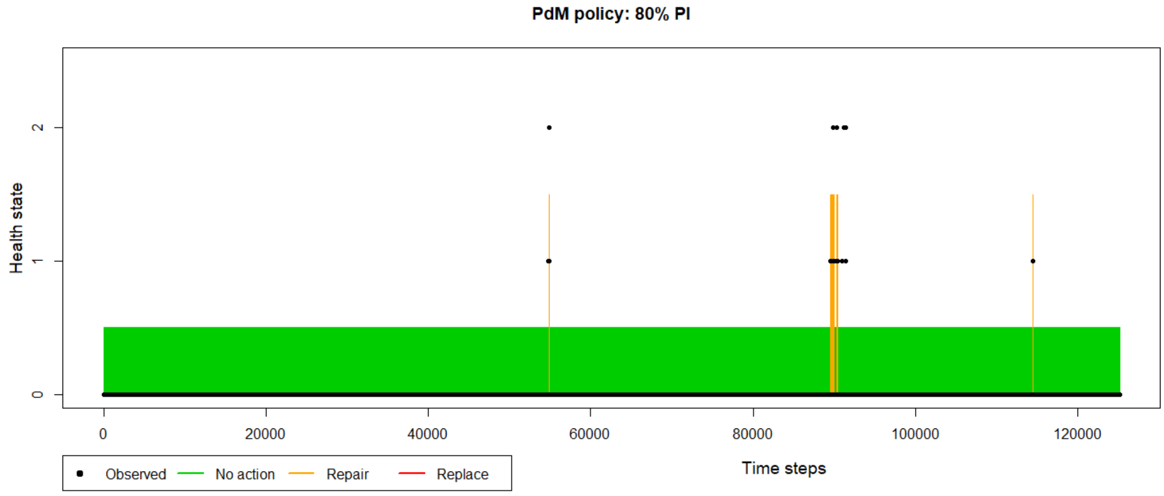
70% PI



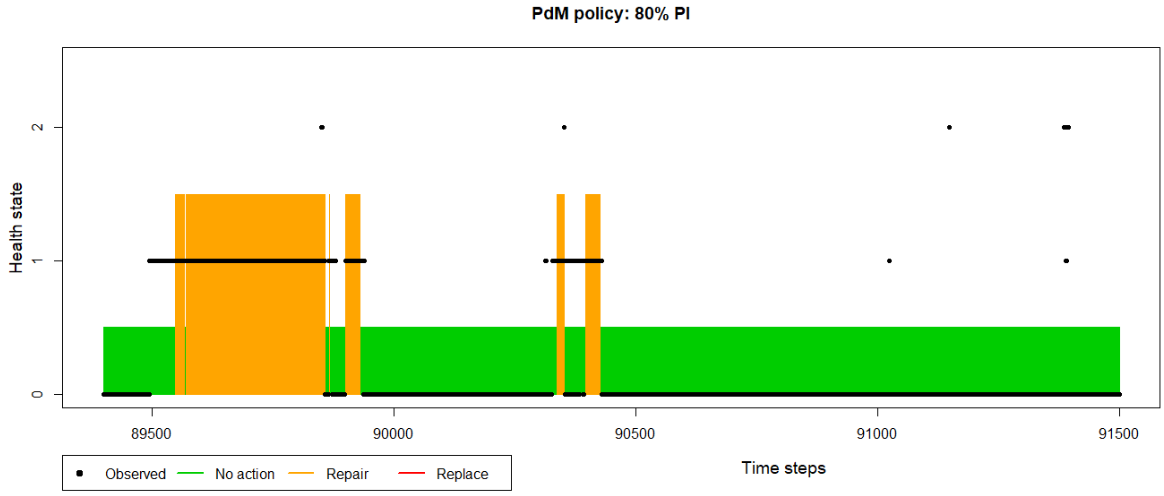


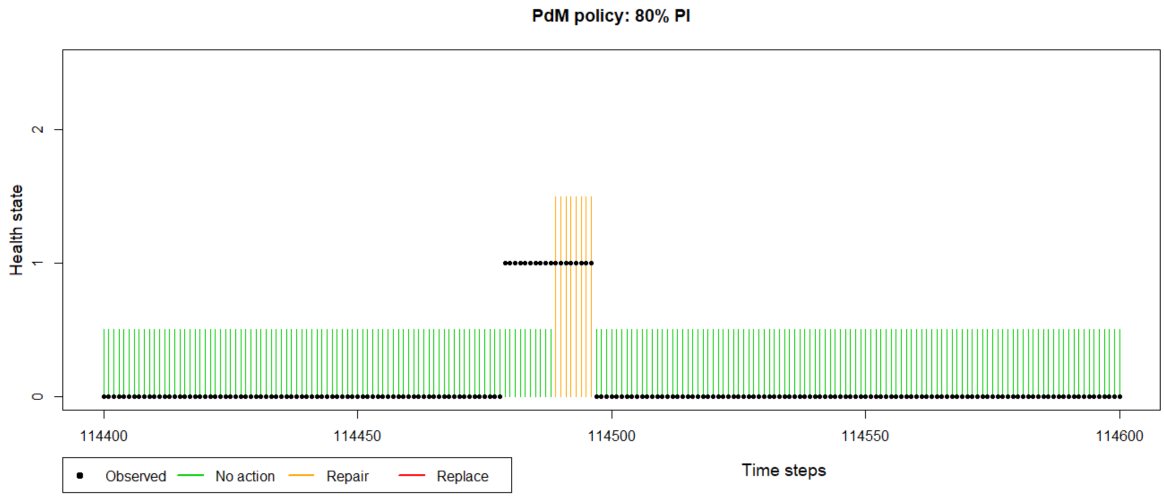

PdM policy: 70% PI
Health state
0
1
2
114400
114450
114500
114550
114600
Time steps
Observed
No action
Repair
Replace

80% PI

