Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Engineering
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Anomaly Detection Using LSTM Neural Networks: a Case Study of the Early Development of a Predictive Maintenance Program

Master's thesis in Reliability, Availability, Maintainability and Safety
Supervisor: Antoine Rauzy
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Abstract

Predictive maintenance (PdM) is expected to reduce the maintenance cost by up to 10% and reduce the frequency of unplanned production disturbances. However, these figures are not verified yet and the industry faces many challenges in implementing PdM. Especially, the availability of labeled data sets, which are necessary for predicting the remaining useful lifetime of equipment, is low. Still, long-short-term-memory (LSTM) neural networks allow early fault detection and root cause analysis based on unlabeled condition monitoring data, which is readily available in the chemical process industry.

PdM requires the integration of IoT networks, databases, software, historical data and knowledge of day-to-day operations of the equipment under study. In addition, the lack of labeled condition monitoring data increases the need for system knowledge to create and evaluate early fault detection models. Thus, the thesis discusses the need for, and presents, a failure mode and symptoms analysis to understand the equipment, possible degradation indicators and how to evaluate the model while also assessing the data quality of the sources of information used.

A case-study that focuses on ten liquid ring compressors, sensor data analysis and model development for fault detection for two different failure modes are then presented. The thesis also theoretically discusses how these models can be used to find a failure's root cause with feature importance analysis.

Lastly, the thesis shows how the experience gained in the case-study can be used when assessing which equipment is likely to be successfully modeled with long-short-term-memory neural networks to detect early fault development and future research necessary in more difficult modeling situations.

Sammendrag

Det er forventet at prediktivt vedlikehold basert på maskinlæring vil redusere kostnader relatert til maskinhavari og vedlikehold med opptil 10%. Mange studier forsøker å definere metoder og algoritmer for å beregne gjenstående levetid på ulike maskindeler eller systemer. Dette er svært utfordrende og ofte baserer slike systemer seg på ideelle datasett. Disse datasettene har gjerne målinger fra systemet i god tilstand, havari og alt i mellom.

I prosessindustrien som er avhengig av høy oppetid, forsøker man derimot å unngå uplanlagt vedlikehold så godt man kan. Derfor mangler det ofte målinger fra systemer i dårligere tilstand. Det finnes da store mengder målinger fra systemet i god eller tilnærmet god tilstand. Dette gjør det vanskelig å beregne gjenstående levetid på utstyret, men åpner for å trene maskinlæringsmodeller til å predikere normaltilstanden for et utstyr slik at man kan oppdage avvik.

Dermed undersøker denne masteroppgaven hvordan man kan bruke svikthistorikk og sensormålinger som allerede samles inn for maskinbeskyttelse og vibrasjonsanalyse til å oppdage sviktmønstre tidligere enn man kan i dag. Dette forsøkes i et case-studie som undersøker dataene fra ti væskeringskompressorer som er i kontinuerlig drift hos Glencore Nikkelverk.

Oppgaven presenterer og forklarer behovet for å undersøke sviktmodene og tilhørende symptomer før man kan lage maskinlæringsmodeller. Basert på undersøkelsene velges det to sviktmoder, som det ønskes å lage avviksmodeller for. En enklere modell for å oppdage behov for vedlikehold i en platekjøler er laget, og det vises til sensoranalyse for å finne ut hvilke målinger som kan gi informasjon om hva som fører til lekkasje i mekaniske tetninger. Til slutt presenteres en teoretisk mulighet for rotårsaksanalyse.

Det diskuteres også hvordan erfaringene som er gjort i denne case-studien kan overføres til annet utstyr og gi et startpunkt for videre utvikling av prediktivt vedlikehold.

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Glossary

Anomaly Detection is the detection of a deviation from an intended system state that can lead to decreased efficiency, partial failures or system failures.

Big-Data refers to data sets that are too large or complex to be dealt with by traditional data-processing application software.

Cloud Computing is completed by computers/servers connected to the internet, instead of local computers.

Data-driven Prognosis uses a training data set to fit a mathematical function to the data set which can then be used to predict an output given some input.

Historian is a database containing historical sensor data at Glencore Nikkelverk.

Industry 4.0 refers to quick changes to technology and industries in recent years due to increasing interconnectivity and smart automation.

Intelecy is a machine learning software based on LSTM neural networks. It is also the name of the company that developed the software.

Interlock is used to prevent a machine from harming its operator or damaging itself by defining conditions where the machine cannot start or must shut down.

Machine Learning is a type of artificial intelligence that allows the software to predict outcomes without being explicitly programmed to do so.

OPC-UA is a standard for data exchange from sensors to cloud applications.

Remaining Useful Life is a subjective estimate of the time an item, component or system is estimated to function according to its intended purpose.

SAP PM is a specific computerized maintenance management system.

Supervised Learning is a type of machine learning algorithm where the training data includes information, commonly called labels, which explain what the model should give as output given the input.

Unsupervised Learning is a type of machine learning algorithm where the training data does not include information of what the output should be, commonly called unlabeled data.

Wedge is software for time-series analysis.

Work Order is a document in SAP PM that specifies what work must be done when, usually maintenance/repair.

Acronyms

AI Artificial Intelligence.

API Application Programming Interface.

CbM Condition-based Maintenance.

CMMS Computerized Maintenance Management System.

DE Driving-end.

EHS Environment, Health and Safety.

FMECA Failure Mode, Effects and Criticality Analysis.

FMSA Failure Mode and Symptoms Analysis.

GNN Glencore Nikkelverk.

IoT Internet of Things.

LSTM Neural Network Long-Short-Term-Memory Neural Network.

NaN Not a Number.

NDE Non-driving-end.

PdM Predictive Maintenance.

RUL Remaining Useful Life.

Acknowledgements

Throughout the process of writing this thesis, I have received a great deal of help and advice.

First, I would like to express my deepest appreciation to my supervisor, professor Antoine Rauzy for his guidance and discussions about the direction of the thesis. Thank you for making me believe in myself.

I also extend my gratitude and appreciation to my contact person at Glencore Nikkelverk, Trond Wilson, for his advice and good spirits, which have been very important to me.

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In addition, I would like to thank my family and loving girlfriend for their support. You are always there for me.

1 Introduction

Many businesses have successfully implemented Condition-based Maintenance (CbM), enabling them to discover emerging failures and pre-emptively maintain or repair equipment. The analysis of sensor data is often based on the analysis of the frequency spectrum of the equipment and static threshold values. However, now businesses are striving toward automating this process by implementing machine learning solutions to detect hidden patterns in sensor data. As a result, there exists extensive research on the topic. However, unlike in the industry, where data sets are usually not labeled and often have few measurements of the system in a faulty state, much of the research focuses on labeled data sets. On the contrary, this paper highlights a possible method for anomaly detection and root cause analysis with an LSTM-neural network which is feasible without labeled data sets.

As the lack of labeled data increases the need for understanding what input machine learning models should have, a failure mode and symptoms analysis has been completed to gain a deep understanding of a liquid ring compressor system. The results from that study include practical experience from business professionals and the importance of such input in developing a novel maintenance program is discussed and shown in the thesis.

Lastly, the assessment of which input to use and a possible definition of a degradation indicator, which is necessary for difficult modeling conditions, are presented. An ensemble of anomaly detection and feature importance analysis for root cause analysis is then proposed. The proposed method is relevant, and a possible starting point in PdM for businesses with limited labeled data but an abundance of unlabeled process and monitoring data from industrial equipment.

The thesis is conducted in collaboration with Glencore Nikkelverk, the project owner, and Maintech AS and Intelecy AS, consultants in the project's machine learning aspect. The project is a part of Glencore Nikkelverk's strategy to become more data-driven in its maintenance planning. They have a tradition of testing new technologies in pilot projects and assessing their use before potentially implementing new solutions on a broader scale and this thesis is rooted in their pilot project.

1.1 Research Objectives and Questions

RQ1: Which frameworks exist for predictive maintenance?

RQ2: What failure/degradation data is necessary for machine learning tools to detect emerging failures effectively?

RQ3: How can the existing sensors in the process industry typically used for machine protection be used to detect emerging failures and facilitate root cause analysis?

1.2 Research Scope

This master thesis aims to research how well the data currently gathered in the process industry is suited to machine learning applications. The paper presents a case study that tries to detect emerging failures on liquid ring compressors - commonly used in the process industry - using machine learning. The model deployed is a Long-Short-Term-Memory neural network, which is trained on historical data. The collected data is used for automatic machine shutdown systems and frequency analysis. As it is common for the industry to have vast amounts of data aggregated, this paper will look at the usefulness of this data. While the data is abundant, it was not necessarily collected with machine learning in mind, which presents a challenge for the industry as they are trying to implement Industry 4.0 technology such as predictive maintenance.

1.3 Limitations

Notable limitations have been the availability of data measurements in the Intelecy software. Information security concerns about connecting the existing software to cloud computing services have delayed the access to sensor data and live data streams to test the software and models in action. However, it was possible to upload sensor data for all the compressors from 01.01.21 to 22.03.22. Still, the number of registered failures in this period was low, so there were few specific cases to investigate. Furthermore, the extraction of this data was time-consuming and would often crash, so this work-around solution is not sustainable in the long run. Ideally, the machine learning models would be trained with a time-series representing a healthy state and later fed testing data from a faulty condition. Thus, it would be possible to see if the model could recognize the known faulty state in that data.

It was possible to access the sensor data through another time-series analysis software called "Wedge" to look at trends and perform statistical analysis. However, the database failed in late May because of some system bug in the software related to a password change. Thus, historical faults could not be investigated as planned. The last option to view historical trends was directly in the ABB control system, but the historical trends are deleted after one year and most of the known failures were further back in time.

2 Method

2.1 Framework

The thesis is largely based on a case-study of the development of a predictive maintenance program for liquid ring compressors. The case study presents the challenges, opportunities and difficulties in developing a novel predictive maintenance program based on machine learning analysis for industrial equipment.

The case-study is preceded by a shorter theoretical section that presents the current focus area of academia to give the reader some context of what the thesis aims to achieve and how the results from this study contribute to the body of knowledge within predictive maintenance applications.

The methodology used in the thesis represents an outcome-driven research, where research starts with a known outcome or result and builds an explanation from the observations seen in the past by archives, interviews or traces as sources to construct a story (*Encyclopedia of case study research* 2010). The methodology is visualized in figure 1. In this case-study the archives can be seen as the failure history, sensor data and experience of industry professionals. By investigating these sources of information closely, hypotheses about the failure modes, failure causes, etc. of the liquid ring compressors are presented and form the base on which further research relies.

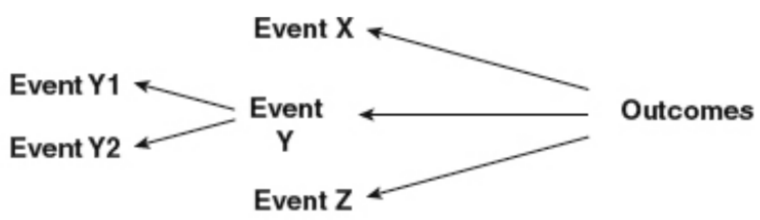


Figure 1: Outcome-driven explanations.

Source: *Encyclopedia of case study research* 2010

One of the limitations that could result from theorizing about the past is that topics of interest may not exist at the time of the study and this would limit the variety, diversity and heterogeneity of the study. In fact, there are examples of that from this case-study. For instance, bearing failures were more frequent in the past, but have been less frequent in the last two years. Thus, it could be that the focus of this study would be quite different if the failure history of the compressors were not the same. Or as *Encyclopedia of case study research* 2010 states for organizations (which in the general sense might as well be historical failures of the compressors): "In the case of organizations, for example, only the ones that survive to produce the outcome of interest will be examined, and the ones that did not survive, or were transformed into something else, are not considered, although there is potentially much to be learned from their contribution and historical significance."

Not the least, there is a risk of constructing an explanation or story to fit the outcome. Knowledge or events may be forgotten over time if there is no documentation or if an event has not been sufficiently reinforced in the memory of individuals or organizations who experienced it.

By assessing the workflow of the case-study, presented in figure 2 and noting the emphasis on historical records, the limitations of the outcome-driven approach should be taken into account when interpreting the results of the case-study.

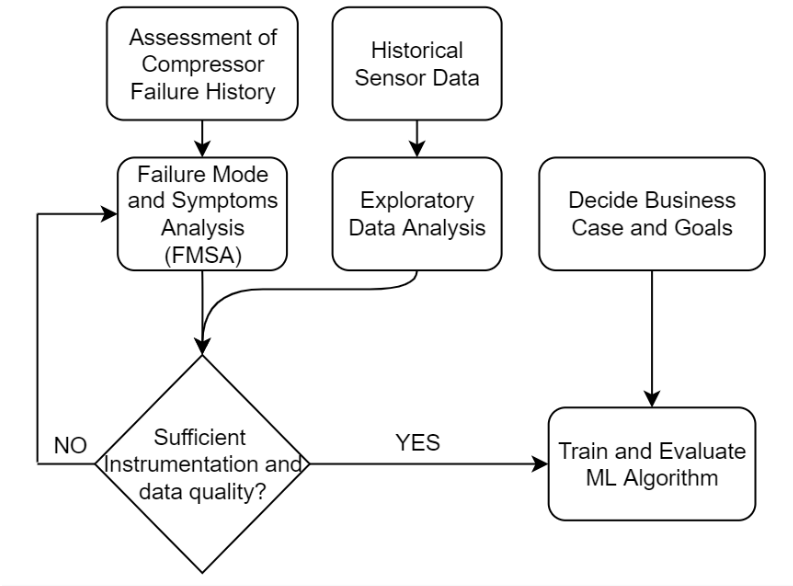


Figure 2: General work flow of study.

Similarly, the book also notes that: "left truncation, a form of sample selection bias, may occur if important elements of a population are not included for study because they are not evident at the time of the outcome, potentially resulting in skewed conclusions." Accordingly, the quality of the results of this case-study can never be higher than that of the failure history, sensor data and in-house experience which it builds on.

2.2 Empirical Data Collection

The first step in the empirical data collection was four semi-structured interviews with different people with hands-on experience with the compressors. The purpose of the interviews was to get an initial idea of the most frequent and serious failures that the compressors experience. More than that, they explained how the different parts of the compressor system work and the current interval- and condition-based maintenance strategies used for the compressors.

The chosen interview style was semi-structured, where a few questions were pre-defined in an interview guide, presented in appendix B. The style of interview was chosen because the pre-defined questions were not necessarily covering all areas that could be of interest. All interviews started by explaining the purpose and goals of the Master Thesis in general and how it would be used in the study, such that the interview subjects could form their own opinion of what information might be useful outside of the questions. Their answers were recorded in a notebook during the interviews. The results are not presented separately in the thesis, instead, the interviews contributed to FMSA process and the results are merged into the final FMSA sheet.

In the beginning phase of the project, it was first necessary that the project group had a deep understanding of the compressor system before being able to decide which direction the project would go. Maintech AS with 20+ years of experience in maintenance optimization from the oil and gas industry led the first workshop and explained FMSA methodology of systematically analyzing the system and the importance of the participation of industry professionals at GNN. The version of the FMSA sheet that was used, has been developed by Maintech and follows the IEC 60812 and ISO 14224 standards.

The project group is interdisciplinary and present at these workshops were:

- Metallurgical engineers (GNN and Maintech)
- Maintenance engineers (GNN and Maintech)

- Maintenance (CbM/vibration) specialists (GNN)
- Data analysts (Intelecy)
- Control systems engineer (Intelecy)
- Process control engineer (GNN)
- Mechanical engineering student (NTNU)

In the three workshops the group had, the compressor system was assessed by a bottom-up approach. All main components, their functions, failure modes, failure causes, etc. were defined and put into the FMSA sheet, presented in appendix A. Based on the results, two failure modes would be the focus of the remainder of the project. During the workshops, many different aspects of the project were discussed. Among other things; data quality, access to sensor data, material selection, soft start systems for the electric motors, consequences of the ideal gas law and Arrhenius relationship for the compressors.

The boundaries of the system under study, presented in figure 3 were also decided by the project group. Within the red lines is the compressor system. In this representation, only one compressor is shown, even if the compressors operate in parallel. Initially, it was planned to use historical data from all three large and seven small compressors and create two models—one for the large compressors and one for the small compressors. After that, though, because the compressors differ slightly in set-up, instrumentation and age, it was decided to focus on one compressor at a time and analyze them separately. As a result of that and the limitations in sensor data access, the choice of which compressors to investigate has been opportunistic and based on whether any known failures were present in the historical records.

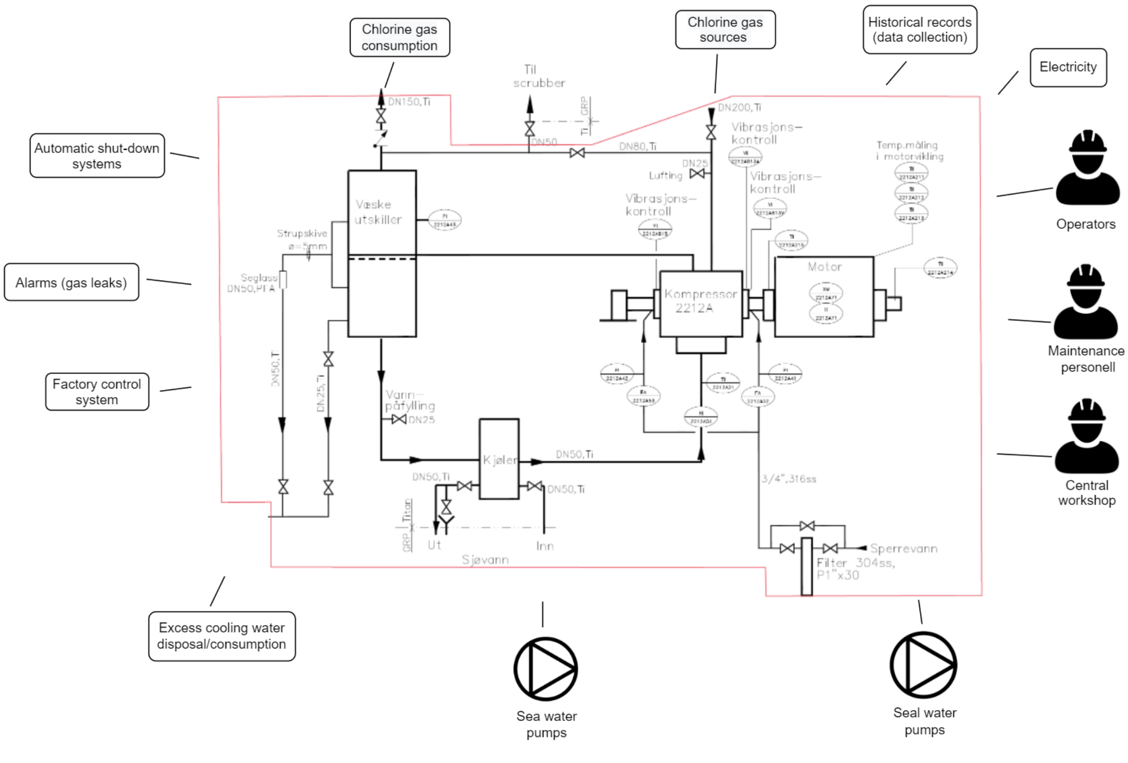


Figure 3: System boundary.

The historical data used in the case study has been sourced from the history of work orders related to the compressors in SAP PM (the computerized maintenance system used at GNN). Specifically, the work orders contain information about:

- Equipment identification number
- Date and time
- Contact person
- Description of maintenance need
- Description of the completed work
- Total cost of maintenance (spare-parts cost and cost of labor)

Lists of relevant work orders and the information mentioned above were exported to Excel but were not complete. Therefore, it was also necessary to look up the work orders in SAP PM and see if there were more information available. Exactly how SAP PM is used varies a little from person to person. Sometimes the maintenance needs were described in different text fields which were not exported to the Excel sheet. Therefore, a ranking based on the failure mode and work order costs was used to select 75 work orders that were more closely analyzed to ensure that all relevant information about failures was found. Of course, more work orders could have been investigated this way, but the analysis findings started to become repetitive and closely resembled what experienced maintenance personnel described as the most common failures in the interviews. During the writing of the thesis, more interesting work orders have been analyzed, but not in a systematic order.

An internal record of more serious chlorine gas leaks in the compressor room has also been available for the project group. It contained records of parts failures and human errors that have led to large gas leaks. It has been useful for the author to understand the multitude of things that can go wrong with such a complex system as the compressors represent. On the other side, it had less information about the specific cases that have been decided to be the focus area of this study and is more related to the day-to-day operations of the plant.

While investigating the work order history, it seemed that some work orders had been used to associate the cost of buying spare parts for all compressors but were registered on a single compressor. Also, sometimes the high cost associated with a work order for a minor repair seemed to indicate that more parts and labor were used than what the description of the work order included. Generally, the work orders could hold valuable specific information but were more suitable for understanding the most common failures and associated costs. In the end, the work order analysis's most significant contribution was knowing when a particular fault had occurred in the past such that the sensor data before and after could be assessed.

The historical sensor data has been accessed through a server, colloquially called Historian, which contains sensor readings for the compressors and the factory in general. The data is available via an Excel add-on package or in Wedge, a time-series analysis software. Sensor data is continuously uploaded to the database, such that in practice, a live data stream is available via the Historian. Additionally, a copy of most of the sensor data for the compressors in the period 01.01.21 - 22.03.22 were uploaded to the Intelecy software to be used in the machine learning model development. In the future, Intelecy will also have access to live sensor data. Lastly, the ABB control system has information about threshold values that will initiate an automatic shut-down of a compressor. It can also be used to look at trends of sensor measurements and shows some simple statistical properties of those but is limited to one year back in time before the data is deleted.

To investigate how the sensor values change according to failure modes, a dashboard containing all sensor tags was systematized in the data analytics program "Wedge." The purpose of the dashboard was twofold first, to have a visual representation of the available sensor readings and secondly, it enables GNN to instantly view and analyze sensor readings from a specific time interval, using the history of work orders with information about failures in SAP to find interesting time intervals to investigate. Also, it is possible to create calculated variables from the sensor readings, often referred to as "soft sensors." During the making of the dashboard, it was clear that not all sensors shown in the PID documents for the compressors were stored in the database and these were then later added to the dashboard. These sensor values were thus not recorded and stored in the database before 10.03.2022.

