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An Integrated Approach towards Predictive Maintenance on Land Drilling Rigs

An Integrated Approach towards Predictive Maintenance on Land Drilling Rigs

By

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Master Thesis

in partial fulfilment of the requirements for the degree of

Master of Science
in Mechanical Engineering

at the Department Maritime and Transport Technology of the Faculty Mechanical Engineering of Delft University of Technology
to be defended publicly on Thursday April 25th, 2024 at 9:30 AM

Cover image: Huisman LOC400 in Delft (Image from Huisman Geo)

Student number:	4602781	
MSc track:	Multi-Machine Engineering	
Report number:	2024.MME.8912	
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Preface

Over a year ago, I was introduced to geothermal drilling for the first time. Although I initially knew little about drilling rigs, I quickly became deeply impressed by the technological advancements in this industry. Simultaneously I recognised the big challenges that this industry still faces during drilling of geothermal wells. Solving these is important, since I believe geothermal energy is a crucial part of the energy transition. I hope that my research can contribute to improving the complex drilling process, ultimately making geothermal energy more accessible. It has been a remarkable journey for me, and I am thankful for the growth and development it has brought me.

This research project was conducted for Huisman Geo. I am very grateful I could do my work here since I was able to learn everything there is to know about drilling in a very short time. Especially I want to thank Leroy Holwerda, Fons Smeets and David Cruickshank for sharing their knowledge and offering me insights about drilling equipment. During my field research in Delft, I was fortunate to experience a geothermal drilling project up close. At the site in Delft, I learned a lot from the Vanguard Drilling crew members. I would like to thank them for sharing their experience and answering all my questions. Overall, everyone at Huisman Geo contributed to providing a great workplace environment for me to finish my research.
In addition I would like to thank the members of my graduation committee, Dingena Schott and Yusong Pang, for their valuable feedback during the meetings we had. Especially the dedicated supervision of Yusong throughout my thesis has helped me to bring the research to a successful conclusion.

The completion of this thesis marks the end of my time as a mechanical engineering student in Delft. During this time, many of my fellow students have become my friends, and they have supported me continuously during the many exams and projects in the past years. They also managed to guide me through difficult phases in my graduation project, even when most of them were busy with their own graduation. Therefore I want to thank all my friends and roommates for their great support.
Last but not least, I want to thank my loving family for their boundless encouragement. Even though they may not have been fully aware of all technical details, they still were able to support me through my work.

Concluding, I am very thankful to complete my time at the Delft University of Technology with this work. I hope that this thesis provides you new insights and I wish you an enjoyable reading experience.

Job Oldenhuis
Delft, April 2024

Summary

Research background

Land drilling rigs are complex machinery carrying out heavy operations, in an industry subject to high standards and requirements, where costs can run high during equipment downtime. Smooth progress during drilling operations is essential in this business, therefore rig operators try to maximise equipment uptime during a project. One of the main challenges towards achieving this, is to implement efficient maintenance on a drilling rig. Currently, poor decision-making methods and too generic maintenance routines are still prominently contributing to ineffective maintenance on drilling rigs, consequently leading to more rig downtime.

Recent digitisation of the drilling industry seems to have opened the doors for advanced maintenance on drilling rig. There is widespread believe that data can be used to achieve informed maintenance decision-making on drilling rigs to maximise rig uptime. Modern research is focused on finding advanced maintenance methods for individual drilling rig components, using artificial intelligence (AI) and other modern technologies. However, installing multiple dedicated maintenance systems on various locations within a drilling rig can increase the complexity for operators. Despite this realisation, there remains a lack of solutions that provide an integrated approach for drilling rig maintenance. There is a perception that such an approach could enhance maintenance effectiveness in the industry.

Research scope

This research is aimed to develop a strategy that can be used to integrate advanced maintenance of drilling rig components at a system level. The main deliverable is a method to develop a model that can ultimately generate real-time advanced maintenance actions for the whole drilling rig. For this purpose, it uses real-time available data on a land drilling rig combined with additional condition monitoring (CM) methods. The main research question at stake is:

How to achieve integrated maintenance for a drilling rig in a model making advanced maintenance decisions on system level, based on real-time data?

Objectives towards answering the main research question are: understanding the complete functioning of a land drilling rig, determining the optimum maintenance strategy, establishing a framework for the model, providing methods for the functions in the model based on available data and finally developing the model so it can be used in a case study.

Research approach

Three phases can be distinguished in the approach of this research, namely the literature study, field research and model development.

In the literature study, first the process of land drilling was explored. The state-of-the-art technology comprising the key components within the five subsystems of a drilling rig is discussed. It can be concluded that since they are involved in all operations, failure of one component will inevitably lead to rig downtime. Conventional reactive and preventive maintenance policies are currently being adopted on drilling rigs, where maintenance actions are grouped in a predetermined schedule. This brings various risks that can eventually lead to excessive maintenance and decrease of drilling rig reliability. However, to increase the rig uptime, the availability of the system should be maximised. It is concluded that a predictive maintenance (PdM) strategy is the best option, using CM to ensure components receive maintenance based on their actual, individual degradation.

After surveying methods for system modelling, a multi-agent system framework is composed to combine PdM of components with decision-making on system level. In this framework, three levels of agents are proposed, were the top level is a centralised system agent making decisions based on information from the subordinate agents. The architecture of the model is designed by first determining the functions of the agents in the framework. Then, appropriate methods to complete these functions are identified and applied. For this matter, the available data on a land drilling rig is analysed.

The field research is conducted during an actual drilling project, involving drilling of two geothermal wells by a containerised rig. Data acquired during this project is assumed to be the general standard of available data for a land drilling rig operator. To gain CM data, sensors are setup on one of the five mud pumps of the rig to measure vibrations in the fluid end. Combined with maintenance records from the same project, this data will be used to develop a PdM module for the mud pump valves in order to partially validate the developed model.

The model is developed starting from the lowest level in the model architecture, the data agents. They are responsible for selection of relevant parameters and preprocessing. For real-time data extraction from a rig SCADA system, API software is proposed. High-pass and Wiener filters are applied to process raw mud pump vibration signals into clean data, ready for further analysis.

Component agents are responsible for assessing the operational status and predicting failure of the dedicated components. A rule-based system is designed to analyse relevant SCADA parameters that determine whether the component is in drilling operation. To predict failure of the components, a survival analysis is conducted, with maintenance records serving as statistical basis. For a dynamic prediction of failure, the Weibull AFT model is introduced, with real-time component deterioration as a covariate. To assess this deterioration, dimensionless signal features are selected from the acquired mud pump vibration data and used in a FL classifier. The FL classifier is validated to rightfully identify degrading components based on the maintenance records. For development of the Weibull AFT model, a dataset is constructed by adding component health conditions to the entries in the maintenance records. Finally, the system agent is developed to classify the drilling rig operational state and uses an expert reasoning system for generation of maintenance actions, focusing on minimising disruption of operations.

To finalise the research, a case study is set up using historical data from the drilling project in combination with artificially induced mud pump failures to partially validate the model and provide proof of concept for the proposed methodology.

Research conclusion

The case study results showed the model gives adequate failure prediction for the mud pump valves during actual operations. Sparsity of the maintenance records resulted in shortcoming when predicting early-life valve failure, however this problem can be tackled fairly easily. Overall, it is argued that the model has a threefold effect on the increase of drilling rig uptime. First, the risk of sudden downtime is reduced since failure prediction based on real-time data can be achieved. Second, the provided method resulted in 93% lifetime utilisation of the components, avoiding excessive maintenance. Third, the resulting maintenance windows give sufficient opportunity for the system agent to plan forthcoming maintenance actions together, limiting disturbance of drilling operations.

This thesis sets a promising step towards PdM of land drilling rigs, and gives options to further expand the integrated approach to maintenance decision-making. Despite the scarcity and mediocre quality of available real-world data applied in this thesis, the results present a positive outlook. A field validation using continuous CM is suggested to give access to additional methods and to reach higher accuracy of the proposed model. Further steps are integration of other component agents into the developed model for eventual implementation in practice. A final recommendation is research towards utilising the model in DT technology, to stimulate advanced use of data in the drilling industry.

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Nomenclature

Abbreviation	Definition
AFT	Accelerated Failure Time
AI	Artificial Intelligence
API	Application Programming Interface
BHA	Bottomhole Assembly
BOP	Blow-Out Preventer
CBM	Condition-Based Maintenance
CM	Condition Monitoring
CPS	Cyber-Physical System
DT	Digital Twin
EPU	Electrical Power Unit
FL	Fuzzy Logic
FMECA	Failure Mode, Effect and Criticality Analysis
HPU	Hydraulic Power Unit
IoT	Internet of Things
MAS	Multi-Agent Systems
ML	Machine Learning
NPT	Non-Productive Time
OM	Opportunistic Maintenance
PdM	Predictive Maintenance
PM	Preventive Maintenance
RBS	Rule-Based System
RUL	Remaining Useful Life
RSS	Rotary Steerable System
SCADA	Supervisory Control And Data Acquisition
SCR	Silicon Controlled Rectifier
VFD	Variable Frequency Drive
WOB	Weight On Bit

Symbol	Unit	Definition
$S(t)$		Survival probability function
x_{HC}		Health condition covariate
τ		Unacceptable survival probability threshold
T_L	hours	Component lifetime
UF		Lifetime utilisation factor

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Introduction

1.1. Research background

To extract gas and liquids from reservoirs deep in the earth core, the fundamental task is straightforward: dig a well into the ground until the reservoir is reached. From the 1850s, the drilling industry began to emerge in order to produce oil and gas [1]. In that time some important technologies for the drilling industry have been developed, in the so-called “Second Industrial Revolution”. These technologies still form the essence of the current drilling industry and have created the base for modern drilling rigs. Over the last years, modern rigs are now also being deployed to drill wells for geothermal energy, which will play a crucial role in the upcoming energy transition.

1.1.1. Drilling rigs and the drilling process

The built structure and equipment necessary for the drilling of a well is referred to as a drilling rig. Drilling rigs can be modular, mobile systems suited for transport, or fixed structures located either on land or on sea. Oil platforms, for instance, are large fixed drilling rigs which can contain other facilities as well to adapt to their remote location, like living quarters or process modules. Drilling rigs take many shapes depending on the type of project and the environment of the project, however the common principle of drilling is the same for all of the deep drilling rigs. The main components and systems on all types of drilling rigs are comparable with those on other rigs. Refer to Figure 1.1 & 1.2 for two examples of drilling rigs operating in different environments but still accommodating the same kind of components.

The fundamental technique that these drilling rigs utilise is called “rotary drilling”. By rotating a drillbit while applying a downward force on the bit, a hole is drilled [2]. To achieve rotary drilling, a drillstring is rotated at surface level by the drilling rig. A drillstring is a series of joined steel tubes, drillpipes, with a durable drillbit at the down end [3]. Drilling rigs therefore also provide tools to connect and disconnect the large, heavy drillpipes and to lift the drillstring out of the hole as well.

While the art of drilling can be described as if it is relatively simple, in practice it often is a very difficult process. As the depth of the wellbore can reach up to 6000 metres, it may encounter different rock formations, leading to increasingly harsh conditions. This results in an increase of factors such as temperature, pressure and stress on the equipment in the hole. Drilling rigs are equipped with a system to monitor and control the conditions down the hole. They circulate a drilling fluid, or simply “mud”, to cool and lubricate the drillbit whilst also keeping adequate stability of the hole.

During drilling, trapped reservoirs of high-pressure fluids and gasses can possibly be encountered. This presents the risk of a sudden pressure change in the hole that can cause the fluids and gasses to shoot out of the hole at the surface. Well control equipment is hence essential on a drilling rig.

It becomes clear that a drilling rig accommodates multiple complex systems to execute heavy operations. If one of these subsystems fails, this brings drilling operations to an immediate halt, since a rig can not operate without one of them. Operating a drilling rig involves expertise of hydraulic, mechanical and electrical engineering as well as a deep understanding of geology and rheology. The drilling industry can be described as a melting pot of multiple disciplines continuously striving to improve drilling operations.

Figure 1.1: The “Transocean Spitsbergen”, a semi-submersible drilling rig capable of drilling at a water depth of 3 kilometres. (Image from Equinor / Kenneth Engelsvold)

Figure 1.2: The Huisman LOC400 mobile land drilling rig. It has a relatively small footprint and features automated drilling systems. (Image from Huisman Equipment)

1.1.2. Maintenance in the drilling industry

One of the challenges in the drilling industry is implementing efficient maintenance on a drilling rig. Obviously, maintenance is an essential aspect of the operations of drilling rigs. An adequate maintenance program is necessary to achieve a high reliability of the rig and, most importantly, have an excellent safety performance [4]. The drilling industry has been plagued with higher than average safety issues [5]. In their literature review, Asad et al. [6] treat numerous accidents in the oil and gas industries from 2000 till 2018 with serious consequences for workers on the involved rigs, concluding that oil and gas drilling operations are three times more hazardous than the construction industry. They add that there is no difference in hazard during onshore and offshore drilling operations. Other reasons for the need of an appropriate maintenance strategy are to sustain compliance to standards and requirements, increase the life of the equipment and increase uptime of the rig [7]. It can be concluded that, based on these reasons, keeping a high standard of maintenance will eventually also save costs in the long run. These financial costs are mostly associated with downtime, commonly referred to as NPT (Non-Productive Time), and can run high in short notice. For instance, NPT caused by equipment failure down the borehole can cost between 100 thousand and 1 million dollars per day [8]. In offshore drilling, NPT can cause rig owners to lose their operating rate income of 450 thousand dollars per day. Smooth progress during drilling operations is essential in this business, therefore reliable rigs are required to maximise uptime [9]. However, incorrect performance of maintenance is still a prominent problem in the drilling industry [10–12].

1.2. Research problem

Despite the importance of reliable drilling rigs, in practice the reliability can still be considered quite low. The majority of accidents and financial losses in the oil and gas drilling industry are caused by equipment failure and human error [10, 11]. Tang et al. [11] mention that ineffective decision-making methods partially contribute to poor maintenance on drilling rigs. This can be substantiated by the findings of Shaipov [12], who observed that poor maintenance routines were an issue for offshore personnel performing maintenance on the valves on a drilling rig. Unclear and “too generic” maintenance procedures contributed to a higher failure rate of these valves. In different drilling environments the same problem is noticeable. A case study on the downtime during the drilling of nine geothermal wells in Kenya identified that equipment failure due to poor maintenance had the highest occurrence [13].

1.2.1. Research gap

In the field of research, there is widespread belief that the recent digitisation of the drilling industry can unlock the full potential of maintenance using data. In the current days, data can be used to achieve informed decision making based on insight, knowledge and forecasting [14–19]. Through literature research it can be found that on component level there are multiple recent examples of advanced maintenance methods using Internet of Things (IoT), Artificial Intelligence (AI) or other modern tech-

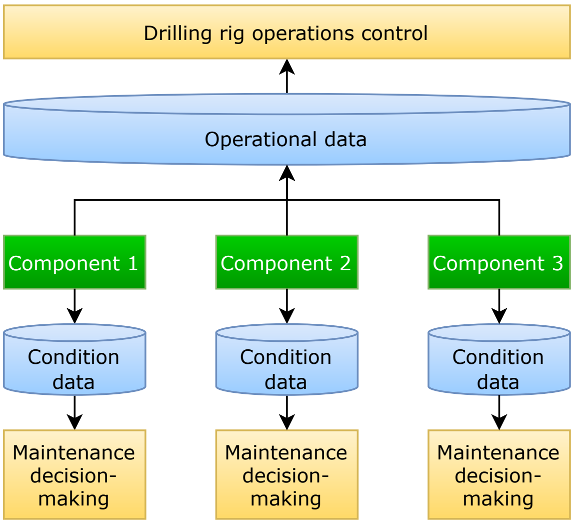


Figure 1.3: Current situation: maintenance strategies are on component level, system operations are not taken into account.

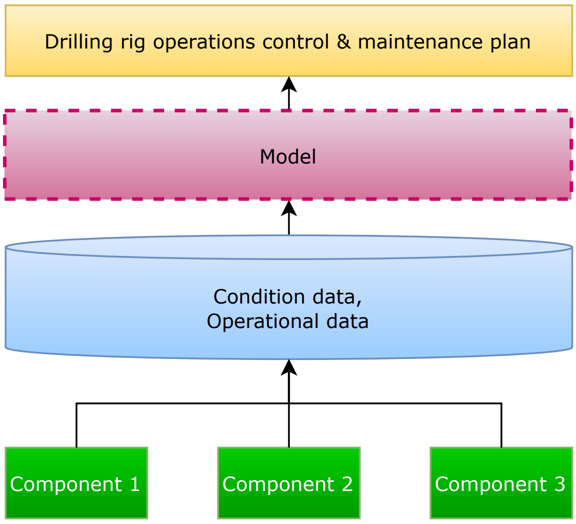


Figure 1.4: Desired situation: data is analysed in a single model, maintenance decisions are integrated in the system control

nologies to increase uptime. However, given the complexity of a drilling rig, it may be hard to effectively apply advanced maintenance on the whole drilling rig. It would now require to separately apply proven advanced maintenance strategies on component level, which on itself can be a quite inefficient process. If individual component maintenance strategies are applied, it could pose the problem of data fragmentation: each strategy will probably store and analyse its data using different systems and methods. Moreover, maintaining components with various different systems and methods will possibly increase the complexity of operations on a drilling rig. An integrated maintenance strategy that provides a holistic view of the rig's health condition and operations to suggest maintenance actions is more desirable. This challenge is also recognised in the broader field of maintenance optimisation research [20, 21]. It is simultaneously acknowledged that system level strategies would require prognostics of all components, but in practice, this is often not possible [21, 22]. However, these references do provide solutions towards this problem. To the author's knowledge, no efforts have been made to find a solution for a drilling rig system yet. Therefore, there is a need to research how to shift the approach of drilling rig maintenance from Figure 1.3 to Figure 1.4.

This is where the research gap can be exposed. Currently, there is a lack of integrated maintenance methods for drilling rigs. Research on advanced drilling rig maintenance focuses on component level and does not consider a holistic approach to rig maintenance. As described above, there is need for a link between the maintenance strategy on component level and the overall drilling rig operations. A complex structure consisting of critical components calls for a balanced and integrated maintenance strategy.

1.2.2. Advanced maintenance

In the research gap statement, the term "advanced maintenance" is introduced. Recognising that this term may not be immediately clear, a precise definition is provided here, since it is an important term in the thesis's goal.

When surveying the mention of "advanced maintenance" in literature, some other terms can be found in the context as well, such as "data-driven", "condition monitoring", "analytics", "Industry 4.0" and "systems". These terms all point to the definition of advanced maintenance. Advanced maintenance steps away from conventional maintenance techniques that schedule maintenance based on average failure rates or after a breakdown. Because in advanced maintenance, data is used to determine the best moment for maintenance. This data may come from condition monitoring (CM) techniques or from historical records. Data analytics in a maintenance system are used to determine the maintenance moments, which may be updated based on new data. New technologies like IoT and AI, which are becoming more available in so-called Industry 4.0, can be utilised in these systems.

So, advanced maintenance can be defined as using data techniques, possibly in a dedicated system, to determine the best moment for maintenance.

1.3. Research scope

This thesis aims to develop a strategy that can be used to integrate advanced maintenance of drilling rig components at a system level. More specifically, the main result of this thesis will therefore be a method for the integration of already available operational data with additional CM methods in a single model that generates maintenance actions for a drilling rig. This will require the selection and application of appropriate algorithms to achieve real-time maintenance decision-making. To validate the methodology, this model will be partially implemented in a CM case study on the mud pump valve system of a drilling rig.

1.3.1. Research objectives

In order to successfully develop an integrated maintenance strategy, various research objectives can be defined. First, it is necessary to gain a thorough understanding of the vital components in the operations of a drilling rig. Secondly, based on the failure properties of these components, the optimum maintenance policy for a drilling rig has to be determined. Third, a method for integrating component-level data into system-level decision-making needs to be identified before developing the model.

Subsequently, the main objective of this research can be achieved, which the development of a model that can realise an advanced maintenance strategy for a drilling rig system based on data from the components. The desired outline of the integrated decision-making process in the final model is depicted in Figure 1.5. Eventually the model should take the shape of an automated virtual model of a drilling rig, capable of recognising the rig's operating state and assessing the health condition of the components and generating maintenance actions based on this data.

The final objective of this research is to partially validate the model and assess the effect of implementation on the uptime of a drilling rig.

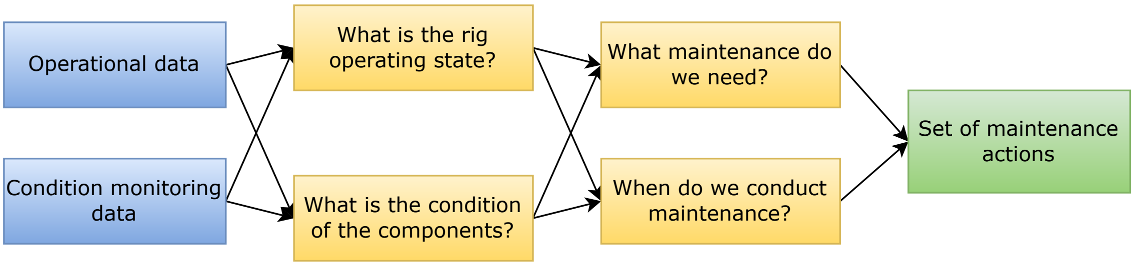


Figure 1.5: Objective of the thesis: decision-making process of the model

1.3.2. Research questions

The main research question of this thesis is:

How to achieve integrated maintenance for a drilling rig in a model making advanced maintenance decisions on system level, based on real-time data?

Research questions in this research to find the answer to the main research question are:

RQ1. How are the core components of a drilling rig involved in the drilling process?
RQ2. What is the best strategy for maintenance on the components of a drilling rig?
RQ3. What is an applicable framework for the integration of component-level maintenance into a system-level decision-making model?
RQ4. How can appropriate methods be applied in the model to utilise available drilling rig data for condition assessment and generation of maintenance decisions?
RQ5. To what extent can implementation of this model in practice improve the uptime of a drilling rig?

1.3.3. Assumptions and boundaries

For the development of the system level model methodology, a land drilling rig will be analysed for several reasons. First, a land drilling rig has the benefit of space and environment. Looking at this type of rigs can make it easier to visualise the system hierarchy for drilling operations [23]. Second, offshore rigs typically contain complex layouts and generally include product processing modules and safety equipment for the (deep)sea environment. This can make it more challenging to identify and isolate the equipment necessary for drilling. Finally, the mud pumps that serve as a case study in this research are part of a geothermal drilling rig, which is a land drilling rig. For drilling operations onshore and offshore rigs fundamentally use the same equipment and procedures. Consequently, regarding the outcome of this thesis, it will be relatively easy to adapt on offshore rigs.

The maintenance of parts of the Bottomhole Assembly (BHA), like the drillbit, Rotary Steerable System (RSS) or other types of mud motors is not taken into account. The reason behind this choice will be be elaborated in section 2.3. This section will state why they are not considered to have effect on the reliability of a drilling rig system.