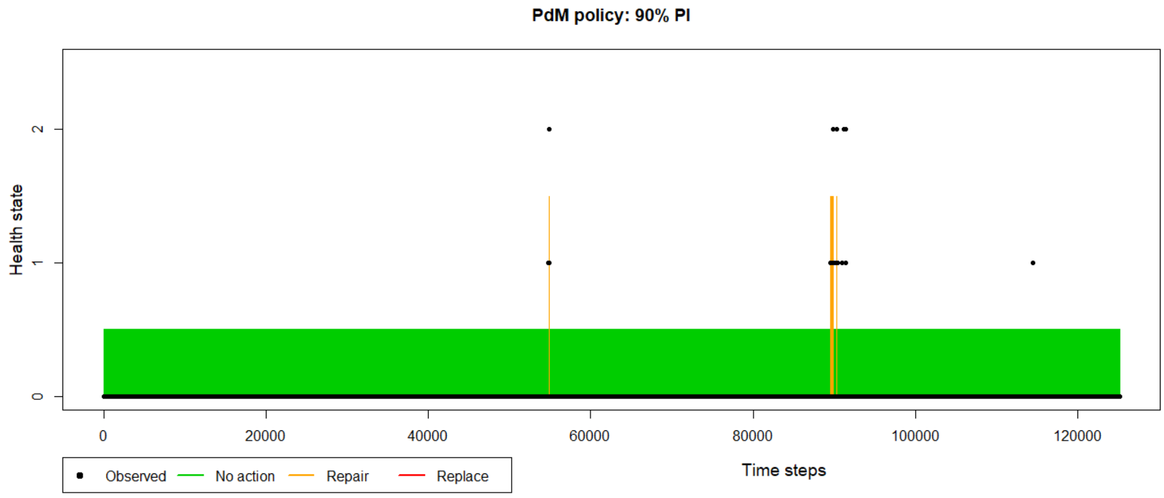

PdM policy: 80% PI
Health state
0
1
2
0
20000
40000
60000
80000
100000
120000
Time steps
Observed
No action
Repair
Replace


PdM policy: 80% PI
Health state
0
1
2
54860
54880
54900
54920
54940
Time steps
Observed
No action
Repair
Replace