2.3 Theory and Literature Study

The primary objective of the chosen literature in the thesis was to document the current focus of PdM and the challenges related to incomplete data sets that often are the main barriers to implementing PdM in the chemical process industry. Thus, the literature reviewed has focused on anomaly detection and root cause analysis in unlabeled data situations within PdM applications. Nevertheless, extensive literature reviews conducted by others were examined to describe the bigger picture in PdM.

Notably, the purpose of the literature assessment was not to conduct an extensive literature research within PdM but to understand where further research is needed and to show how the aim of this thesis contributes to the current research. Lastly, the purpose was to find literature that could aid in the development of the maintenance program for the compressors.

NTNU's library search engine Oria was used to search for literature. Search strings used were: ("predictive maintenance" OR "anomaly detection") AND ("machine learning" or "anomaly detection"). Also, while reading extensive literature reviews, referenced articles on anomaly detection were analyzed as well. The assessed articles were only selected if they were peer-reviewed and published in trusted academic journals. Additionally, a book on practical time-series analysis was assessed based on the supervisor's recommendation.

The literature review of PdM case studies was conducted to answer the following research questions. The review did not seek to explain the concept of PdM and focused on real applications of PdM and practical information and ideas to implement PdM. The articles were also selected on the basis that they hold valuable information that might be applicable at GNN.

Research Questions

- Q1: Which machine learning techniques are used to perform PdM?
- Q2: What kind of equipment is subject to PdM?
- Q3: How is machine learning employed in the PdM applications?
- Q4: What kind of data is used to train the models?

Exclusion Criteria

- Articles that do not present a case study
- Articles dated before 2017
- Articles that are not peer-reviewed

Search string: ("predictive maintenance" OR "PdM") AND ("machine learning" or "machine learning technique")

3 Theoretical Background

3.1 Introduction

Maintenance comes in many forms and can be categorized by the degree of pro-activeness, which decides when the equipment is repaired. Maintenance scheduling is complex, and even predicting failure times of single components is not a novel task. Consequently, predicting failures of equipment consisting of a great number of components is even more challenging. Thus, many frameworks have been developed for how to schedule maintenance actions. Figure 4 below showcases what is generally acknowledged as the main types of maintenance today. Corrective maintenance (Level 1) refers to maintenance completed after a failure has occurred. The higher levels all have some degree of pro-activeness, starting with maintenance completed at certain intervals, which could be based on previous failure times or the manufacturer's recommendations. Preventive maintenance relies on nonlinear parametric models to decide maintenance intervals, while condition-based maintenance decides when maintenance is necessary by monitoring equipment health; usually, maintenance is completed when a monitored value reaches a threshold value. At level 5, predictive maintenance uses machine learning and statistical models to predict machine failures based on machine health indicators. These could be vibration signals, environmental conditions, operation modes, etc. Lastly, prescriptive maintenance (PsM) tries to extend the concept in predictive maintenance by using the predicted failures to recommend real-time measures - operating and maintenance decisions - to counteract failures and aid production scheduling as well (Gordon et al. 2020). It should also be noted that these concepts overlap, and definitions may vary depending on the author. Some authors also regard preventive and interval-based maintenance as the same, and condition-based and predictive maintenance as the same.

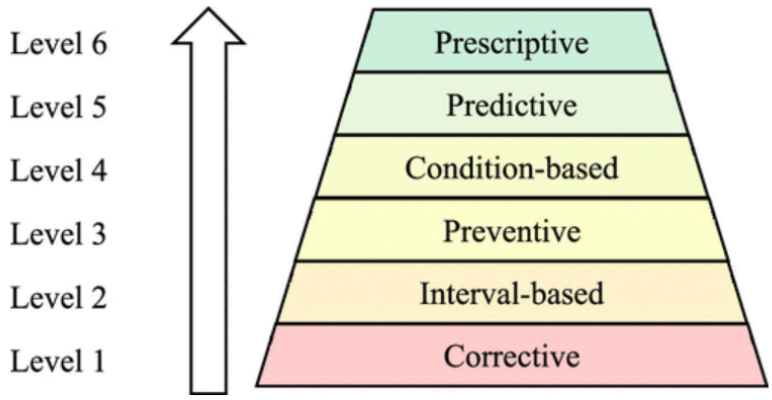


Figure 4: Maintenance types.

Source: Gordon et al. 2020

However, it must be emphasized that predictive or preventive maintenance is not better than corrective maintenance per se. Importantly, which strategy to select should be closely assessed to ensure cost-effectiveness. Often corrective maintenance is the simplest to implement and most cost-effective strategy. On the other side, if failures are dangerous or costly, the higher levels could be better choices but are more complicated to implement. A closer look at maintenance strategy selection is presented by Andersen 2021.

3.2 Predictive Maintenance

In predictive maintenance (PdM), three activities are generally present: detection, diagnosis and prognosis. First and foremost, a failure or emerging failure must be detected by sensors and then, based on which sensors and the corresponding sensor values, a diagnosis can be inferred. Lastly, if there is a degradation pattern, the remaining useful lifetime of the system or component can be estimated. Together, the combination of this information is valuable to maintenance management as it enables better planning of production and reduced costs related to corrective maintenance. In the literature, many different data-driven analytical models aim to realize this. However, to what degree these possible improvements can be achieved is not verified yet (Hermansa et al. 2022).

As stated, prognostics is central to predictive maintenance and is defined as the prediction of a future problem in a system. Similarly, forecasting predicts a future sensor value and can also be used to predict unacceptable health by defining a threshold value for that sensor (Namuduri et al. 2020).

The analytical models are based on machine learning and statistical models and rely on multiple types of data; time-stamped measurements of physical properties, condition-data, environmental conditions and process measurements. This is often coined multi-variate data and has become increasingly accessible with the development of the Industrial Internet of Things (IIoT), as visualized in figure 5.

Predictive maintenance is expected to improve equipment up-time by 10-20%, reduce overall maintenance costs by 5-10%, and reduce the time spent planning maintenance by 20-50% (Gordon et al. 2020). However, the application of machine learning classification and regression methods has some clear limitations. These models can only be trained to recognize and predict failures if there is enough historical data from the system in a failed state. Additionally, most systems have several failure modes, which may be rare and dangerous events. To put it simply, what we are trying to achieve is dependant on what we want to avoid, eg. breakdowns and costly maintenance. Thus, data sets for industrial machines rarely contain enough data addressing failure modes to train classifiers and regressors. However, in these cases it is possible to use outlier detection methods to identify measurements indicating an upcoming failure (Hermansa et al. 2022).

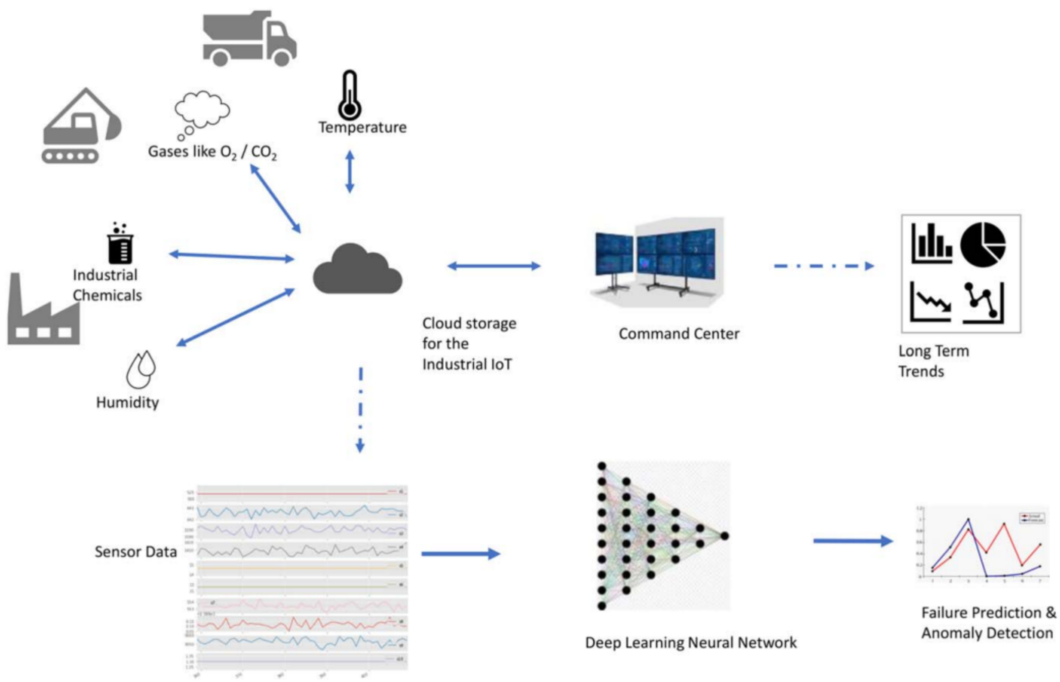


Figure 5: Visualisation of an industrial sensor network.

Source: Namuduri et al. 2020

Nordal and Idriss El-Thalji 2021 highlights that technical requirements and specifications must be considered to standardize guidelines to design PdM-ready equipment. The ISO 13379-1 and ISO 17359 standards stipulate the implementation of condition-based maintenance (CbM), showing how to monitor failure propagation through failure mode and symptom analysis (FMSA). However, the are no standards regarding PdM-ready equipment. Whereas CbM requires installation of sensors and data acquisition systems, PdM also requires that the hardware is aligned with the software to perform the required detection, diagnosis and prognosis. Additionally, PdM combines data from sensors and enterprise-level data of varying quality. It must be decided what the failure symptoms of failure mechanism are and what sensors could detect that symptom. Later, extracting meaningful features and data analysis techniques must be selected to detect the symptom as early as possible, diagnose and preferably predict. To add to that, the system must consider fluctuating operation, different load situations and fault interactions. Combined, these issues make predictive maintenance hard to accomplish in practice.

All together Nordal and Idriss El-Thalji 2021 summarizes four different requirements of PdM:

1. ”the symptoms identified must be clear and easy to track”
2. ”the diagnosis technique must involve reliable and accurate algorithms that enable detection of the failure mechanism at the preferred stage (incipient, degraded, or critical).”
3. ”the prognosis technique must facilitate reliable and accurate RUL estimation”
4. ”these aforementioned requirements must be able to manage transient operational characteristics (e.g., fluctuation, change of loading), multiple failures, and failure interactions.”

3.3 PdM Assessment Matrix

According to Nordal and Idriss El-Thalji 2021, technical analysis is an integral part of reaching a detailed understanding of system criticality and risk assessment. FMECA and FMSA are well-known and standardized bottom-up approaches. Both methods have the same objective of giving a holistic view of the total risk for a system. Where FMECA examines the effect and consequences of specific failure modes for that system, FMSA is more directed at detecting failure modes and linking failure modes to specific monitorable symptoms using sensor technology. As such, FMSA is well suited for the preparatory phase of a developing PdM and CbM.

Symptoms / Faults	Current	Torque	Speed	Vibration	Temperature	Coast down time	Axial flux	Oil debris	Acoustic emission
Eccentric rotor	•			•			•		
Bearing damage	•	•		•	•	•		•	•
Unbalance				•					
Misalignment				•					

Figure 6: General FMSA.

Source: El-Thalji 2019

However, El-Thalji 2019 notes that during and after making a FMSA worksheet, many more questions arise and should be answered. For example, one might ask; should we measure all symptoms or only the most critical symptoms? Do we have the sensors necessary to detect these symptoms? How early could they be detected? How will we handle fluctuations in the measured symptom? What about different operation modes? For sure, there are many considerations to contemplate and the author of this study proposes what is called a PdM Assessment Matrix, shown in figure 7. This model was further developed to include quantifiable ranking of the different failure modes and symptoms for the development of PdM-systems by Nordal and Idriss El-Thalji 2021 and is included in ISO 13379-1. It is a further development of FMSA and seeks to incorporate more technical requirements of detection and prognosis in PdM, which are not addressed in FMSA.

System ______
Subsystem ______
Component ______
Design Lead ______
Core Team ______

PdM Analysis (PdMA)

Key Date ______

FMEA Number
Prepared By
Date
Revision Date
Page

Scale
H High
M Medium
L Low

System	Maintainable Item	Potential Failure Mode(s)	Probability of Occurrence	Severity of Consequences	Criticality rank	Failure symptoms	Detection Earliness			Effectiveness (Clarity)	Dependability (Fluctuation)	Detection Criticality	Tracking Indicators	Tracking Clarity	Tracking Earliness	Tracking reliability	Tracking Criticality	Prediction Indicators	Precision (Future loading)	Scope (how far)	Sensitivity (Fluctuation)	Prediction Criticality
							Detectability of Critical failure (Completion)	Detectability of Degraded failure (Propagation)	Detectability of Incipient failure (Initiation)													
Electric Generator	Rotor	Eccentric rotor				Current	H	M	L	M	L											
						Vibration	H	M	H	H	H	Required	RMS	H	M	L	sufficient	Extrapolated RMS	L	L	L	sufficient
		Unbalance				Vibration	H	H	H	H	H	Required	FFT, Peak at 1X	H	H	H	Sufficient	Extrapolated Peak-Value (FFT)	M	M	M	sufficient
		Misalignment				Vibration	H	H	H	H	H	Required	FFT, Peak at 1X, 2X,3X	H	H	H	sufficient	Extrapolated Peak-Value (FFT)	M	M	M	sufficient
	Bearing	Bearing fault				Current	H	M	L													
						Torque	H	M	L													
						Vibration	H	H	M	M	M	Required	FFT, Peak at Natural Frequency	H	H	M	sufficient	Projected Peak-Value (FFT)	M	M	M	sufficient
						Temperature	H	L	L	L	L											
						Oil-debris	H	M	M	M	M											
						Accoustic emission	M	H	H	M	M											
	Other components																					
Other systems																						

Figure 7: PdM Assessment Matrix.

Source: El-Thalji 2019

3.4 Data-Driven Prognosis

Usually, when modelling complex systems there are not any known physical relations or mathematical equations available to model the degradation pattern (of course, using physical relations can offer support, but not describe the full dynamics). Thus, the option falls on data-driven prognosis. It is based on observed or measured values of different parameters available from the system. Oftentimes there will not be any specific measurement that can give a clear indication of the degradation level of the system, and the degradation must be estimated based on several measurements (e.g., voltage, rotational speed and many more). How the degradation indicator is calculated, must be decided for each individual system (Yin 2021).

How one assesses the system's degradation level can be divided into three categories: fault detection, fault isolation and fault estimation, shown in figure 8. The category used depends on the goal of the system modelling. If only fault detection is necessary a binary degradation indicator is sufficient. For fault isolation or classification of the state of the system a degradation indicator separating several states of the system is possible too. Lastly, a continuous representation of the system state is also possible, which is closely related to the ultimate goal of PdM: predicting the remaining useful lifetime (RUL).

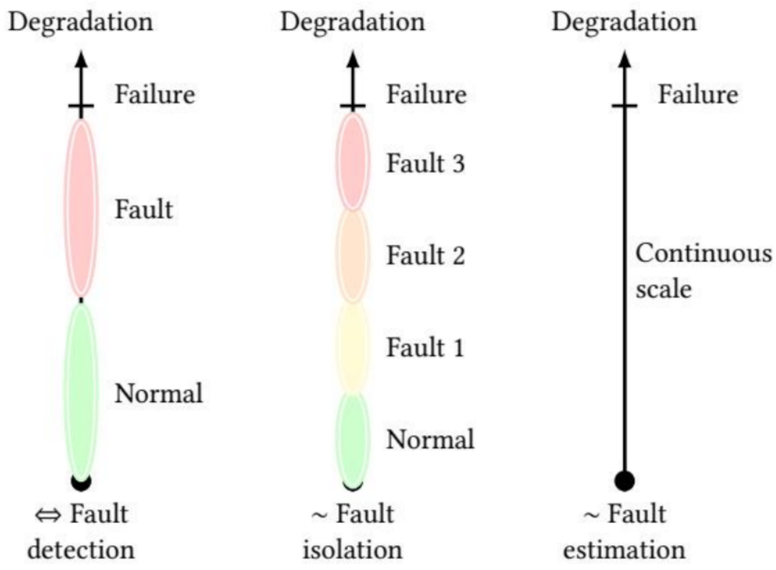


Figure 8: Degradation indicator models.

Source: Yin 2021

Generally, the steps included in any data-driven prognosis include the steps shown in figure 9.

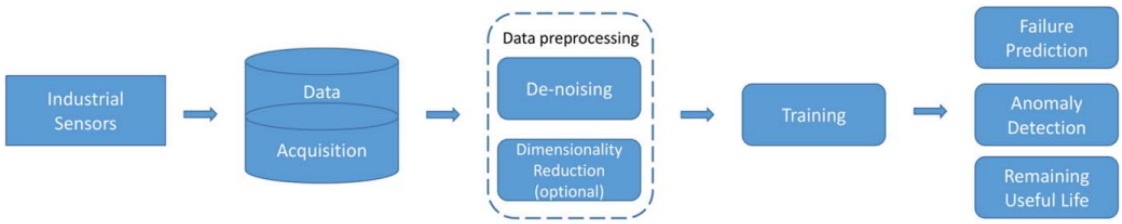


Figure 9: Data analysis pipeline.

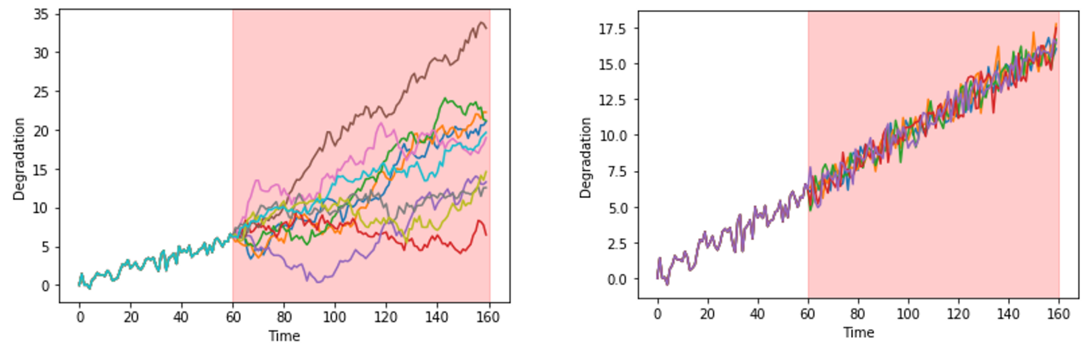
Source: Namuduri et al. 2020

There exist several statistically based data-driven prognosis methods. The most-well known being simple linear regression that estimates the relationship between a dependent variable and one or more explanatory variables.

$$Y(t) = X(t) + \varepsilon(t) \tag{1}$$

Where $Y(t)$ is the observed condition and $X(t)$ is the actual condition at time t. $\varepsilon(t)$ is the random error from the measurement. Assuming that the observed degradation pattern continues in time, the time before the degradation reaches a certain threshold, can be estimated by Monte-Carlo simulation.

Another possibility is to study the degradation increments between time t_n and t_{n+1} and use statistical analysis to fit a distribution to the observed degradation increments. By using known maximum likelihood estimators (MLEs) to decide the parameters of the distribution, the degradation pattern can then be simulated using a Wiener or Gamma process. Again, using Monte-Carlo simulation and recording when each simulation hits a threshold degradation value, the RUL can be estimated based on observed degradation until time t_k. In figure 10, the system has been monitored until $t_k = 60$ time units, and ten simulated degradation paths are shown in the red area. However, even if these models give useful estimations of RUL, they are built on top of underlying assumptions of the Wiener and Gamma process and - usually - these assumptions cannot be veri-



(a) Wiener process with drift.

(b) Linear regression and simulation.

Figure 10: Examples of statistical data-driven models.

fied (Zschech et al. 2019). Therefore, the main focus of this chapter will be on machine learning methods.

In both of these models the RUL can represented as a stochastic time-dependent variable and presented either by the mean or by a histogram showing the distribution of the RUL from the Monte-Carlo simulation.

Supervised learning is the most used machine learning algorithm. Here, training data is supplied with target variables, often called labels, which explain what the model should give as output given the input data.

$$D = \{x_i, y_i\}_{i=1}^{N} \tag{2}$$

Where x_i represents a vector of independent variables and y_i represents the value of the dependent variable for the ith sample. N represents the number of data samples. After the model has been trained it can be used to predict labels given the input data. The predicted labels are then compared to the real labels. One such accuracy measurements can be mean squared error, as shown in equation 3 below, but there exist many others which and the use of them depends on the specific application.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(\hat{y} - y)^2 \tag{3}$$

Unsupervised learning is another machine learning algorithm where the target variables are not available. The data can be represented very similarly as in equation 2, but without the target variable y_i.

$$D = \{x_i\}_{i=1}^{N} \tag{4}$$

Where x_i represents a vector of independent variables for the ith sample. N represents the number of data samples. Clustering, dimensionality reduction and denoising are examples of unsupervised tasks. Because there are no target variables to check the results against, unsupervised learning is a very challenging task and an area of research.

Generally, in the context of PdM, there are three main situations a business who wants to use machine learning to analyze process data might find themselves in. First, in the ideal situation, the business has a large amount of data from the system in a healthy state and in a faulty state, and corresponding labels(information) for each state. In that case, supervised machine learning techniques are suitable and if there is a concrete degradation pattern, its success in predicting RUL is well documented. However, this requires a fully representative training data set that reflects the behavior of the system in healthy and faulty condition and under different operating conditions, which as mentioned before; is highly unlikely for systems that require high availability and are rigorously maintained to avoid unplanned and/or dangerous events. Thus, the authors of Zschech et al. 2019 highlights the need for a distinction based on data availability to determine what machine learning approach to adopt.

Naturally, the second case is that the data set is only partially labeled, which could be the result of maintenance actions that are completed long before a severe or catastrophic failure occur. In turn, making the data set incomplete and truncated. Here, semi-supervised methods can make use of both labeled and unlabeled data. One such method is proposed by Yuan and Liu 2013. Additionally, linear regression, Gamma or Wiener process simulations can be used to estimate RUL if the assumptions are suitable for the given system or can be verified.