Data availability for this rig is assumed to be real-time operational data and real-time online CM data. This means there should be an accessible CM method available for key components in the drilling rig that is proven to work. Through previous literature research, this assumption can be substantiated, since for the main components in the drilling rig various CM solutions have been validated [24].

It has to be acknowledged that due to limitations in time and resources, the methodology can only be validated partly. The mud pump valves, located in the fluid end of the mud pump, will be modelled according to the proposed methodology to serve as a case study. It is assumed that implementing the methodology on other parts of the drilling rig will yield about the same results in terms of effectiveness for maintenance. However, this also means it will not be possible to actually generate a complete maintenance scheduling for the rig, but it will only be possible to reason how the maintenance will be improved and how the uptime will increase.

1.4. Research approach

In order to find an answer to the research questions, the research consists out of multiple phases using different methodologies. The first phase is the literature review. The objective of the literature review is to gather a thorough understanding of drilling operations, maintenance theory and system modelling. These three fields of knowledge are merged to establish a framework for the maintenance model. The outcome of the literature review will provide the answers to RQ1-3 and can be used in a later stage to assist in finding appropriate methods for the model.

The second phase is a field research, which is being conducted concurrently with the literature review. In the context of this thesis, vibration signal data is gathered by placement of sensors on a mud pump's fluid end that is in operation during a drilling project. Combined with logged operational data from the drilling rig SCADA (Supervisory Control And Data Acquisition) system and mud pump maintenance records, data is acquired to use in the development of the model. However, the field research also contributes to gaining knowledge about signal processing for use in a failure diagnosis system. More importantly, this field research gives crucial insights into the actual operations during a drilling project, enhancing understanding about the drilling rig as a system and exposing opportunities for maintenance improvement. Finally, experiences from the field research can help in the discussion of the results of this thesis.

In the third phase of the research, the proposed model is developed and (partially) validated. The methods applied in the model are validated individually using the acquired data, where the methods providing diagnostics and prognostics are validated for the mud pumps only. Then, the historical op-

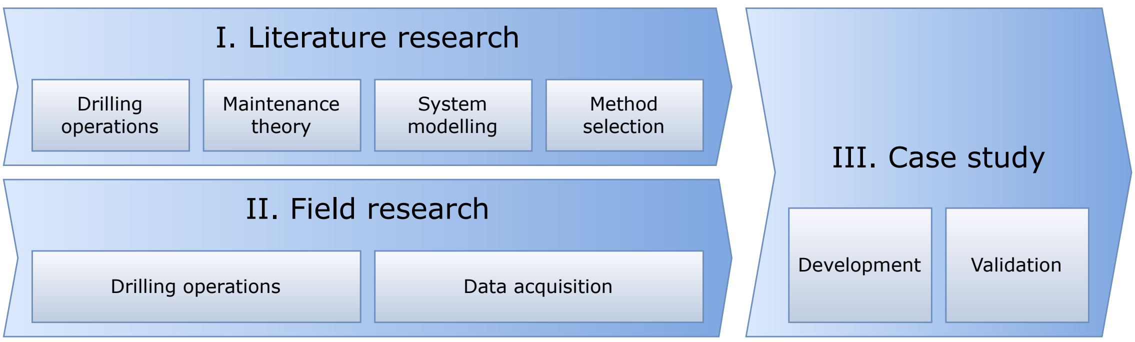


Figure 1.6: Diagram illustrating the three phases of the research, with the main activities highlighted for each phase.

erational data is merged with synthetic failure data sets to validate and test the effectiveness of the complete model in various different cases of simulated mud pump failure. The accuracy of upcoming failure prediction will serve as performance indicator to test the improvement of the drilling rig maintenance and uptime. Finalising this phase will answer the last two remaining research questions, RQ4-5.

1.5. Thesis outline

This thesis is divided in three parts. Part I of this thesis will cover the literature review. First, an equipment analysis in chapter 2 identifies the core components of a land drilling rig. These components will form part of a system tree that represents the overall structure of a drilling rig. The involvement of these components in the main drilling procedures is explored as well, answering RQ1. This chapter will conclude by giving the common failure modes of the components in preparation for development of an adequate maintenance approach. Secondly, the field of maintenance methods will be explored to find the optimum maintenance policy for a drilling rig in chapter 3, addressing RQ2. For this purpose, different maintenance concepts will be explained and classified in a maintenance overview. The third and final chapter in this part is chapter 4, where methods for the modelling of complex systems will be surveyed to find an applicable approach for integrated maintenance. In this chapter it will be explored what the key characteristics of these methods are and they will be applied to form a framework of the model, to conclude RQ3.

Part II of the research will focus on the design and development of the model, also including validation. In chapter 5 the desired functions in the model are identified. To find appropriate methods to realise these functions, generally available data on a land drilling rig is analysed. Based on characteristics of this data, the framework model will be used to select and design the methods. These methods are applied and validated individually in chapter 6 to proof they are useful and appropriate for the desired model. For validation, data acquired during the field research is utilised, therefore this chapter also provides information about how the field research was conducted. By the end of this chapter, the developed model is finished and RQ4 can be answered. Finally, in chapter 7 implementation of the complete model is partially validated with a case study, using real historical data combined with simulated component failure. The case study goal and design is elaborated and the simulation results are provided in order to form a conclusion on RQ5.

The final part of this thesis is chapter 8, where the developed model and the overall research are reviewed. The conclusion will provide answers to all research questions, highlighting the main contributions of this research and suggesting directions for future research based on limitations of this work.

I

Literature Research

2
Equipment analysis

This chapter will elaborate on the equipment of interest in this research, a land drilling rig. A closer look will be taken at the components of a land drilling rig to explore how they are involved in drilling operations, in order to address RQ1.

Basically, the operations of a land drilling rig are quite simple. A drillbit at the end of a long series of joined pipes, the drillstring [3], is rotated for the purpose of creating a well. During this rotation, a downward force is applied to the drillbit as well in order to penetrate the rock [2]. To withstand the high pressure and loads in the borehole, drill pipes in a drillstring are usually made out of steel or aluminium alloys. The combined weight of these pipes can be several hundreds metric tonnes, which has to be lifted by the drilling rig. The drillstring can be extended by joining a new pipe at the surface level and threading them together with sufficient torque. When the drillstring is pulled out of the hole, this process reverses and the drill pipes are disconnected at the surface. Drilling operations are 24/7 and can take up to a couple of months. A drilling rig must be able to carry out these continuous, heavy operations in a precise and safe manner.

2.1. Drilling rig subsystems

Arnaout et al. [25] divide the functionality of a drilling rig in three main sub-systems: the rotary, circulation and hoisting systems. Hilmawan and Basri [26] describe two more sub-systems: a blowout prevention (BOP) system and a power supply system. An overview of the subsystems can be found in Figure 2.1. These five systems are in continuous operations during the drilling process. A drilling rig will no longer function properly if one of these systems happens to experience a failure. In random order, each subsystem will now be analysed in detail to explore the involved components.

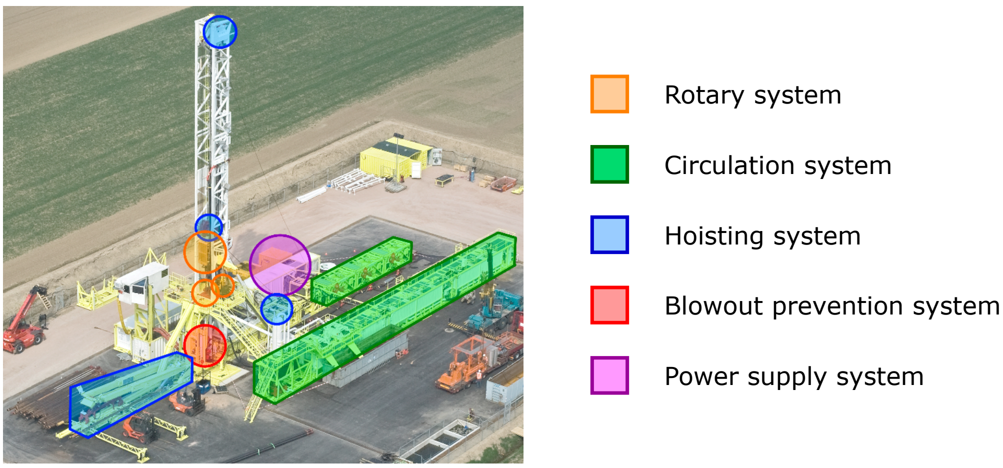
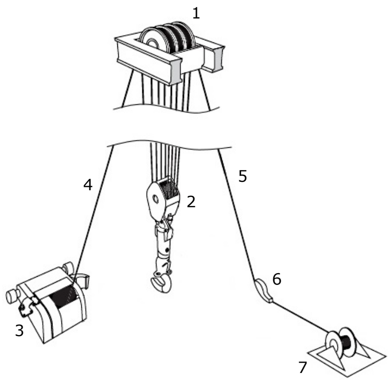


Figure 2.1: The five subsystems on a drilling rig system, the typical locations on the rig are highlighted (Image from Huisman Equipment)



1. Crownblock
2. Travelling block
3. Drawworks
4. Fast line
5. Dead line
6. Dead line anchor
7. Reserve drum

Figure 2.2: Schematic overview of components in a hoisting system
(Image based on https://ngelmumigas.files.wordpress.com/2010/11/hoist.png)

2.2. Hoisting system

To facilitate the lifting and lowering of drill string and other necessary equipment in and out of the wellbore, drilling rigs are equipped with a hoisting system (see Figure 2.2).

The most visible part of the hoisting system is the derrick, or mast, which holds most of the equipment. The height of the derrick determines the length of new drill pipe that can be connected to the drillstring. Therefore, taller derricks can be needed to save time while drilling deeper wells [23]. Derricks are built to withstand external compressive loads and wind loads. The derrick is usually elevated by a substructure to provide space for the BOP system under the rig floor [2]. A derrick is a static steel structure and will therefore not be involved in the maintenance strategy. However, it is important to note that they require a safe design according to standards.

The crown block is located in the top of the derrick. The travelling block is suspended from the clown block by wireline and a series of pulleys, to provide a mechanical advantage. The top drive is attached to this travelling block [2]. Additionally, the pipe elevators can be attached to the travelling block but generally they are connected directly to the top drive system. The wireline is hoisted by the drawworks. The fast line runs from the drawworks to the first pulley on the crown block. The dead line runs from the last pulley of the crown block to the reserve drum. The reserve drum acts as a wire storage, as the drawworks drum can not fit all the wireline in the system. The dead line anchor has a load indicator, measuring the weight on bit (WOB), which is a critical parameter in drilling operations [23].

2.2.1. Drawworks

The drawworks, depicted in Figure 2.3, can be considered as a heavy duty hoist winch and is the key component in the hoisting system. Drawworks are powered by AC or DC drive systems and may contain a gear system to adequately transfer power to the winch. Dual drum drawworks drive two winches at each side of the drill lines. To illustrate this principle, referring to Figure 2.2, the reserve drum is driven as well. This offers various advantages like redundancy of the winches, reduced wire speed and improved efficiency. Some of these dual drum systems run the same line back and forth on the winches. This allows for transferring of the wire: each part of the wireline will then get used during drilling operations, strongly reducing overall fatigue stress on the wireline.

The brake system is an important component in the drawworks. It assists in safe control of the travelling block's movement. Drawworks typically use two different brakes for this purpose. The main brake, or stationary brake, is used to stop the winch and hold the wireline. Where older rigs used band brakes, hydraulic disc-brakes are currently more commonly used. The main brake should be redundant as in case of failure there should always be a possibility for emergency braking. Auxiliary brakes control the descent rate of the travelling block and can therefore be referred to as dynamic brakes. These brakes are mostly integrated in the drive motor of the winch. Since modern drawworks are based around the drive motors and these engage full torque at zero speed, they can also be used to hold the wireline. Therefore in practice the main brake is rather used as a parking brake when the travelling block needs to be held for a longer time (e.g. more than 20 minutes).

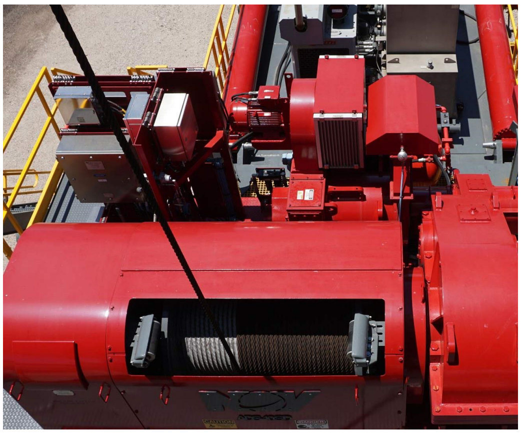


Figure 2.3: This drawworks is driven by two motors and has a rating of 1800 horsepower. (Image from NOV)

Figure 2.4: A horizontal to vertical pipe handling system. (Image from Huisman Equipment)

2.2.2. Pipe handler

In the trend of automation, efforts have been made to reduce the amount of intensive manual operations on a drilling rig and thus increasing the safety of drillers. The goal of these automated, supporting systems is mainly to aim for hands-free pipe handling [27, 28]. Pipe handling and -racking machines can provide the lifting and movement of drill pipe on the rig floor, from the pipe rack to the top drive for connection. There are various types of pipe handling machines as described by Reid [27], depending on the dimensions of the derrick and the drillfloor and if the pipes are oriented horizontally or vertically (see Figure 2.4 for an example). It is consequently hard to describe the typical pipe handler, but it will essentially consist out of hydraulic grippers to hold the pipe and a hydraulic extending arm structure to move the pipe above the drillhole. If the pipes need to horizontally move over to the rig floor, a trolley system might provide this travelling motion.

2.3. Rotary system

The system that provides torque for the rotation of the drillstring and drillbit is called the rotary system. Simpson [23] states that for vertical wells the rotation of a drillstring at surface level is sufficient for a reliable and reproducible result. However, when the target is not vertically directly under the drilling rig, rotation from the surface is getting more difficult. In those cases rotation of the drillbit is additionally achieved down the wellbore. Mud motors or RSS are examples of downhole rotary equipment. This section will elaborate on these downhole tools and clarify why they will be left out of scope. The surface level rotary system on a drilling rig mainly consists of a top drive and most drilling rigs are also still fitted with a rotary table too. Additionally, a iron roughneck provides torque on the rig floor for the (dis)connection of drill pipes.

2.3.1. Top drive

A top drive is the primary component in the rotary system and is attached on the travelling block, moving vertically up and down the derrick. Drill pipe is attached directly to the top drive, which then provides torque with an electrical or hydraulic motor. A top drive system also includes components to provide torque for the connection, lift drill pipe up the derrick and provide passage for the drilling fluid. Although it is a complex and quite expensive setup, a top drive can offer great efficiency because it allows to consistently connect large stands of drill pipe. When using a top drive the length of new drill pipe is only limited by the vertical clearance between the rig floor and the bottom of the top drive, which can be raised to the top of the derrick [29]. As Simpson [23] explains, it can result in up to 4 times less connecting actions necessary during drilling compared to the old kelly and rotary table system. Top drives were introduced in 1982, and are considered as essential equipment since the mid 90s [30].

In a top drive, three subsystems can be identified (see Figure 2.5). The primary subsystem is the drivetrain or power swivel, mainly consisting out of multiple motors. The torque and speed of these motors is translated to the rotating head of the top drive by a gearbox. This gearbox can regulate the torque and speed necessary for the drilling phase. The pipe handling subsystem consists out of multiple components. The pipe elevator is suspended under the top drive by the elevator links. The elevator

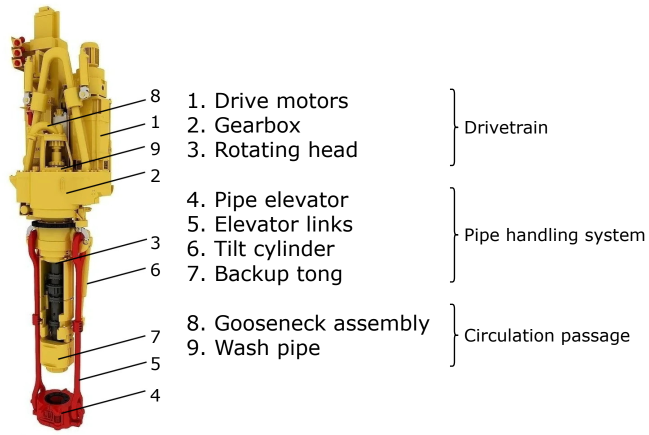


Figure 2.5: Overview of key components in a top drive system.
(Image from lakepetro.com, based on [31] and https://sc04.alicdn.com/kf/HTB1dnx6b7xz61VjSZFrq6xeLFXaO.jpg)

consists out of a clamp that holds the top of a drill pipe. The drill pipe can then be lifted vertically in the derrick, above the rotary table. Hydraulic tilt cylinders can control the position of the elevator, either to reach or move away from the drill pipe. Finally, the top drive has a gooseneck assembly, which can be connected to the drilling fluid circulation system. The wash pipe connects the static gooseneck with the rotating pipe and seals the high-pressure fluid. These components allow for the circulation of drilling fluid through the drillpipe (see section 2.4).

2.3.2. Rotary table

For many decades all drilling was done by rotary table rigs [23]. A kelly bushing would function as a mechanical adapter between the rotary table and the kelly, a square or hexagonal cross-section pipe, to enable rotation of the drillstring. Now that land drilling rigs are equipped with top drive systems, rotary tables are no longer needed to provide torque. However, most rigs will still have a rotary table fitted with a master bushing and slips system [23]. Slips are necessary to support the weight of the drillstring in the well when the latter is disconnected from the top drive. Traditional slips are wedge-shaped devices that are placed in the opening of the master bushing by floor workers. In this opening, they have inserts to provide enough grip to hold the drillpipe in place. After making or breaking the connection, the slips have to be removed from the rotary table. Gradually, they are being replaced by power slips, a modern automated version integrated in a rotary table (see Figure 2.6 for an example). Power slips use hydraulic power to close the opening around the drill pipe and to hold it in place.

2.3.3. Iron roughneck

Iron roughnecks are machines that can automatically connect and disconnect drill pipe, a process that used to be done by rig workers with the use of chains, tong wrenches and brute force. These systems therefore not only make the connection process smoother, they also eliminate the danger of fast swinging tools on the rig floor, drastically improving safety [27]. Only the name reminds of the heavy human operation they now take over: rig workers that manually connect and disconnect the drill pipe are called roughnecks. As can be seen in Figure 2.7, an iron roughneck is a combination of automated spinning wrenches and clamping jaws. The lower jaw provides enough torque to hold the drillstring while the spinning wrenches screw the new drillpipe on the string. Then, the upper jaw clamps the pipe and slightly rotates to tighten the threaded connection with sufficient torque. Iron roughnecks are generally powered by hydraulics.

2.3.4. Bottomhole assembly

The drillbit is located at the very end of the drillstring and is usually connected with stabiliser pipes. There are various drillbits suited for the various conditions in the hole, this means the drillbit is changed a couple of times during the drilling project. The drillbit, stabilisers, tracking devices and other equipment used down the hole is all part of the BHA. In the last few years, the BHA is playing a critical role in directional drilling.

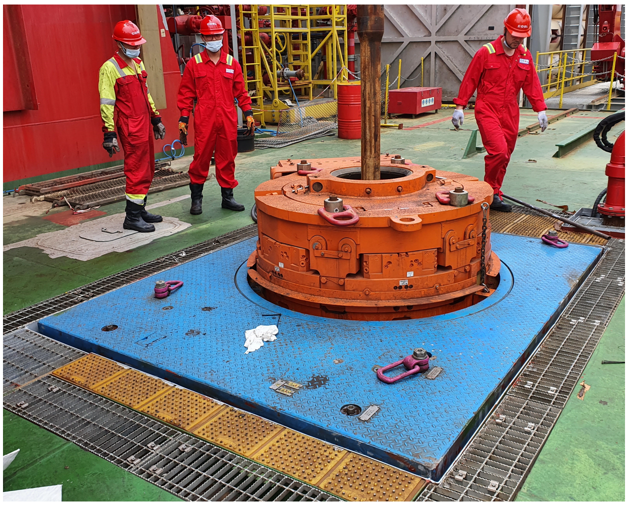


Figure 2.6: Offshore rotary table with power slips. (Image from Huisman Equipment)

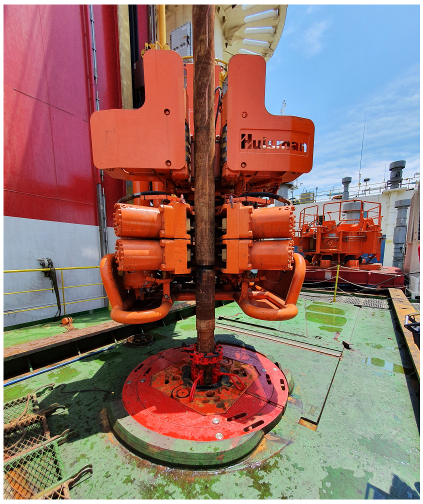


Figure 2.7: Offshore iron roughneck handling drill pipe. The drillstring is supported by manual slips. (Image from Huisman Equipment)

Directional drilling may sometimes be necessary to reach a target that is not vertically directly accessible, due to topographical or legal barriers. Additionally, directional drilling allows for having multiple wells originating at the same surface location, which can reduce drilling costs [32]. Directional drilling is made possible by using a specialised BHA, the RSS, depicted in Figure 2.8. For directional drilling, separate rotation of the drillbit is needed as well as an offset of the drillbit with respect to the drillpipe. Separate rotation of the drillbit is mostly achieved by a mud motor or a drilling turbine, which both use drilling fluid to rotate a rotor, driving the drillbit through a transmission. The bit can be tilted by either push-the-bit tools, which apply a side force to the formation with actuator pads, or point-the-bit tools, which offset the drillbit axis internally. Both methods require the feedback of sensors to then electronically control the system [33]. This technology results in excellent drilling direction control in challenging earth formations [23]. Additionally, the electronics in a RSS share real-time sensor measurements to provide continuous directional information, used for Measurement While Drilling (MWD) [34, Chapter 3].

Is the BHA part of a drilling rig?

While the BHA is essential for drilling operations, it is generally not considered an integral part of a drilling rig system. Every project, the function of a drilling rig is to handle and rotate the BHA and provide mud circulation. The BHA however, has a specialised function that is different per project, or even per section of the drilled well. Since selecting and controlling a BHA requires a different expertise than operating a drilling rig, most drilling project owners will outsource the BHA to an external party. Therefore, downtime due to the BHA will not be accounted to drilling rig downtime. BHA operators, commonly known as directional drilling companies, will preventively change the BHA after a certain amount of operating hours to prevent downhole failure. Maintenance on the BHA is then performed at a separate location, usually after the drilling project is over.

It is complex to include the BHA in a maintenance strategy for the drilling rig system, because of various reasons. First of all, logistically, to perform maintenance on the BHA, it needs to be pulled out of the hole. This operation alone might take several hours. Due to the BHA's inaccessibility when it is down the well, it can not be serviced at the same rate as the drilling rig system at the surface. Furthermore, transferring qualitative data from the BHA to the surface during drilling operations is restricted by the downhole conditions. Communication from the downhole to the surface is now done through drilling fluid pulsation or radio signals, but is limited to simple commands. The technology is not there yet to transfer condition monitoring signals to the surface.