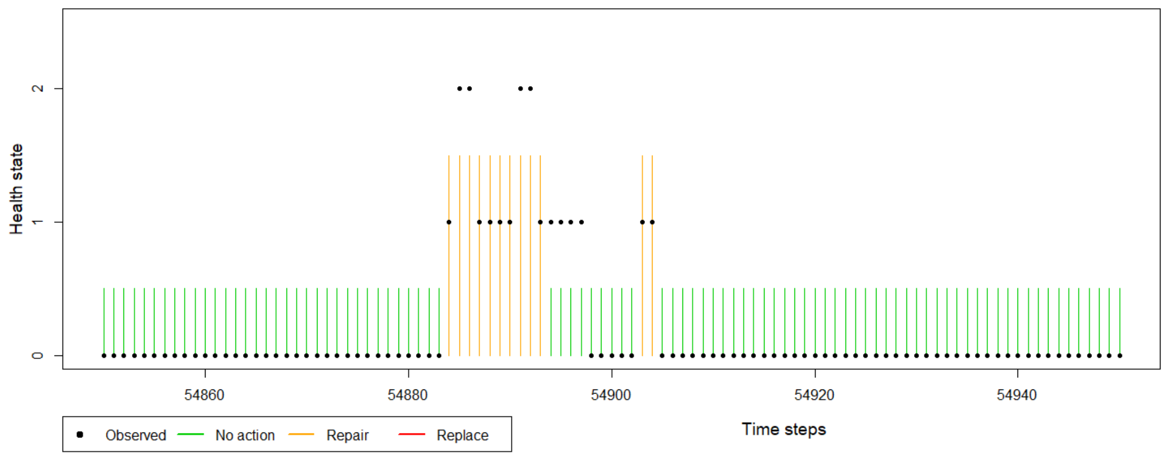

PdM policy: 80% PI
Health state
Time steps
Observed
No action
Repair
Replace


PdM policy: 80% PI
Health state
Time steps
Observed
No action
Repair
Replace

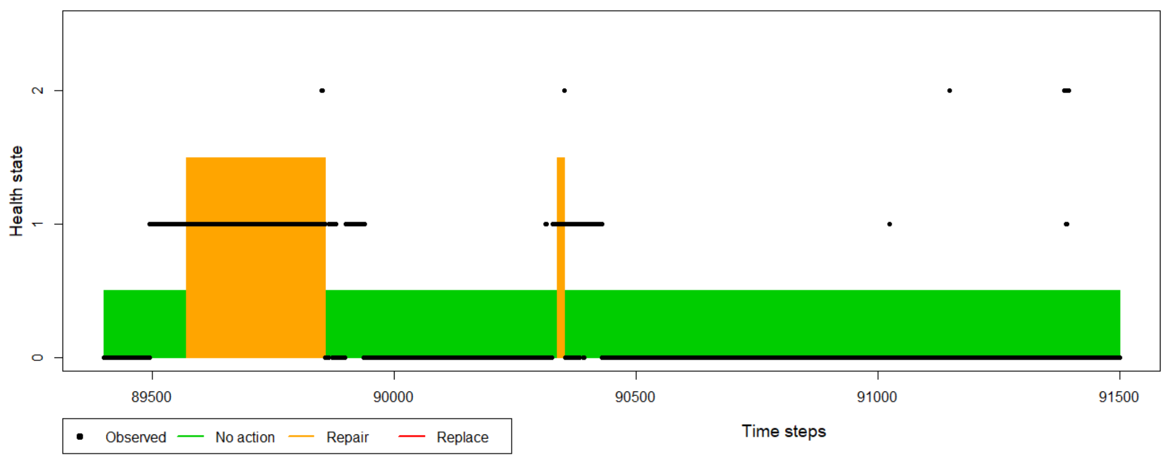
90% PI


PdM policy: 90% PI
Health state
Time steps
Observed
No action
Repair
Replace

PdM policy: 90% PI



PdM policy: 90% PI



PdM policy: 90% PI