The third case is when no labeled data set is available and manual labeling of data sets is considered too expensive because of the efforts required to integrate field knowledge of experienced people and systematically go through potentially years of sensor data. An additional challenge is present when there are no direct measurements (sensors) indicating the degradation level of the system and the degradation must be estimated based on several measurements. Here, it is possible to use product quality as a label, which is generally available in the manufacturing industry, but it is not guaranteed that this information can be directly linked to the degradation of a particular machine in a complex manufacturing line. Thus, unsupervised machine learning techniques are the only option left. This area of PdM is the least researched and Zschech et al. 2019, claims that, to the best of their knowledge, they present the first case-study using completely unlabeled data with unsupervised machine learning in the context of PdM.

3.5 Anomaly Detection

An anomaly is a deviation from an intended system state that can lead to decreased efficiency, partial failures or system failures. Traditionally, detection methods for anomalies have been based on statistical and non-time-dependant models, for example static threshold values. These methods, however, fail to address the complexity and evolving nature of anomalies and the cause of the anomaly is often unknown in complex systems. Now, with the increased use of artificial intelligence and new developments within deep learning networks, especially the Long-Short-Term-Memory (LSTM) neural networks have shown the ability to detect anomalies while also taking the temporal and contextual characteristics into account (Lindemann et al. 2021).

Anomaly detection is used to cope with a variety of different natures and use-cases, where time-series anomaly detection in predictive maintenance is one application of many. It is also commonly called outlier detection, rare events or novelty detection and are used with different intentions depending on the application. Within predictive maintenance, anomaly detection algorithms identifies singular points that may affect not only that instant but also a subsequent interval and such that that an intervention to counter-act the anomaly can be initiated (Carrasco et al. 2021).

According to Lindemann et al. 2021, existing surveys on anomaly detection techniques hardly consider deep neural networks and LSTM architectures. These surveys mostly differentiate between statistical, classification-based, clustering-based and information-theoretic approaches. Thus, techniques as principal component analysis (PCA), support vector machines (SVM), k-nearest-neighbor (k-NN) algorithm or different types of correlation analysis are the focus of the investigations.

Specifically, for the Intelecy software used in this case-study, anomaly detection is realized in two parts: prediction of the expected level using a variety of input parameters depending on the specific case and a comparison of the measured level vs. the predicted level. Then, algorithms that detect spikes and slower drifting from the expected behavior are used to identify an anomaly. The prediction model is called a "Nowcast" and can be seen as a model that predicts the level for a given output now (not ahead in time), given all the latest input data. In practice, that means that the long-short-term-memory deep network that the system built on top of is trained with time-series data from the system in a known healthy state in different modes of operation and predicts the expected behavior of the output variable. In that way, the model cannot predict the system's behavior when it is not functioning as expected and anomalies can be detected. Again, the importance of having a clear indicator of degradation is also present here, as the Intelecy software predicts only one sensor value and identifies anomalies based on the difference between the predicted value and measured value from a real-life sensor.

After a model has been trained with a time-series from a known healthy state, representing as many variations of normal operation as possible, the user must assess the model performance by testing it on a period with a known fault or detrimental conditions. There are two user-defined variables for anomaly thresholds that define the difference between anomalous and expected behavior:

- A short anomaly threshold value used to detect anomalies where the threshold is exceeded on data with a ten minute moving average.
- A spike anomaly threshold value used to detect anomalies where the threshold is exceeded on data without any smoothing or rolling averages.

According to Intelecy's data analysts, the input data should not be cleaned, except to assess if the sensor data is trustworthy and correct. Otherwise, data cleaning should be completed by software before storing it in a database, so all the input data is consistent over time. While this might sound conflicting to the theory presented earlier, where data cleaning techniques are an essential part, Intelecy has some built-in data cleaning and highlights the need for realistic training data which reflects the normal operation conditions not only of the technical system under study but of the data collection system as well. Notable things that are expected to happen are, for example, data fallouts or NaN (not a number) conditions. For the model to cope with such conditions, these errors should not be removed from the training data. The software has numerous possibilities for filtering out anomalies that may result from data errors and is also a part of the testing and validation process. In the end, this allows the model to function effectively in a live setting where anomalies are identified in real-time.

A dashboard showing identified anomalies can be viewed in a web-page user interface or be connected to some other notification program by an application programming interface (API).

3.6 Root Cause Analysis

In case of a detected anomaly, it is also necessary to infer a root cause, such that specific maintenance actions may be planned. Alfarizi et al. 2022, which developed an integrated fault detection, fault-classification and root cause analysis tool based on Extreme Gradient Boosting, propose to infer root causes based on feature analysis. By reviewing which features explain the variance of the fault data the best, one can assume that the logical cause of variance in that feature is the root cause of the failure. In their research, based on the PHM Challenge 2021 data set collected from a real-world industrial setting, the most important signals (and corresponding calculated features) for different failures are based on feature importance analysis. Contrary to the case-study in this project, the data set is labeled, which allows them to use the predicted classes of faults to decide the root cause as well.

Intelecy software also integrates feature importance analysis and other analysis methods that can be used to analyze faults after they occur, but cannot do so automatically. Importantly, because there are no labels available, the user must define a "quality indicator" and what ranges of this variable is wanted. The term "quality indicator" refers to the most frequent application of feature analysis: to decide which factors influence product quality the most. In the abstract sense though, a certain sensor value can be viewed as good or bad quality. Specifically related to predictive maintenance, a degradation indicator could be assessed this way.

Intelecy can then assess which features impact the most on realizing the defined quality. Figure 11, shows a snapshot of this tool where the amperage of compressor B is used as an example. The user defines whether good quality is higher or lower than specific threshold values. Additionally, the user can specify a no-decision-area between the low and high thresholds to better separate anomalous and normal behavior.

Figure 11: Intelecy quality analysis.

The example shown in figure 11, yields the feature importance ranking shown in figure 12 with a goodness of fit of 91,9%. Again, because this deals with unlabeled data, the importance of understanding the system under study is greatly increased because the user must assess which data to analyze. The software also does not factor in causality when trying to explain what influences the data. Therefore, the term "shit in, shit out" is important to keep in mind. For instance, in this example, Intelecy ranks the output pressure as the most important feature explaining the amperage. In reality though, amperage is much more likely to explain the output pressure, not the other way around. The point is, the analyst must take system knowledge into account to effectively use feature importance analysis. If done correctly, conclusions about the root causes of failures can be inferred.

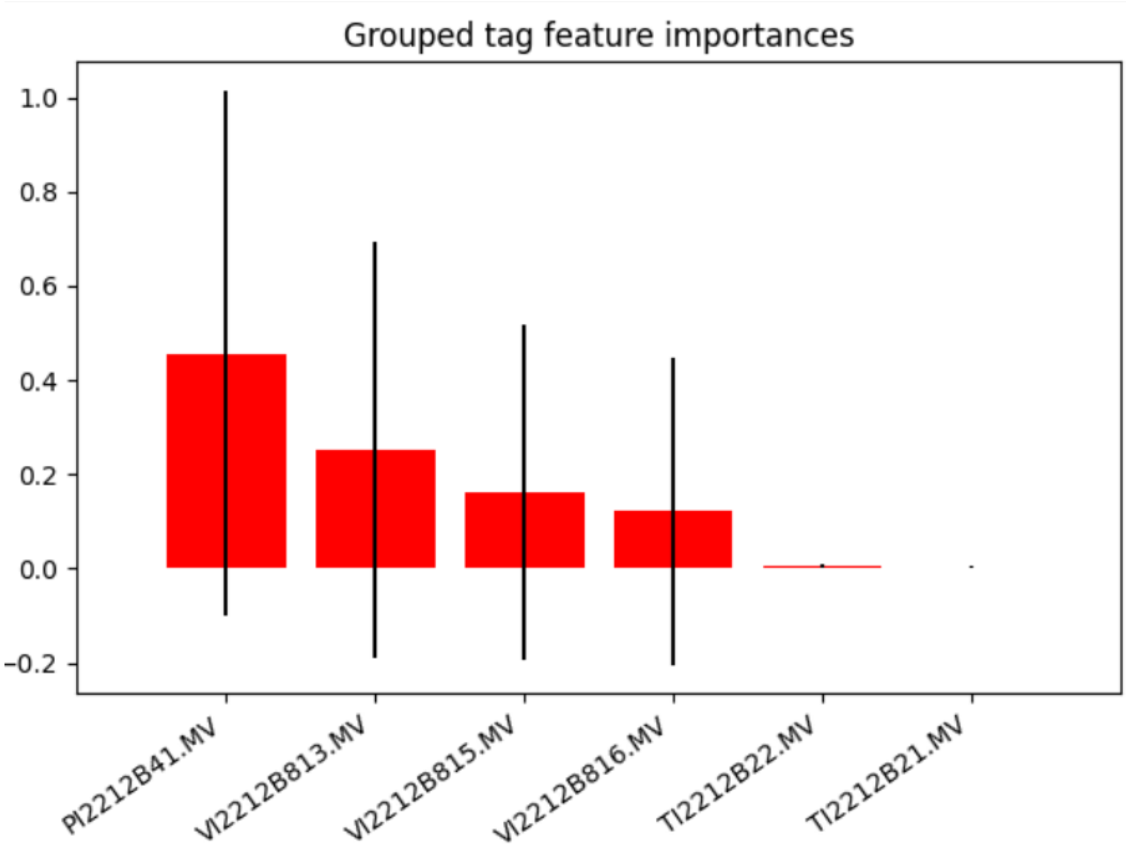


Figure 12: Intelecy feature importance.

3.7 Predictive Maintenance Case Studies - Literature Review

According to Andersen 2021, business professionals at Glencore Nikkelverk (GNN) have asked for more PdM proof of concepts and Yunusa-Kaltungo and Labib 2021 found that: "Case studies in maintenance decision making and optimization are underrepresented in current literature despite a consensus that there should be a reasonable connection between the theory and practice of maintenance." Thus, this chapter highlights and briefly explains a few possible ways to design a PdM system according to the literature. The reader is kindly asked to read the referred articles for a full explanation of the material.

Generally, in an extensive literature review conducted by Carvalho et al. 2019, it can be seen in figure 13 that PdM is a relatively new area of research. The first mention of PdM in the literature was in 2009, and since 2012 there has been an upwards trend in the number of articles published.

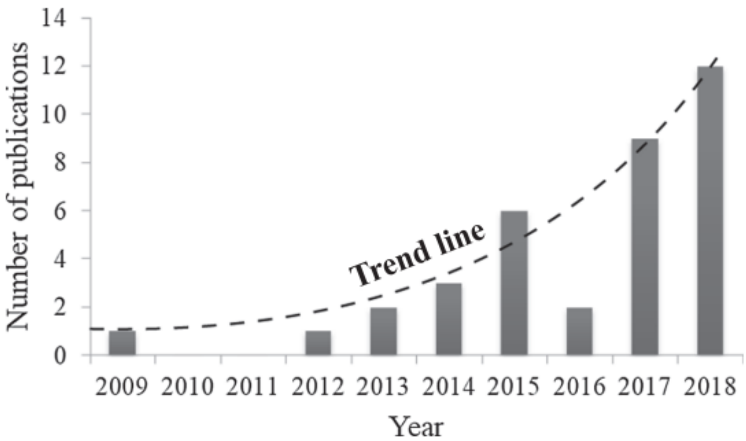


Figure 13: Number of papers per year.

Source: Carvalho et al. 2019

Chen et al. 2020 analyzed time-series data of the closing and opening rates of a pneumatic cylinder used in the automotive industries. The model deployed was a deep learning neural network. The authors of this study examined the degradation process based on the action times and gathered a data set, shown in figure 14. Where a good state means that the cylinder closes and opens quickly. The data suggested that the degradation was monotonously increasing in time (action time of cylinder increases). A model trained with time-series data with the action time of the cylinder was later implemented on a live data stream and was able to diagnose the cylinder as either a normal, degraded or faulty state. The authors conclude, "Currently there are sufficient data sets available for equipment reliability evaluation. Although the multi-source sensing data collected by large-scale industrial processes are increasing rapidly, it is still difficult to model the complex performance degradation process. In the context of industrial big data, data-driven algorithms of equipment reliability prediction are of great significance in both academic and engineering environments". Reading the article, it is clear that the case study is regarded as a simple one because of the clear degradation pattern (measurement of the action time) and the possibility of collecting a labeled data set.

	Sample number of the resetting process of the cylinder	Sample number of the falling process of the cylinder	Sample number of the rising process of the cylinder	Proportion of training set in the whole data set
Good	2976	3107	3270	0.68
Fair	1563	1543	1225	0.72
Poor	213	102	257	0.65

Figure 14: Details of data samples in verification.

Source: Chen et al. 2020

In another study, Bampoula et al. 2021 used an LSTM-autoencoder system to predict failures in a steel production facility, specifically on a rolling mill machine. It was outfitted with sensors giving 27 measurements from the machine and the environment every 45 seconds. The authors state that it was a very challenging task to decide the correct set of parameters that may be associated with potential failures. To cope with this, they plotted and examined the historical data and a factory expert's knowledge and maintenance records to identify patterns to select the most essential features. They defined three states for the machine: "initial"(healthy), "intermediate," and ”bad.” Using historical data and maintenance records, they created one data set for each state and trained the model to recognize these. The study concludes, ”The main limitation of the proposed approach is that the use of multiple neural networks to identify the status and the RUL at higher resolution can be very difficult, as the system may predict fault classifications and may not be able to recognize neighbor states. Another limitation of this approach emerges from the need for maintenance records for labeling the data sets and the need for large amounts of good quality data with maintenance events such as component breakdowns.”

4 Case-Study

This section presents the methods used in the case study. The section presents the different phases of the project and shows what methods and analyses have been done to reach the results presented.

It should be noted that the system under study is complex, and to the author's best ability it is described carefully. The intent being that the reader can get a practical sense of the system before presenting a more comprehensive study in the form of a failure mode and symptoms analysis (FMSA). The findings from that study form the baseline for the specific components investigated and subsequent analysis presented later.

4.1 Introduction

The case study focuses on ten liquid ring compressors in the KL department. The compressors function in parallel and draw in chlorine gas from two sources: the electrowinning cells and the electrolyte dechlorification system. Three compressors are supplied gas from the electrowinning cells and seven from the declorification system at GNN. However, both sub-systems direct the pressurized chlorine gas to the same outlet pipe and supply the tanks that dissolve the raw material using hydrochloric acid and chlorine gas (yellow line in figure 15). To put it simply, if the two or more compressors fail simultaneously, the production could be reduced/stopped and this will cause financial losses. Another important consideration is the environment, health and safety (EHS). These compressors are heavy machinery and failures could result in person injuries. Furthermore, the chlorine gas itself is poisonous and poses a danger to people if the seals rupture or if the compressors have a catastrophic failure. The compressors transport about 10-15 tons of chlorine gas per hour, depending on the electrical current supplied to the electrowinning cells.

The first compressors of the small type were installed in the 70s and more has been added over the years to cope with increased production and the corresponding increase in chlorine gas production/consumption. In the early 2000s, they installed one more large compressor, with twice the capacity of the small compressor type and two more at a later point. The compressors are fitted with numerous sensors. Though not all compressors are equipped with the same sensors, sensor data is available for many years back. Consequently, Glencore Nikkelverk (GNN) has a lot of in-house knowledge and data related to these compressors and seeks to incorporate that into the PdM pilot project.

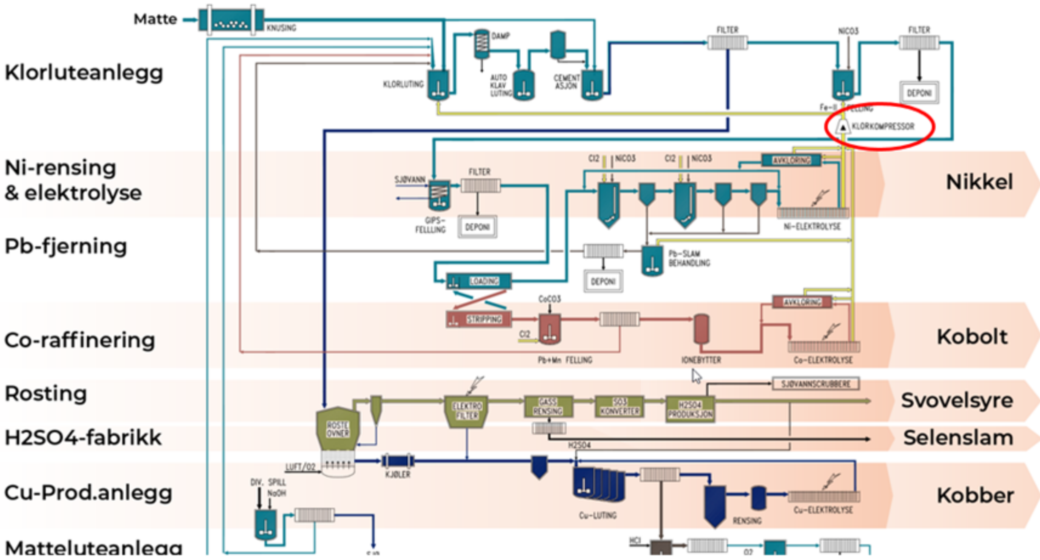


Figure 15: Simplified process overview.

Source: Glencore Nikkelverk.

The compressors can operate reliably for an extended time and rarely have unexpected failures that are so serious that the production is stopped. Additionally, a liquid ring compressor is an inherently reliable design as there is only one moving assembly within the compressor, namely the shaft, impeller and mechanical seals. Together with the redundant compressors fitted at GNN, the compressor system is highly reliable. Thus, the usefulness of this case study may be questioned regarding expected results. However, as stated by GNN, their main priority is developing and testing Industry 4.0 technology before eventually investing more time and resources into the project. Therefore, the compressors were selected for this project because of the many sensors and historical data available. Of course, the drawback is that there are fewer known cases of failures. Nevertheless, even if unexpected failures are rare, the cost of maintenance is still high. Hence, if it is possible to extend maintenance intervals and get early warnings of failure, that would contribute to lower maintenance costs as well.

An early-stage plan and overview of the project are presented below.

Challenge

- Large maintenance costs. Yearly average of three million NOK last five years.
- Average production loss the last two years because of compressors has been 50 tons Ni/year.
- Failure of one or more compressors has implications for production and maintenance.

Goal

- Develop, test and evaluate Maintenance 4.0 technology.
- Detect emerging failures earlier than today and predict remaining useful lifetime.
- Reduce the yearly maintenance cost by 20% for the compressors (0.6 MNOK/year).
- Reduce the yearly production loss by 20% (10 tons Ni/year).

Hypothesis Predictive maintenance with machine learning technology can give early warnings of failure based on historical and live data measurements, in turn enabling Glencore Nikkelverk to have more targeted maintenance and reduce the frequency of unplanned stops.

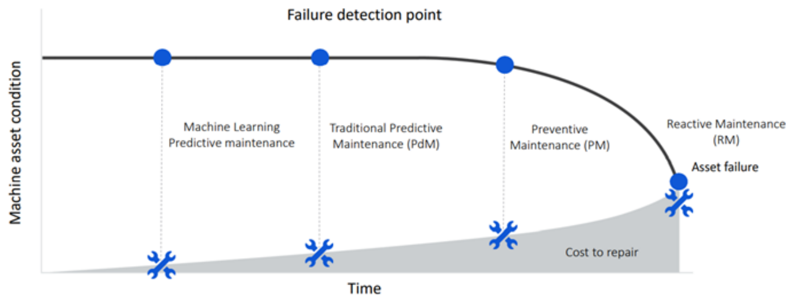


Figure 16: Predictive Maintenance illustration.

Source: Glencore Nikkelverk.

Plan

- Establish a foundation to test machine learning in predictive maintenance in the chlorine compressor room.
- Implement and train machine learning algorithms on the live and historical data.

Risks

- Use of confidential information.
- Access to compressors vs. disturbing ongoing production.
- Lack of internal competence to follow up the pilot project.

Usefulness and Unresolved Issues

- If the project is successful, the experience gained could apply to other process equipment.
- Available resources (internally and externally) and competence to complete the project.
- Technical solution.
- Access to necessary data and computer systems.

4.2 System Description

The compressors, both the large and small type, are liquid ring compressors. However, as the large and small type differ slightly in set-up, they are described separately.

The main components in the large compressors are:

- Casing
- Mechanical seals, with seal water supply
- Impeller
- Fixed-speed electric motor
- Safe units (regulating flow and pressure of seal water)
- Driving-end (DE) and non-driving-end (NDE) bearings
- Gas/liquid separator
- Heat exchanger
- Coupling
- Non-return valve

Similarly, the small compressors have the same main components, except these have a reduction gear fitted to lower the RPM and only one mechanical seal. The layout can be seen in figure 19.

The compressors work by rotating the eccentric impeller (A) such that the working fluid, which is water at GNN, is cast out towards the casing (C) by centrifugal forces. At working speed, this liquid ring rotates together with the impeller, effectively sealing off the compartment between the liquid ring and the impeller blades. At the intake port (D), the volume of the compartment is low and as the impeller turns half a revolution the volume increases and draws in chlorine gas. After a half revolution, the compression stage starts as the volume in the compartment decreases and pressure increases towards to discharge port (E).