To summarise: in the industry BHA are not considered part of the drilling rig operators' responsibility. Additionally, technological challenges would first have to be overcome in order to conduct advanced maintenance on the BHA during drilling operations. Therefore it is decided that the BHA is not an integral part of a drilling rig system.

Figure 2.8: The Bottomhole Assembly of a Rotary Steerable System. (Image from NOV)

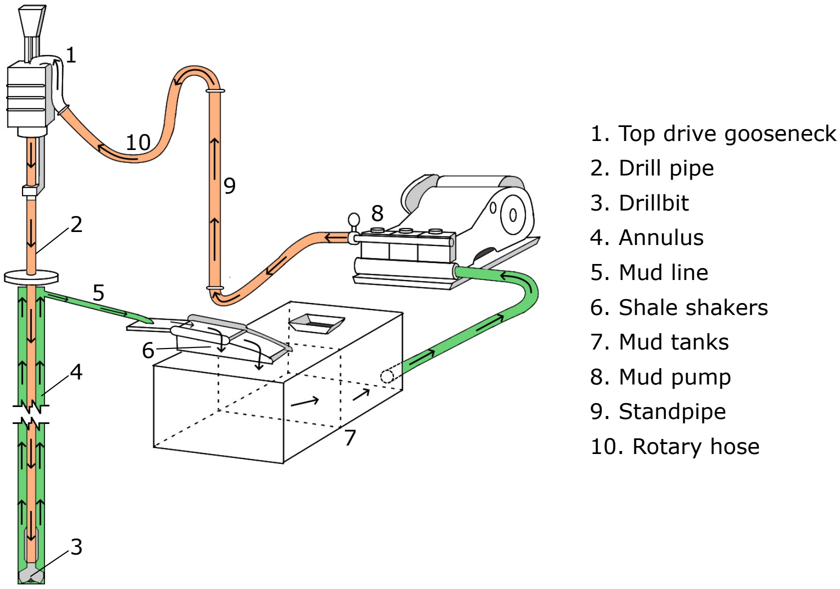


Figure 2.9: Schematic overview of a typical circulation system in a drilling rig. The mud flow is indicated with arrows and colours to indicate the state of the mud. (Image based on [35])

2.4. Circulation system

The complete circuitous path of components that the drilling fluid, or mud, travels through, is called the circulation system. The mud pumps are therefore described as the heart of the circulation system, as they make sure the mud is moving through this system with sufficient flow and pressure, just like the heart does for the blood in a vertebrate. Mud is essential during the drilling process, as it (i) removes cuttings from the wellbore, (ii) lubricates and cools the drillbit and (iii) controls reservoir pressure to prevent other fluids and gasses from entering the well [23]. See Figure 2.9 for an overview of the components of a typical circulation system and the flow of the mud. From this image, the circulation path can be described [34]. The mud, which is a mixture of either water or oil with solid additives, is mixed in the mud mixing tank before going to the fresh mud tank. From this tank, it is pumped to the standpipe, a vertical pipe running up the derrick. The pressure of the mud is usually measured in the standpipe. The standpipe is connected to the gooseneck of the top drive with a flexible rotary hose. The mud then flows through the inside of the drill pipe to the BHA by mud pumps. From nozzles in the drillbit, the mud with cuttings passes through the annulus back up the surface, where it leaves the borehole via the mud line. It then flows through contaminant-removal equipment before returning back in the mud tanks.

2.4.1. Mud pumps

Guo and Liu [36] describe the mud pumps as the heart of the circulation system. Piston pumps with reciprocating positive-displacement mechanisms have become the prevailing choice in contemporary drilling. The advantages of this type of pump are (i) the ability to move high-solids-content fluids laden with abrasives, (ii) the ability to pump large particles, (iii) reliable and easy in operations and maintenance and (iv) the ability to operate in a wide range of pressures and flow rates. There are multiple types of reciprocating mud pumps, depending on the number of pistons and the piston action. Duplex pumps pumps have two cylinder double-action strokes and triplex pumps have single-action strokes in three cylinders. Triplex pumps are more generally used in practice, because they are cheaper and lighter in weight. Moreover, their output is characterised by relatively smaller pressure pulsations compared to duplex pumps, which is beneficial in practice [2, 35].

In a triplex mud pump two main sections can be distinguished: the power end and the fluid end. The power end is driven by a powerful electric or diesel motor, either mounted directly on the drive shaft or via a belt drive. The torque and rotation is translated to a huge crankshaft, which drives three pistons. Liners are the interchangeable inner surface of the cylinder in which the piston moves. They can be made of metal or ceramics and are designed to withstand the high pressure, coarse environment of the fluid end and the friction forces of the piston. If the liner size decreases, the flow rates decreases as well but the working pressure of the pump will increase [2, 36]. Valves in the fluid end open or close depending on the movement of the piston to move the drilling fluid through the pump.

Drilling rigs can equip multiple mud pumps in series or may use a single high-power mud pump, depending on the project and drilling fluid used.

2.4.2. Mud cleaning equipment

Contaminant-removal equipment includes multiple components where the mud will flow through before returning to the mud tank. It will first pass through shale shakers. Shale shakers are composed of one or more vibrating screens, removing approximately 85% of the cuttings [36]. The mud is then degassed, which is important to keep control of the downhole formation pressure [34, Chapter 2]. A degasser can be of a vacuum pump type or a conventional gas-liquid seperator [36]. After that, the mud will go through a desander, desilter and a decanting centrifuge . The combination of a desander and a desilter is called a mud cleaner. These are all types of hydrocyclones, characterised by their conical-shaped portion. In this cone centrifugal forces are created, resulting in a vortex, separating the last solids from the liquid [34, 36]. In the mud tank, the level of drilling fluid is measured to calculate if their is a loss or gain of mud. An increase in mud loss or gain indicates a potential problem with the stability of the well.

2.5. Blowout prevention system

As described in section 2.4, mud is used to control the expected pressure in a reservoir, but this pressure can suddenly turn out to be higher [23]. This will result in a liquid or gas “kick” in the well. A kick is a slug flow of formation liquid and/or gas that flows from the reservoir to the surface, rather rapidly. If this kick can not be controlled properly and will reach the atmosphere at the surface, this is called a blowout [37]. The consequences of a blowout can be disastrous. A BOP is a critical piece of component that must not fail in case of a blowout.

2.5.1. Surface BOP

A surface BOP is designed to contain the high pressure from the well and stop flow to the surface, while well control techniques can be applied to regain control of the well pressure. As a BOP can contain multiple types of prevention equipment stacked onto each other, it is sometimes also called the BOP stack. Stacks are designed for redundancy purposes. There are mainly two types of preventers: a ram-type BOP and an annular-type BOP [37].

Annular preventers use a circular rubber packing unit with a high tensile strength that effectively seals the annular around the drillstring. It is usually the first preventer used when a well needs to be closed [34, Chapter 2].

Ram-type preventers, or BOP rams, have two packing elements on opposite sides that close the well by moving toward each other. They can be categorised in blind rams and pipe rams. Pipe rams have an opening in the packing elements, so that they match the diameter of the drill pipe and can

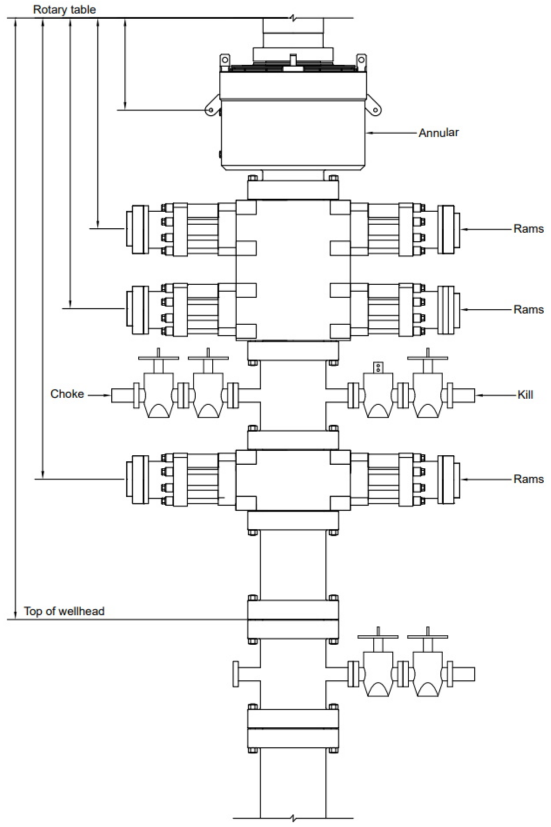


Figure 2.10: Typical surface BOP stack. (Illustration from API Standard 53, 2016, pp 45)

seal the annular surrounding the drill pipe. Because drill pipes come in different diameter sizes, it is important to use a matching pipe ram. One might notice this working principle is the same as an annular preventer. The choice for just sealing of the annular of the well, is to allow for drilling mud to still be circulated down the inside of the drillstring to safely direct the kick to the surface [37]. It might however be necessary to also seal inside the drillstring. A blind ram is designed to completely shut the well if there is no drillstring in the well. However, if this is unintentionally not the case, a blind ram will probably flatten the drill pipe but not completely close it. Blind shear rams, or just shear rams, are designed to shear the drillstring when closed. The drill pipe is deformed in such a way, or rather cut, so that the complete flow from the well can be stopped. As this results in irreversible damage of equipment, shear rams are used only when all the other preventers have failed to close the well.

As mentioned before, a combination of these preventers and other equipment is assembled in a BOP stack. A typical BOP layout is explained in detail by Islam and Hossain [34, Chapter 2]. Basically, a BOP stack contains a blind ram preventer, pipe ram preventer and an annual preventer. A casing head connects the BOP stack with the outer casing of the well at the bottom. Between ram preventers, a drilling spool is located, allowing choke and kill lines to be attached to the BOP stack. A casing spool is attached above the casing head, its outlets should only be used in case of an emergency. As explained by Bourgoyne et al. [2], the kill and choke lines are used to pump fluid into the annulus and release fluid from the annulus respectively. Fixed on top of the BOP stack is equipment that can divert the flow of drilling fluid away from the rig floor, commonly diverters or rotating head [37]. A typical BOP stack assembly is depicted in Figure 2.10.

BOPs are operated hydraulically. Accumulators are used to provide the hydraulic power necessary. The accumulator system is controlled by a BOP control panel on the rig floor and can close the BOPs in less than five seconds. It is commonly located on the surface next to the drilling rig, just like the choke manifold. This is a manifold consisting out an arrangement of lines, valves and chokes, designed to control the flow from the well annulus. It can for instance be used to control the pressure and divert kick slugs to burning pits [34, Chapter 2].

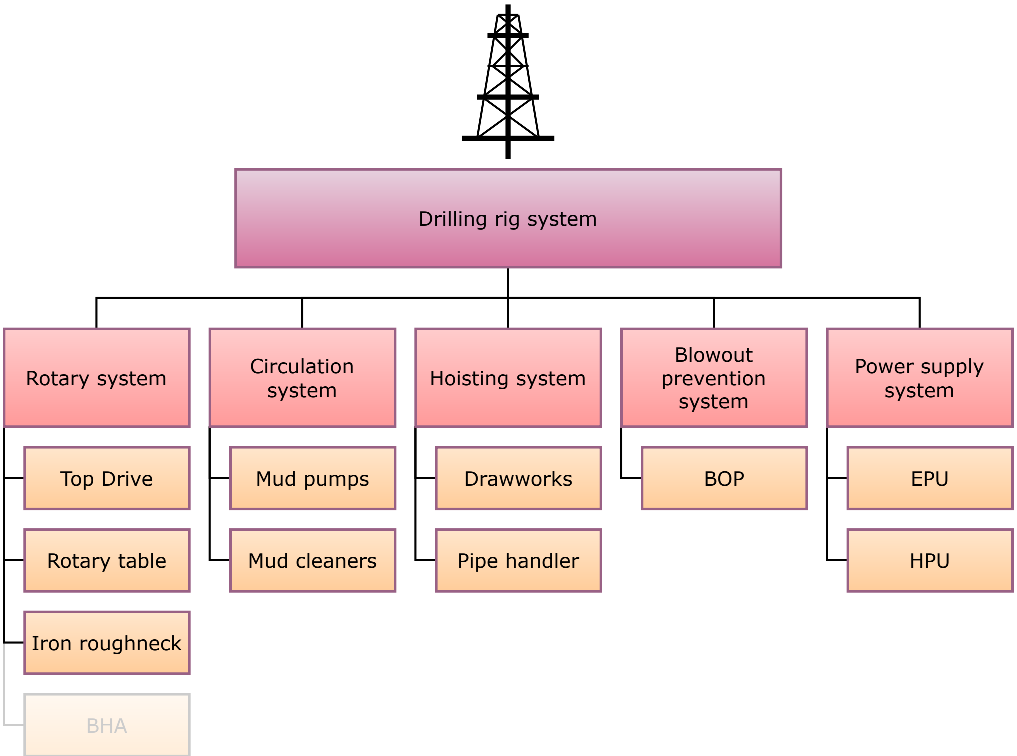


Figure 2.11: The critical components of a land drilling rig.

2.5.2. Internal BOP

Internal or inside BOPs, commonly IBOP, are check valves placed inside the drillstring. They allow for pumped drilling fluid to pass down the drillstring but prevent formation fluids from rising up inside the pipe [34, Chapter 2]. They are usually integrated in the top drive system [38].

2.6. Power system

The power for the rig is provided by electrical power generators in parallel configuration. Sudden loss of power is very undesirable for rig safety, so commonly there are multiple redundant generators [23]. These generators can either be diesel- or gas-fuelled generators. Drilling rigs operating on land may have the opportunity of being connected to the electric power grid. Not only is this an emission free and environmentally friendly option, it can also be more cost-efficient than using fuel-powered generators [39]. The electrical source is connected the power distribution system. This system contains silicon controlled rectifiers (SCR) or variable frequency drives (VFD) to give a direct current or alternating current power output respectively. These drives are housed in an electrical power unit (EPU) that adequately distributes the power from the source to the components of the drilling rig using switchgear.

To store and provide a stable supply of hydraulic fluid to various equipment, a drilling rig also equips a hydraulic power unit (HPU). A HPU contains components to pump, store, filter, cool and heat hydraulic fluid. The HPU also has various valves and gauges to control and monitor the hydraulics in the drilling rig.

2.7. Key components of a drilling rig

From the analysis of the components in the subsystems of a drilling rig, the critical components can be identified (see Figure 2.11). These components are involved in the main drilling rig operations and account for the vast majority of maintenance on the rig. They will therefore be the focus of the integrated maintenance method in this thesis. As indicated, the BHA is left out of scope from now on.

2.8. Standard operating states

To visualise how the key components in a land rig cooperate, the standard operating states in drilling operations are elaborated in this section. The focus will only be on the operations requiring the drilling rig, so the wellsite preparation and the detailed process of well completion are out of scope. Arnaout et al. [25] define the sequence of operations on a drilling rig through the following basic operations: (i) drilling, (ii) making connection, (iii) running in hole, (iv) pulling out of hole, (v) breaking connection and (vi) cleaning hole. A drilling rig also assists during the casing and cementing of the well [40]. The sequence of these operations is repeated until the target depth is reached, after which the well is completed and ready for production.

Drilling

During drilling, the top drive provides the rotation of the drillstring. The drawworks play an important part in drilling, because they control the WOB. The circulation system is in continuous operation during drilling to bring the cuttings to the surface and control the downhole conditions. The speed of drilling is dependent on the rate-of-penetration, which indicates the speed at which the drillbit is capable of breaking through the rock formation, and the length of drillpipe stands. The length of a stand is dependent on the height of the derrick mast. Therefore, taller drilling rigs require less connections.

Making or breaking connection

When a new stand of drillpipe can be added to the drillstring, drilling is seized and circulation is stopped. The slips are being placed in the rotary table to support the weight of the drillstring. Then, the top drive disconnects from the drillstring and is subsequently hoisted to the top of the mast by the drawworks. A new drillpipe is then brought into position above the rig floor by the pipehandler. The bottom of the new drillpipe stand is then connected to the drillstring by the iron roughneck, after that the top drive is connected to the top of the stand as well. Finally, after the slips are removed, circulation starts again and drilling can continue.

This routine is called making a connection. Breaking a connection is the opposite and follows the same routine as above, but reversed. Prior to making/breaking connection, a driller may move the drillstring up and down the mast whilst circulating mud. This is called washing up and is done to remove any potential cuttings around the BHA before circulation is turned off [41].

Tripping: running in or pulling out of hole

Occasionally, the drillstring is being pulled out or ran into the hole, for instance to change the BHA. This is called making a trip, or just: tripping. During pulling out, stands are pulled out and disconnected one by one. So, the process of breaking connection is repeated many times. In this process the top drive is not directly connected to the drillstring, but the elevators of the top drive are used to hoist the load. Continuous circulation is unnecessary while pulling out of hole, however it may be started when it appears the drillstring might become stuck in the hole. In this rare case, the top drive obviously will be connected to the drillstring.

Running drillpipe in the hole is the reverse process of pulling out of the hole, which means connections are made until the BHA is at the desired depth. Again, it is not necessary to connect the top drive since the elevators can hoist the drillstring, unless circulation is needed.

Casing and cementing

A well consists of multiple sections, each with a decreasing wellbore diameter as the well extends deeper. The well is designed in multiple sections to ensure sufficient flow rates during production.

After a section of a certain wellbore diameter is completed, the drillstring is removed and the casing is ran into the hole for that section. Casing are pipes that are placed in the hole to prevent it from collapsing, but also to prevent formation fluids or gasses from entering the well via the sides [25, 40]. The casing is secured by cement, which is pumped in the annulus of the casing and the hole. To handle the casing, a casing tool is used to handle the casing pipes with the travelling block or top drive. After cementing a section, the drillbit will then first drill through the bottom cement layer in order to drill the next section.

2.9. Common failure modes of critical components

Through the criticality analysis in the equipment documentation and communication with rig operators, some of the frequent failure modes of the critical components in a land drilling rig during drilling operations have been found. This means these failure modes will significantly impact the uptime on a drilling rig. The failure modes are listed in Table 2.1. The failing parts in these critical components are given, as well as the cause and nature of the failure mode.

From this table, some interpretations can be made that are useful for later determination of maintenance strategy. First, it can be seen that for the BOP system no common failure modes have been found. The surface BOP is a critical safety system but is therefore not in a continuous operation during drilling operations. However, it is important that the accumulator can provide sufficient pressure to activate the BOP, which can only be controlled through testing. Second, a larger majority of the failure modes involve the loss of a certain parameter important for good operations. This means it would be beneficial to use monitoring of operational parameters to assist in scheduling of maintenance. Third, the causes of the failure modes can be divided in four natures, which can be used to select appropriate CM methods. This will be discussed in chapter 5.

2.10. Conclusion

This chapter has described the process of land drilling and the state-of-the-art technology that is used for drilling. The rotary drilling process requires sufficient torque and rotation of the drillstring, as well as equipment to handle the drillpipes that make up the drillstring. To control well conditions, drilling fluid needs to be circulated and safety equipment must be present on surface level. To complete these various complex functions, the land drilling rig can be divided into five subsystems.

To answer RQ1, in these subsystems core components can be identified that are in simultaneous operation during the standard operating states and procedures in a drilling project. The core components are depicted in Figure 2.11 per subsystem of the drilling rig. Since these components each play a role in all drilling operation procedures, it can be concluded that their failure will inevitably cause loss of performance or even downtime. Common failure modes of these components are identified. The natures of these failure modes can be categorised in wear, electrical, hydraulic and mechanical failure. In the next chapter, it will be discovered how these components are currently being maintained and how maintenance can be improved.

Table 2.1: Common failure modes of drilling rig components, sorted per drilling rig subsystem.

Components	Failure mode	Parts	Possible causes	Nature
			Rotary system	
Top drive	Loss of mud pressure	Wash pipe, gooseneck	Faulty seal or connection	Wear
	Loss of rotation / torque	Gearbox	Bearing failure, overheating, bad lubrication	Mechanical
	Loss of rotation / torque	E-motor	Encoder failure, overloading, overheating	Electrical
	Faulty pipe elevators	Tilt cylinder, elevator	Hydraulic failure, control problem	Hydraulic
Rotary table	Loss of rotation	H-motor	Hydraulic failure, bearing failure	Hydraulic
	Excessive friction	Axial-radial bearing	Structural damage, bad lubrication	Mechanical
	Loss of slips power	Power slips	Hydraulic failure	Hydraulic
Iron roughneck	Incorrect torque	Jaw cylinders	Hydraulic failure	Hydraulic
	Loss of spinner rotation	H-motors	Hydraulic failure, bearing failure	Hydraulic
	Loss of grip	Jaws, spinners	Worn inserts, worn spinner rollers	Wear
			Circulation system	
Mud pumps	Loss of mud pressure	Valves, liners	Worn-out valves, worn-out liners	Wear
	Loss of mud pressure	Pulsation dampener	Worn-out bladder	Wear
	Loss of mud pump torque	Gearbox	Bearing failure, gear failure	Mechanical
	Loss of mud pump torque	E-motor	Encoder failure, overloading, overheating	Electrical
Mud cleaners	Faulty shaker motion	Shale shaker	Worn bearings, loose mounts, structural damage	Mechanical
	Loss of shaker motion	E-motor	Encoder failure, overloading, overheating	Electrical
	Loss of hydrocyclone pressure	Centrifugal pump	Bearing failure, structural damage, overheating	Mechanical
			Hoisting system	
Drawworks	Loss of rotation / torque	E-motor	Encoder failure, overloading, overheating	Electrical
	Loss of rotation / torque	Gearbox	Bearing failure, bad lubrication	Mechanical
	Brake failure	Main brake	Brake worn, structural damage, contamination	Mechanical
Pipe handler	Loss of grip	Gripper pads	Worn gripper pads	Wear
	Loss of grip force	Squeeze cylinder	Hydraulic failure	Hydraulic
	Faulty pipe handler arms	Tilt cylinder	Hydraulic failure	Hydraulic
			BOP system	
–	–	–	–	–
			Power system	
EPU	Drive failure	VFD, SCR	Overheating, contamination, overloading, disconnection	Electrical
	Switchgear failure	Switchgear	Overheating, contamination, disconnection	Electrical
HPU	Pump failure	Hydraulic pump	Bearing failure, structural damage, overheating	Mechanical

3

Maintenance concepts

To explore how maintenance on land drilling rigs is conducted and how it can be improved, first the theory behind maintenance and important related definitions will be introduced. Then a reflection is made on the drilling industry to reason why current adapted maintenance strategies might be ineffective to improve drilling rig availability. This chapter will then provide the different concepts of maintenance in practice, including advanced maintenance concepts. When all these concepts are explained, the optimum maintenance policy for a drilling rig can be identified, providing the answer to RQ2.

3.1. Introduction to maintenance theory

Deighton [42] states that the aim of maintenance management is twofold. Firstly, to maximise equipment and systems availability. Secondly, to ensure that maintenance resources are optimised. In other words, a successful maintenance strategy should improve equipment reliability while reducing the cost of ownership. In his book Birolini [43] describes reliability as the probability that equipment will perform its required function under given operating conditions for a stated time interval. Qualitatively, one can simplify this to the ability of equipment to remain functional. When the equipment stops performing its required function, this is defined as a failure. This might sound like a simple concept, but like Birolini [43] and Tinga [44, Chapter 1] both indicate, the term is not unambiguous and it can become difficult to identify failure on complex equipment or systems.

The availability of a system can be quantified using the mean time to failure (MTTF) and mean time to repair (MTTR). With a constant failure rate, and assuming equipment is repairable and as-good-as-new after each repair, Birolini [43] states the MTTF now becomes the mean operating time between failures, the MTBF. This is similar to Tinga's [44, Chapter 5] definition of mean time between maintenance. Both give the MTTR (in Tinga's work: MDT) as the time to repair the equipment. From both references, the following formula can then be deduced to assess the point availability of equipment:

$$A = \frac{\mathrm{MTBF}}{\mathrm{MTBF} + \mathrm{MTTR}} \tag{3.1}$$

Equation 3.1 shows how the availability is dependent of the reliability of a component and maintenance effectiveness. Reliable equipment will have a low failure rate, thus increasing the MTBF. Effective reparation will restore the equipment to the state of availability while keeping the MTTR as low as possible. However, more factors will affect availability, like the maintainability and accessibility of the equipment. From this it is clear that maintenance plays a decisive role in assuring a high availability level. Therefore it is necessary to design a dedicated, effective and efficient way to conduct maintenance on equipment. This is called a maintenance strategy [44, Chapter 5]. Selecting a maintenance strategy strongly depends on the object of interest. So, there is no perfect maintenance strategy to suit all equipment and all circumstances. More often than not, different maintenance concepts are blended to meet the specific needs of a facility [42].

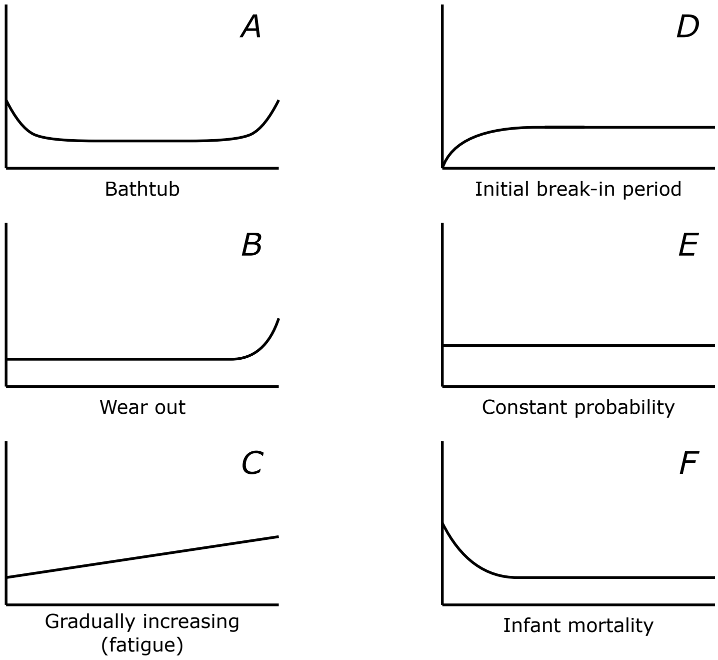


Figure 3.1: Pattern curves of failure probability over time. Patterns A,B and C show a probability of failure related to equipment age. The failure probability patterns D, E and F are mostly constant, therefore they do not relate to age. (based on[19, 45])

3.2. Conventional maintenance policies in the drilling industry

Various sources from different backgrounds state that the current maintenance conducted on drilling rigs is not effective enough [11–13]. The reason for poor maintenance on drilling rigs, can be attributed to mainly conventional approaches to maintenance policies that are currently being adopted. These are mostly corrective policies or maintenance based on inspection intervals and replacement cycles, so conventional variants of preventive maintenance (PM) [11, 16]. Devold, Graven, and Halvorsrød [16] explain that this type of maintenance is often applied to equipment classes instead of a dedicated method for each equipment part. This has undesirable effects on the drilling rig because (i) equipment with different failure rates often unjustly receive equal maintenance, (ii) to avoid failures as much as possible short inspection intervals are used, leading to high maintenance costs and (iii) excessive maintenance leads to more chance of human error, which can result in even more equipment failure. So, scheduled maintenance can sometimes actually reduce the reliability of a system and this may well be the cause in the drilling industry. This statement can also be substantiated by the failure patterns of United Airlines aircraft components described by Nowlan and Heap [45] in their report (Figure 3.1). These patterns can be divided into two groups: age-related failure (A,B,C) and non-age related failures (D,E,F). 89% of the components analysed fell in the latter group. This exposes the weakness of scheduled maintenance: it assumes the equipment's condition will degrade with age. But why would one perform maintenance if the equipment is still in good condition, knowing that the larger majority of failure is not even related to age [16, 19]? Additionally, ineffective decision-making methods partially contribute to poor maintenance [11]. Nowadays, data can be used to achieve informed decision making based on insight, knowledge and forecasting [14, 19]. However, most systems lack to convert the data into useful information that can be used for decision making [16]. Also, inadequate data management systems can fail to retain important records that could be required for future decision making [7].

It becomes clear that drilling rig operators ideally should step away from maintenance based on intervals, but how can they improve? To determine the best maintenance strategy for components of drilling rigs, in the following sections a complete survey on maintenance policies will be conducted. This survey will gather insights into maintenance concepts, both advanced and conventional. The conclusion will reflect on the requirements of drilling rig maintenance and identify the desired strategy from the discussed policies.

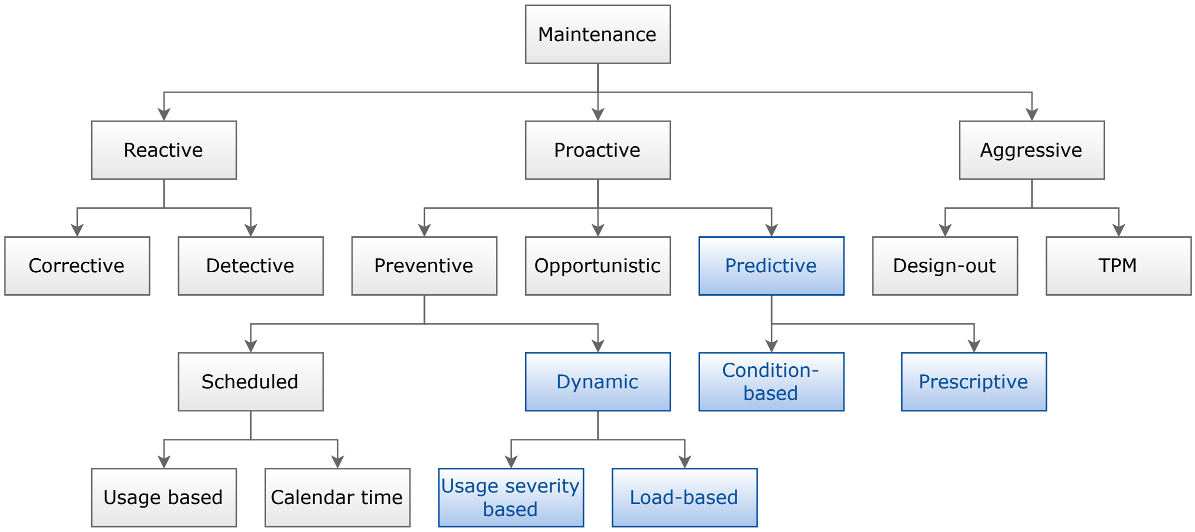


Figure 3.2: Overview and classification of different maintenance policies, based on Tinga [44, Chapter 5]. The advanced maintenance policies are highlighted in blue.

3.3. Classification of maintenance policies

Maintenance strategies use various different maintenance policies and concepts. There is however not a clear, single classification of maintenance concepts out there. The classification given in this chapter is mostly based on the overview given by Tinga [44], but puts predictive maintenance (PdM) on the same level as PM policies, like Deighton [42] does in his overview. This is done deliberately to highlight the significant difference in approach of these concepts. One could indeed argue that all PdM strategies aim to perform maintenance before failure, and are therefore “preventive”, but the key principle of these concepts is just not comparable, as will become clear later on. Therefore, in this chapter, maintenance concepts are first classified as reactive, proactive or aggressive. This classification is not uncommon and for instance also used by Swanson [46] in her paper on the relationship between maintenance and performance. In these three classes, there are multiple maintenance policies, all varying in complexity, applicability and costs. A schematic overview of the classification of maintenance policies is given in Figure 3.2. In this figure, the advanced maintenance policies are highlighted in blue. Each policy will be explained and the methods to achieve successful implementation of this policy will be given as well.

3.4. Reactive maintenance

Reactive maintenance strategies, aim to perform reparation during or after failure. They do not pursuit failure prevention but focus on minimising the disruption that equipment failure can cause. Therefore they are considered as the most conventional concepts of maintenance.

3.4.1. Corrective maintenance

If equipment is repaired after it has failed, this is called corrective maintenance. Failure of a component mostly becomes clear because the system will break down and stop operations. Corrective maintenance tasks include inspection of the failed system to identify the failure mode and perform reparation to make the equipment available again [42]. Rather than preventing the failure, Corrective maintenance focuses on bringing equipment back to operation in the shortest time possible, reducing the impact of equipment failure. Some practical techniques to achieve this are trained service crews, improving the maintainability of equipment and having redundant equipment [47].

To perform efficient corrective maintenance, a good fault diagnosis is necessary. Wang et al. [48] propose a corrective scheme for systems with complicated failure mechanisms. They use numerous methods to identify the failure modes and the propagation of these failures in the system, and do not only consider failure probability but also the detectability and severity of a failure to determine the order of corrective maintenance on the system.

Run-To-Fail

The deliberate choice of not performing maintenance on a system until complete failure, so without performing maintenance, is called Run-To-Fail. The advantage of this concept is a fully utilised lifetime of the component, only performing maintenance or replacing the component when necessary. The disadvantage is the unexpected failure of a system and associated downtime, costs and most importantly sudden exposure to safety hazards. While Deighton [42] argues that this strategy is sometimes used for economic advantage, Motaghare, Pillai, and Ramachandran [49] state that this concept will actually give the highest costs for maintenance.

3.4.2. Detective maintenance

Detective maintenance applies when a functional test points out failure of a component. When a failure is detected during this test, the failure may already have occurred before the moment of testing. It differs from corrective maintenance, as the equipment in this case is not always operating, thus not immediately revealing the failure [44, Chapter 5]. This concept therefore mostly applies on protective equipment, that needs to be available at emergencies but is rarely in active use [50].

3.5. Aggressive maintenance

Aggressive maintenance policies aim to improve equipment operations to reduce the number of failures, rather than conducting excessive corrective maintenance. This concept is therefore also called improvement maintenance.

3.5.1. Design-out maintenance

Design-out maintenance is a strategy that goes straight to the core of the reliability issue and redesigns the component to eliminate shortcomings, thus reducing future failures [51]. When equipment falls in repeating failure patterns and it has become obvious that the equipment is no longer capable of confirming to the expected reliability standards, one might chose to use design-out maintenance [52]. Successful application of this policy uses thorough failure investigation before a systematic selection of the optimal solution to eliminate the reliability issue. Like Mughanyi, Mbohwa, and Madanhire [52] show, the results of design-out maintenance are equipment design modifications that in some cases even become registered as patents.

3.5.2. Total Productive Maintenance

Total Productive Maintenance (TPM) is more of a maintenance management philosophy than a policy. It was developed and first successfully applied in Japanese automotive factories and can also be classified as a lean tool like Kaizen and 5S, which were all developed in the same environment to support just-in-time manufacturing [46]. Most of the tools used in TPM are similar to those in Total Quality Management (TQM), but TQM focuses on improvement of the product quality where TPM focuses on improvement of equipment operations and production. It makes maintenance a vitally important part of a business. Simultaneously TPM aims to improve employee morale and job satisfaction [53].

TPM enables employee cooperation and partnership for maintenance improvement. Production workers and office employees are involved in teams, where they aim to improve the equipment performance by communicating current and potential equipment issues.. Maintainability improvement teams work to improve the way maintenance is performed, for instance aiming for more proactive strategies and training production workers for small maintenance tasks, so that specialised maintenance workers can be used on more important issues [46, 53]. Maintenance prevention teams work together to improve the equipment design, which will result in equipment that is better to maintain and operate [46].

While implementing TPM requires some initial investments and a total commitment from all employee functions, it can result in positive results for a facility [53]. TPM primarily focuses on manufacturing processes, but some parts or principles from the TPM philosophy can be applied in other industries as well.

3.6. Proactive maintenance

Preventive, opportunistic and predictive maintenance can all be classified as proactive maintenance strategies. They aim to perform maintenance before the failure of components. The key of proactive maintenance is therefore scheduling the ideal moment to perform the maintenance. The benefit proactive maintenance can offer is less breakdowns during operations, ideally preventing NPT. A pitfall however is performing excessive or incorrect PM, which can rapidly increase the costs. There are many different policies in proactive maintenance, that all contribute to finding the optimal solution for an efficient maintenance strategy.

3.6.1. Opportunistic maintenance

Opportunistic maintenance (OM) policies use the dependency of components in a system to carry out maintenance on multiple components as the opportunity arises [54]. Maintenance is conducted on a component that is not immediately required, yet undertaken in order to provide advantages in terms of time, transport costs etc. OM is mainly triggered when another component in the same system is actually in need of maintenance [44, Chapter 5].

OM is implemented by creating a preplanned set of proposed maintenance activities and then act based on this plan when the opportunity arises. The choice to conduct this policy can be justified by technical and economical benefits. In terms of other maintenance policies, Ab-Samat and Kamaruddin [54] explain that OM is basically conducting corrective maintenance on one component and conducting PM on the other dependent components. They argue that applying OM can be especially effective in preventing breakdown in continuous systems, but the principle is still open for improvement.

3.6.2. Preventive maintenance

PM aims to replace or repair components before failure occurs. PM emerged as an alternative concept to corrective maintenance in the 1950s and has been adopted for the emerging technologies since then, as these kept increasing in complexity. The basic principle of PM is to conduct predetermined maintenance tasks that are derived from experiences and analysis of component functionalities and lifetimes. The maintenance on components is conducted before they are expected to fail and is scheduled during dedicated time, to minimise NPT in equipment operations. PM therefore requires proper planning [55]. As Tinga [56] states, the key issue of PM is to correctly determine the maintenance intervals. A short interval might be more effective, but can lead to excessive maintenance. A larger interval might be more efficient, but failure might occur. Two approaches to this problem can be distinguished: (i) scheduled and (ii) dynamic PM.

Scheduled intervals, time-based

Fixed intervals are used to schedule the maintenance of equipment. These intervals can be based on calendar time (e.g. monthly or yearly), or on operating hours (usage). The first concept is called time-based maintenance and is also known as periodic-based maintenance. In time-based maintenance, there are various ways to determine the maintenance time interval.

The simplest way is to follow the interval recommendation of the equipment manufacturer. Following this recommendation is not very useful for a effective and efficient maintenance strategy [57]. Labib [58] names three reasons why manufacturer recommendation is usually not applicable: (i) each machine works in a different environment, (ii) manufacturers do not have the same experience of machine failures as those who operate and maintain them and (iii) manufacturers might recommend very frequent replacements to keep spare part sales up high.

The second reason Labib [58] gives, indicates a better strategy: using the experience of maintenance workers. The knowledge from technicians and engineers that have worked a longer time with the machine can be used to determine time intervals. They have a sense for the equipment and have learned from previous failures the equipment might have had. Ahmad and Kamaruddin [57] state that this is a conventional practice of time-based maintenance. One drawback however, is that when skilled personnel quits their job, the experience might go out the door as well.

Therefore, most time-based methods aim to determine the optimal interval through a statistical approach, using failure time analysis [57]. Tinga [56] refers to this approach as model-based scheduled maintenance. Figure 3.3 shows the process of a model-based scheduling. This requires user-based data containing equipment time-to-failure records. A reliability model is then created, which takes into account a failure probability distribution like normal, exponential or the Weibull distribution [57]. The Weibull distribution is widely used in reliability engineering because it can be applied on various aging classes with varying failure rates [55, 57]. This statistical or reliability model will return equipment characteristics like MTTF and failure rates, that can be used in a decision-making process to determine

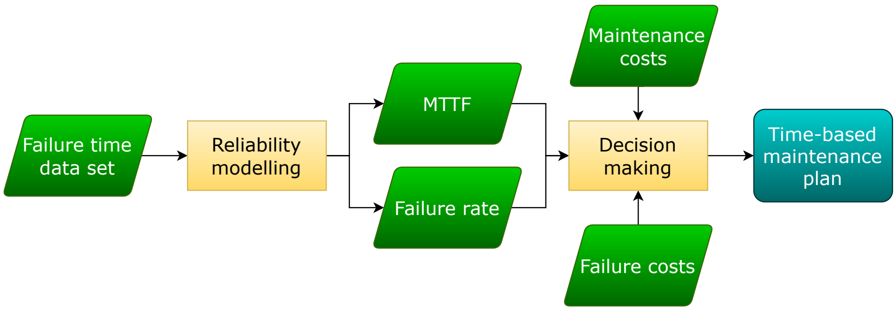


Figure 3.3: The general process of a statistical approach to time-based maintenance scheduling. (Image based on [57])

the optimal maintenance plan. In this process, the costs of failure, maintenance and part replacement are also taken into account to determine an optimal maintenance interval [57]. Basri et al. [55] line out some examples of applied methods in their literature review on PM planning, like Markov Chains, SIMAN simulation or linear programming. The type of decision-making method used depends on the state and configuration of the system and its components. Some time-based scheduling problem solutions integrate the reliability modelling directly in the decision-making process [55].

The result of a time-based maintenance plan, regardless of the approach, is a fixed interval of time between maintenance. As Tinga [56] states, for equipment that is running continuously at constant speeds in a constant environment or at least with minimal variation in usage and degradation over time, calendar time-based maintenance is very suitable. However, for equipment that is not used constantly in operations, it is better to apply usage-based scheduled maintenance, taking into account the actual usage of the system. This concept is also called usage based maintenance. It prevents the planning of very conservative calendar time intervals by taking a usage indicator like operating hours or, in case of a vehicle, kilometres travelled. While usage-based maintenance can give a more efficient interval, it still has the assumption of constant environment and little variation in usage loads [56]. In most operations, this is not the case. Therefore, the main shortcoming of fixed interval PM is that it uses quite some assumptions and will therefore sometimes lead to an approach of the equipment condition that deviates from reality. That will inevitably lead to failure, resulting in extra costs.

Dynamic intervals

As an upgrade of fixed interval PM, Tinga [56] proposes more sophisticated approaches to time-based and usage-based maintenance. These approaches also consider the severity of usage and the internal loads of equipment. These methods aim to take away the uncertainty of usage variation and degradation that time-based maintenance has and can be used to update the required maintenance intervals [44, Chapter 5]. To achieve this, different characteristics of the equipment over time are monitored, like rotational speed, power setting etc. In load-based maintenance, the internal loads in the component over time are also measured, like strain and temperature. Both can give more insight in both relations between usage-to-load and load-to-life [56]. This information can then also be considered in the reliability modelling (see Figure 3.3), providing more accurate MTTF and failure rate results for various usage modes. This can finally be used for determining maintenance intervals depending on the distribution of usage modes.

In a more recent research, Assis and Marques [59] give a concept that can be used on a periodic maintenance calendar for critical equipment. The base of this concept is assuming a Weibull distribution for the reliability of the component and initially determining a set of maintenance intervals that make sure the reliability between these intervals is kept below a pre-set threshold, while keeping inspection, repair and potential failure costs to a minimum. This gives a time interval that gradually decreases over time. When during maintenance test results return to be negative, the resulting maintenance calendar is adjusted dynamically over time, according to the new information. Assis and Marques [59] conclude that applying this method can yield a self-adjusting maintenance strategy.

PM that used dynamic intervals can come close to the ideal maintenance interval in which there is a perfect trade-off between efficiency and effectiveness. Although they do not approach reality as close as PdM can do, they can help reduce the uncertainty of PM, while still being relatively cheap to implement [44, Chapter 6].

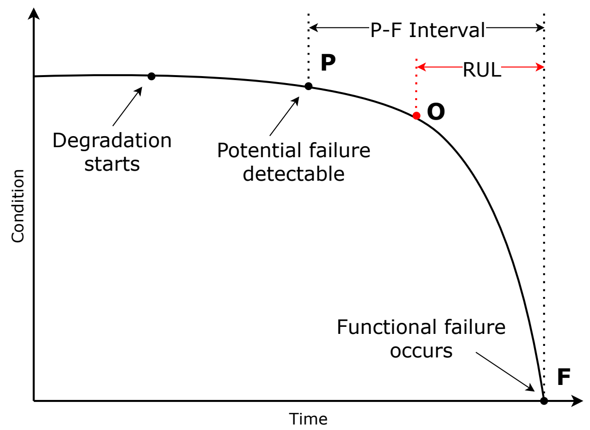


Figure 3.4: A general P-F curve: relation between observance of a potential failure (P) and the actual failure (F). The RUL from a certain observation (O) is highlighted as well. (Image based on [44])

3.7. Predictive maintenance

PdM can be classified as an advanced proactive maintenance strategy. It involves determining the optimal moment for maintenance through model or data analysis.

3.7.1. Remaining useful life

The goal of PdM is maximisation of the time interval between maintenance tasks without the occurrence of equipment failure. Using the actual operating condition of the equipment, PdM can predict the future state of equipment, also depending on historical operation or degradation behaviour data [49]. One could say PdM basically involves three tasks: CM, diagnostics and prognostics. Diagnostics is conducted to detect, isolate en identify potential faults and failure modes [60]. Generally, diagnostic methods aim to use pattern recognition in order to detect and classify a failure or fault. But just monitoring a condition parameter until it exceeds a critical value that requires immediate action, will not improve reliability of the system. Therefore a prognostic method is required to determine the best future moment of maintenance [44, Chapter 6]. Where prognostics might seem superior to diagnostics, as it can prevent failure, it should not replace diagnostics. Diagnostics is still needed to give accurate maintenance decision support when an unpredicted fault is occurring [61]. Prognostics relies on fault indicators and degradation rates, which are in the outputs of diagnostics [60]. The aim of a prognostic method can be shown with a P-F curve as illustrated in Figure 3.4. This curve shows the degradation of a component over time. Most equipment will start to degrade once it has been taken into operation. In the early stages this is not noticeable and the performance of the system will not be affected. However, from a certain point in time, a CM system will be able to detect an anomaly that points to an upcoming failure. This point is called **P** and the point of actual functional failure is called **F**. The available time for maintenance on the system is the P-F interval, or also called the delay time. The delay time of equipment is very essential for the success of a PdM policy, as small delay times require flexible maintenance strategies while large delay times allow for large opportunity windows for the clustering of maintenance [44, Chapter 6]. Prognostics are needed to estimate the remaining useful life (RUL), which is the time to failure F, measured from any point on the P-F curve [60, 62]. In Figure 3.4 the RUL at observation time **O** is depicted. Note that the RUL is not the same as the delay time. To conclude, a PdM strategy revolves around achieving the most precise forecast of the RUL of a component or system.