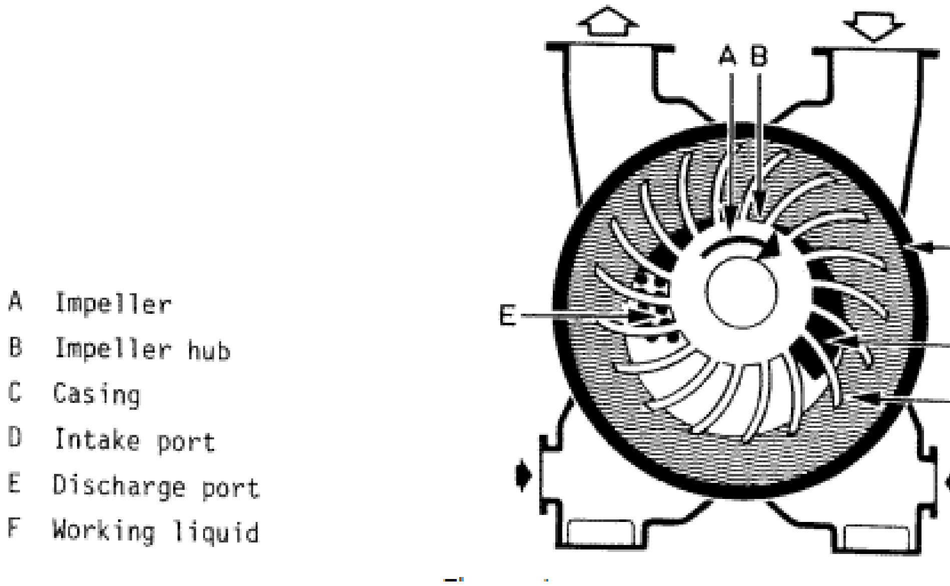


Figure 17: Liquid ring compressor operating mechanism.

Source: Compressed Air & Gas Institute

The compressors are designed such that some working liquid exits the discharge port with the compressed gas. The expelled gas and liquid then enter the separator. The function of the separator is, of course, to separate the gas from the liquid but also to ensure the correct working liquid level for the liquid ring to have the right thickness. This is achieved by piping from the gas separator back into the compressor; thus, the water level in the separator is the same level within the compressor (see figure 19). The separator water level (and thus the water level within the compressor) is self-regulated in that the water can flow out of the separator through an orifice at the correct liquid height. A level sensor was experimented with earlier, but it failed to give reliable measurements because there is a continuous flow of water into the separator and very turbulent (splashing) conditions within it. At GNN, the chlorine gas also contains water vapor that condensates during the compression stage, so there is usually a continuous flow of water out of the system.

The compression stage increases the temperature of the gas and thus the working liquid as well. Consequently, the system is fitted with a heat exchanger where sea water is used to cool the working liquid which in turn cools the gas. The flow of the working liquid is realized by the expelled liquid/gas mix into the separator, and gravity does the rest. For the remainder of the thesis, the working liquid is therefore referred to as the cooling water.

The compressors are equipped with double mechanical back-to-back seals with a seal water supply which provides the lubricating film in the seals, removes particles resulting from wear at the seal faces and cools the seal. The seal water pressure is higher than that of the compressor house, so an initial leakage will likely be water into the compressor instead of chlorine gas out of the compressor (especially important EHS consideration). As water is an inherent part of the compressor design, this is not catastrophic but an unwanted event because of increased water consumption and related costs. Seal water can also leak out of the seals.

An overview of the main components and their functions are presented in a functional architecture diagram in figure 18. Additionally, the process and instrumentation diagram in figure 19 shows the layout of a single compressor system of the large type.

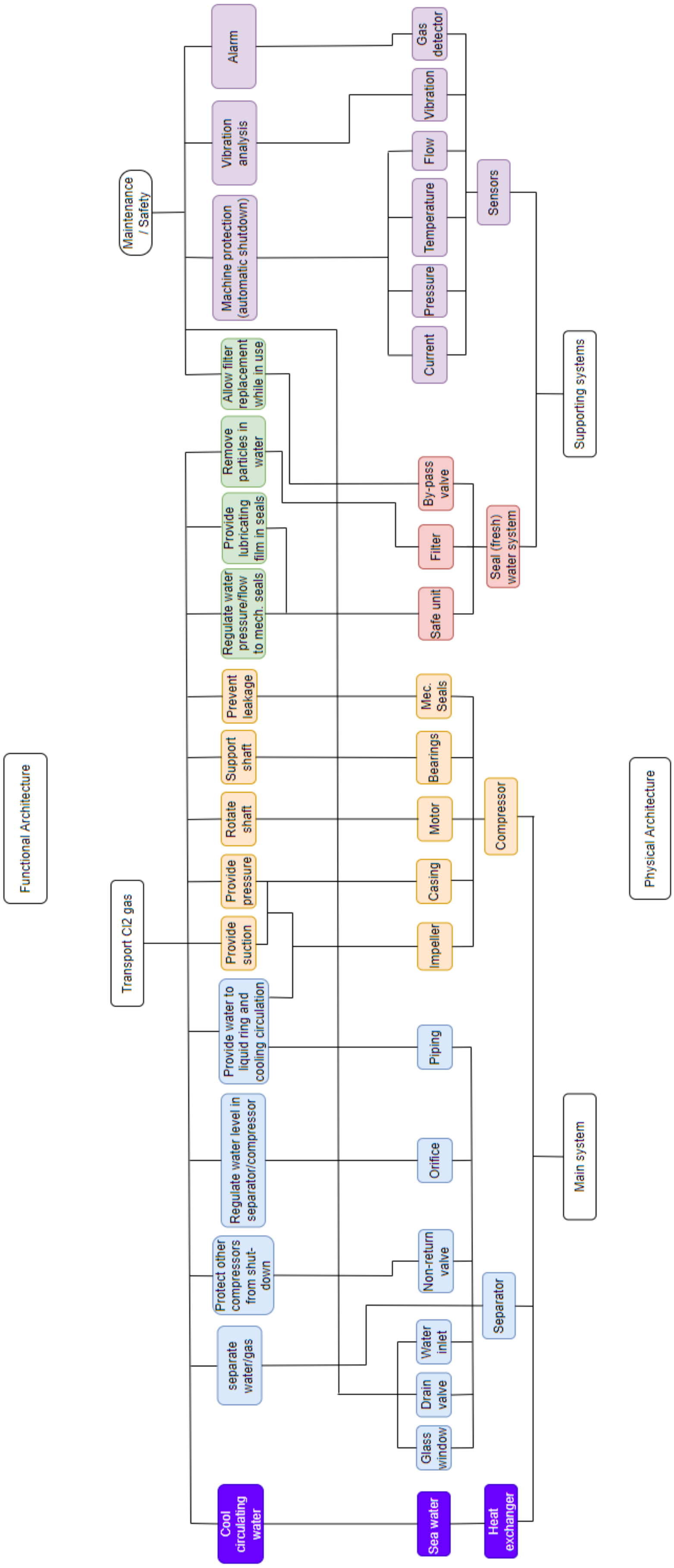


Figure 18: Functional/physical architecture.

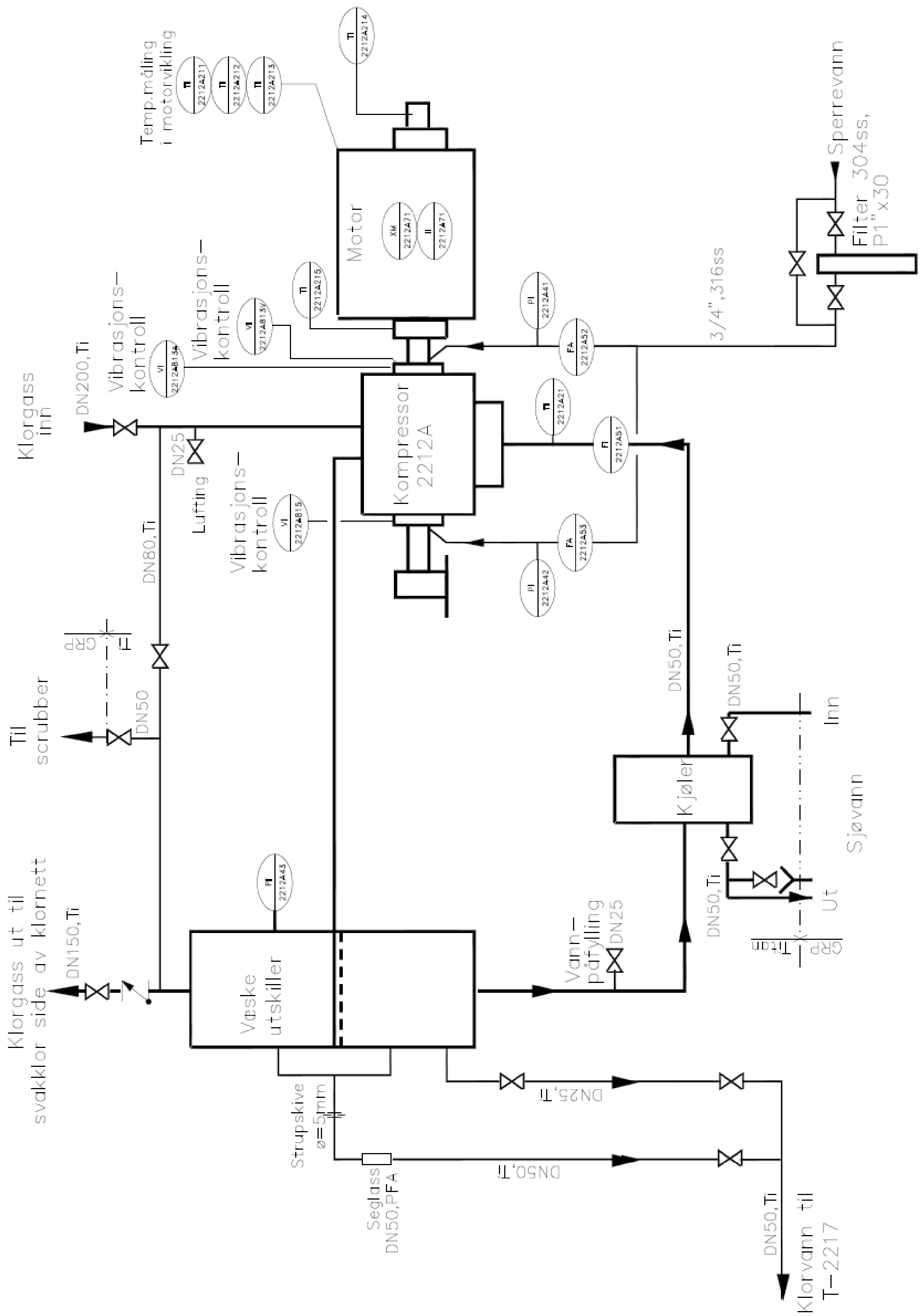


Figure 19: PID large compressors.

Source: Glencore Nikkelverk.

4.3 Use Cases

The compressors have four main use cases that they will encounter.

- Normal operation
- Maintenance
- Start-up
- Shut-down
- Stand-by

Normal operation

During normal operation, the compressors run at a fixed speed of 1250 RPM. There are numerous inspections completed regularly by shift workers that operate the plant. They will inspect the amount of flow and pressure of seal water and, if necessary, adjust the safe units manually. These manual adjustments can be seen in the seal water pressure data as spikes or sudden drops in the seal water pressure. Unfortunately, there are no records of when or how often shift workers manually adjust seal water flow and pressure.

Additionally, workers check that the cooling water temperature has not increased significantly since the last inspection every two weeks. If that has indeed happened, they will backflush the sea water side of the heat exchanger such that mussels that grow inside the sea water cooling system are removed. Mussels get stuck at the heat exchanger inlet before the sea water enters the thin plates of the heat exchanger. The control system also has low and high alarms at 40 and 60 degrees Celsius, respectively. The compressor will automatically shut down if the cooling water reaches 60 degrees. Backflushing is achieved by stopping the flow of sea water by closing a manual valve before the inlet and opening a valve to the atmosphere (see the blue valves in figure 22a). Then the backpressure from the sea water outlet pipes will reverse the flow of sea water and removes the mussels. It can significantly improve the cooling effect of the heat exchanger and reduce the temperature of the cooling water by 10 degrees Celsius shortly after backflushing. However, how effective it is varies from time to time and eventually, the heat exchanger must be replaced.

Maintenance

The compressors are regularly maintained, but the extent to which they must be disassembled depends on the maintenance work. In the case of any maintenance which opens the system to the atmosphere, say a pipe or the heat exchanger, the compressors need to be drained of the service liquid and flushed because the water inside is saturated with chlorine gas and could pose a danger to maintenance personnel. Shift-workers complete this in full protective gear. Minor maintenance work like replacing the heat exchanger does not require complete dissembling but can be done on-site. More extensive overhauls where bearings, seals, impellers, etc., are replaced are completed in the central workshop and the compressors are thus completely disassembled and assembled on-site again. Replacement of seal water filters can be done while the compressor is in use by running the water in by-pass lines.

Start-up

During start-up, typically after some sort of maintenance has been completed, the compressors must be filled with the correct amount of water (service liquid) and the couplings must be aligned with a laser tool and the seal water pressure and flow must be present. As seal water is shut off to complete overhauling, it is of utmost importance that the technicians remember to turn the manual valves for the seal water supply before start-up. Else the mechanical seals will fail rapidly or at least sustain damage that will considerably shorten the seal lifetime. The compressor must be filled with the correct amount of water during start-up. The large compressors need about 0,5 cubic meters of water. The water used in the compressor comes from the seal water supply. Consequently, it is essential that the compressor is not filled with water too quickly because this can cause the seal water pressure to drop. If the pressure inside the compressor becomes higher than the seal water pressure, it can damage the seals.

Stand-by

There are usually a few compressors on standby. In that case, it has happened before that the bearing balls have been damaged because the weight of the shaft is supported by the same bearing balls for an extended amount of time. This can cause fretting, which is when wear occurs at a single spot due to small vibrations under load. In addition, in the compressor room, it is believed that the other compressors nearby create vibrations carried through the floor and negatively impact the bearing life. Thus, the maintenance inspectors also occasionally turn the shaft by hand to counteract that effect.

4.4 Current Condition-Monitoring of the Compressors

The compressors are equipped with a large number of sensors and the purpose of these sensors can be categorized into three main blocks:

- Process control sensors
- Machine protection sensors (interlocks)
- Condition monitoring sensors

Because of the different purposes, not all of them are recorded and stored in the Historian. For example, are boolean values (on/off) generally not stored because of capacity issues in the process control system (ABB800xA) and these are instead used for process control. The two latter categories are more overlapping and some sensors used for machine protection are also used in condition monitoring and stored in the Historian. Currently, all stored sensor data goes through the process control system.

Additionally, the instrumentation of the compressors is set up differently depending on the type of compressor and some compressors have more sensors than others. All sensors that are currently stored in the Historian are shown in table 1.

4.5 Available Big-Data

The sensor data for the compressors is sampled every nine seconds and stored in a database. The database contains all measured values in a time-series for each compressor and can be exported to Excel or other formats. The database is unlabeled e.g. there is no information about whether a specific interval of measured values correspond to the compressors being in a faulty or healthy state. However, it is possible to check in SAP when repair or maintenance has been completed, in that manner the data could be labelled manually, but that is outside the scope of this thesis. Generally, the sensor network in the whole factory totals 75 thousand tags(sensors) and the data size amounts to about 100MB of sensor data per day stored in the Historian.

Although the sampling frequency can be decided by the process control engineers, the standard sampling rate is 0,11 Hz (one sample every 9 seconds) and all the sensors fitted at the compressors use this sample frequency. The sensor data is also compressed, which is achieved by not recording a new timestamp if the change in value is less than 0,05%. The Historian handles this by setting the new value of the new timestamp to the same as the previous one, in that way the time-series data is consistently nine seconds apart.

NaN-values, which seem to be frequent and randomly distributed in the sensor data, has implications for the software used in the case-study as well. While Wedge replaces NaN-values of the time-stamped value with the previous measured value, Intelecy sets it equal to zero. Exactly how this affects the performance of the machine learning models and which solution is the best is not

		Compressor									
		Large			Small						
Sensor Description	**Unit**	**A**	**I**	**J**	**B**	**C**	**D**	**E**	**F**	**G**	**H**
Seal water pressure NDE	Bar	x	x	x	*not relevant*						
Seal water pressure DE	Bar	x	x	x							
Pressure output	Bar	x	x	x	x	x	x	x	x	x	x
NDE bearing vibration, acceleration	G	x	x	x							
DE bearing vibration, acceleration	G		x		x	x	x	x	x	x	x
DE bearing vibration, velocity	mm/s	x		x							
NDE bearing vibration, envelope	env	x		x							
Cooling water temperature	deg. C	x	x	x	x	x	x	x	x	x	x
Motor winding temp. U	deg. C	x		x							
Motor winding temp. V	deg. C	x		x							
Motor winding temp. W	deg. C	x		x							
NDE bearing temperature	deg. C	x		x							
DE bearing temperature	deg. C	x		x							
Gas temperature	deg. C	x			x	x	x	x	x	x	x
Cooling water flow	m3/h	x	x	x		x					
Motor current	Amp	x	x	x	x	x	x	x	x	x	x
DE gearbox vibration, acceleration	G	*not relevant*			x	x	x	x	x	x	x
NDE gearbox vibration, velocity	mm/s				x	x	x	x	x	x	x
Engine power	kW									x	x

Table 1: Sensor overview

known. For shorter periods (minutes or less) of consistent NaN measurements, setting the value to zero might be detrimental to the performance. On the other side, if a sensor fails and the last real value it measured is recorded for a longer period, this could make it hard to detect that the sensor is in fact faulty.

4.6 Failure Mode and Symptoms Analysis

This chapter focuses on the findings and decisions made after the FMSA had been completed.

It was decided that the project would focus on two different failures of the system. An assumed simple case, to verify that it is indeed possible to detect failures early and a more challenging case to test the technology. The two cases selected were:

- Simple: detection of loss of cooling capacity in the heat exchanger
- Challenging: detection of incipient leakage in mechanical seals

Now, the first case was regarded as relatively simple because there are sensors available that measure the cooling water temperature, and rising temperatures would likely indicate a loss of cooling efficiency in the heat exchanger. In other words, there is a direct measurement that tells something about the condition of the heat exchanger. Rising temperatures are mostly caused by mussels etc. clogging up the heat exchanger on the sea water side and growth of something called "klortyggis" which is a sticky substance found in piping transporting chlorine gas at GNN. It is not known exactly what it is, nevertheless, its detrimental effect is well-known at GNN and it is assumed to grow over time.

The second case was selected because industry professionals at GNN report that the mechanical seals in the three large compressors have been the main problem they encounter and it is not known why. The mechanical seals in the large compressors mostly last 2 years or more unless a leak of chlorine gas/water occurs. In that case, the seals must be replaced, usually between 3-4 months later. Thus, GNN wants to monitor and model the development of these leaks in the large compressors. A leaking seal can be detected visually, as can be seen in figure 24 (severe leakage). However, exactly what happens before a seal becomes degraded is often unknown. Compared to the first case, direct measurements indicating failure or the reach of some threshold limit are not available for the mechanical seals. A linear relationship with some variable is also not known, except wear of the seal faces which is time-dependent. Thus, the hope is that Intelecy's deep learning long-short-term memory system could identify hidden relationships in the sensor data.

The findings from the FMSA process are presented in tables 3, 4 and 5. It is important to note that the symptoms presented in the FMSAs are possible symptoms that could indicate an upcoming failure, whether they are viable for detection is answered in the exploratory analysis. Some columns have been left out in this extract of the FMSA sheet for presentation purposes. Additionally, some information that was deemed to be of no interest, e.g. failure modes that GNN has not had any issues with in the past, was left out of the presented tables. The complete FMSA sheet is included in appendix A where the most important information is in green bold text and the least important information is in red text. Unfortunately, the appendix is not readable in a printed copy of the thesis, but it is possible to zoom in the digital PDF too see the entire document.

Maintech AS also inspected other common technical aspects that affect the mean-time-before-failure:

- Precision installation/tolerances of bearings
- Balanced impeller
- Soft-start systems
- Solid foundation

- Hard shims used between foundation and base plate
- Solid bolts (preferably studbolts)
- Lubrication (According to Maintech AS, studies have shown that 63% of failures result from poor lubrication)
- Clean medium (chlorine gas)

4.7 Establishing Normal Range of Sensor Values

To draw conclusions from the sensor readings it is first needed to have an idea of the mean and variance of the sensor values. Additionally, it could be relevant to know how different sensor values correlate and depend on each other, such that failures could be detected by assessing the typical correlation between sensor readings. Later when deciding the input of the machine learning models, knowing which variables correlate strongly also gives an indication of which sensors might be superfluous.

To establish normal conditions corresponding sensor values the dashboard made in "Wedge" was utilized. Wedge calculates statistical properties and a correlation matrix for each compressor. The results are shown in table 2 and figure 20. The same calculations has been completed for all compressors, with data from one week sampled every nine seconds and one year sampled once per day and is available in the attached excel sheet "Normal operation - sensor statistics - correlation matrices". Even if the statistical properties and correlation matrix presented here, can give indications about the normal state, it is important to recognize its limitations as well. According to the Nyquist criteria, the sampling frequency must be at least twice the highest frequency contained in the signal, or information about the signal will be lost. Thus, the correlation and statistical properties of the pressure and vibration, which are high-frequency signals, must be treated accordingly. Temperature, on the other hand, is a low-frequency signal and the results here are more thrust-worthy.

Measurement	Unit	Average	Deviation	Maximum	Minimum
Kompressor-NDE-ACC	G	0,5332	0,02563	0,6374	0,4493
Kompressor-DE-VEL	mm/s	2,845	0,103	3,459	2,414
TempLagerNDE	deg.	48,21	0,6174	49,38	47,28
TempLagerDE	deg. C	56,1	0,7137	57,57	55,08
TempViklingW	deg. C	74,8	0,7106	76,24	73,75
TempViklingV	deg. C	76,62	0,746	78,03	75,19
TempViklingU	deg. C	75,4	0,778	76,95	74,06
Temp. kjolevann	deg. C	27,72	0,7272	29,06	22,45
Trykk mot scrubber	bar	1,676	0,01816	1,801	1,541
Trykk sp.vann aksel	bar	2,604	0,02594	2,691	2,485
Trykk sp.vann aksel	bar	2,925	0,04508	3,042	2,773
Strom klorkompr	amp	275,5	2,65	290	264,7
Mengde kjolvann	m3/h	12,58	0,07267	12,94	12,07

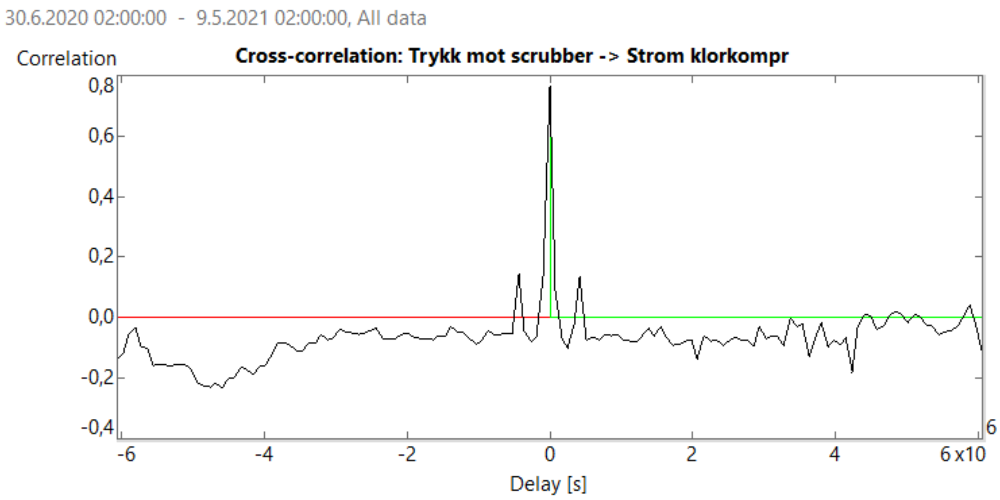
Table 2: Statistics - compressor J - 1 week - 10 sec sampling

In a highly statistically dependent system, such as the components in a compressor, correlation between different sensor readings is expected and do not necessarily indicate that these predict each other. Often they change at the same time because of some other driving factor (Nielsen 2019). This can be illustrated by calculating the cross-correlation, which is useful for determining the time delay between two signals. From figure 20, the correlation between output pressure and amperage is 0.76, indeed a strong correlation. However, from the cross-correlation, shown in figure 21, it is evident that increasing amperage does not predict the pressure output of the compressor ahead in time, rather they change together simultaneously. Hence, amperage does not give any indication of future pressure outputs.

30.6.2020 02:00:00 - 9.5.2021 02:00:00, All data

	Temp. kjolevann	Trykk mot scrubber	Trykk sp.vann aksel	Trykk sp.vann aksel	Strom klorkompr	Mengde kjolvann	Kompress or-NDE-ACC	Kompress or-DE-VEL	TempLage rNDE	TempLage rDE	TempVikl ingW	TempVikl ingV	TempVikl ingU
Temp. kjolevann	1	0,28	-0,1	-0,01	-0,14	-0,41	-0,52	-0,38	0,64	0,63	0,64	0,63	0,63
Trykk mot scrubber	0,28	1	-0,11	-0,06	0,76	0,023	-0,09	0,057	0,22	0,24	0,29	0,29	0,3
Trykk sp.vann aksel	-0,1	-0,11	1	0,89	-0,1	0,024	-0,1	-0,18	0,0039	0,035	0,015	0,021	0,018
Trykk sp.vann aksel	-0,01	-0,06	0,89	1	-0,07	-0,09	-0,29	-0,26	0,15	0,16	0,16	0,17	0,16
Strom klorkompr	-0,14	0,76	-0,1	-0,07	1	0,72	0,56	0,65	-0,32	-0,29	-0,24	-0,24	-0,23
Mengde kjolvann	-0,41	0,023	0,024	-0,09	0,72	1	0,74	0,86	-0,84	-0,82	-0,83	-0,83	-0,82
Kompressor-NDE-ACC	-0,52	-0,09	-0,1	-0,29	0,56	0,74	1	0,76	-0,67	-0,62	-0,65	-0,66	-0,64
Kompressor-DE-VEL	-0,38	0,057	-0,18	-0,26	0,65	0,86	0,76	1	-0,7	-0,69	-0,69	-0,69	-0,69
TempLagerNDE	0,64	0,22	0,0039	0,15	-0,32	-0,84	-0,67	-0,7	1	0,99	0,99	0,99	0,99
TempLagerDE	0,63	0,24	0,035	0,16	-0,29	-0,82	-0,62	-0,69	0,99	1	0,99	0,99	0,99
TempViklingW	0,64	0,29	0,015	0,16	-0,24	-0,83	-0,65	-0,69	0,99	0,99	1	1	1
TempViklingV	0,63	0,29	0,021	0,17	-0,24	-0,83	-0,66	-0,69	0,99	0,99	1	1	1
TempViklingU	0,63	0,3	0,018	0,16	-0,23	-0,82	-0,64	-0,69	0,99	0,99	1	1	1

Figure 20: Correlation matrix - compressor J - 1 year - 1 sample/day.



Contribution direction			Strongest correlation	Process delay [h:m:s]
Trykk mot scrubber	-->	Strom klorkompr	0,764	00:00:00
Strom klorkompr	-->	Trykk mot scrubber	0,764	00:00:00

Figure 21: Cross-correlation - Compressor J. - 1 year - 1 sample/day.

4.8 Heat Exchanger - Model Development

(a) Heat exchanger.

(b) Mussels from backflushing.

Figure 22: Heat exchanger.

As mentioned earlier, in the heat exchanger case, there is a direct measurement indicating the state of the heat exchanger, namely the temperature of the cooling water. Thus, in this case, there was far less need for a deep exploratory data analysis and there was a known failure of the heat exchanger at compressor B in the available sensor data. Being that model development is easy with the Intelecy software, a trial-and-error method is quite effective.

The data and model predictions and anomalies detected are presented in figure 23. As you can see, the cooling water temperature was increasing and showed a higher variance (the shaded area around the curve shows the variance) until 15. August, when it was taken out of production to replace the heat exchanger and left in standby for a while. Then, as it is put back into production in the middle of October, the temperature drops significantly, before it is likely clogged by mussels again and backflushed to restore the performance.

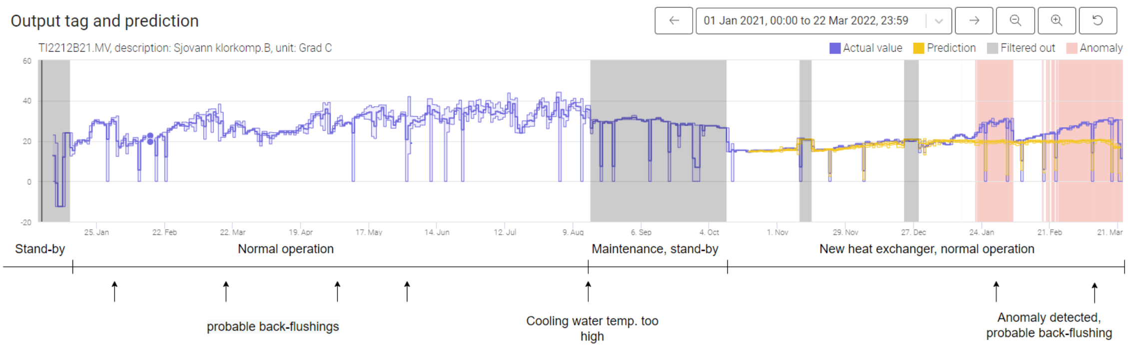


Figure 23: Anomaly detection model.

It must be strongly emphasized that the training period used in this model was far too short and it has not been tested with data it has never seen before. While the model successfully detects the two spikes in cooling water temperature at the end, the model has been tuned to do just that for the given input. Consequently, this model should not be seen as anything more than an example of how the model is developed and tuned to correctly identify anomalies. If it would perform as well in a live setting remains to be verified.

The model was trained on all available sensors for compressor B:

- Pressure output
- DE bearing vibration
- Gas inlet temperature
- Motor current
- DE gearbox vibration, acceleration
- NDE gearbox vibration, velocity
- Chlorine gas concentration

The grey area has been filtered out such that it does not identify anomalies when the average motor current is less than 50 amps over ten minutes. That way, the model can run on live data without user input and incorrect anomaly warnings. It also allows the model to resume monitoring again after start-up of the compressor and gives at least ten minutes before it would detect an anomaly. The delay avoids false alarms because the start-up conditions often deviate a lot from the norm before they are quickly restored.

FMSA: heat exchanger											
Function	Failure Mode	Failure Cause	Failure Mechanism	Local Effect	Effect on other components	System Effect	Existing Control Measure	Detection Method	Symptoms	Correlation	Comments
Cool chlorine gas and circulating water (cooling water)	Does not sufficiently cool gas and water	Growth of ”klortyggis”, cooling water side	Reduced flow of cooling water	Reduced cooling efficiency	Generally higher temp. in the system	Reduced transportation of gas	Temperature inspected every two weeks, heat exchanger replaced every two years	Increased temperature in cooling water, low alarm at 40 deg. C and high alarm at 60 deg. C	Increase in temperature sensor TI2212x21	Sea water temperature	Need more knowledge about ”klortyggis” and how fast it grows.
									Reduced flow of cooling water, measured by sensor FI2212X51	Higher temperatures	Flow sensors only available for the large compressors, unsure of how much ”klortyggis” affects the flow.
		Mussels etc. clogs the intake of the heat exchanger, sea water side	Reduced flow of cooling water	Reduced cooling efficiency	Generally higher temp. in the system	Reduced transportation of gas	Back-flushing to remove mussels	Increased temperature in cooling water, low alarm at 40 deg. C and high alarm at 60 deg. C	Increase in temperature sensor TI2212x21	Mussel growth increases during the summer, decreases in winter	Need an indicator for when back-flushing is done.
									Reduced flow of sea water	Higher temperatures	No sensors for sea water flow

Table 3: FMSA: heat exchanger

4.9 Mechanical Seals - Exploratory Analysis

(a) Healthy mechanical seal.

(b) Leaking mechanical seal.

Figure 24: Pictures of healthy/leaking seal.

Generally, the mechanical seal design is quite complicated even if its function is simple. The design of the mechanical seal installed in the large compressors is shown in figure 25. There are many things that can go wrong, however, causes of leakage can be divided into two categories: seal face opening and component failure, for example, corrosion of the springs that push the seal faces together. As can be seen in the FMSA table, there are many possible symptoms of leakage in the seals which necessitates a discussion of the degree of exactness that is wanted in diagnosing the cause of leakage. For the purpose of this study though, the goal is to first be able to detect the conditions which may cause to a leakage in the seals in the near future. Of course, if any detrimental conditions are found, actions that could negate these conditions and improve the reliability of the seals will also be discussed and the results will be used as a baseline for which sensor data might be able to indicate these conditions in a live data stream.

As the mechanical seals are fastened to the shaft, vibrations in the shaft are also present in the seals and could cause damage to the seal faces or other components in the seals. Vibration in the shaft stem either from an imbalance in the shaft, worn/damaged bearings or a misaligned coupling. This further complicates the case and increases the number of symptoms that could indicate an impending leakage, and makes it difficult to know which variables contribute the most to a leak in the mechanical seals.

Additionally, there are no obvious measurements that could give a direct indication of the healthiness of the mechanical seals. In the FMSA it was theorized that leakage could be detected by assessing the seal water pressure and temperature. In theory, a leakage would cause minuscule pressure drops, at least before the safe unit has a chance to restore the pressure to its pre-defined pressure level. Other possible symptoms identified were increased power consumption, increased engine temperature and change in the flow and temperature of seal water through the mechanical seals. However, the change in engine temperature and power consumption is believed to be negligible and there are currently no sensors measuring the temperature of seal water. The next sub-chapter documents the analysis performed and the results thereof in assessing how the mechanical seals could be monitored.

4.9.1 Seal Water Temperature

If the seals become degraded it is expected that they will produce more heat because of increased friction in the seal faces. That could theoretically be detected by a temperature increase through the seals. Of course, a temperature increase through the seal is expected because one of the functions of the seal water is to cool the seals. Thus, there is both the need to establish normal temperature increases in the seal water and to see if this would become higher when the seals are degraded.

To investigate this, the equipment inspector at the KL department has been taking daily measurements with a handheld infrared temperature measurement device, to see if this is in fact the case. The measured difference in seal water temperature at the inlet and outlet is presented in figure 26. Though, to date (15.06.22), the data collected is not sufficient to conclude what the normal temperature increase is, nor are there any known failures in the mechanical seals of compressors I and J. Also, the temperature of the seal water was measured at the seal water hoses, not directly from the water. Thus, the trustworthiness of the measurements can be questioned. The data set is not complete because measurements were not taken at weekends and the equipment inspector was away for some time.

All the same, it is interesting to note that the seal water temperature increase in the different seals differ. However, as described more closely in the next chapter, the safe units that regulate the flow and pressure of water into the seals, seem to not function properly under fluctuating conditions. Therefore, the difference in seal water temperature increase could be because the mechanical seals have different seal water flow rates, which would affect the temperature difference between the inlet and outlet.

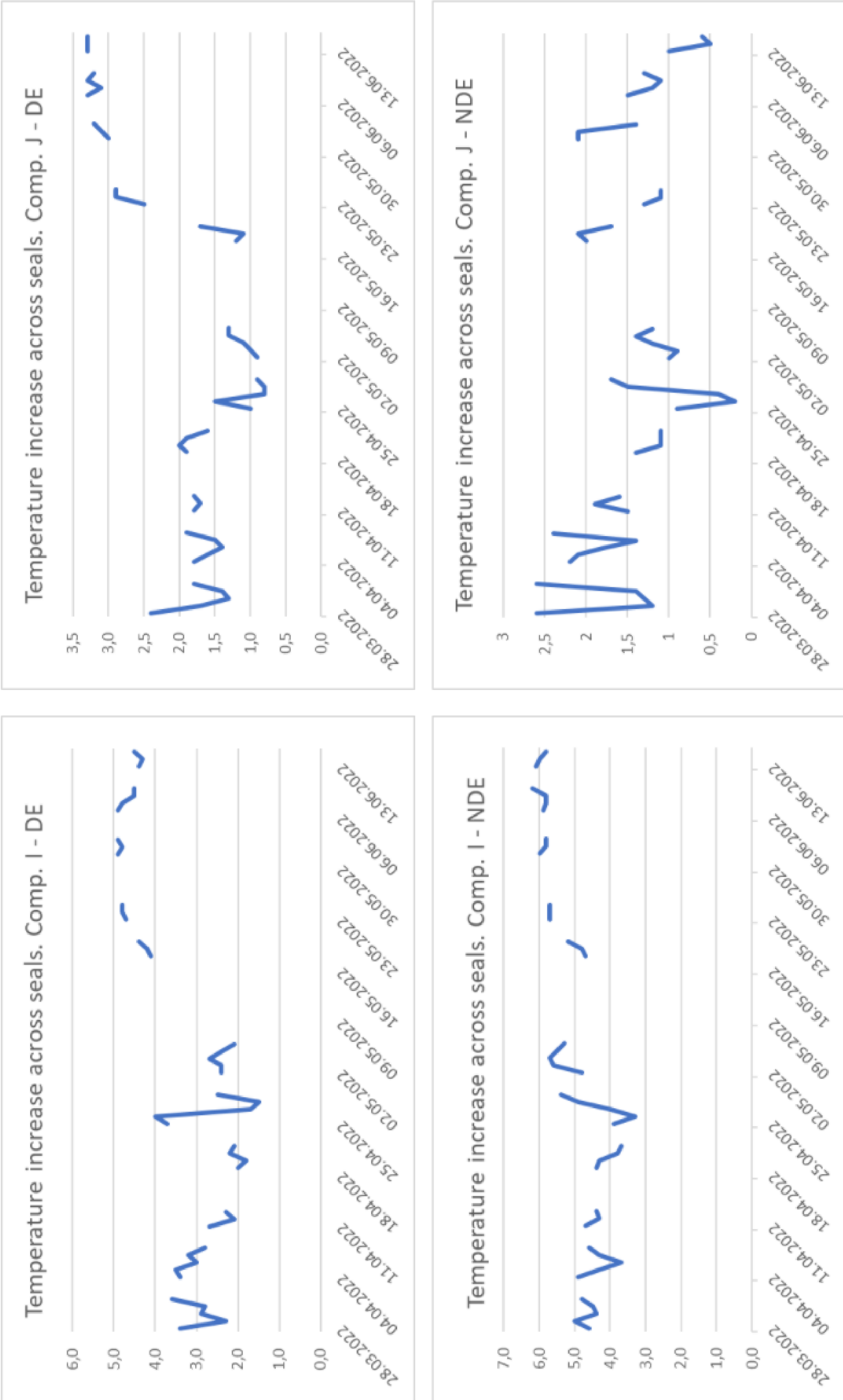
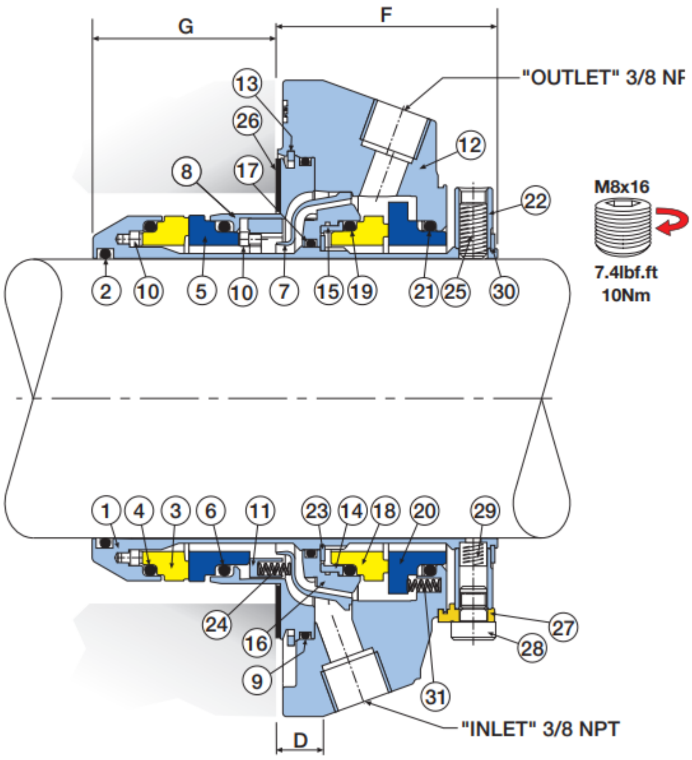


Figure 26: Difference between inlet and outlet seal water temperature.



Item	Description	Material
1	Sleeve	316L SS
2	Sleeve O Ring	AES-ELAST / EPR / FFKM / FKM / TFE/P
3	Internal Rotary Face	Carbon / SiC / TC
4	Internal Rotary Face O Ring	AES-ELAST / EPR / FFKM / FKM / TFE/P
5	Internal Stationary Face	Carbon / SiC / TC
6	Internal Stationary Face O Ring	AES-ELAST / EPR / FFKM / FKM / TFE/P
7	Deflector	316L SS
8	Gland Insert	316L SS
9	Gland Insert O Ring	AES-ELAST / EPR / FFKM / FKM / TFE/P
10	Internal Drive Ring/Pin	Stainless Steel
11	Internal Spring Plate	316L SS
12	Gland	316 SS
13	Gland Insert Snap Ring	Stainless Steel
14	External Drive Ring/Spring Plate	316L SS
15	External Drive Ring/Pin	Stainless Steel
16	External Rotary Holder	316L SS
17	External Rotary Holder O Ring	AES-ELAST / EPR / FFKM / FKM / TFE/P
18	External Rotary Face	Carbon / SiC / TC
19	External Rotary Face O Ring	AES-ELAST / EPR / FFKM / FKM / TFE/P
20	External Stationary Face	Carbon / SiC / TC
21	External Stationary Face O Ring	AES-ELAST / EPR / FFKM / FKM / TFE/P
22	Clamp Ring	316L SS
23	Circlip	Stainless Steel
24	Springs	Alloy 276
25	Drive Screws	Stainless Steel
26	Gasket	AF1/GFT
27	Setting Clips	Brass
28	Setting Clip Screws	Stainless Steel
29	Anti-tamper Screws	Stainless Steel
30	Circlip	Stainless Steel
31	Springs	Alloy 276

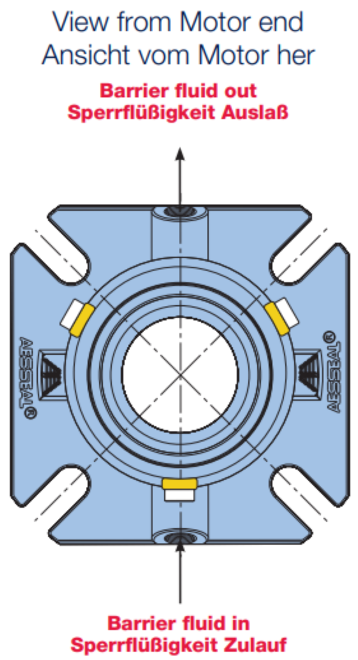


Figure 25: Mechanical seal drawing

Source: AES Seal

FMSA: Mechanical Seals											
Function	Failure Mode	Failure Cause	Failure Mechanism	Local Effect	Effect on other components	System Effect	Existing Control Measure	Detection Method	Symptoms	Correlation	Comments
Prevent leakage of chlorine gas and water to the atmosphere while allowing low friction rotation	High friction between ceramic plates	Wear from particles	Poor filtration or by-pass valve left open after maintenance (human error)	Leak of seal water and/or chlorine	None	Chlorine gas leak	Gas detector and/or visual inspection	Gas detector and visual inspection	Increased power consumption and motor temp.	Pressure drop over filter	Expected lifetime 3-4 months with this failure mode. Normally greater than 2 years lifetime.
		Lack of seal water	Failure in seal water supply or manual valve closed at start-up (human error)	Increased temp.	None	Complete failure of system	Flow meter	Manual inspection	Change in seal water flow or pressure	Time without flow	Potential case for establishing degradation pattern. Interlocks should be implemented in ABB800xA such that the compressors cannot start without seal water supply.
		Vibration	Misalignment	Leak of seal water	Increased temp.	System failure	Low freq. vibration measurement and visual inspection at overhaul	Inspected at overhaul	change in vib. signal	Increased power consumption, motor temp., increased temp in seal water	No sensors available to measure temp. increase over the seals

Table 4: FMSA: mechanical seals (large compressors).