3.7.2. Approaches to predictive maintenance

In PdM, there are many approaches to predict the RUL, as visualised in Figure 3.5. A first distinction can be made between data-driven or model-based approaches [63–66]. Model-based approaches employ mathematical modelling to describe the system or component in a numerical manner. This can be based on analytical, statistical or physical information or properties of the asset [63]. Reliability statistics of historical fault data can be used for fault prediction by using a series of probability density functions. Some of the methods using reliability statistics include Weibull distribution, Bayesian belief network and fuzzy logic (FL) [64]. FL and other rule-based models can also be described as knowledge-based

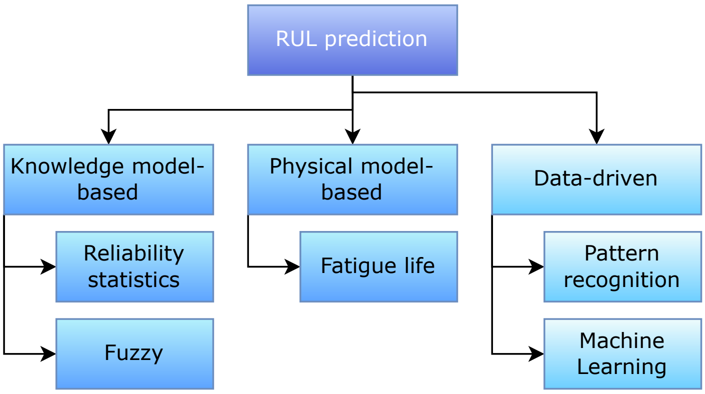


Figure 3.5: Approaches to RUL prediction in PdM

approaches, since these methods reduce the complexity of the system and consider the system as a whole based on known information [65]. Physical model-based approaches will reflect the performance degradation of the system using virtual physical failure and fatigue life models. They do not require extensive collection of data, however designing a physical model that closely resembles reality may need the assistance of an expert [64]. Recent advances in computing techniques have enhanced the feasibility of model-based approaches, given that these models require substantial computational resources for computation [63].

Data driven methods use big amounts of data obtained from equipment in operation by adequate sensor deployment [63, 64]. This data is then processed and analysed using pattern recognition, machine learning or other AI solutions [65]. One of the common used data-driven methodologies for PdM is condition-based maintenance (CBM), which will be elaborated in the following section. If the data is not gathered by already existing process sensors, which are already part of the equipment [67], a CM technique as described in subsection 3.7.4 can be implemented.

3.7.3. Condition-based maintenance

CBM plays a significant role in maintenance, management and sustainable operations of various sectors. Its increase in utilisation is related to the technological advancements in CM devices in terms of electronics and communication. It has become more important with the progress in the field of automation engineering [62]. For CBM, one needs a CM system that monitors the value and variance in a critical parameter of a piece of equipment.

A typical CBM process is shown in Figure 3.6. In general, it follows three main steps [61]:

1. **Data acquisition**: obtaining data relevant to the system health
2. **Data processing**: handling and analysing the data for a good understanding and interpretation
3. **Decision-making**: recommending an efficient maintenance strategy

During data acquisition, data is gathered form targeted equipment. This data can be categorised into two types: (i) CM data and (ii) event data. The first are the measurements related to the health and condition state of the equipment. The latter includes information on events that happened to the equipment, like failures and causes or maintenance activities, and is usually gathered manually [61]. CM data is usually acquired by strategical placement of sensors. There are various types of sensors that can serve for diverse monitoring purposes [61, 62]. Although there are now wireless technologies to reduce the cost of installation of hardwired sensors, a sensor system is still a significant upfront investment to be made. Furthermore, the sensor system will also require maintenance [42]. The data from the sensors is commonly stored in computerised maintenance management systems [44, Chapter 8, 61].

The first step of data processing is data cleaning to ensure the data is error-free [61]. There are various methods for data cleaning which can for instance be aimed at reducing signal noise [68] or sensor fault detection and isolation [69]. The next step involves analysing the data with the use of various AI models, algorithms and tools. The data gathered in CBM can be of one of the following types [61]:

1. **Value type**: single values data collected at a specific time, e.g. temperature or pressure

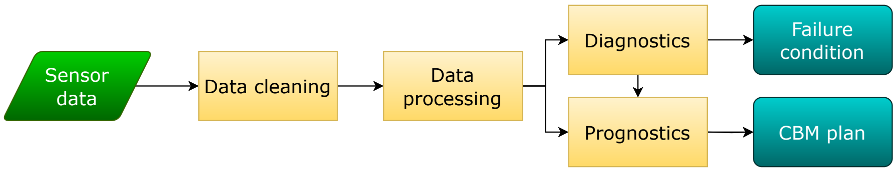


Figure 3.6: The general process of condition-based maintenance. (Image based on [61, 70])

2. **Waveform type**: time series data collected over a time interval, e.g. vibration or acoustic
3. **Multidimensional type**: multidimensional information, e.g. infrared thermographs, visual images

Depending on the type of data, numerous techniques are available to process the data. Some examples are wavelet transformations, neural networks, feature recognition, signal processing and AI [62].

The last step in CBM is maintenance decision-making, this is where the tasks of diagnostics and prognostics are involved. In decision-making, there are numerous methods and approaches. The output of a CBM process is then a maintenance decision based on either the prognostics RUL estimation or, in case of failure, the diagnostics failure analysis.

3.7.4. Condition monitoring techniques

There are various CM techniques that are widely used in PdM and CBM, that all focus on monitoring a critical condition parameter. Common techniques are vibration analysis, acoustic analysis, lubrication oil analysis, particle analysis, corrosive analysis, thermal analysis and performance analysis [67].

Vibration analysis is used for rotating equipment and is one of the most popular CBM techniques [57]. Vibration sensors can detect offsets in vibration rates, that can indicate failures such as imbalance, misalignment and bearing or gear damage. The types of sensors used for vibration analysis are accelerometers or sensors to measure displacement or velocity [44, Chapter 6]. The output of a vibration analysis is waveform data that can be compared with reference data of “healthy” equipment to detect anomalies.

Related to vibration analysis, acoustic analysis can detect anomalies in acoustic waveform data that indicate failure. The fundamental difference however, is that acoustic sensors do not have to be mounted on the equipment and are therefore less intrusive [57]. Acoustic analysis can also be used to detect high frequency noise that can be caused by the leaks of valves, pipes or vessels [44, 67]. The acoustic monitoring technique for frequencies higher than 30kHz is also called ultrasonics monitoring.

Oil or lubricant monitoring analyses the degradation and contamination of oil, hydraulic fluids and lubricants. This technique can give a proactive indication of upcoming equipment failure because wearing equipment will contaminate the oil [42, 67]. It is even possible to analyse the contamination particles in the oil to identify the part of the equipment that is wearing and the dominant wear mechanism [44, Chapter 6]. Oil analysis can therefore safeguard both the oil quality and the components using the oil [57]. Methods and tools used in oil analysis are imaging systems that use pattern recognition, or magnetic plugs that can detect the amount of particles in lubricant flow [44, Chapter 6].

Corrosion monitoring is mostly applied to static equipment in drilling industries and maritime industries, which is situated in corrosive environments. This monitoring used to be achieved by periodic inspections, but in the recent years there are corrosion sensors that can be used for continuous monitoring. Equipment that can be subject to corrosion is coated, therefore monitoring the condition of the coating is important too [44, Chapter 6]. There are numerous methods and tools used in corrosion monitoring. For instance, electrical and electrochemical techniques aim to monitor variance in current or resistance that can be caused by corrosion. Other techniques can indicate cracks or loss in wall thickness, like acoustic analysis or radiography [71].

The last notable CM technique is thermal analysis, which can be achieved in a few different ways [42]. Thermography uses infrared thermometers or even infrared cameras to measure the heat radiation of a system. It can be hard to interpret the results of thermography, because of interfering radiation of other systems in the proximity or the reflection or radiation on walls or other equipment. However, comparative analysis with thermography can still give good insight into the condition of a system [44, Chapter 6]. Applications of thermography are electrical systems or rotating equipment, such as bearings and motors. Thermal point measurement measures the temperature with a sensor at an equipment surface. These sensors are mostly thermocouples and are fixed to critical points such as pumps or bearings. They directly monitor the temperature in a single value data type [42].

3.7.5. Prescriptive maintenance

Going one step further than CBM and other PdM techniques, prescriptive maintenance aims to control the occurrence of equipment failure [65]. Where diagnostics answers the question “Why did it happen?” and prognostics answers “What will happen when?”, this policy aims to answer “How can we make it happen?” [72]. Matyas et al. [73] describe that thanks to the digitisation of the industry (the Fourth Industrial Revolution or Industry 4.0), prescriptive maintenance will be the new era of maintenance.

A prescriptive method should be able to predict required maintenance measures and prescribe a course of actions based on analysis of historical data and real time data. One of the challenges in prescriptive maintenance is therefore the collection and management of complex data sets [73]. In their paper, Nemeth et al. [72] give various machine learning methods to overcome this challenge, like data sampling and defining datasets for training, test and validation. This data is then used to predict failure, much like prognostics giving RUL estimation during PdM. But, in addition to PdM, prescriptive maintenance also involves a prediction of the effect of different potential maintenance actions on the future state of the equipment. It uses smart technologies like AI and machine learning mainly in model-based approaches to solve this prediction problem and makes a decision to provide actionable solutions [72–74].

Prescriptive maintenance is a quite new concept and therefore there is still a lot of work to be done in this field. Although there is potential for this concept, Nemeth et al. [72] mention that it is hardly implemented in practice. In the field of research, Choubey, Benton, and Johnsten [74] state there is a lack of consensus on the mode of prescriptive maintenance and the scope of solutions.

3.8. Conclusion

In order to find an answer to RQ2, the optimum maintenance policy can now be selected from the survey in this chapter. To help improve the reliability of a drilling rig, drilling rig operators should adopt a maintenance strategy that:

- takes into account the actual degradation of the components
- does not group components with different failure rates
- adapts to the different harsh environments in which drilling rigs operate
- maximises uptime
- actively assists in maintenance decision-making.

In the broad sense, drilling rigs require proactive maintenance, since reactive strategies will not minimise rig downtime and aggressive strategies do not fit the diverse operations of a drilling rig. Considering proactive strategies, preventive methods are conventionally being applied on drilling rigs. But as already explained in section 3.2, this eventually can have a negative effect on the equipment and is believed to be contributing to the low reliability of drilling rigs. By implementing a *PdM strategy*, the components in a drilling rig can receive maintenance based on their actual degradation, which may vary based on their operations and environment of operation. PdM is the best policy for a strategy that fits the requirements mentioned above.

However, the pitfall of a PdM strategy for a drilling rig is that it can represent an disintegrated collection of component-specific methods that fail to consider the overall operation of the system. The following chapters in this thesis will therefore focus on developing a holistic approach to PdM on a drilling rig by integrating components into system-level decision-making.

4 System modelling

The goal for the remainder of this thesis is to find a holistic approach to the application of PdM on a drilling rig. For this purpose, it is necessary to first identify an applicable framework for the modelling of the drilling rig system to support in the decision-making for the PdM strategy. In this chapter, approaches that are used to model equipment systems are discussed to find the answer to RQ3. For clarification, in this chapter a system model is defined as a digital model that can:

- comprehend the operations of individual components as well as the whole system
- estimate the health condition of components and predict the RUL
- decide what maintenance is necessary and what is the best moment to conduct maintenance

For these tasks, it uses real-time available data as well as historical data. Various common used paradigms of system models are discussed. Examples of applications of these models in PdM strategies are given as well. Finally, this chapter selects a framework that can be used to model a drilling rig in a holistic PdM strategy.

4.1. Mathematical model

Mathematical modelling is a broad term that aims to simulate a physical system with mathematical computations. The goal is to predict the behaviour of this physical system within its environment [75]. Ran et al. [76] state that in PdM, mathematical models can calculate the outcome of physical processes that have impact on the health condition of a component or system. Using a mathematical model will reduce the physical system to (a set of) key equations or theories that can approximate the current and future states. Their accuracy depends on the assumptions in the area of failure mechanisms and reliability statistics, and on the selection of critical components in the system. The general process of mathematical modelling is depicted in Figure 4.1. Since this is a broad subject, there are various approaches to mathematically modelling a physical system. This section will elaborate on statistical models and physical failure models.

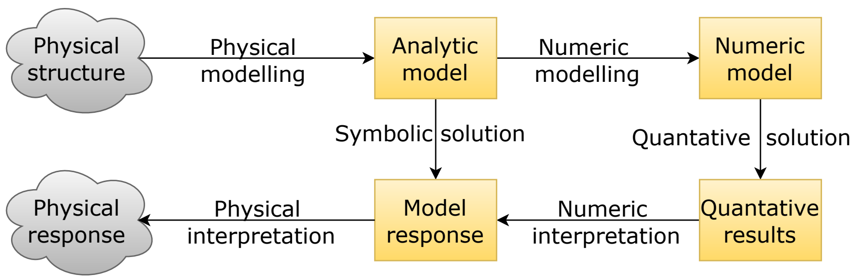


Figure 4.1: Overview of the mathematical modelling process (Image based on [75]).

4.1.1. Statistical modelling

To predict the failure of components, statistical models characterise the degradation of components by a time-dependent stochastic process. Some examples of these stochastic processes are Markov chains and Gaussian, Wiener and Gamma processes. The uncertainty and randomness of failure can be approximated with a stochastic process. The parameters that determine the degradation processes, for instance the MTTF (refer to section 3.1) can be deducted from historical data [22, 77]. These parameters can be updated if new data provides evidence for this matter.

Statistical models aim to give an estimation of the system reliability, which is a function of the components' reliability. However, as mentioned by Lee and Pan [78], in practice multi-component systems have complex forms with uncertainties in the system reliability structure, rather than having a deterministic relationship. Moreover, these dependencies in the system can be of different nature, e.g. economic, stochastic or structural dependence [79]. Taking into account these dependencies, the model can result in a decision process that groups maintenance actions on components in the system [20, 79]. In other words, these models will also incorporate OM actions into a PdM strategy if this results in better cost or reliability performance of the system.

Bayesian networks

A powerful tool in statistical modelling is a Bayesian network. It can represent the inference of a set of random variables and is therefore suited to model the probabilistic dependencies of components in a system [60, 80]. A Bayesian network can be explained as a number of nodes, connected by arcs that represent a direct causal influence between nodes in an acyclic pattern, so that following the directions from a node can never result in a closed loop. The nodes represent random variables that can take on distinct states or levels. The causal influence is quantified using conditional probabilities. Therefore each node has a conditional probability distribution, presented by a table that defines probabilities for each state of the node, given the states of its parent nodes. If a node has no parents, its state is dependent of unconditional probability, a.k.a. marginal probability [60]. To create a Bayesian network, the system is broken down into manageable, smaller subsystems and critical components of these subsystems can be identified [80]. In Bayesian networks, "the probability inference of an event is conditional on the observed evidence" [81]. So if, in time, new evidence occurs, that is data containing new variables, the network can be improved and the probabilities are updated. This process is called Bayesian updating, and will result in a posterior probability distribution [60, 80].

A Bayesian network can be used to integrate failure probability models in a system reliability assessment model. The work by Lee and Pan [78] is an example of this approach. To achieve PdM for a complex system, they employ Markov chains for the degradation of components, integrated in a Bayesian network to predict the system reliability.

4.1.2. Physical failure

If the physical failure mechanisms in a system are understood, they can be modelled to predict the failure based on the loads that govern this mechanism and how these loads are related to the operational use of the system [21]. Typical failure models are fracture, fatigue, creep, and they can be related to loads like stress, strain, temperature, electrical current, for example. Important relations in a physical failure model are usage-to-load and load-to-life relations, which can model the life consumption of a load at a certain operation rate. These models therefore require monitoring of the usage and the loads on the system to give an accurate prediction of the RUL of components [21]. The overall system will contain multiple components with different failure mechanisms. To determine what failure mechanisms are dominant in the system and what components are critical to the life of the system, a failure mode, effect and criticality analysis (FMECA) must be performed [56]. The criticality of a component determines the threshold for the failure probabilities in a system and will trigger a maintenance action.

FMECA

FMECA is a bottom-up method that starts at the component level of a system. It is a variation of an FMEA, which stands for Failure Mode and Effects Analysis. An FMEA aims to find the failure modes of each component and what would be the effects of these failures on other interacting components [82, 83]. It was originally developed by the US military as one of the first methodical techniques for failure analysis in the 1940s, and is now commonly used in a wide number of industries [42]. A structural FMEA is performed with a team consisting of diverse expertise (e.g. design, operations, maintenance, software, electrical etc.) as this will increase the number of identified possible failures. As mentioned by Peeters, Basten, and Tinga [83], standards can provide guidelines for performing an FMEA. The results of an FMEA are recorded in a spreadsheet, named the FMEA worksheet. The format of these worksheets varies depending on the output requirements of the FMEA [42, 83]. An FMECA extends the analysis by also including a criticality analysis. The failure modes are then prioritised for corrective action, based on the failure probability and severity of failure. This is done by rating the failure mode from 1 to 10 on (i) a severity indicator, (ii) an occurrence indicator and (iii) a detectability indicator. These three ratings make up the risk priority number [82, 83]. This number can then be recorded in the FMECA worksheet to later identify the critical failure modes. Langlo [9] for instance used a threshold value of 50, identifying all failure modes with a higher risk priority number as unacceptable risks. The main steps in performing an FMECA are [9, 42]:

1. Defining objectives and expectations of the analysis
2. Ensuring that the scope of equipment to be analysed is clear
3. Defining the equipment systems, subsystems and components and their relationships
4. Identifying the failure modes with causes and effects for each equipment system, subsystem and component
5. Performing a criticality analysis for each failure mode

4.2. Multi-agent system

In multi-agent systems (MAS), a decision-making system is constructed from multiple “agents”. Agents are entities in the system that can independently make decisions and can use a “collective mind” to achieve their own goal. To achieve their goals, agents may cooperate by exchanging information or resources [84]. While there are various ways to design the architecture of a MAS, it is common to broadly classify these designs into four types of architectures, also depicted in Figure 4.2 [85]:

- **Centralised:** there is a social platform, or control centre, that has full control over the system decision-making. The agents communicate with this centre by sending data and receiving maintenance recommendations. The control centre can be considered as the “main agent” as it is the only one that actually analyses the data and does the decision-making.
- **Hierarchical:** in this architecture lower-level agents perform simple tasks and provide information to intermediate agents, who account for most of the decision-making in the system. The control centre is the highest level and has full control of the communications in the system, assigning groups and tasks to the intermediate agents.
- **Heterarchical:** in addition to a hierarchical architecture, heterarchical structure allows for horizontal communication between agents. The control centre decides which agents can communicate with each other by mean of a clustering algorithm.
- **Distributed:** all intermediate agents are in the same level of hierarchy, and take independent decisions without supervision of a higher-level control centre. The agents therefore have peer-to-peer connections and are stimulated to establish collaborations.

In a PdM strategy, Palau, Dhada, and Parlikad [85] state that the lowest-level agents can standardise incoming data and pass it on to higher levels. Depending on the MAS architecture, the intermediate agents perform analytic tasks and give a prognostic task of the equipment they are associated to. The control centre agent will mainly form clusters of agents and make maintenance decisions.

MAS can be very agile and adaptive to the situation of the physical equipment. To prove this, Rocha, Peres, and Barata [86] designed a MAS containing three types of agent. A component monitoring agent, which collects data from the physical component, is the lowest level entity in the system. Then, a higher-level component monitoring agent retrieves the pre-processed data from a set of lower-level component monitoring agents, as well as from a computational device related to the system. On the highest level, a cloud of output coordinator agents collects all the data from the other agents. From here, the data is sent to external entities capable of performing higher level analysis. The authors state this architecture is capable of reducing the workload of a monitoring system on the work floor and it is possible to plug and unplug components without the need to reconfigure the software.

Reinforcement learning is a field of AI that is applicable on MAS. In reinforcement learning, an agent is given one or multiple objectives and is aware of the environment he is operating in. Through trial and error, either rewarded or punished for its actions, the agent learns the optimum way to achieve

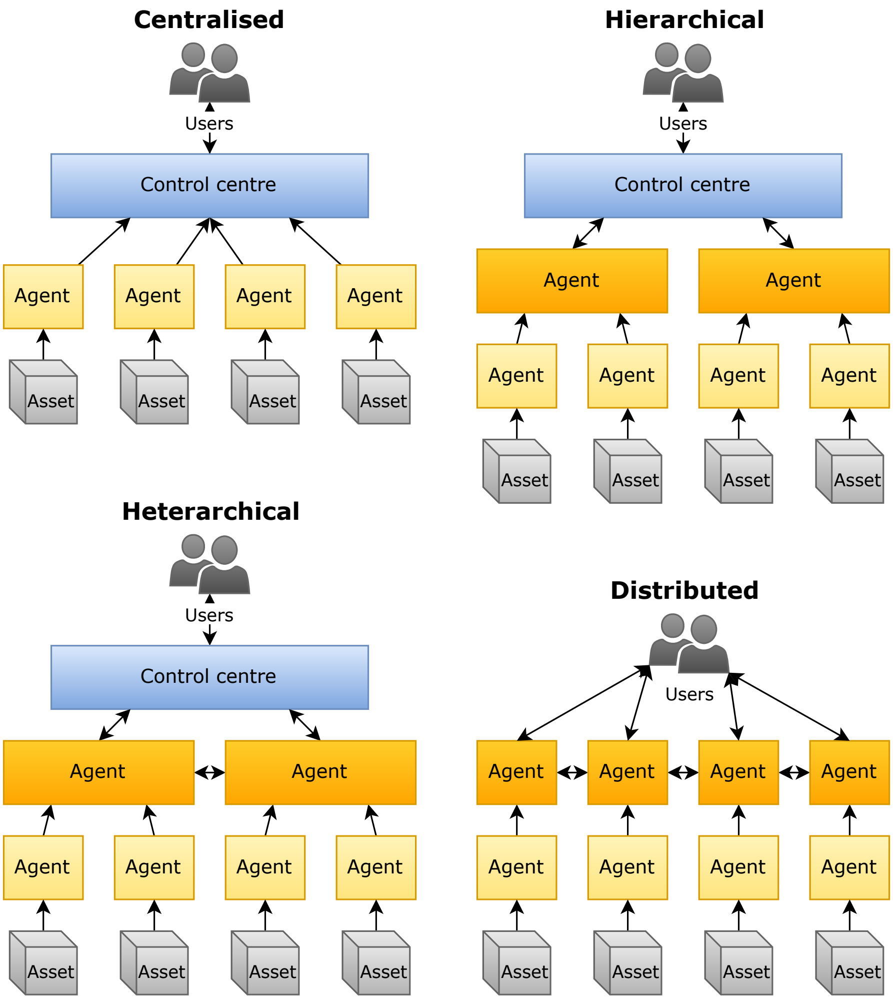


Figure 4.2: Different architectures of multi-agent systems (based on [85])

its objective(s). Ruiz Rodríguez et al. [87] use this concept in a PdM model that focuses on the task scheduling in the PdM decision-making process. Each agent is assigned to a piece of equipment in a larger facility and learns to keep machines in the working state as long as possible. However, it has to move out of breakdown and maintenance states as soon as possible, so it learns to identify the best technician to perform the maintenance in the shortest amount of time.