4.9.2 Seal Water Pressure

Initially, as the team considered the boundaries of the system for this study, the supply of seal water was defined as outside the boundary. However, by looking at the trends of the sensors at the large compressors some questions arose. Specifically, the highly fluctuating pressure measurements in the seal water were a bit of a mystery. From table 2, the results from the initial analysis to establish healthy "levels" for the sensors showed that:

1. $PI2212I41_{avg} = 2.6$ bar and $PI2212I41_{max} = 2.7$ bar (Trykk sp.vann aksel)
2. $PI2212I42_{avg} = 2.9$ bar and $PI2212I42_{max} = 3.0$ bar (Trykk sp.vann aksel)

However, comparing these results to the trend in figure 28, figure 29 and figure 27 in the period 20.05.2021 - 25.05.22, it is clearly evident that something has happened. In this period there were pressure spikes upwards of 11 bar. According to the the seal manufacturer, "Good-practice" seal water pressure is 1-2 bar above the compressor pressure output, which is 1,7 bar on average at GNN, such that the wanted seal water pressure is about 2,7-3,7 bar.

To investigate this further, the physical placement of pressure sensors was checked against the safe units that regulate flow and pressure into the mechanical seals. In the PID these are not indicated, therefore, it was verified that the sensors were downstream of the safe units. Additionally, the pressure measurements from the sensors and the manometer at the safe unit fitted at each seal water line were compared. The manometers for the two compressors in use were maxed out and could not tell us the pressure. This is important because mechanics use the manometers when adjusting the safe units.

Next, the ABB control system was searched for the pumps that supply the seal water pressure, which is common for all the chlorine compressors and other equipment in the KL department. The pressure in each seal was compared with the supply pressure. Note that the pressure measurement for the seal water supply is the highest line in all three figures. The pressure drop that is seen down to the seal pressures is expected due to the length of travel in pipes. For compressor I (figure 28) the seal pressure is stable around 2,7 bar at the drive-end, but at the non-drive-end, the pressure follows the same erratic trend as seen in compressors A and J (figure 29 and 27). This shows that the pressure fluctuation stems from the seal water pumps and that the safe units do not reliably regulate the seal water pressure as intended.

From the graphs it was initially thought that only one of the safe units was functioning properly, that is, supplying a steady pressure of about 2,7 bar. As it turned out, after looking at the trend of the seal water pressure again after the maintenance stop on the 31.05.22, PI2212I41 constantly showed a pressure measurement of about 2,7 bar, with some variation as well. However, during the maintenance stop, the seal water pumps were shut off and the pipes drained of water. As the sensor still measured 2,7 bar, the sensor is obviously incorrect and should be replaced. This would likely not have been discovered if the sensor readings were not checked again after the maintenance stop and show the importance of assessing the data quality before analyzing it.

It was theorized that the highly fluctuating seal water pressure could be the cause of the early leakages, but the mechanical seals are rated to withstand up to 26 bar pressure such that the pressure spikes are well below the limit. Therefore, this investigation could not conclude that this contributes to early leakages. Nevertheless, the safe units should provide a stable pressure to the mechanical seals and it is still not known how the rapid change in seal water pressure affects the mechanical seals. Also, as can be seen in figure 25, the inlet and outlet of seal water should be oriented at 6 O'clock and 12 O'clock, respectively. Some of the mechanical seals had the outlet and inlet inverted, which may also adversely affect the expected lifetime of the seals.

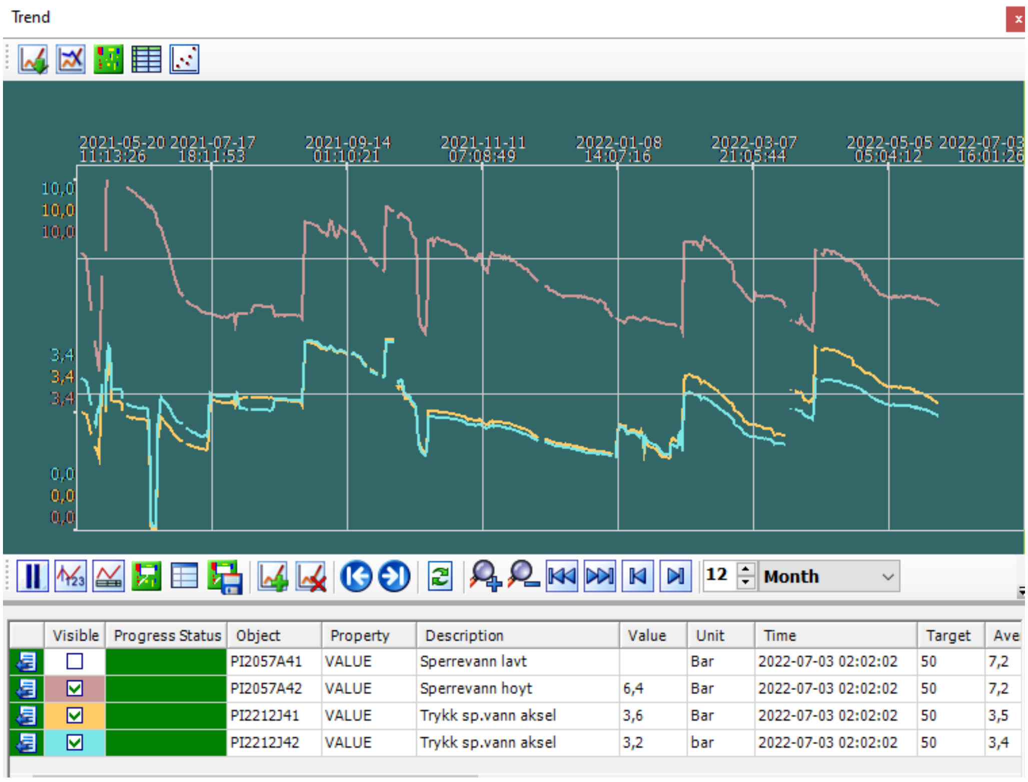


Figure 27: Compressor J: Seal water pressure vs. seal water supply pressure

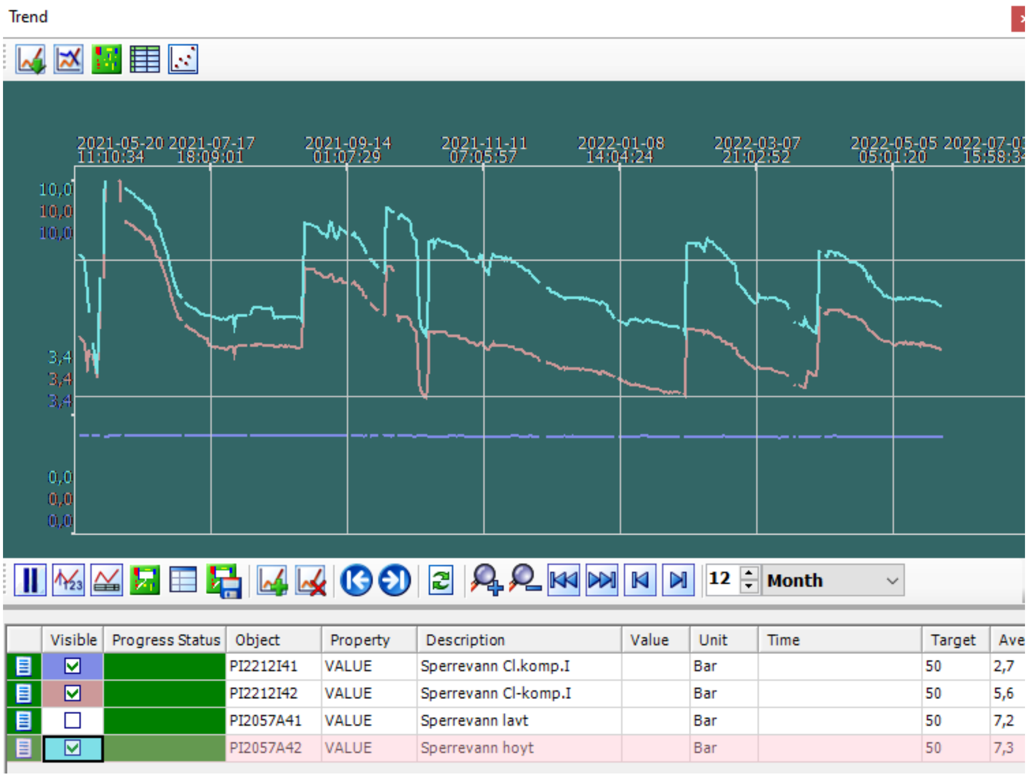


Figure 28: Compressor I: Seal water pressure vs. seal water supply pressure

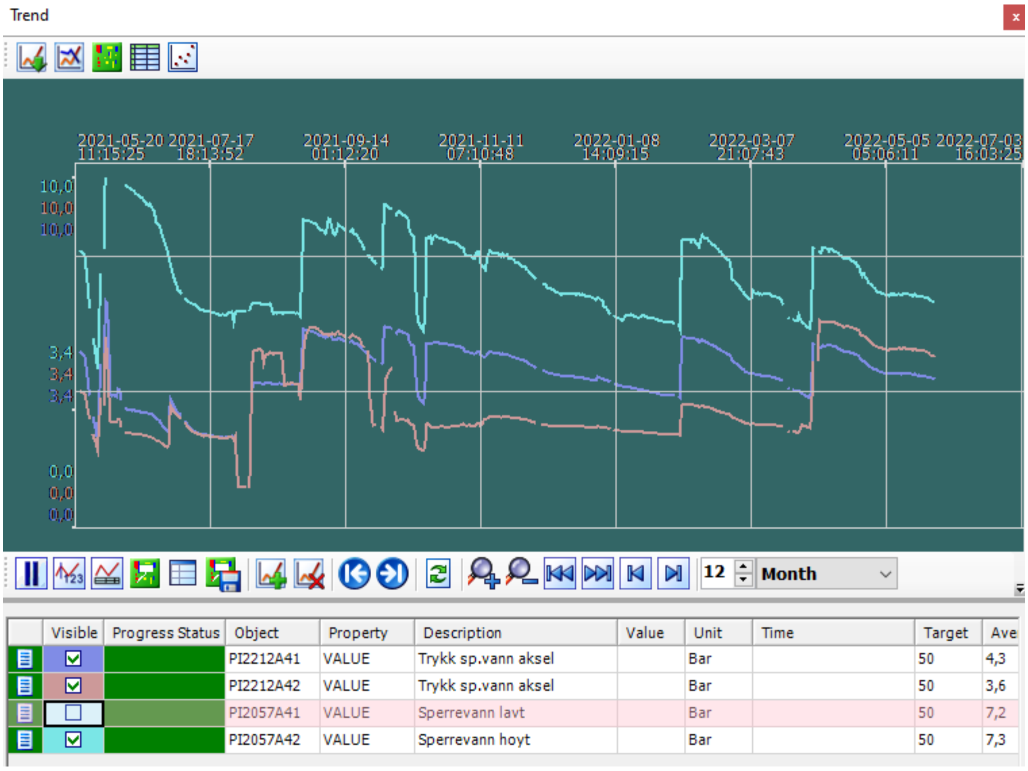


Figure 29: Compressor A: Seal water pressure vs. seal water supply pressure

More insight into the behavior of the seal water pressure fluctuations can be gained by studying parallel coordinates plots generated with Intelecy software. To generate this plot, the raw sensor data was first segmented into 1-hour segments and then features were calculated for each segment. The choice of features was the mean and standard deviation in pressure for each mechanical seal. This choice was made to even out fast fluctuations often seen in pressure signals, such that longer periods of sustained high pressure (greater than 3 bar) could be identified. Also, on the contrary, the standard deviation feature is useful to identify very fluctuating periods, which also could be of interest and indicates the signal-to-noise ratio.

A parallel coordinates plot is useful to study multi-dimensional data sets. In this instance, the first column from the left and the color of the line indicate the timestamp from the first sample in each one-hour segment. This enables us to see the temporal development of all the seal water pressure measurements in the same plot. Particularly, in figure 31, the plot shows that the standard deviation of the pressure in each segment in each seal has been low at the end of the period, towards the end of March 2022. However, throughout the period there have been shorter time periods where the seal water pressure has varied substantially.

According to Intelecy, sensor values in a particular operation mode should not vary significantly when the system is healthy for their software to effectively analyze and find meaningful relations in data sets. Therefore, the seal water pressure readings are unfit for use in the software because of the highly fluctuating sensor values currently seen. In other words, seal water pressure is likely not a good indicator of seal leakage even if the fluctuating pressure could be a cause of the early leakages seen in the past. In the end, seal water pressure is discarded as a possible input parameter in the deep learning model development.

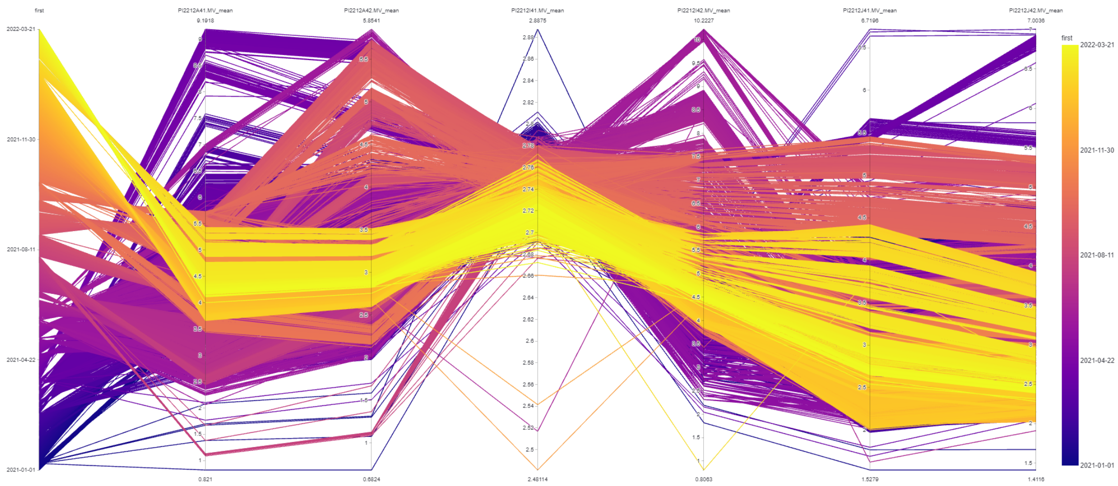


Figure 30: Parallel coordinates plot: 1h segments, mean pressure

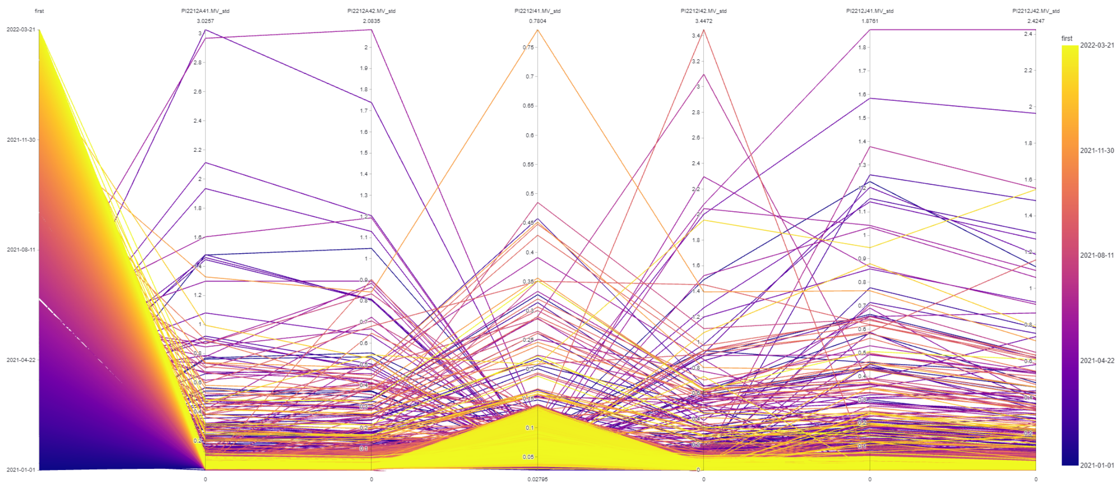


Figure 31: Parallel coordinates plot: 1h segments, standard deviation

4.9.3 Bearings

Vibration is a known mechanical seal killer. Because degraded bearings can contribute to more vibrations that will be transferred through the shaft into the seals, these measurements are possible indicators of impending leaks in the mechanical seals.

The bearings are already monitored by SKF vibration analysis software, which transforms the vibration time-series signals to the frequency spectrum and allows specialists to analyze the state of the bearings. The same vibration sensors are used in this project. Still, the means of accessing them are different. These measurements are only sampled at 0,11 Hz, far lower than what is used in the SKF software (vibration analysis software is dependent on sampling frequencies up to 25000Hz) to diagnose failures of components. That means that the vibration measurements available in this project can only give indications of the magnitude of the vibrations present in the bearings and not be used for diagnosis in the same way. These low-frequency measurements are also used for automatic machine shut-down and are known to be trustworthy.

Again, using parallel coordinates plots to study the historical vibration data, the vibration signals are generally more stable than the seal water pressure. Besides some outlier periods in the mean and standard deviation features for the vibration signals, seen in figure 32 and 33, respectively, the data is more suited deep learning model development.

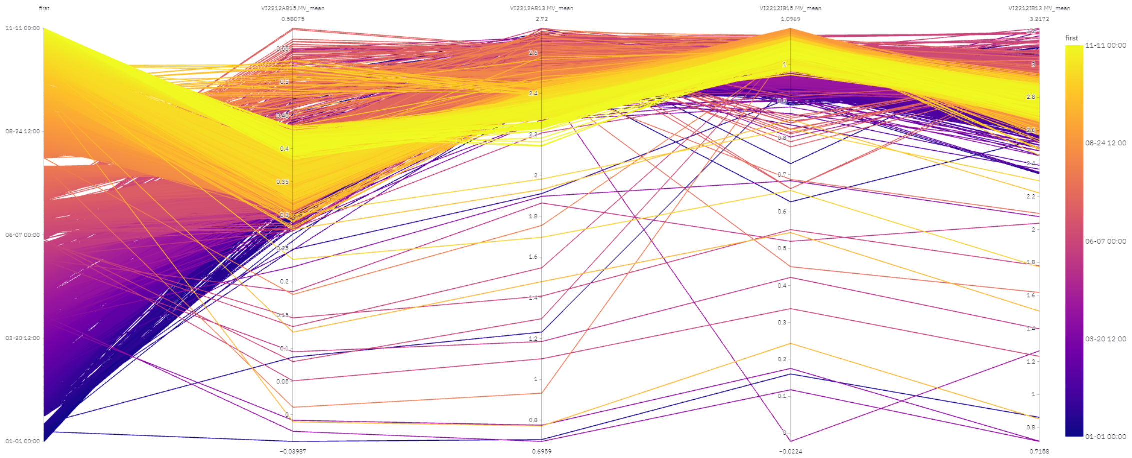


Figure 32: Parallel coordinates plot: vibration, 2h segments, mean

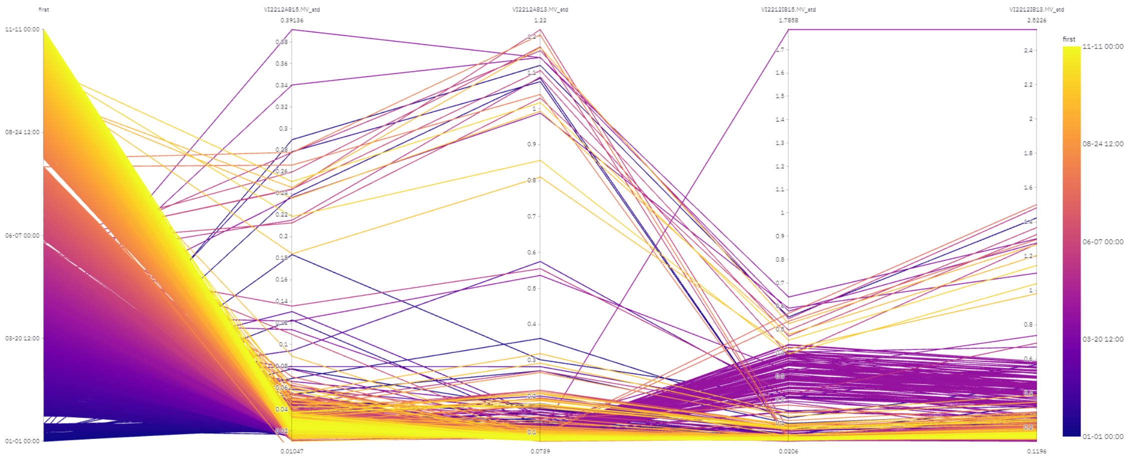


Figure 33: Parallel coordinates plot: vibration, 2h segments, standard deviation

FMSA: Bearings											
Function	Failure Mode	Failure Cause	Failure Mechanism	Local Effect	Effect on other components	System Effect	Existing Control Measure	Detection Method	Symptoms	Correlation	Comments
Support shaft	Does not support shaft, vibrates	Long service time, overload	material fatigue, plastic deformation	Vibration/ noise	Wear on mechanical seals, impeller and casing	System failure	High-frequency vibration measurements		Change in vibration measurements, bearing temperature, motor effect and temperature	Service time	
		Slack / wrong tolerances	Wear or incorrect installation	Rotation of outer bearing ring	Vibration and heat development	System failure	High-frequency vibration measurements, visual inspection	Manual inspection	Change in vibration measurements, bearing temperature, motor effect and temperature	Time since replacement of bearings	Not an issue the last two years.
		Fretting (in stand-by for too long)	Ball bearing fatigue from vibration	Wear on mechanical seals, impeller and casing	Increased temp.	System failure	High-frequency vibration measurements, rotation of shaft while in stand-by	Change in vibration measurements, bearing temperature, motor effect and temperature	Noise	Time in standby	Not possible to measure noise in the compressor room.

Table 5: FMSA: bearings

5 Results and Discussion

Going through the failure mode and symptoms process has been beneficial because it documents the inherent knowledge and competence related to the equipment in question. It serves as a guide for what is known about the system and what is unknown. Moreover, having an inter-disciplinary group present was quite interesting and more than once people were able to build on each other's fields of knowledge. One example being, as we started to analyze the time-series data. While the analysis showed some interesting lows for some sensor values, knowledgeable employees at GNN, would quickly point to that being a result of the weekly harvesting of nickel cathodes, which reduces the flow of chlorine gas. The point being that data analysts cannot effectively operate in a vacuum, they need to cooperate with those who have the "hidden" information. Hidden in the sense that it is not readily available to someone new to the process or equipment. Similarly, maintenance engineers and mechanics traditionally do not possess data analysis skills. The FMSA process effectively enables that information to surface. Specifically, information related to normal operation, adjustments made in seal water pressure and backflushing of the heat exchangers has been important to understand the collected data and make sense of it. For example, it was assumed that sudden drops in cooling water temperature had to be the result of measurement errors, but an experienced operator could tell us that backflushing has a rapid effect on the temperature. In hindsight, the project group should have included someone with more experience in the daily operation of the compressors, not just people with maintenance experience.

However, as is, the historical work orders generally do not contain enough information about failures to effectively extract failure modes and symptoms thereof. Thus, for the FMSA process to become more beneficial in the future, clear work order writing policies are a must. Especially, the content of the work order should be more in line with the FMSA process and be based upon the different elements that the FMSA tries to document. According to Maintech AS, the same pattern is seen in most businesses: work orders are written for the maintenance personnel's own overview but less focused on documenting issues for the future. As work order writing is a manual process involving people, training and a change of focus is needed. Of course, changing organizational aspects are easier said than done but an important step nonetheless. At GNN, they are also aware of this issue and working on improving the work order writing, but admit that there is still room for improvement. Consequently, the findings of the FMSA presented in this report were mainly based on the experience of maintenance personnel.

If the heat exchanger anomaly detection model can be verified in a live setting later, it could well be used to extend the maintenance interval beyond the current two-year interval at GNN. The model has been successful in identifying when there is a need for backflushing to remove mussels. It should also be trained on a period of more than a full year because mussel growth is seasonal and a much larger issue in the summer. Further, it has not been verified if it can detect the growth of "klortyggis". Even so, mussels have been the largest issue by far, and it could be that trying to detect "klortyggis" growth would not be worth the trouble and cost of installing more sensors. Anyhow, the verification of the models is dependent on live data access, which has been a major limitation throughout the project this far. The performance of the model must be verified when the issues related to data security are solved and a willingness to not replace the heat exchanger is also necessary to test whether the maintenance interval can be extended beyond the present two years.

In regard to the challenging case of detecting unwanted conditions that may lead to a leak in the mechanical seals, the results are not conclusive. The lack of a clear answer as to why the seals have sometimes started to leak earlier than expected has a range of possible causes that must be assessed. Without clear measurements that could differentiate the causes and something to compare them against, model development is difficult.

One possible way forward is to define a cumulative degradation indicator, as mentioned in the literature for data-driven prognostics. However, a degradation indicator must be defined for each specific case and is not clear exactly how that could be done. Based on the findings so far, it could be possible to define multiple different degradation indicators. In practice, that would mean soft sensors, e.g. calculated variables. These can be defined either in the Historian or in Intelecy and is a feasible option. A variable integrating the information of all the identified symptoms contributing to seal leakage could be defined by a linear combination of the different sensors value and be accumulative to capture the "load" the seal has sustained over time, as in equation 5. However, it is very hard to verify the underlying assumptions of a linear combination of sensor values. Thus, this should merely be regarded as a proposition and not an answer to how a degradation indicator could be defined.

$$DI = \sum_{i=1}^{N} \sum_{j=1}^{C} \omega_i \cdot S_{i,j} \tag{5}$$

Where ω_c is a weight larger than zero that must be empirically decided, C indicates the number of sensors evaluated, N indicates the number of timestamps and S is the normalized sensor value at a specific timestamp for each sensor. The input of the degradation indicator should also be statistically independent to make sure that sensor values do not cancel each other out or increase together because of some other driving factor. The correlation matrix calculated from the sensors in the compressors showed that many measurements correlate, at least in the compressors. Still, statistically dependent inputs are easily avoided by assessing the correlation matrix.

Ideally, a cumulative variable should be reset after maintenance and thus there is also a need to integrate information from the computerized maintenance system, which in and of itself is a challenge because of varying work order data quality in SAP PM. Even if a process control sensor could be used to this effect, a shut-down does not necessarily mean that the system has been repaired and does not always give a complete picture of all repairs completed. Thus, if the goal is that an anomaly detection system should operate independently without sporadic input of operators, mechanics, etc., integration with SAP and, again, clear policies of work order writing are important for such a system to function.

A cumulative degradation indicator can then be simulated by a Wiener process or by linear regression in Python. However, previous attempts at similar use of machine learning techniques in Python at GNN, have shown that the programming skills necessary to make in-house developed software that function together with other software such as the Historian, are major barriers for these projects. Thus, GNN prefers to leave the software specifics to professionals. Consequently, Intelecy's no-code industrial AI is welcomed, even if it comes at the expense of less freedom to tune the machine learning models.

Another option for the degradation indicator could be a non-cumulative indicator, which would integrate more easily into the Intelecy anomaly detection software, as in equation 6. With this kind of degradation indicator, Intelecy's Nowcast model could be used to define anomalous conditions and actions to negate possible detrimental conditions can be taken.

$$DI = \sum_{i=1}^{C} \omega_i \cdot S_i \tag{6}$$

The hypothetical model must then be trained on a time-series representing normal conditions, preferably a time-series after replacement of the seals, as we have not conclusively identified which conditions cause the leakage in the seals. The next stage is essentially a waiting game. Some leakages must be allowed to occur if such a strategy is to succeed. After a known leakage, the behavior of the degradation indicator can be assessed to see if it did in fact increase or decrease as would be necessary for the Intelecy software to detect an anomaly. In other words, the degradation indicator should stay more or less constant, much like is seen in the heat exchanger model in figure 23, while the mechanical seals are new and functioning properly. After a known leakage, the historical data and calculated degradation indicator should be increasing or decreasing before the leakage was detected.

Suppose a degradation indicator based on several sensors can be used to detect anomalies. In that case, root cause analysis could be performed using the Intelecy's feature importance analysis, which has shown promise in the literature, to see which features (and which sensor) have had the most significant impact on the degradation indicator. The most important features would then be linked with the probable failure cause by investigating the failure symptoms identified in the failure mode and symptoms analysis. Figure 34 presents a visual representation of the idea.

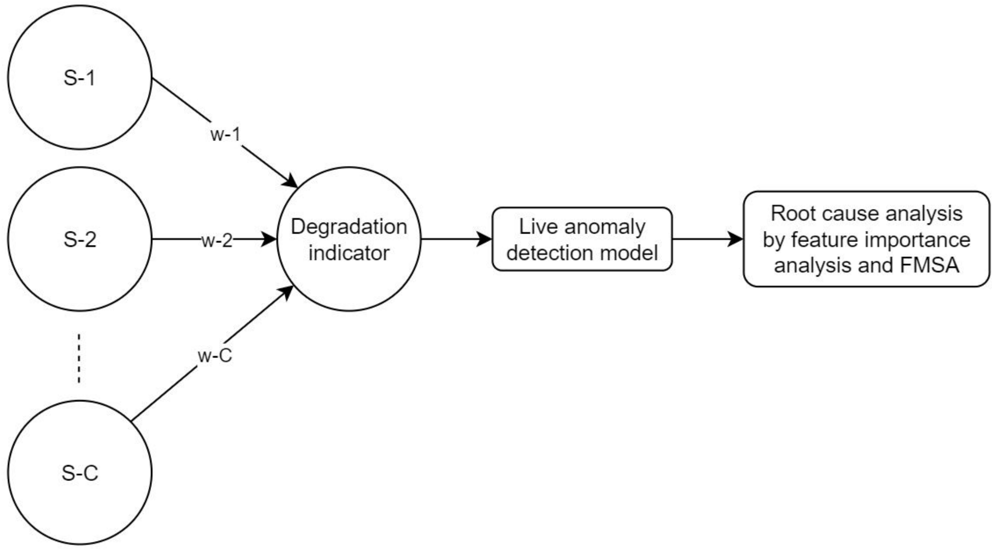


Figure 34: Root cause analysis model.

The necessary testing of the developed models, though, relies on access to live sensor measurements. According to the IT department at Glencore Nikkelverk and Intelecy, linking the database to the Intelecy software is a straightforward process because the software used in this project is based on the OPC-UA IEC62541 standard for data exchange from sensors to cloud applications. Unfortunately, data security concerns have slowed the process and eventually deemed too risky to connect the database with the cloud. As a result, GNN and Intelecy are trying a work-around solution not including access to the cloud or internet. This will likely give sensor measurements every 45 seconds instead of nine seconds. Accessing every fifth timestamp allows the historical data to be used without much hassle. That solution will likely be sufficient because the degradation patterns related to the compressors do not develop that quickly.

Without testing the proposed models the risk of fitting a story to fit the outcome, which is a possible weakness of outcome-driven research, is large and difficult to uncover before the models are tested in real-life. Thus, emphasis should be placed on the fact that more testing is needed in general.

Even if the necessary testing has not been done yet, the case-study has shown that deep-diving into failure history and historical sensor data often uncovers new knowledge about the system. For example, it was found that not all sensors were stored in the database and that the safe units do not reliably regulate the seal water pressure. It was also seen that some manometers that mechanics use to adjust the seal water pressure were faulty which has implications for the day-to-day operation of the compressors. Moreover, it was discovered that one of the seal water pressure sensors was faulty. Lastly, possible human errors were identified, such as forgetting to open the manual valves for the seal water before start-up. Thus, the addition of interlocks in the factory control system that would make it impossible to start the compressors without seal water flow were discussed too. In the end, an in-depth study often gives value outside of the initial goals of the study.

In terms of the goal of the pilot project to detect failures earlier than today, more time and testing of the proposed solution are necessary. However, the project has succeeded in developing a platform that can also be used for other equipment. The ease with which models can be created with Intelecy software, given a good degradation indicator, has also been shown. Thus, GNN has learned how to select equipment that could be maintained according to an ensemble of an anomaly detection model and feature importance analysis.

The findings of Nordal and Idriss El-Thalji 2021 about the requirements of PdM explain the requirement of the degradation indicator quite well. It must be easy to track, reliable and accurate enough to detect anomalies and manage transient operational characteristics. In the case-study, the simple and challenging case were mainly separated by the availability of a degradation indicator that fulfills these requirements. If GNN decides to scale up the project and look at more equipment, assessing possible degradation indicators for each case is a crucial step, at least if one would like to grasp the "low-hanging fruit" first. More effort should be invested into defining good degradation indicators that fulfill the requirements in more challenging cases, such as detecting anomalies in mechanical seals.

As was seen in one of the case-studies from the literature, machine learning techniques were well suited to diagnose the condition of pneumatic cylinders based on the measured action time. At GNN, there are also many pneumatic cylinders used across the factory. Thus, if there was invested time and effort into collecting a labeled data set of action times from PLS systems at GNN, many cylinders could likely be monitored to achieve early fault detection. Even if labeled data sets have not been the focus of this study, Intelecy software can also be used to forecast sensor values if labeled data is available. However, being able to diagnose a cylinder as either "good", "fair" or "poor" as in the study by Chen et al. 2020, would likely be enough to aid maintenance planning and would be feasible given access to PLS data. Particularly, the pneumatic cylinders used in the shears and welding machine are important for production throughput at GNN and could be a good starting point. In addition, because the cylinders are standardized for different sizes, collected data sets would likely apply to many other machines used at GNN.

Generally, the case-study is part of a larger strategy at GNN to become more data-driven in its decisions. Hence, applications of the LSTM neural network and feature importance analysis should also be experimented with outside of maintenance. For example, related to quality control and process control, feature importance analysis could well be used to establish which factors contribute to more excellent metal quality or enhanced production. Contrary to the compressors, where quality measurements do not directly relate to the compressors because they only transport gas, quality measurements could be used as labels in other parts of the production process that contribute more directly to the metal quality or production throughput. With 75 thousand tags available and an extensive historical database, lessons learned about getting started with big data analysis are essential in the bigger picture at GNN.

6 Further Work

Based on the findings of the thesis so far, a natural next step is to develop a general recipe for degradation indicator definition. Because of the vast amount and diversity of industrial equipment used in the chemical process industry, one would have to define many different categories of degradation indicators. For example, rotating equipment is often fitted with vibration sensors, so further work should include a discussion of how different vibration measurements may indicate a failure. Moreover, how should the different measurements like humidity, temperature and other operating parameters be weighted in contrast to more direct degradation indicators, such as the temperature of the cooling water in the heat exchanger.

In the research by Tajiani et al. 2020 on roller bearing RUL estimation using vibration signals, a suitable health indicator was selected based on which features correlate most strongly with time by calculating "Spearman's Correlation Coefficient" under the assumption that the ideal degradation path is monotonously increasing. A similar approach could be used to decide which features to include in a degradation indicator for a mechanical seal anomaly detection model and could fit well into how Intelecy's software identifies anomalies.

7 Conclusion

Anomaly detection models based on LSTM neural networks for industrial equipment can be easy to create given access to data and a good degradation indicator. However, much testing is required to verify the anomaly detection models. Nevertheless, if they can be used to either plan maintenance before a failure or extend maintenance intervals, they will likely contribute to lower maintenance costs soon.

Still, more effort and testing must be given to developing a degradation indicator for cases with no clear-cut relationship between the measured sensor values and the system's degradation level.

In cases where a degradation indicator of sufficient quality is present, root cause analysis can also be implemented with feature importance analysis. Thus, given time and continuous improvement efforts based on an ensemble of LSTM neural network anomaly detection and feature importance analysis, the maintenance strategy of a given system can be optimized.

The proposed ensemble method applies to equipment other than the liquid ring compressors assessed in this thesis but requires extensive system knowledge, a well-functioning IoT network and software integration to be applicable in practice. Not least, root cause analysis requires skilled data analysts.

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Appendix

A FMSA

MainTech

FMEA - FAILURE MODE AND EFFECT ANALYSIS SYSTEM/DESIGN/PROCESS **IEC 60812/ISO 14224**

Main system / Sub-system	Part/Operation name.	Drawing-Part No.	Machine No.	Functional Specification-Technical Regulation (link if possible)	Supplier	1
System Main Function / Operational mode	Date Performed	Date Time Updated	Status - Hardware/Digital modell	Issued by	Project	Issue
System i normal produksjon		28.03.2022 12:32				

PART			CHARACTERISTICS OF FAILURE										1st RATING			
nr	Komponent	Operasjonell tilstand	Funksjon	Plausibelt Sviktmodus	Sviktmodus kode	Sviktårsak	Plausibel Sviktmekanisme	Lokal effekt	Effekt på andre komponenter	Slutteffekt - System effekt	Eksisterende kontrolltiltak	Prøving - Simulering Deteksjonsmetode	Po	S	Pd	RPN
1	VENTIL	Åpen	Lukke prosess på signal	Lukker ikke		Får ikke deaktivert styresignal	Frost i pilotventil	Ventilen leverer til prosessen	Prosessen blir ikke forsvarlig avstengt	Farlig situasjon	Ingen	Ingen	6	8	8	384
2	Væskeutskiller	I drift	Skille ut vann fra gass	Skiller ikke ut vann fra gass												
3				Skiller for lite vann fra gass		Feil nivå										
4				Lekkasje		Feil nivå										
5			Gi riktig nivå på kompressor	Gir for høyt nivå på kompressor		Ugunstig driftsforhold	Ventil har blitt lukket uten å burde det	Økt vibrasjon	Tap av impeller	Havari						
6				Gir for lavt nivå på kompressor		Væskenivået blir for lavt	Vann har ikke blitt fylt på	Økt vibrasjon	For lite væske i kompressor							
				Ventil mellom væskeutskiller og kjøler stenges												
7	Plateveksler i titan	I drift	Skal kjøle ned gassen	Kjøler ikke gassen tilstrekkelig		Lav strømning	Begroing, klor-side	Redusert gjennomstrømning	Redusert kjøleeffekt	Lavere produksjon av gass	Kalenderbasert rengjøring, filter -> problemet er blitt mindre	Økt temperatur				
							Begroing, sjøside									
							Feil justerte ventiler	Redusert gjennomstrømning	Redusert kjøleeffekt	Lavere produksjon av gass	Kalenderbasert rengjøring, filter -> problemet er blitt mindre	Økt temperatur				
							Tette siler - fremmedelementer i sjøvann	Redusert gjennomstrømning	Redusert kjøleeffekt	Lavere produksjon av gass	Kalenderbasert rengjøring, filter -> problemet er blitt mindre	Økt temperatur, sil skylles når trykkfallet over sil når et nivå				
							Trip i sjøvannspumper	Redusert gjennomstrømning	Redusert kjøleeffekt	Lavere produksjon av gass	Kalenderbasert rengjøring, filter -> problemet er blitt mindre	Økt temperatur				
8						Lekkasje	Pakningsbrudd (aldring)	Lekkasje av sjøvann eller klorvann	Redusert kjøleeffekt	Økt temperatur	Visuelt for sjøvann, gassdetektorer 5ppm for klorvann	Klorsniffer oppdager klorvannslekkasje				
9							Korrosjon (Ti)	NA								
10							Overtrykk i sjøvannsystem	Lekkasje av sjøvann eller klorvann	Ingen	Kan gi følgeskade som vedvarende lekkasje						
							For lavt tiltrekningsmoment/avstand på platepakke	Lekkasje av sjøvann eller klorvann	Redusert kjøleeffekt	Økt temperatur	Visuelt for sjøvann, gassdetektorer 5ppm for klorvann					
11	Sjøvannsystem	I drift	Levere sjøvann til plateveksler	Leverer ikke sjøvann		Tett	Egen analyse									
12						Lekkasje										
13	Kompressorhus	Trykksatt	Holde trykk	Holder ikke trykk		Lekkasje	Indusert fra overhaling	Lavere væskenivå	Skade på impeller	Stans	Gassdetektorer 5ppm for klorvann					
			Pakningsflate													
			Strukturell støtte til lager													
			Strukturell støtte til bolter													
14	Impeller	I drift	Rotere kompresjonsvæske	Roterer ikke lenger kompresjonsvæsken tilstrekkelig		Vibrasjon	Oppstart transient i forhold til væskenivå	Rubbing grunnet Ubalanse i aksling	Prosesstans	Havari	Online Vibrasjonsmåling					
						Vibrasjon	For høyt væskenivå	Rubbing grunnet ubalanse	Prosesstans	Havari	Online Vibrasjonsmåling					
						Matrialtretthet	Utmatting	Havari	Prosesstans	Havari	PT av impeller ved KV					
							Begroing	Havari	Prosesstans	Havari	PT av impeller ved KV					

	MainTech AS FMSA										ACTION-STATUS				2nd RATING					
nr	Symptom:	Symptom #	Korrelasjonsmetode	Hovedmetode	"Soft sensor" - virtuell sensor	Valgt Måleteknikk	Frekvens	Lokasjon	Maskinlæring tidstrender	Utfyllende kommentarer	Anbefalt aksjon	Planlagt aksjon	Ansvarlig	Oppfølgingsdato	Po	S	Pd	RPN	Verifikasjon - signatur	Status
1	Hva opplever vi da?		Hvilke indikatorer kan avdekke at dette er i ferd med å skje?	Hvordan kan dette oppdages?											1	8	6	48		R
2															3	3	4	36		
3															1	5	8	40		
4															5	3	4	60		
5															1	3	4	12		
6										Kan være et problem ved oppstart at vannet forsvinner					1	3	4	12		
7	Økt tempertur på vann etter kjøleren	1	Sjøtemperatur	Sjekk av korrelasjon mot sjøvannstemperatur	Kjøleeffekt er et eksempel på en soft sensor, men som ikke er relevant her uten temp. ut måling					Spesielt problem ved oppstart. Trenger indikator på når det back-flushes.										
	Endring i flow etter kjøler	2			Derivert/integrert signal															
	Endring i motoreffekt	3			Derivert/integrert signal															
	Endring i motortemperatur	4			Derivert/integrert signal															
	Endring i klorkonsentrasjon	5			Derivert/integrert signal															
	Endring i gasstrykk i væskeutskiller	6			Derivert/integrert signal															
	Endring i vibrasjon lager	7			Derivert/integrert signal															
	Endring i temperatur i lager	8			Derivert/integrert signal															
	Samme som, men ikke påvirkning på flow i samme grad																			
	Samme som over, men med step-change og ikke gradvis over tid. Vil ikke ha påvirkning på flow, i og med at det ikke struper klor-siden									Ikke et fokus her, men vil kunne se det med sensorikken.										
	Samme som for feil justerte ventiler, men med saktere utvikling																			
8																				
9																				
10																				
11																				
12																				
13										Det har skjedd, men ekstremt sjeldent										
14										Sprekksøker ved FV										
	Endring av vibrasjon i lager	7	Driftstid etter bytte		Torsjonsmåler motor-kompressor															
	Endring av temperatur på lager	8			Fourier/rainflow på vibrasjon med amplitude/frekvens															
	Endring i motoreffekt	3			Derivert/integrert signal															
	Endring i motortemperatur	4			Derivert/integrert signal															
	Samme som over, men antagelig større vibrasjoner									Spesielt viktig for start-stop										