4.3. Cyber physical systems

In the Industry 4.0, Cyber-Physical Systems (CPS) are considered as one of the main enablers. CPS is a multidisciplinary approach, integrating technologies such as IoT, control systems, big data and real-time applications [88]. The main goal of CPS is to create a bi-directional interaction between the physical world and the cyber space [89]. Where abstract models like mentioned in section 4.1 and section 4.2 can operate independent from the physical equipment and only require periodically updating, CPS need to be connected real-time [88]. Three main components of CPS can be distinguished [89]:

- **Communication:** rather than relying on traditional single-network data collection methods, CPS communication channels must comply with high standards, ensuring lossless transfer, no delay, low energy consumption, shared access, and sufficient bandwidth capacity. The key elements of CPS are sensors and actuators that are interacting with the physical world for data exchange. These devices must guarantee that any changes in the physical world induce changes in the cyber world, and vice versa.
- **Control:** CPS use intelligent controllers to monitor and process physical process variables in real-time. Control commands are generated based on predetermined rules through data processing

and analysis. The actuators in the physical world execute the control directives.

- **Computation:** in CPS, two types of computational techniques are commonly applied: model-based and metamodel-based methods. Model-based methods can take various forms, for instance physical, mathematical or simulation models. They are enhanced by incorporating various algorithms to handle computational challenges in the CPS control system. These methods can however be very complex and increase computational cost. Therefore metamodels are utilised to serve as an less computationally expensive method for these computational challenges.

For an automated CBM approach, Al-Najjar, Algabroun, and Jonsson [90] developed a CPS that can automatically fulfil four tasks: (i) gather the data required to monitor the health of the machine, (ii) recommend actions or send work orders, (iii) conduct specific maintenance actions and (iv) report about remaining maintenance actions that are to be done manually. To achieve this, they state the CPS has to consist out of the following units: a measuring system that gathers data and accounts for the signal processing, a “brain with intelligence” that also stores the data in a database, and an interface with actuators and controllers. In this system, bidirectional communication is necessary to report the successful or unsuccessful completion of tasks.

To establish collaborative proactive maintenance, Papa, Zurutuza, and Uribeetxeberria [91] describe a CPS approach that use distributed processing chains, which transform raw data into knowledge while minimising the need for bandwidth. At different levels in the system, local sensing and decision-making functions are performed. Data flows automated through the different levels in the system until the desired information is extracted and delivered to the right people or machines for maintenance. This way, each component in the CPS is engaged in the achievement of the common goal of maintenance optimisation. Moreover, this collaborative ecosystem can be deployed on every scale, for asset maintenance or service-based maintenance for clients. It can result in a hyper-platform that allows to connect smaller ecosystems on different platforms into a larger one [91].

4.4. Digital twin

Digital Twin (DT) is a popular paradigm in Industry 4.0 that combines a physical modelling approach with real-time data analysis. A DT is defined as a virtual and simulated model of a physical entity, process or system involving automated communication between the physical object and virtual model [92–94]. DT technology generally consists out of three parts: the virtual model in the virtual space, the physical system in the physical world and the data interface between the physical world and the virtual space. Although, when referring to a DT, usually just the virtual model is meant. Regarding CPS (see section 4.3), it can be said that this is characterised by a physical asset and its DT. In other terms, a DT represents the prerequisite for the development of a CPS [95].

Some of the key technologies to enable a DT are 3D modelling technology, status monitoring and display technology, VR technology, data storage and high-performance computing technology, data acquisition and transmission technology, lifecycle data management and model driven technology [92]. The essential constituents of DT technology are [96]:

- **Sensors:** distributed throughout the system, sensors create signals that enable the twin to capture operational and environmental data related to the physical system in the real world.
- **Data:** the data from the sensors is aggregated and combined with other data, like design specifications, enterprise systems or external data feeds.
- **Integration:** sensors communicate the data to the digital world through integration technology (e.g. edge, communication interfaces and security) between the physical and digital world, and vice versa.
- **Analytics:** the data is analysed by algorithmic simulations and visualisation routines to produce insights.
- **Digital twin:** the DT itself is the application that combines the elements above into an almost real-time digital model of the physical world and system. The objective of the DT is to identify unacceptable deviations from optimal conditions. Such a deviation can either indicate a simulation error (which is undesirable of course) or an opportunity for an action on the physical system.
- **Actuators:** if there is necessity for an action in the real world, the DT can produce the action with actuators to trigger the physical process. This would be required for a CPS. In most cases, human intervention is needed to conduct the actions on the physical system.

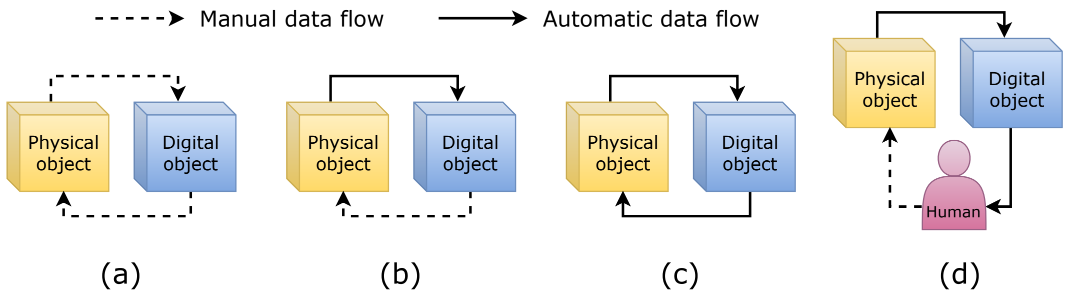


Figure 4.3: Classification of DT based on level of data integration: (a) digital model, (b) digital shadow, (c) DT and (d) DT with human integrated in the decision loop. (Image based on [63, 99, 101, 102])

As mentioned, the virtual model is the digital representation of the physical system, therefore the actual DT itself [97]. Virtual models can be a three-dimensional geometric model that describes the physical system in terms of shape, size, tolerance and structural relationships [93]. With physical properties (e.g. speed, wear, force), the model can reflect physical effects on the system (e.g. deformation, fracture, corrosion). Behaviour models and rule models can describe the behaviour and response of the physical system, and can give logical abilities to provide reasoning, evaluation and decision-making [93]. A communication platform, or data interface, is used to ensure the flow of data and control signals between the physical system and virtual model [97].

4.4.1. What defines a digital twin?

DT technology has been around for some time and has garnered significant attention from both the industry and academia [98]. However, during this time, some misconceptions about the true definition of a DT have also emerged, which can partially be declared by the complexity of the concept [63]. Some people generally describe a DT as a digital version of a physical object, while this does not cover the true concept of DT [99]. Since there is no single way to deploy or design a DT, broad approach to application exist which may strongly differ in level of integration [100]. This results in some businesses developing digital models of their assets and inappropriately naming it a DT [94]. In their literature review Kritzinger et al. [99] acknowledge this misconception and propose three subcategories in digital modelling to make a classification based on level of data integration (refer to Figure 4.3a-c).

(a) **Digital Model**: this is a digital representation of a physical object without any form of automated data exchange between the physical and digital object. Note that the physical object may not have been fully realised yet. Therefore digital models may be utilised for simulations of planned factories, mathematical models of new products or other applications that do not require any form of automatic data integration. If the physical object experiences a change in state this will not have a direct effect on the digital object and vice versa.

(b) **Digital Shadow**: the digital object is automatically updated if the state of the physical object changes. This can for instance be achieved by a sensor system. Data coming from the digital object still needs to be manually processed for change of the physical object [63].

(c) **Digital Twin**: a bidirectional and automatic data interaction between the physical and digital object exists. This allows the digital object to take on the role of controller for the physical object. A change in state of the digital object will directly alter the condition of the physical object and vice versa.

Therefore, it can be concluded that a DT stands out from a digital model through an active, two-way interaction between the physical entity and its digital representation [94]. In addition to the classification in Figure 4.3a-c, Moyaux et al. [102] argue that a human can be integrated in the decision loop of a DT as well (Figure 4.3d). They present various arguments for human integration, concluding an unsupervised automated connection between a model and the physical system is rarely desirable in practice. In their point of view, a DT should give suggestions based on the state of the physical system, and these suggestions may be updated if the DT detects they are not followed in the physical world. This definition corresponds better to the desired role of a DT in a maintenance strategy, since it is not yet possible to let all maintenance be conducted by robots.

Finally, in their article devoted to finding the boundaries between models and DT, Wright and Davidson [103] give three criteria that should be met in a DT in order to add value in the desired field of application:

- The model should be sufficiently *physics-based* that updating parameters based on measurement data is a meaningful thing to do.
- The model should be sufficiently *accurate* that the updated parameter values will be useful for the desired application.
- The model should run sufficiently *quick*, in order to make decisions about the application within the required timescale.

If these three criteria can be met, the developed model can be used in a DT solution.

4.4.2. Modelling levels

In the modelling phase of a DT, different levels of modelling can be used for the components or subsystems, depending on the available data and knowledge about the physical objects [101, 104–106].

- **White box**: the exact functionality and working mechanisms of the physical object are known. The model structure is therefore identical to reality. A white box model can provide insight into the relationships between different variables in the system through a transparent, well-defined set of equations. The level of accuracy can be determined by using complex high-level numerical methods or reducing those to simplified analytic models to accelerate the simulation time.
- **Grey box**: parts of the model are exactly known, but theoretical data is needed to complete the model. This data can either be learned, derived or measured. The structure still resembles reality to some extent. Since these models use the physical laws derived from white box models and the statistical learning abilities of black box models, they can also be described as hybrid models. The ratio between physical information needed for the white box-part and statistical information for the black box-part determines the accuracy of the grey box model.
- **Black box**: there is no knowledge of the internal workings. Therefore the entire model needs to be learned based upon observations. The behaviour of the twin is similar to the physical counterpart while the internal structure is of entirely different nature. This internal structure for instance consists of (multi-)regression methods, artificial neural networks, Bayesian belief networks or other comparable AI solutions. Black box models can therefore be updated when new data becomes available.

4.4.3. Digital twin for predictive maintenance

In PdM strategies, the use of a DT can play a critical role in predicting and avoiding equipment failure [63, 94]. Theoretically speaking, DT can combine both a physical model-based and data-driven approach for a reliable hybrid PdM strategy. The equipment can dynamically be modelled with high accuracy based on physical laws. Meanwhile the DT acquires real-time data and stores historical running data that can be used for improvement of the virtual model. The real-time data, acquired through sensors, is also used for real-time prediction algorithms [64]. The virtual model can also be used for what-if analyses to study unexpected scenarios without using the physical asset itself [93]. A set simulation can be performed on the DT to reveal aspects that cannot be identified by using only collected information from the real machine. Future operations of the machine can be simulated to create failure profiles or to plan maintenance activities based on the DT simulation results [107].

The RUL can be predicted with a DT using a combination of physical failure models, modelling gear crack, fatigue, wear and other deformation models, and ML methods mostly for classification and regression tasks . Classification is used to indicate categorical targets such as state of the equipment. Regression is used for continuous targets such as the RUL prediction [66]. Prediction of the RUL and the state of the equipment after maintenance, can be improved by including more characteristics of the operation in the DT. It is therefore necessary to have historical running data for the calibration and validation of predictive models. This historical data can be acquired through real world measurements, but it can also be generated in a synthetic manner [63].

4.5. Modelling a drilling rig system

The aim of this chapter is to find a model framework that can be used to make decisions on the PdM of components on a system level. First requirements are defined to assist in the selection of an appropriate framework. Then this section will reflect on the mentioned methods to see whether they can be beneficial in the modelling of a drilling rig system. Finally, an applicable framework will be proposed.

4.5.1. Requirements of the system model

- **Integration of component-level maintenance solutions to system-level decision-making**. The main contribution of this thesis is to find a holistic approach to drilling rig maintenance, therefore this requirement should be met in the proposed framework.
- **Functional based on available data**. A few times this chapter has already mentioned to identify an *applicable* framework, meaning it should be functional based on the available data on drilling rigs. It is assumed that this data consists of SCADA data, which are operational parameters gathered by the rig operational control system used to operate the rig, CM data and maintenance records of the commonly maintained components on the rig.
- **Easily modifiable model structure**. It is not uncommon that components are changed or added between drilling rig operations. Other reasons to modify the model are to change or add a CM method or to alter approach in component PdM. Therefore, it is desirable that an improvement does not require a complete revision of the system model, but rather allows to alter the relevant parts of the model.

4.5.2. Reflection on discussed modelling methods

Statistical modelling of a drilling rig will result in an abstract model of the system that determines the system reliability as a function of the components' reliability. This means that the dependencies in the system have to be known, or at least be estimated as close to reality as possible. For successful application, the historical operations and maintenance data need to be analysed to determine an approach to the uncertainties in the system reliability structure. It will require the application of expert knowledge to successfully model the drilling rig and formulate the goals for the model to achieve. Due to the complexity of a drilling rig, it may be hard to find a statistical modelling approach that can generate accurate decisions, regardless of the operation environment.

For a drilling rig, physical failure modelling requires knowledge of all the loads in the system and the dominant failure mechanisms of the components. Analysis is then needed to determine the criticality of components and their condition impact on system level. Loads and other environmental conditions that have influence on these mechanisms need to be monitored for the components. Then, based on predefined calculations this data can determine the health condition of the drilling rig equipment. Rather than estimating an RUL, exceeding thresholds will trigger maintenance actions on the rig. Like statistical modelling, physical modelling requires expert knowledge and it may be hard to capture all the factors of influence in the complex system of a drilling rig.

While mathematical modelling can form the base for a drilling rig model, it might not be an appropriate method to model the drilling rig system. The uncertainties and complexity of the system is hard to capture in a solely mathematical model. Furthermore, it is not a method that offers specific benefits for the modelling of a system compared to other approaches.

A MAS is a method that proposes some distinct advantages for system modelling. The components of a drilling rig can be modelled as agents interacting with their environment, in a MAS. A centralised agent can gather information from these agents to determine the optimal actions that can benefit the system performance. The architecture of the MAS can be chosen and customised to fit the properties of the drilling rig. This strongly resonates with the requirement of integrating component-level maintenance solutions into a system-level decision-making system. Development of a MAS can reduce the complex drilling rig to a structured model that can be expanded by adding behaviour rules, AI methods and new component agents if necessary.

With the recent advancement in sensor technology and IoT, DT has become a popular concept in the drilling industry. Especially offshore drilling rigs, which operate in remote locations, are a popular subject for the application of DT to enable real-time control on a centralised location using a digital shadow. The decision-making of these DTs should be predominantly with the rig operator, but a DT can greatly assist in real-time decision-making by rendering the data more user-friendly for the operator. Moreover, employing a DT can generate useful operating data to gain insights into the running history of the rig. However, it appears that DT can not yet be applied in practice, particularly in terms of the automated connection to drilling rigs, which remains in a premature stage. There are limited examples of DTs using actuators in a CPS solution, in other words fully autonomous drilling rigs. Instead, digital

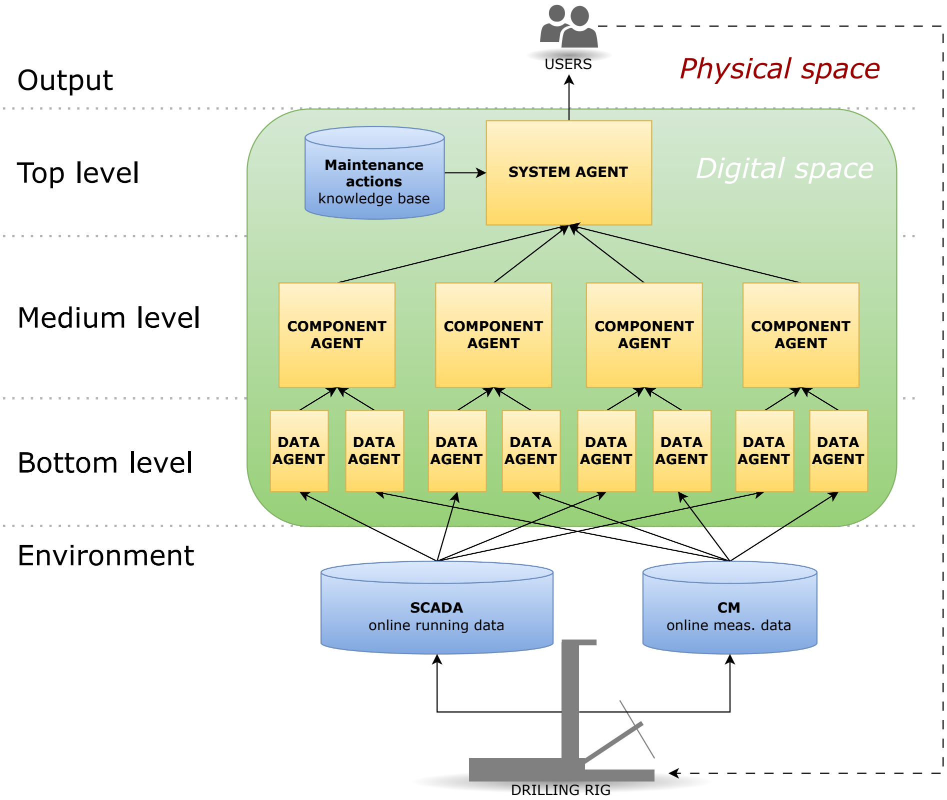


Figure 4.4: The hierarchical multi-agent system framework proposed in this thesis.

shadows are slightly being applied for continuous equipment monitoring and maintenance decision-making. Therefore there seems to be potential value to first develop DTs of drilling rigs with human operators integrated in the feedback loop.

4.5.3. The proposed system model framework

This thesis will propose a hierarchical MAS as depicted in Figure 4.4. More specifically, the model will schedule maintenance actions, based on SCADA and CM data that is representing the physical environment. The lowest level contains data agents that process the raw data from the environment. This data is fed to the data agents in real-time. Processing may include filtering of CM data and selection of relevant parameters from the SCADA system. The cleaned data is passed on to the component agents. These component agents give an assessment of the operation status and RUL of the physical component and communicate their conclusion to the system-level agent, the controller. The goal of the controller is to give a real-time classification of the rig operating state and predict the locations for upcoming maintenance actions in the system. Options for maintenance actions can be provided in a knowledge base for the controller agent to choose from. Based on the inputs, the controller will provide and update maintenance windows that can be adhered to by the operator to optimise drilling rig uptime. Since the digital model is updated automatically when new data is fed into the model, it can be classified as a digital shadow (refer to subsection 4.4.1). The operator is the link back to the physical system: they can decide to follow up a real-time suggestions and alter the system, by conducting maintenance. The component agents in the digital model will detect possible changes, consequently updating the information to the controller agent. Therefore maintenance on the drilling rig will complete the information feedback loop.

4.6. Conclusion

From RQ3, requirements for the model framework can be deduced. In addition to the main function of integrating component-level maintenance solutions to system-level decision-making, the model framework must be effective based on available data and have an easily modifiable structure to be “applicable”. After surveying various frameworks, the MAS framework in Figure 4.4 is proposed as an applicable framework. It is able to combine component-level prognostics solutions with a single, centralised maintenance decision-making model. Since the framework processes and analyses data from the equipment in real-time it can be classified as a digital shadow. Operators can cooperate in the model-equipment interaction by acting on maintenance suggestions from the model. The proposed framework is applicable on land drilling rigs since it is functional with available operational and CM data and does not require exact knowledge about dependencies between components in the system. As a bonus, this model will be able to determine operational status based on real-time data of the components, which allows for better insights in the operational performance of the drilling rig.

Selection of this framework answers RQ3 and concludes the literature research of this thesis. Part II of this thesis will focus on finding the correct methods to implement in this framework, in order to achieve successful fault recognition, RUL prediction and maintenance decision-making.

II

Design & Development

5
Selection of methods

This chapter will identify appropriate methods for the functions of the agents in the proposed model framework (subsection 4.5.3). By selecting these methods, a component of RQ4 can be answered. First, the tasks, functions and actions of the agents in the model will be discussed in detail. Then the available data will be analysed. This data includes operational parameters from the drilling rig SCADA system and CM data. To find appropriate methods, the functions of the model are reintroduced starting from the lowest level in the model. For each of these functions, an adequate method will be elaborated that will be used in the design. Each discussed method can be classified as one of the PdM approaches surveyed in subsection 3.7.2 & 3.7.3. Finally, this chapter will expand the visual framework in Figure 4.4 by assigning functions and methods to the agents and indicating the information flow in the model.

5.1. Scope and functions of the agents

To identify the functions of the model, this section will discuss the agents from bottom to top-level.

5.1.1. Data agents

The model receives raw data from either one of the two sources in the environment. The first data source is the SCADA system, which collects operational data from the equipment that is necessary for the control of the rig. The other source of data is the CM system, which may differ per component, but will mostly consists out of sensors connected to a digital-to-analog converter and additionally a local storage device. The input of the data agent is therefore raw, digital data either in value type or waveform type. The main task of the data agent is send data to the component agents after it is cleaned based on the agents' requirements. Since an agent can either receive data from the SCADA system or the CM system, the input of two data agents are required per component agent. The tasks of these two types of data agents is however similar.

Data preprocessing

The main purpose of data preprocessing is to provide accurate, clean and complete data that can be used for analysis. Successful data preprocessing will result in data that can directly be fed into an analysis system to obtain reliable results. In the context of this research, operational data will have to be selected and integrated into a dedicated dataset for each component agent. Raw time-series data, e.g. vibration data from accelerometers on a mud pump, will have to be filtered to remove noise and possible offsets.

5.1.2. Component agents

In this framework, each component agent represents a component group that needs to be scheduled for maintenance by the system agent. E.g., in a land drilling rig, the top drive system may have a component agent for the gearbox but also one for the e-motor and the tilt cylinder. The component agent receives cleaned data from the data agents. This data is used for the two main tasks of the agent:

- Classifying the current operational state of the component

- Predicting the RUL of the component

The RUL is dependent on the current operation, the running time but also the health condition of the component. Therefore, in order to accurately predict the RUL, the component agent is required to assess the health condition too:

- Health condition assessment

After completion of these functions, the component agent creates a dataset containing the operational status and the RUL that can be send to the system agent to be used in the centralised decision-making process.

Operational state classification

Based on the operational dataset, the component agent estimates the operation in which it is involved, in other words the current operational state. While for some components this may be a binary state (on/off), for some components it may be useful to classify a state out of multiple possibilities. A component agent communicates its state to the system agent. Based on that communication, the system agent can evaluate the current operation of the whole drilling rig. This is important for the scheduling of maintenance actions. However, assessment of operation is also necessary to keep track of the running hours of the component, which is important for the later prediction of the RUL.

Health condition assessment

Also known as diagnostics, estimating the health condition of a component revolves about quantifying the physical state. The health condition should be assessed on a measurable scale. For example, when assessing the health condition assessment of a bearing, vibration monitoring may be deployed. The data agent will send cleaned time-series signals to the component agent. From these vibration signals, the component agent can extract signal characteristics such as peak frequencies and signal energy. Typically, the values associated with a “healthy” component are known for these characteristics. The degree to which the measured characteristics deviate from the “healthy” standard can determine the health condition of the component. Therefore, successful diagnostics revolves around identifying and extracting relevant, measurable features from the data that can accurately estimate the component’s condition.

RUL prediction

This function is also known as prognostics. The purpose of RUL prediction is already explained in subsection 3.7.1, recapitulating: a PdM strategy revolves around forecasting the actual RUL in the most precise way possible. Methods for prognostics are also briefly discussed in subsection 3.7.2. In the proposed model, the component agent will estimate the RUL based on at least three parameters:

- The amount of running hours since the last maintenance
- The operating state, quantified to a degree of usage severity
- The health condition as assessed by the agent

These three factors will always have an influence on the RUL. Based on the component, other factors may be known to have an influence on the RUL. The component agent will use an appropriate model that incorporates all the relevant factors to obtain an accurate RUL prediction, which is then to be communicated to the system agent.

5.1.3. System agent

On the top level of the proposed model, the system agent can be found. The system agent receives a dataset containing the operating state and an RUL prediction from each component. Based on these datasets, the system agent must complete two functions:

- Autonomously comprehend the current operation of the whole land drilling rig.
- Schedule maintenance actions in a decision-making process

The system agent is also responsible for the output of the model to the user. Therefore its output will be in the shape of a dataset that can be integrated in the drilling rig user interface and provide information that is comprehensible for the operator.

Operational state classification

Like the component agents do for the component, the system agent must determine the operational state the whole system takes part in, based on the states of the components. This is the first step in the centralised decision-making process of the model. Determining the current operation is necessary to know when maintenance actions on the drilling rig can optimally be performed. Additionally, automatically keeping record of the drilling rig operational state can be beneficial for the operator to analyse the progress on a drilling project.

Maintenance decision-making

For each component agent, the system agent has to schedule maintenance actions. The scheduling of maintenance actions should comply with a PdM strategy, so the parts will be replaced based on their RUL. Therefore the agent refers to the RUL supplied by each component agent and can consult a user-defined database containing failure mode scenarios and associated maintenance actions. The controller agent is expected to continuously maintain overview of all components and their operations, and to intervene when a component is expecting to fail soon. Moreover, the controller agent can also decide to group maintenance actions, suggesting OM (refer to subsection 3.6.1) actions to minimise the number of maintenance moments. It becomes clear that the desired decision-making process can be divided into several sub-tasks:

- understanding the RUL of each component
- identifying components that are expected to fail soon
- consulting a database to find the appropriate maintenance action
- schedule the priority maintenance action together with potential OM actions

This process requires data comparison, reasoning, matching and scheduling. The output of the decision-making process should be a suggestion for a maintenance action, in the form of a time window or a prompt to immediately conduct maintenance.

5.2. Available data

As mentioned before, raw real-time data enters the proposed model. This section will describe this available data and will also state how it can be utilised after preprocessing.

5.2.1. Operational state data

From the SCADA system, an enormous amount of data is available that are used in the control system of the drilling rig. Some of these parameters are shown on the drilling rig user interface to give the driller overview about the operations of the components. Based on a combination of those parameters, an experienced driller can independently assess the current performance of the drilling rig and comprehend the operating mode. With some operational parameters, discrepancies can already be detected that may indicate an upcoming failure, however recognising this from the data requires knowledge and expertise. The data agent will have to extract this relevant data from the SCADA system.

A general SCADA system lots of data is collected to completely control the operations of the rig. In addition to measurements derived from machines like torque, speed and load cells, drilling rigs are fitted with switch sensors that indicate activation or completion of local movements. These switches can also be used to send alarms to the operator.

5.2.2. Condition monitoring data

CM data can be collected according to one of the techniques mentioned in subsection 3.7.4. For operational purposes, drilling rigs may already be fitted with temperature sensors and oil contamination sensors. Note that while these sensors can theoretically be used in a CM strategy, they are in practice used to trigger operational alarms. Other CM techniques need to be deduced based on the failure modes of the components in a drilling rig. This research assumes that for each component agent, a dedicated CM technique can be applied that has proven to be sufficient for later RUL prediction analysis. Examples of various CM techniques are given in subsection 3.7.4. Analysing the nature of frequent failure modes of a drilling rig in section 2.9, some CM techniques can be deduced. These are listed in Table 5.1.

The raw CM data gathered will be subject to noise from the harsh environment of drilling rig operations. First, this noise has to be removed to obtain a “clean” signal. From this clean signal, features can be extracted for diagnostics and prognostics according to the CM technique.

Table 5.1: CM methods per nature of common failure modes in a drilling rig.

Failure mode nature	CM method
Wear	Vibration analysis, acoustic analysis
Mechanical	Vibration analysis, corrosion monitoring
Electrical	Thermal analysis, voltage/current signature analysis
Hydraulic	Oil or lubricant analysis

5.2.3. Maintenance records

Please note that this type of data is not real-time data for the data agents, but it is only used during development of the proposed model. In particular for development of most reliable RUL prediction methods, maintenance records are necessary to determine and quantise the parameters that affect the RUL. In practice, for equipment that needs regular maintenance, the running hours of replacement parts are recorded. From this data, it can also be determined if a part was replaced due to an unacceptable condition or because this was a preventive replacement.

In a basic data analysis, the component running hours can offer some quick insights to improve the maintenance strategy. Based on these hours, one can easily determine the mean time before failure of parts. This value can help to determine the point availability of the component with the formula provided in section 3.1. However, it must be noted that in most cases the running hours before failure are subject to a high variability, emphasising that the running hours should not be the single indicator for maintenance. This is another argument for the use advanced maintenance concepts to improve equipment operations.

5.3. Data preprocessing

The following sections will discuss the methods chosen for the functions of the agents in the proposed model, starting with the data agents. Their task is to preprocess raw data, introduced in the previous section, and form a dataset to the demand of the connected component agent.

5.3.1. API request

To be able to use operational data in the model, it first needs to be extracted from the SCADA server. In a drilling rig, field devices and sensors collect data that is necessary for the control of process and operations (see Figure 5.1). Via a modbus connection, these devices transport the data to the Programmable Logic Controllers (PLC) or Remote Terminal Units, which locally acquire the data and trigger actions on the physical system based on programmable logic. The data is collected from the PLC by edge gateways, which can for instance be local computers, that first process the data before transferring it to the SCADA server. From this SCADA server, the system is controlled, data is logged in a database and updates are provided to the user interface [108].

An Application Programming Interface (API) can be used to extract the data from the SCADA server. Simply described, an API can be considered as the translator between the SCADA server and an application outside the system. They retrieve the requested data in the desired particular format. There are contextualised APIs available that support the specific SCADA application, so that the model does not have to deal with database terms but with immediate operational terms. Finally, APIs can allow to push back information to SCADA, which means it can be possible to run control software without having to program a PLC [109].

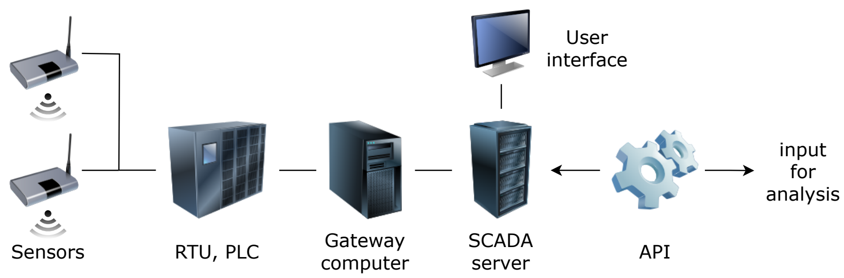


Figure 5.1: Schematic overview of the components in a SCADA system from sensor to API software.

Each data agent will use an API to request the demanded parameters from the SCADA system in the desired format. If there is no new data value available from a requested parameter, the data agent can forward fill the last known value to provide a complete updated dataset.

5.3.2. Noise filtering

Since raw sensor data will most likely contain some noise, it is desirable to remove this noise before the data is used for feature extraction. Noise filtering is necessary for this purpose.

In a time signal, it may occur that a certain frequency is dominant in the time signal, while these frequencies may not be relevant for the features to be extracted. This band of frequencies may be interfering with the desired time signal. For instance, for a vibration signal, lower frequencies may be dominant in the signal, while the higher frequencies are of greater interest for analysis. Also, a DC component may be interfering with the clean signal. In these cases, a linear filter can be used to decrease or remove a predetermined range of frequencies from the signal. Example of these filters are high-pass, low-pass, band-pass and band-stop filters [110]. For this purpose, Butterworth filters are usually employed. An important reason for the use of Butterworth filters is their “maximally flat” property, meaning they do not locally peak the signal level around the cutoff frequency. A fourth-order Butterworth filter will have clean and steep cutoff characteristics [111].

For environmental noise in the signal that is not clearly bound to specific frequencies but rather a random process, statistical filters can be deployed. The Wiener filter was originally developed as a method to reduce the noise in an image but can be a good method to reduce random noise in a one-dimensional time-series signal [112]. It assumes that the observed, discrete-time noisy signal $x(n)$ consists of a clean signal $s(n)$ polluted with a stationary noise signal $e(n)$:

$$x(n) = s(n) + e(n) \tag{5.1}$$

The goal is to obtain a signal $y(n)$ using the filter $h(n)$:

$$y(n) = x(n) * h(n) \tag{5.2}$$

Since $y(n)$ should resemble $s(n)$ as much as possible, the goal is to minimise the mean-squared error

$$\text{MSE} = \sum_{n=-\infty}^{\infty} (s(n) - y(n))^2 \tag{5.3}$$

The Wiener filter in the frequency domain ω is:

$$H(\omega) = \frac{E[SX^*(\omega)]}{E[XX^*(\omega)]} = \frac{E[R_{SX}(\omega)]}{E[R_{XX}(\omega)]} \tag{5.4}$$

For a time series signal, the adaptive linear Wiener filter can be used for pointwise calculation of the output signal for sample n:

$$y(n) = \mu_x + (x(n) - \mu_x)\frac{\sigma_x^2}{\sigma_x^2 + \sigma_n^2} \tag{5.5}$$

Here μ_x is the local mean of the input signal. σ_x^2 and σ_n^2 are the local variance of the input signal and the noise, respectively. In practice a window size of n samples is determined before starting the algorithm, to form a neighbourhood per sample where the local mean and variances can be calculated [112]. Doing this for each sample n in a time series signal, the adaptive linear Wiener filter algorithm is able to smooth out the signal. Therefore the Wiener filter is a good choice to remove environmental noise from sensor measurements.

5.4. Rule-based operational state classification

As discussed in the data analysis section, there are some clear correlations between the different operational parameters, which can quite easily be interpreted by an expert. Rule-based systems (RBS) can convert the expert’s knowledge in a set of predefined decision rules that can classify the data, without the need of data feature extraction. The result is an accurate translation of human data interpretation into a model, which makes it a form of white box modelling. However, the model will only perform as good as it is programmed, this means the rules need to cover all instances and do not exclude any situations. Developing a RBS requires the formulation of a set of “if x then y” statements to deduce the class of the data point. Switch sensors in the operating system, which emit a binary signal, or equipment parameters that only need to be interpreted as “on” or “off” can be modelled with conditional rule-based modelling. This method is applicable for the operational state classification in the middle-level component agents and the top-level system agent.

Hayes-Roth [113] gives five key properties of an RBS:

1. An RBS incorporates practical human knowledge in conditional if-then rules.
2. The skill of an RBS increases proportional to the extension of their knowledge base.
3. A wide range of complex problems can be addressed by selecting and applying appropriate rules.
4. From the set of rules, an RBS can adaptively determine the best sequence to execute.
5. The conclusions of an RBS can be explained by retracing the logic of each rule used in natural language.

An RBS consists out of an inference engine, and a knowledge base. The inference engine selects relevant rules, evaluates the rules and returns output based on input facts. These rules can be collected from the knowledge base in an RBS. Rules consist of a condition and a consequence, typically following the if-then structure:

$$A \implies X \tag{5.6}$$

In this equation, fact A represents the initial assertion considering the system’s state. If presence of multiple facts lead to one single consequence, this can be taken into account with one rule:

$$A \wedge B \wedge C \implies Y \tag{5.7}$$

For the analysis of operational parameters, RBS can also evaluate if a parameters falls in a certain interval in order to classify the operating state. For instance:

$$0.1 < A \leq 1 \implies Z \tag{5.8}$$

5.5. Fuzzy logic-based diagnostics

As discussed in subsection 3.7.3, after preprocessing, the CM data is ready for diagnostics. Extracted features that determine the health condition can be selected and analysed. As mentioned before, the method for feature extraction relies on the chosen CM technique, depending on the component. It differs per agent and is therefore not a generic method. The method used for the case study on the mud pumps will be described in the next chapter. However, to determine the health condition based on these features, all agents can use the same method.

Health condition assessment introduces the concept of uncertainty to the model. From measured features, a conclusion about the health condition can only be drawn up to a certain probability, in other words, the evaluation will lack precision. To deal with this uncertainty, FL is introduced as a method for the equipment health condition assessment. If there is a certain degree of uncertainty about some values, fuzzy rules can be applied [60]. Developed by Lotfi Zadeh in 1965, FL introduces a degree in the verification of a condition, allowing for a condition to be something other than the “crisp” states true or false. In other words, the extent to which a condition variable is true can have a value between 0 and 1. This is called the membership degree and fuzzy subsets are characterised by membership functions, which can have a shape based on statistical studies (e.g. sigmoid, hyperbolic, exponential etc.). Using FL provides flexibility in reasoning as inaccuracies, uncertainties and subjectivities can also be taken into account [114]. The translation of uncertain values into fuzzy values is referred to as fuzzification. Using fuzzy values gives the advantage of eliminating the need to describe events or states numerically [115]. An example of fuzzification using membership functions is given in Figure 5.2. From these membership functions, an RBS can then be established using the fuzzy variables (so in this example for a car’s rpm: low, medium and high). The output of the evaluation is again a fuzzy value, which has to be defuzzified to obtain a numerical output value.

FL is a popular method to deal with uncertainty. Apart from application in an RBS, fuzzy values can also be used in various AI methods, like neural networks. When developing a fuzzy RBS, establishing the membership functions for fuzzification requires extra knowledge and work, on top of the work required for the design of the inference rules.

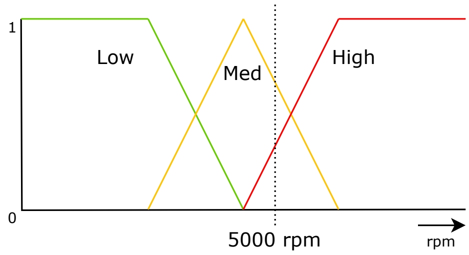


Figure 5.2: Example of the fuzzy membership functions of a car's engine rpm. The numerical input value is 5000 rpm. When fuzzified, the input is: high = 0.33, medium = 0.67.

5.6. RUL prediction

The degradation of components in a drilling rig system is dynamic, uncertain and mostly unknown, so a method to model this degradation will have to be found. The degradation will be dependent of the age, operating state and the estimated health condition, however the correlation between these factors and the RUL is unknown.

5.6.1. Survival analysis

From maintenance records, a survival analysis can be conducted. Survival analysis is a statistics topic that is used in reliability engineering but also in medical and biological studies [116]. The goal of survival analysis is to find the survival function $S(t)$ that represents the probability of survival at time t. The definition of survival in this context is that the event of failure has not occurred up to that point in time. The survival function can be fitted to available maintenance records data, containing lifetimes of equipment before failure (see Figure 5.3). This survival function is derived from the hazard function $h(t)$ that represents the probability of failure in the next time period $t+1$. From the hazard function, we can derive the cumulative hazard function:

$$H(t) = \int_0^t h(u)du \tag{5.9}$$

Then, derive the survival function:

$$S(t) = \exp(-H(t)) \tag{5.10}$$

The inverse of the survival function is the cumulative distribution function, which presents the probability of failure occurring on or before time t:

$$F(t) = 1 - S(t) \tag{5.11}$$

Both $S(t)$ and $F(t)$ can form the base for prediction of RUL in a reliability-based prognostics [117].

5.6.2. Weibull distribution

The survival function can be found by fitting a known probability distribution to the maintenance data [117]. The Weibull distribution, originally applied to model particle size distribution, is a popular continuous probability distribution that is commonly used in survival analysis because it only uses two parameters but is flexible and accurate enough to model time-to-event data in real-world applications [116]. The Weibull distribution function is:

$$f(x;\lambda,\rho) = \frac{\rho}{\lambda}(\frac{x}{\lambda})^{\rho-1}\exp(-(x/\lambda)^{\rho}) \tag{5.12}$$

The Weibull survival function can then be derived as:

$$S(t) = \exp(-(t/\lambda)^{\rho}) \tag{5.13}$$

In this function, ρ determines the shape of the function. If $\rho = 1$, the failure rate is constant over time. If $\rho < 1$ or $\rho > 1$, the failure rate decreases or increases respectively. λ determines the scale of the function. The value of λ indicates the time t at which 63.2% of the parts has failed.

An example of the development of a Weibull survival model fit can be seen in Figure 5.4. A Weibull survival function is fitted based on the data in Figure 5.3.

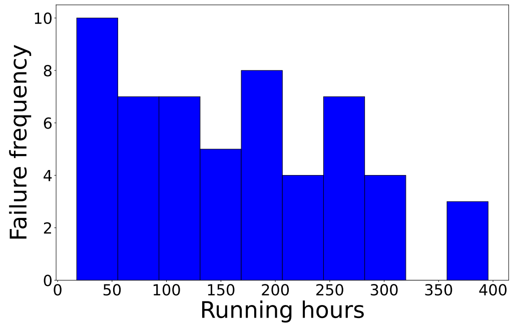


Figure 5.3: Example of the hours before failure of parts, plotted in a histogram.

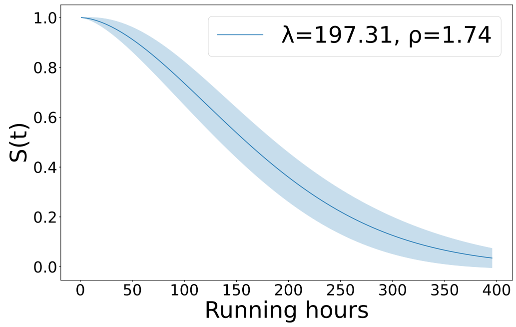


Figure 5.4: The Weibull survival function of the failure data presented in Figure 5.3.

The data for the fit of the Weibull model can be expanded by adding analysis of failure observations. For instance, if the maintenance data represents the running hours of parts, there might also be data available for parts that have not yet failed. These data points contain running hours of a part that has survived up to that point, but might fail in the future. But at what point in time the part will fail is unknown. In other words, the event of failure is not yet observed. This is called right-censored data. These data points can make a better fit for the Weibull model. The running hours data is then presented as in Table 5.2, here the most-right column represents the observed events. The effect of incorporating right censored data in the Weibull fit is shown in Figure 5.5. Both λ and ρ increase, which can result in a difference of around 60 hours at the same survival probability.

Table 5.2: Example of right-censored data of the maintenance records of a mud pump

Running hours	**Covariate 1**	**Event observed**
45	1.751	0
85	1.062	1
110	1.839	1
114	0.738	0
...	...	...

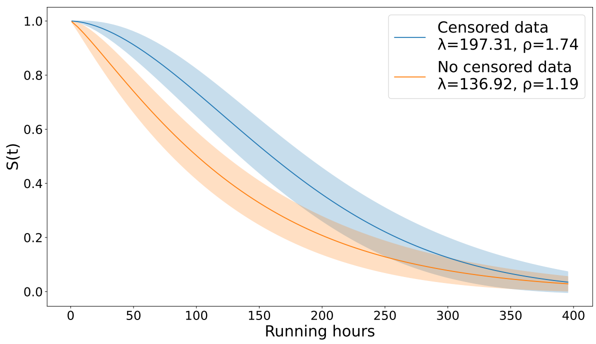


Figure 5.5: Example of the effect of right censored data on the Weibull survival function.

5.6.3. Accelerated failure time model

While the Weibull model can provide a good fit based on runtime, it is mostly a static model dependent on time. In practice the actual survival probability can be dependent on other variables in addition to running hours: covariates. To model the effect of covariates on the survival function, the principle of Accelerated Failure Time (AFT) modelling can be used. Weibull AFT models are dynamic models used in reliability engineering to predict the lifespan of machinery but can also be applied to other prediction problems, like food shelf-life or in medical context [118]. In case of a Weibull AFT model, the parameters λ and ρ will be dependent on covariates. The model is parameterised:

$$\lambda(x) = \exp(\beta_0 + \beta_1 x_1 + \dots + \beta_n x_n) \tag{5.14}$$

$$\rho(y) = \exp(\alpha_0 + \alpha_1 y_1 + \cdots + \alpha_m x_m) \tag{5.15}$$

The Weibull AFT survival function will have the form:

$$S(t; x, y) = \exp(-(\frac{t}{\lambda(x)})^{\rho(y)}) \tag{5.16}$$

The RUL can be calculated by first estimating the time t_τ where the threshold survival probability τ is first reached, representing the minimum acceptable survival probability. t_τ can be found in terms of x, y by calculating $S(t_\tau) = \tau$. Since the RUL at current time t is of interest, the general Weibull AFT survival function can be used to formulate the RUL as a function of t, x, y:

$$RUL(t; x, y) = \lambda(x) * (-\ln(\tau))^{(\frac{1}{\rho(y)})} - t \tag{5.17}$$

5.7. Expert system for maintenance decision-making

For the centralised decision-making process, a method has to be found that can perform data comparison, reasoning, matching and scheduling. The method should also have been proven to be compatible with using a knowledge base. These tasks can be executed in a wide-used variant of an RBS, namely the expert system. These systems are also known as knowledge systems, since the knowledge base in this type of RBS plays an important role. Kusiak and Chen [119] state that developers of expert systems have to consider three issues: the knowledge representation, the inference engine and the knowledge acquisition. Knowledge representation concerns the structure of the knowledge base. Traditional if-then rules as discussed in section 5.4 are one of the options. For facts that need to be consulted in a scheduling problem, a frame structure can be used. A frame contains slots corresponding to attributes related to the objects it represents. E.g., in case of a drilling rig maintenance activity, the frame `topdrivegearboxfailure` could have attributes `work location` and `duration`. The third representation Kusiak and Chen [119] mention is a semantic network. A semantic network connects objects with semantic relationships, such as `is located`, `has` and `is subject to` among others.

The inference engine in an expert system includes the deployment of rules, operators and patterns matching methods to establish the control strategy of the system. Three types of control strategy can be found in expert planning and scheduling systems [119]:

1. Meta-rules to control the reasoning process. In simpler terms, they can be considered as rules about the rules in the knowledge base.
2. Search operators to search the state space. They can for instance reduce the number of states to be searched in a knowledge frame by using constraints.
3. Pattern matchers to activate algorithms or modules when a pattern is detected, in other words when two or more conditions are met that trigger new rules.