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PART				CHARACTERISTICS OF FAILURE									1st RATING				MainTech AS FMSA										ACTION STATUS				2nd RATING					
nr	Komponent	Operasjonell tilstand	Funksjon	Plausibelt Sviktmodus	Sviktmodus kode	Sviktårsak	Plausibel Sviktmekanisme	Lokal effekt	Effekt på andre komponenter	Slutteffekt - System effekt	Eksisterende kontrolltiltak	Prøving - Simulering Deteksjonsmetode	Po	S	Pd	RPN	Symptom	Symptom #	Korrelasjonsmetode	Hovedmetode	"Soft sensor" - virtuell sensor	Valgt Måleteknikk	Frekvens	Lokasjon	Maskinlæring tidstrender	Utfyllende kommentarer	Anbefalt aksjon	Planlagt aksjon	Ansvarlig	Oppfølgingsdato	Po	S	Pd	RPN	Verifikasjon - signatur	Status
			Komprimere gass	Komprimerer ikke til det trykke den skal													Samme som over																			
15	Aksling	I drift	Gi dreiemoment til impeller	Slitasje i lager og tettning		Slitasje	Abrasjon fra mekansisk tettning	Lekkasje, vibrabrasjon	Prosessstans	Havari							Endring av vibrasjon i lager		Driftstid, vibrasjonsnivå, antall overhalinger, FV-intervallet, type grease, temp. på grease, antall kast på aksling		Derivert/integrert signal															
			Støtte lager																																	
			Støtte tetning																																	
16	Lager (A, I og J)	I drift	Støtte roterende aksling	Støtter ikke aksling, vibrerer mer enn design		Manglende fett	Slitasje	Varmgang/vibrasjon/støy	Slitasje på tetning, impeller og hus	Havari	Vibrasjonsmålinger - høyfrekvent																									
						Feil fett - forurensing	Slitasje	Varmgang/vibrasjon/støy	Slitasje på tetning, impeller og hus	Havari	Vibrasjonsmålinger - høyfrekvent																									
						For mye fett / varmgang	Slitasje	Varmgang/vibrasjon/støy	Slitasje på tetning, impeller og hus	Havari	Vibrasjonsmålinger - høyfrekvent																									
						Stillstand - Fretting	Utmatting fra mikrovibrasjon	Vibrasjon/støy	Slitasje på tetning, impeller og hus	Havari	Vibrasjonsmålinger - høyfrekvent	Støy (før havari)					Endring av lagervibrasjoner	7	Høyere nivå ved oppstart, stillstandstid		Derivert/integrert signal					BPFO										
																	Endring av lagertemperatur	8			Derivert/integrert signal															
																	Endring av motoreffekt	3			Derivert/integrert signal															
																	Endring av motortemperatur	4			Derivert/integrert signal															
						Lang driftstid - Overbelastning/ Spalling	Utmatting og plastisk deformasjon	Vibrasjon/støy	Slitasje på tetning, impeller og hus	Havari	Vibrasjonsmålinger - høyfrekvent						Endring av lagervibrasjoner	7	Driftstid/antall omdreininger		Derivert/integrert signal															
																	Endringer av lagertemperatur	8			Derivert/integrert signal															
																	Endring av motoreffekt	3			Derivert/integrert signal															
																	Endring av motortemperatur	4			Derivert/integrert signal															
						Feil toleranser - slarke	Slitasje	Rotasjon av ytterring	Vibrasjon og varmgang	Havari	Vibrasjonsmålinger - høyfrekvent						Endring av lagervibrasjoner	7	Lagerbytte		Derivert/integrert signal					Hovedproblem for lager. Hovedproblemet med lager er for A,I og J) ikke vært problemer de siste 2 årene.										
																	Endring av lagertemperatur	8			Derivert/integrert signal															
																	Endring av motoreffekt	3			Derivert/integrert signal															
																	Endring av motortemperatur	4			Derivert/integrert signal															
18	Mekanisk Tetning	I drift	Tette for lekkasje av klorvann under lave friksjonsforhold	Stor klorvann-lekkasje over tetning		Slitasje fra partikler i vann	Manglende eller for dårlig filtrering	Lekkasje av sperrevann og eller klorvann	Ingen	Klorlekkasje	Filterbytte (gjøres når trykkfallet DP over filter er for stort. Sjekkes en gang i uken)	Klorsniffer, periodisk dråpetelling av sperrevann, støy					Endring av motoreffekt	3	Trykkfall over filter, dråpetelling av sperrevannslekkasje (stigende trend)		Derivert/integrert signal					Ikke korrelert med lagervibrasjoner. Forventet levetid 3-4 måneder ved denne sviktmoden, normal levetid lengre enn 2 år (for store, lenger for de små). Trykk og flow på sperrevann er antagelig ikke symptomer.										
																	Endring av motortemperatur	4			Derivert/integrert signal															
						Brudd i keramiske plater	Ubalanse i aksling eller impeller, støt. Manglende sperrevann. Vibrasjoner	Lekkasje av sperrevann og eller klorvann	Ingen	Klorlekkasje		Klorsniffer, visuelt på sperrevannslekkasje (inspeksjonsrutiner 1 gang i uka)					Endring av flow av sperrevann	11	Antall start og stopp, stor sperrevannslekkasje inn på kompressoren eller ut (stigende trend)		Derivert/integrert signal					Antagelig liten/ingen endring av effekt på motor. Sperrevannstilførsel ligger mellom 1-3l/min stabil ved mindre noen endrer den.										
																	Endring av trykk på sperrevann	12			Derivert/integrert signal															
						Slappe fjærer	Siging	Lekkasje av sperrevann og eller klorvann	Ingen	Klorlekkasje		Klorsniffer, periodisk dråpetelling av sperrevann							Dråpetelling av sperrevannslekkasje (stigende trend)																		
				For høy friksjon mellom karbonsete og keramisk sete		Manglende sperrevæske	Svikt i sperrevann tilførsel	Varmgang	Ingen	Havari	Flow vakter						Potensiell case for å bekrefte normalsituasjon for en tetning som har vært utsatt for manglende sperrevann.		Flowvakt tid uten sperrevann							Hovedproblemet er friksjon fra vibrasjon og tap av sperrevæske. Kan være et problem ved oppstart av kompressorene. (Flowvakt ikke en del av Historian)										
						Vibrasjon	Feiloppretting	Lekkasje av sperrevann	Varmgang	Havari	Vibrasjonsmålinger - lavfrekvent						Endring av lagervibrasjon	7	Vibrasjonsanalyse om opphavet til vibrasjonen, step-change etter nylig gjort FV, økning av lekkasje av sperrevann		Derivert/integrert signal. Fouriertransformasjon av vibrasjonsignal.					Opplever at levetid er rundt 2 år										
																	Endring av lagertemperatur	8			Derivert/integrert signal															
																	Endring av motoreffekt	3			Derivert/integrert signal															
																	Endringer av motortemperatur	4			Derivert/integrert signal															
							Feilmontering	Lekkasje av sperrevann	Varmgang	Havari	Vibrasjonsmålinger - høyfrekvent	Trykkprøving av tetning ved overhaling burde fange det opp.					Endring av lagervibrasjon	7	Økt støy, men ikke store økninger i lagervibrasjon, step-change i støy/motoreffekt/temperatur etter nylig skifte/FV av tetning, økning av lekkasje av sperrevann		Derivert/integrert signal					Antagelig lave vibrasjonsøkninger i lager, men kan måles som støy. Kan være et problem hvis montering har skjedd uten rotasjon.										
																	Endring av lagertemperatur	8			Derivert/integrert signal															
																	Endring av motoreffekt	3			Derivert/integrert signal															
																	Endring av motortemperatur	4			Derivert/integrert signal															

PART				CHARACTERISTICS OF FAILURE									1st RATING				MainTech AS FMSA										ACTION-STATUS				2nd RATING					
nr	Komponent	Operasjonell tilstand	Funksjon	Plausibelt Sviktmodus	Sviktmodus kode	Sviktårsak	Plausibel Sviktmekanisme	Lokal effekt	Effekt på andre komponenter	Slutteffekt - System effekt	Eksisterende kontrolltiltak	Prøving - Simulering Deteksjonsmetode	Po	S	Pd	RPN	Symptom:	Symptom #	Korrelasjonsmetode	Hovedmetode	"Soft sensor" - virtuell sensor	Valgt Måleteknikk	Frekvens	Lokasjon	Maskinlæring tidstrender	Utfyllende kommentarer	Anbefalt aksjon	Planlagt aksjon	Ansvarlig	Oppfølgingsdato	Po	S	Pd	RPN	Verifikasjon - signatur	Status
																	Endring av sperrevanns-temperatur over tetning	13	Eksisterer ikke nå.																	
						Utslitt	Aldring-slitasje	Lekkasje av sperrevann	Varmgang	Havari	Vibrasjonsmålinger - høyfrekvent						Endring av sperrevanns-temperatur over tetning	13	Driftstid, ikke step-change på endringer, økning av lekkasje av sperrevann, ikke økning i lagervibrasjon, antall start/stop		Derivert/integrert signal					Spørsmål til Glencore: Hvordan oppdages det at tetningen er utslitt? Hvordan ser vibrasjonsmålingene ut før og etter byttet?										
				Korrosjon fra atmosfære																																
19	Fundament	I drift	Støtte kompressor strukturelt			Skeivt	Korrosjon	Vibrasjon	Vibrasjon	Havari	Vibrasjonsmålinger - lavfrekvente																									
20	Kobling	I drift	Overføre moment fra motor til kompressor	Overfører ikke moment		Løs akselklemme	Løshet fra Vibrasjon	Varmgang, vibrasjon, støy	Ingen rotasjon av impeller	Ingen kompresjon																										
						Brudd																														
			Ta bort bøyemoment fra feil oppretting	For stort vinkelavvik		Feil oppretting																														
						Løshet/manglende chims																														
			Ta bort aksielle krefter fra feil oppretting			Feil oppretting																														
						Løshet/manglende chims																														
			Sikre montasjerom																																	
21	Elektrisk motor	I drift	Gi dreiemoment til kobling	Gir ikke dreiemoment		Åpen krets, viklingsbrudd	Utmatting	Stans	Alt stopper	Havari							Endring av motortemperatur	4			Derivert/integrert signal															
																	Endring av lagervibrasjon	7	Endring av vibrasjonsnivå		Derivert/integrert signal															
																	Endring av motoreffekt	3			Derivert/integrert signal															
																	Endring av motor-turtall	9			Derivert/integrert signal															
																	Endring i klorkonsentrasjon	5			Derivert/integrert signal															
																	Endring i gasstrykk i væskeutskiller	6			Derivert/integrert signal															
																	Endring av væskestrøm inn på kompressor	10			Derivert/integrert signal															
						Lagerbrudd	Utmatting	Stans	Alt stopper	Havari																										
						Lukket krets, kortslutning-isolasjons	Utmatting	Stans	Alt stopper	Havari																										
24	Motorfundament	I drift	Gi støtte for motor																																	
25	Motorstyring VSD?																																			
26	Sperrevæske system	I drift	Gi ren trykksatt sperrevæske til kompressortetning	Gir ikke trykksatt væske til kompressortetning		Tett filter	Manglende FV	Varmgang fra friksjon i tetning	Varmgang	Havari	FV filterbytte årlig, flowmåling - trykkvakt. Ukentlig inspeksjoner						Endring av motoreffekt	3	Driftstid, ikke step-change på endringer, økning av lekkasje av sperrevann, økt støy, men ikke økning i lagervibrasjon. Går raskere enn åpent filter		Derivert/integrert signal					Veldig lite problemer med sperrevann forutenom når tetninger ryker. Spørsmål til Glencore: Hvordan oppereres bybass-ventil - manuell. Se tetning tett filter.										
																	Endring av motortemperatur	4			Derivert/integrert signal															
																	Endring av flow av sperrevann	11			Derivert/integrert signal															
																	Endring av trykk på sperrevann	12			Derivert/integrert signal					Under trykkvakt-toleranse										
				Gir forurenset spærreveske til kompressortetning		Åpent filter	Partikler kommer inn	Slitasje i tetning, lekkasje	Varmgang	Havari	FV filterbytte årlig, flowmåling - trykkvakt. Ukentlig inspeksjoner						Endring i motoreffekt	3	Driftstid, ikke step-change på endringer, økning av lekkasje av sperrevann, økt støy, men ikke økning i lagervibrasjon. Går saktere enn tett filter		Derivert/integrert signal															
																	Endring i motortemperatur	4			Derivert/integrert signal															
																	Endring av flow av sperrevann	11			Derivert/integrert signal															
																	Endring av trykk på sperrevann	12			Derivert/integrert signal					Under trykkvakt-toleranse										
						Bypass-ventil blir stående åpen	Partikler kommer inn	Slitasje i tetning, lekkasje	Varmgang	Havari	FV filterbytte årlig, flowmåling - trykkvakt. Ukentlig inspeksjoner						Endring av sperrevanns-temperatur over tetning	13	Driftstid, ikke step-change på endringer, økning av lekkasje av sperrevann, ikke økning i lagervibrasjon.	Skriv på alle syptomnummer 13: Mål temperatur på innløp og utløp på sperrevann til tetningshus.						Spørsmål til Glencore: Er det mulig at dette kan skje uten at trykkvakt fanger det opp? - flowvakt står etter bypass/filter.										
27	Gir tannhjul	I drift	Redusere turtall fra motor til kompressor																																	
			Overføre moment fra motor til kompressor	Overfører ikke moment		Brudd	Utmatting	Vibrasjon	Vibrasjon	Havari																										
28	Girolje	I drift	Smøre girhjul og girlager	Smører ikke tilstrekkelig																																
29	Gir glidelager	I drift	Støtte giraksler	Slakke		Utmatting	Slitasje																													
				Feilstilling		Feil oppretting/montasje	Prosedyre																													
30	Gir oljepumpe	I drift	Levere trykksatt olje til smøring av glidelager	Leverer ikke trykksatt olje		Brudd?																														
31	Ventiler	I drift					Lekkasje gjennom membran				5-årig skift, lekkasje fanges opp av klorsniffer															Problemet er blitt mindre etter annet matrialvalg										
32	Rør	I drift																																		
33	Instrumentering	I drift	Styre kompresjons prosessen	Styrer ikke prosessen		Åpen krets																														
						Lukket krets																														
						Driftet i stykker		Slutter å måle	Får ikke inn vibrasjonsmålinger	Varmgang	Ser på datastrømmen															Ikke et problem så lenge det oppdages, kobles ut når det oppdages										
34																																				
35																																				
36																																				
37																																				

B Interview Guide

09.03.2022
Glencore Nikkelverk
Kristiansand

Interview guide

Purpose

The purpose of the interviews is to gather information and develop an understanding of the most common and serious failure modes and symptoms thereof for the chlorine compressors The results gathered will be used in an initial analysis of failure modes and be used in a master thesis at NTNU.

Content

Generally, the interview will focus on questions related to the failure modes and symptoms thereof for the chlorine compressors in the KL department at Glencore Nikkelverk.

Structure

The interviews are be semi-structured. The questions below is meant as a starting point for a discussion and the interview subjects are free to include any other information they may find meaningful.

Anonymity

The personal data of the interview subjects is guaranteed to not be shared. No personal information about the interview subjects will be used in the thesis and notes will be deleted after the thesis has been completed.

Questions

Q1: Which failure modes have the highest costs in terms of spare parts?

Q2: Which failure modes have the highest costs in terms of lost production?

Q3: Could you rank the mentioned failure modes in terms of frequency?

Q4: Regarding the mentioned failure modes, what is the root cause of these failures?

Q5: Regarding the mentioned failure modes, how are these detected? Are there any early signs of failure?

Q6: Is there anything else you would like to highlight?

NTNU
Norwegian University of Science and Technology

C Temperature Measurements - Mechanical Seals

Temperaturmåling akseltetning SIHI Klorkompressorer (ny type)

Pos. nr.	**2212A**				**2212I**						**2212J**					
Lokalisasjon på kompressor	DE	DE	NDE	NDE	DE	DE	DE	NDE	NDE	NDE	DE	DE	DE	NDE	NDE	NDE
Vannretning	Inn	Ut	Inn	Ut	Inn	Ut	differanse	Inn	Ut	differanse	Inn	Ut	differanse	Inn	Ut	differanse
28.03.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	19,8	23,2	3,4	15,2	19,8	4,6	18,6	21,0	2,4	12,7	15,3	2,6
29.03.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	20,7	23,0	2,3	15,0	20,0	5,0	19,1	20,8	1,7	14,3	15,5	1,2
30.03.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	19,2	22,1	2,9	15,2	19,6	4,4	18,5	19,8	1,3	14,1	15,4	1,3
31.03.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	19,5	22,3	2,8	15,0	19,5	4,5	18,2	19,6	1,4	14,0	15,4	1,4
01.04.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	19,3	22,9	3,6	14,7	19,5	4,8	18,1	19,9	1,8	13,3	15,9	2,6
02.04.2022																
03.04.2022																
04.04.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	19,1	22,5	3,4	14,3	19,2	4,9	18,0	19,8	1,8	13,6	15,8	2,2
05.04.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	19,6	23,1	3,5	14,8	19,1	4,3	18,3	19,9	1,6	13,7	15,8	2,1
06.04.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	18,9	21,9	3,0	14,9	18,6	3,7	17,7	19,1	1,4	13,7	15,5	1,8
07.04.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	18,6	21,8	3,2	14,7	19,0	4,3	17,8	19,3	1,5	13,8	15,2	1,4
08.04.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	18,9	21,7	2,8	14,7	19,3	4,6	17,7	19,6	1,9	13,1	15,5	2,4
09.04.2022																
10.04.2022																
11.04.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	18,8	21,5	2,7	14,5	19,2	4,7	17,8	19,6	1,8	14,0	15,5	1,5
12.04.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	19,3	21,4	2,1	15,4	19,7	4,3	17,4	19,1	1,7	12,8	14,7	1,9
13.04.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	19,0	21,3	2,3	15,1	19,5	4,4	17,1	18,9	1,8	13,0	14,6	1,6
14.04.2022																
15.04.2022																
16.04.2022																
17.04.2022																
18.04.2022																
19.04.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	19,1	21,1	2,0	15,2	19,6	4,4	17,4	19,3	1,9	13,8	15,2	1,4
20.04.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	19,5	21,3	1,8	15,4	19,7	4,3	17,3	19,3	2,0	14,1	15,2	1,1
21.04.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	19,4	21,6	2,2	15,9	19,7	3,8	17,6	19,5	1,9	14,4	15,5	1,1
22.04.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	19,8	21,9	2,1	16,2	19,9	3,7	18,2	19,8	1,6	14,7	15,8	1,1
23.04.2022																
24.04.2022																
25.04.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	21,5	25,2	3,7	17,0	20,9	3,9	19,8	20,8	1,0	15,4	16,3	0,9
26.04.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	20,8	24,8	4,0	16,9	20,2	3,3	19,5	21,0	1,5	15,0	14,8	0,2
27.04.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	21,1	22,8	1,7	16,9	20,9	4,0	19,9	20,7	0,8	15,2	15,6	0,4
28.04.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	21,0	22,5	1,5	16,1	21,0	4,9	19,8	20,6	0,8	14,7	16,2	1,5
29.04.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	20,5	23,0	2,5	15,9	21,3	5,4	19,8	20,7	0,9	14,8	16,5	1,7
30.04.2022																
01.05.2022																
02.05.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	20,4	22,8	2,4	16,0	20,8	4,8	19,6	20,5	0,9	15,2	16,2	1
03.05.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	20,7	23,1	2,4	15,5	21,1	5,6	19,0	20,0	1,0	15,3	16,2	0,9
04.05.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	21,0	23,7	2,7	15,8	21,5	5,7	19,5	20,6	1,1	14,5	15,7	1,2
05.05.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	20,8	23,2	2,4	16,0	21,5	5,5	19,1	20,4	1,3	14,8	16,2	1,4
06.05.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	21,1	23,2	2,1	16,2	21,5	5,3	19,3	20,6	1,3	15,2	16,4	1,2
07.05.2022																
08.05.2022																
09.05.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	21,5	23,8	2,3	16,5	21,9	5,4	19,5	21,0	1,5	15,1	16,5	1,4

10.05.2022																
11.05.2022																
12.05.2022																
13.05.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	22,2	25,1	2,9	17,3	22,6	5,3	20,3	21,8	1,5	15,2	16,9	1,7
14.05.2022																
15.05.2022																
16.05.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	23,3	27,1	3,8	18,6	23,4	4,8	21,0	22,5	1,5	15,6	17,5	1,9
17.05.2022																
18.05.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	23,3	27,4	4,1	18,7	23,4	4,7	21,2	22,4	1,2	15,5	17,5	2
19.05.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	23,7	27,9	4,2	18,9	23,7	4,8	21,5	22,6	1,1	15,8	17,9	2,1
20.05.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	23,9	28,3	4,4	19,0	24,2	5,2	21,4	23,1	1,7	16,5	18,2	1,7
21.05.2022																
22.05.2022																
23.05.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	24,3	29,0	4,7	19,4	25,1	5,7	21,7	24,2	2,5	18,2	19,5	1,3
24.05.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	24,3	29,1	4,8	19,6	25,3	5,7	21,7	24,6	2,9	18,5	19,6	1,1
25.05.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	24,5	29,3	4,8	19,9	25,6	5,7	21,9	24,8	2,9	18,7	19,8	1,1
26.05.2022																
27.05.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	24,7	29,5	4,8	19,8	25,7	5,9	21,8	25,0	3,2	19,1	20,1	1
28.05.2022																
29.05.2022																
30.05.2022																
31.05.2022																
01.06.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	24,9	29,8	4,9	19,9	25,9	6,0	22,2	25,2	3,0	19,2	21,3	2,1
02.06.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	25,0	29,8	4,8	20,1	25,9	5,8	22,4	25,5	3,1	19,4	21,5	2,1
03.06.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	25,0	29,9	4,9	20,4	26,2	5,8	22,5	25,7	3,2	20,0	21,4	1,4
04.06.2022																
05.06.2022																
06.06.2022																
07.06.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	25,2	30,1	4,9	20,5	26,4	5,9	22,6	25,9	3,3	20,3	21,8	1,5
08.06.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	25,2	30,0	4,8	20,6	26,4	5,8	22,8	25,9	3,1	20,7	21,9	1,2
09.06.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	25,5	30,0	4,5	20,9	26,7	5,8	22,9	26,2	3,3	20,9	22,0	1,1
10.06.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	25,3	29,8	4,5	20,6	26,8	6,2	22,8	26,0	3,2	20,8	22,1	1,3
11.06.2022																
12.06.2022																
13.06.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	25,5	29,9	4,4	20,8	26,9	6,1	23,0	26,3	3,3	20,8	21,8	1
14.06.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	25,9	30,2	4,3	21,2	27,2	6,0	23,2	26,5	3,3	21,1	21,6	0,5
15.06.2022	Ikke i drift	Ikke i drift	Ikke i drift	Ikke i drift	25,7	30,2	4,5	21,3	27,1	5,8	22,9	26,2	3,3	20,9	21,5	0,6
16.06.2022																
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