Finally, knowledge acquisition revolves about the method to include (new) knowledge into the system. Depending on the type of knowledge base, there are many ways to gather and implement new knowledge. A common tool is to conduct an expert questionnaire.

5.8. Design summary

The design in Figure 5.6 can be considered as the general model architecture this thesis proposes. Application of this model should be feasible for every drilling rig and it should be able to provide a holistic approach to advanced maintenance. The data agents in the model gather raw data from the SCADA system and CM system. API requests can be used to extract data from the SCADA servers. Sensor data can be cleaned, using high-pass, band-pass or low-pass filters to remove specific frequency ranges and Wiener filters to remove random environmental noise. The data agent feeds cleaned data to the dedicated component agent. The component agent must determine the operational state and the RUL of the component. The operational state is derived from the SCADA parameters with a RBS. To determine the RUL, the health state must be classified to. Relevant features from sensor data are extracted and used in a FL classifier, to deal with the uncertainties of the feature values. Then, the operational state and health state are used in a survival model to determine the RUL. Each component agent communicates the operational state and RUL to the centralised system agent. Here, the current drilling rig system operation is determined and used in an expert decision-making system in combination with the components' RUL. For these decisions, the system agent can consult a knowledge base

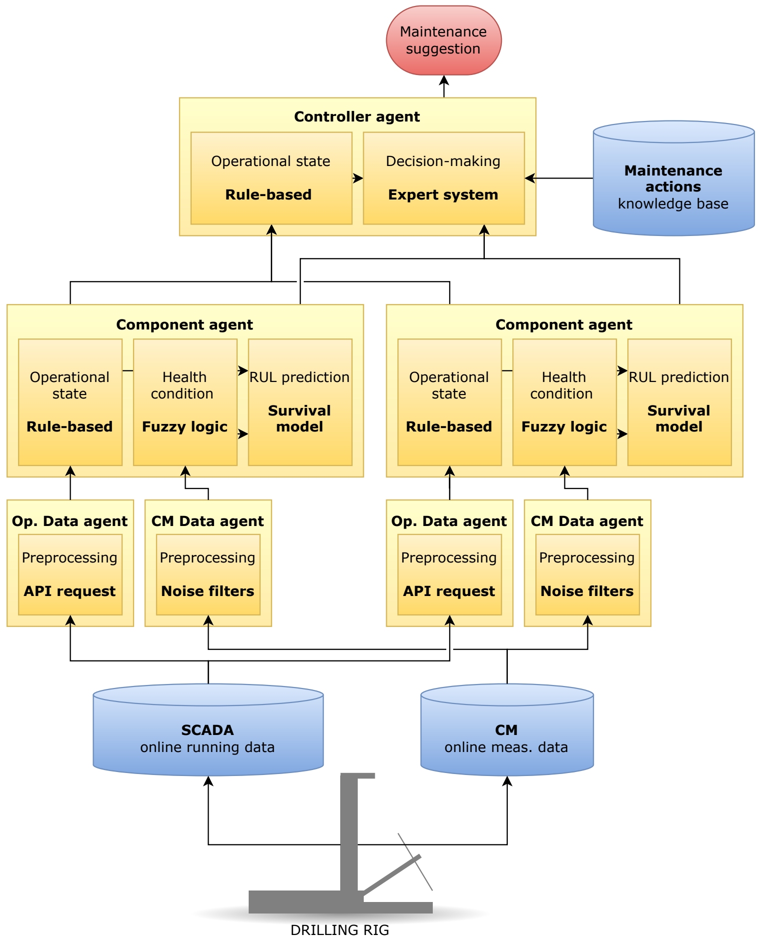


Figure 5.6: Overview of the proposed model, including the demanded functions per agent. The methods to perform these functions are given as well. Information flow is indicated with arrows.

containing all relevant information for maintenance on the drilling rig. The output of the model is a potential maintenance suggestion that is updated in real-time.

5.9. Conclusion

Based on the available data in the drilling rig, appropriate methods have been proposed to ultimately generate real-time maintenance decisions. This also required the assignment of functions to the agents in the proposed MAS framework.

In the model, CM data is cleaned from environmental noise before being analysed by the component agents. Diagnostics is performed by the component agents using FL to handle uncertainty in the condition assessment process. To generate maintenance decisions, the components' RUL is the critical variable. The RUL is determined through survival model prognostics, using maintenance records as a statistical base and covariates in the Weibull AFT model for a dynamic failure prediction. The system agent can use an expert system to generate maintenance suggestions based on the operational state, RUL and predetermined knowledge.

This chapter has proposed a general architecture for the model, presenting the theory of the selected methods and stating the reason behind selection. By selecting these appropriate methods based on the available data, a part of RQ4 has been addressed. It has yet to be validated how the methods can contribute to achieve integrated advanced maintenance. Moreover, this chapter has not answered how these methods can be applied to implement the model in practice. Therefore, the proposed methods will be applied using data collected during the field research in the next chapter.

6

Application of selected methods

Now that the methods to be applied in the development of the model are selected, this chapter will elaborate how to actually develop the model. The model is to be partially validated by using actual CM data of the mud pumps in the drilling rig. Therefore, only the component agents of the mud pumps will perform diagnostics and prognostics and provide real-time RUL. Other component agents will be developed just for the purpose of classifying overall system operating state. This chapter will first select an adequate CM technique for the mud pumps and elaborate the data acquisition process in the field research. The data preprocessing, feature extraction and diagnostics will be developed based on the selected CM method. Then, the RUL prediction method will be applied and validated. Finally, the system agent is realised to finish the development of the model.

Through the application of all previously chosen methods by the conclusion of this chapter, RQ4 will be answered. A complete summary of the created model is given in the last part of this chapter. This model is later used in the case study.

6.1. Mud pump vibration monitoring

A dominant failure mode in the mud pumps, is excessive wear of the valve-seat combination in the fluid end (Figure 6.2). When this combination is worn, the whole valve-seat assembly has to be replaced. This happens regularly during the drilling process, since a worn out valve assembly will reduce the efficiency of the pump and in a later stage it can cause a worn out fluid module. Since valves wear quicker than the seats, and valve wear also triggers seat replacement, the valves are the main focus of the field research.

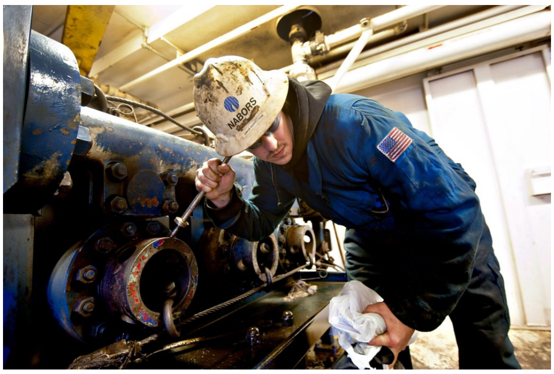
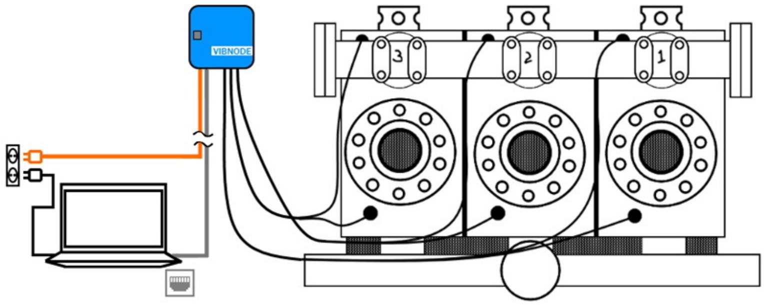


Figure 6.1: A driller is using a metal rod to listen to the fluid end of a mud pump. (Image from Bloomberg / Daniel Acker)

Figure 6.2: Worn mud pump valve and seat. On the seat (top-right), starting corrosion is visible. The plastic valve insert is torn. (Image taken during field research)



(a) Schematic depiction of setup

(b) Attachment of vibration sensors on the mud pump.

Figure 6.3: Overview of method for mud pump vibration data acquisition during the field research.

6.1.1. Background

The valves are subject to different types of wear, namely mechanical or sliding wear [120], erosion and corrosion [121]. The result of this wear is that the valves close less smoothly, which may be accompanied by increased vibrations, eventually causing a distinctive sound. Currently, in the absence of CM systems, this sound in the valve assembly is now detected by ear. By holding a random metal tool within reach against the fluid end of the mud pump and the other end to the ear, like a kind of simple stethoscope, a driller can listen to the vibrations in the fluid end (see Figure 6.1).

The replacement of wearing valves has great potential for the application of CM. Over the last few decades, there have been various efforts made to detect the wear of the valves in an early stage using real-time monitoring. Early attempts focus on pressure monitoring, as slight loss of pressure can indicate the start of leakage [122]. This method requires intrusive sensors with a high accuracy, since larger pressure fluctuations mean that the leakages are severe [123]. Accelerometers are used to measure high frequency vibrations that indicate leakage of the valves [123, 124]. The majority of the research in CM of the fluid end focuses on acoustic emission (AE) signals. These are elastic waves that propagate through the equipment and can be detected using piezoelectric AE sensors. So far, there is one example of a field validated tool that uses AE for the prediction of valve leakage [125].

6.1.2. Data acquisition

For the mud pump, accelerometers are chosen as sensors in an online vibration monitoring system. They measure the true acceleration in m/s^2. Six accelerometers are placed on the side of the fluid end, each in the proximity of a discharge or suction valve (Figure 6.3b). They are secured in place by strong magnets. The sensors are connected via a coaxial cable to a data acquisition unit that is located at the side of the mud pump. This unit is then connected to a power supply and a laptop, fitted with software and a database to store the acquired vibration signals (Figure 6.3a). For the data acquisition phase of this research, this was a temporary setup, however, this kind of setup could also easily be integrated into the drilling rig for constant CM. The sensors can be fixed to drilled holes in the structure via a threaded end. The data acquisition unit could be connected to the SCADA system via a modbus protocol.

The data acquisition unit sequentially triggers the sensors to measure each 30 minutes. At each trigger, multiple measurement tasks can be performed per sensor. The tasks performed in this field research were (i) capturing a 10kHz acceleration spectrum and (ii) recording a 3200ms acceleration time signal. This means that for further application of the methods no continuous real-world CM data is available.

6.2. Development of the data agents

The data agents gather raw data and process it, in order to adequately send the data in the right format to the corresponding agents. For the majority of the data agents this mainly means to select the right parameters and forward fill to continuously supply operational data. The developed data agent for the mud pump also gathers the CM data and filters the signal so a clean signal can be used for analysis and feature extraction.

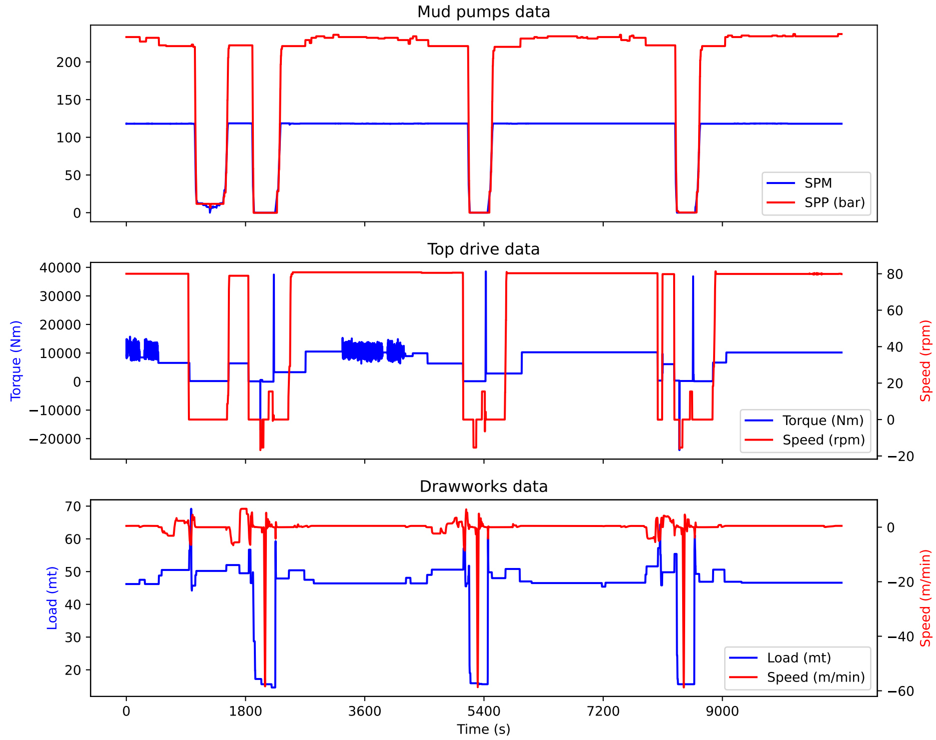


Figure 6.4: Parameters in operational data that are necessary for determining the rigs overall operational state, plotted per source component

6.2.1. SCADA parameter selection

Since the case study only focuses on the maintenance of the mud pumps, additional to the mud pumps three other component agents are necessary to determine the operational state of the drilling rig. These are the drawworks and the top drive. From the SCADA system, each data agent will pass on the following parameters:

Top drive:

- **Torque**: the top drive provides torque to turn the drill string. The torque increases when a section is being drilled. The top drive generates a high peak of torque when making or breaking a drillpipe connection.
- **Speed**: indicates the rotational speed of the drillstring, derived from the speed of the top drive e-motor and the gearbox ratio.

Mud pumps:

- **Standpipe pressure (SPP)**: the pressure of the mud is measured before passing through the rotary hose to the drillpipe. During drilling, it is essential to have a sufficient SPP.
- **Strokes per minute (SPM)**: the strokes of the mud pump give an indication of the operational performance of the pump.

Drawworks:

- **Speed**: the speed of the travelling block serves as an indicator of the motion of the top drive in the mast, providing information on both the rate and direction of its movement.
- **Load**: a load cell measures the hook load. The hook load is a combination of the weight of the top drive and the attached drillstring.

In Figure 6.4, these six basic parameters are plotted per source component for a duration of 90 minutes.

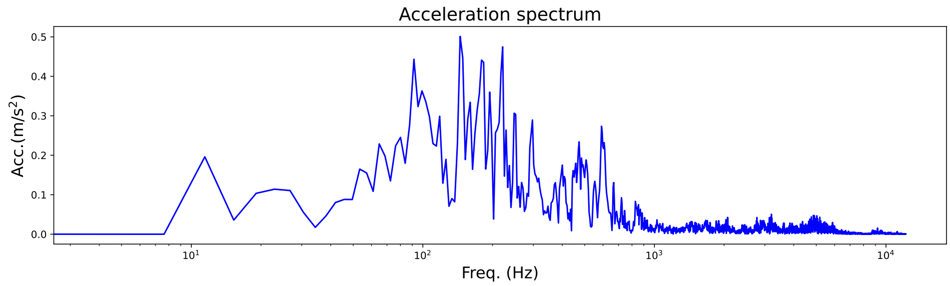


Figure 6.5: Acceleration spectrum of a mud pump. From this spectrum, it can be concluded that the lower frequencies of the acceleration signal are very dominant.

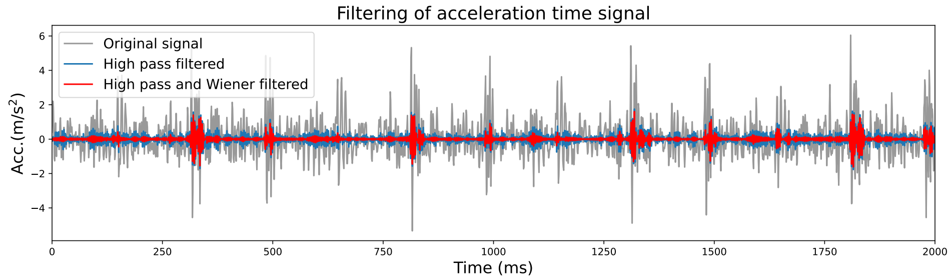


Figure 6.6: One second sample of a time series signal, first filtered by a high-pass filter and subsequentially by a Wiener filter.

6.2.2. Vibration signal filtering

The acquired vibration signals from the mud pumps are subject to noise. Because the mud pumps in the field research were mounted in container-sized frames and interconnected on the ends of these frames, there is inference of structure-borne vibrations transferred from other mud pumps as well. Two signal filters are applied and designed to obtain a clean signal.

From the acceleration spectrum of the signal (Figure 6.5), it can be deduced that there is a dominant band in the lower frequencies, with some peaks around 50 - 250Hz. However, for vibration analysis, the higher frequencies are actually of interest. This rumble peak is apparent in all spectrum measurements, meaning it is also polluting the measured time series signals. Therefore, first a high-pass filter is applied to the signal to enhance the distinction of the peaks in the time series signal. A fourth order Butterworth filter is chosen for this purpose because of its steep cutoff characteristics with a flat bandpass frequency response. Based on the acceleration spectra and through trial-and-error tweaking during the feature extraction process the final cutoff frequency is 240Hz.

The high-pass filter removes most of the signal rumble, but there is still some random noise pollution visible in the time series signal. To help reduce the random noise, an adaptive linear Wiener filter is applied, with a window size of 3ms. The algorithm as explained in subsection 5.3.2 is applied in the model to reduce the noise according to the Wiener filter.

The result of the time-series filtering can be seen in Figure 6.6. The signal is significantly cleaned and the vibration peaks corresponding to the valve impacts can be distinguished more easily. However, the high-pass filter has reduced the signal level of the peaks, which should be taken into account during signal analysis and feature extraction.

6.3. Development of the component agent

The component agent classifies the operational state and predicts the RUL of the component. Subsequently the operational state and RUL are communicated to the system agent. In the developed model, the drawworks and top drive agent only classify the operational state. Since the case study will focus on the maintenance of the mud pumps, the mud pump agents will be fully developed and include feature extraction, diagnostics and prognostics.

6.3.1. Rule-based operational state classifier

The operational state is determined with conditional rules. This method is validated in subsection 6.4.1, where the rule-based classification from the component agents and system agent is combined. For the development of a rule-based system, knowledge about the operations of the components is necessary.

Mud pumps operational state

The operational state of a mud pump can be deduced from the SPP and the SPM. The SPP is measured in the standpipe located at the derrick and is the general indicator if there is sufficient circulation. The SPM is measured per mud pump and indicates if the pump is running or not. Since the mud pumps are working in line, not all mud pumps have to be working in order to have circulation. Therefore, three states are possible for the mud pump:

0. No circulation
1. Online - mud pump is running
2. Offline - there is circulation but the pump is not running

From Figure 6.4, it can be seen that SPM and SPP do not increase steadily but rather sudden. With threshold values derived from this historical data, the following classification algorithm is applied:

if SPP < 50 **then**
  $s \leftarrow 0$
else
  if SPM ≥ 20 **then**
    $s \leftarrow 1$
  else
    $s \leftarrow 2$
  end if
end if

Drawworks operational state

From the drawworks data, multiple operations can be distinguished, just from reading the load cell and line speed. The operation is first dependent on the load on the load cell, which is either the weight or the top drive or the weight of the top drive and drillstring combined. Then the line speed can help determine the other states. The possible states are:

0. Not involved in drilling: slightly adjusting the top drive position, reaming up, moving just the top drive up or down the derrick, holding the top drive in a stationary position.
1. Drilling
2. Tripping: either pulling string out of hole or running the drillstring in the hole.

From analysis, it is determined that the minimal load of a top drive and drillstring combined is 20 tons. The line speed when drilling is between 0.1 and 1 meter per minute. The direction of the line speed also determines the direction of the top drive. The classification algorithm for the drawworks is:

if $-0.1 <$ speed < 0.1 **then**
  $s \leftarrow 0$ (holding top drive stationary)
else
  if speed ≤ -0.1 **then**
    if speed < -1 **then**
      if load ≥ 20 **then**
        $s \leftarrow 2$ (Pulling out of hole)
      else
        $s \leftarrow 0$ (Moving top drive up the mast)
      end if
    else
      $s \leftarrow 0$ (Reaming up or adjusting the top drive position)
    end if
  else
    if speed > 1 **then**
      if load ≥ 20 **then**
        $s \leftarrow 2$ (Running in hole)
      else
        $s \leftarrow 0$ (Moving top drive down the mast)
      end if
    else

if load ≥ 20 **then**
$s \leftarrow 1$
else
$s \leftarrow 0$ (Adjusting the top drive position)
end if
end if
end if
end if

Top drive operational state
The speed and torque of the top drive can determine how the top drive is involved in drilling operations. Positive speed and torque imply a clockwise movement of the drillstring. By analysing historical data, thresholds are selected that if exceeded simultaneously indicate the top drive is drilling. This requires use of the logical operator **and**. No other states can be derived from the top drive, leaving just two options:

0. Not involved in drilling
1. Drilling

The applied algorithm:
if torque ≥ 1000 **and** speed ≥ 12 **then**
$s \leftarrow 1$
else
$s \leftarrow 0$
end if

6.3.2. Feature extraction

From the cleaned mud pump vibration signal, various features were extracted to identify features that can be used for estimation of the health condition, or moreover the appearance of condition degradation in the vibration signal. To select relevant features, vibration signals recorded 24 hours before replacement of a valve in a fluid module and 24 hours after replacement are used. In total, 130 “old” vibration signal samples and 109 “new” samples were analysed. For each sample, various features were extracted. These features are:

- Peaks above threshold: the number of peaks above a threshold that is 50% of the maximum peak value in that sample is counted.
- The root mean square (RMS): gives an approximation of the overall energy of a signal. It is calculated by taking the square root of the mean value of the signal squared: $x_{RMS} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i^2)}$.
- The absolute mean of the signal: gives an approximation of the average signal amplitude. Calculated as: $x_{MAV} = \frac{1}{n}\sum_{i=1}^{n}|x_i|$.
- The peak value: the maximum absolute value present in the sample.
- Shape factor: this is a dimensionless characteristic of the signal shape. It is calculated by dividing the RMS by the absolute mean of the signal: $SF = \frac{x_{RMS}}{x_{MAV}}$.
- Impulse factor: gives an approximation of the “peakiness” of the signal, the impulsiveness. It is dependent on the absolute mean value and the peak value: $IF = \frac{x_{max}}{x_{MAV}}$.
- Crest factor: also gives an approximation of the development of peaks in the signal, but is dependent on the RMS: $CF = \frac{x_{max}}{x_{RMS}}$.
- Kurtosis: calculates how outlier prone the signal is. $x_{kurt} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^4}{(\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^2)^2}$.

The features are plotted in a box plot to identify a difference between the old and new samples. From Figure 6.7, various observations can be drawn. Firstly, features like RMS, peak value or the absolute mean do not highly differ between new and old samples. However, researches like Yoon et al. [124], Kyllingstad and Nessjøen [123] use RMS amongst other features to identify condition degradation of the valves. Multiple reasons can explain why in this CM analysis they do not assist in identifying worn valves. The data was captured during actual drilling operations and not during experiments with artificially damaged valves. This means the amount of degradation during the recording was not actually

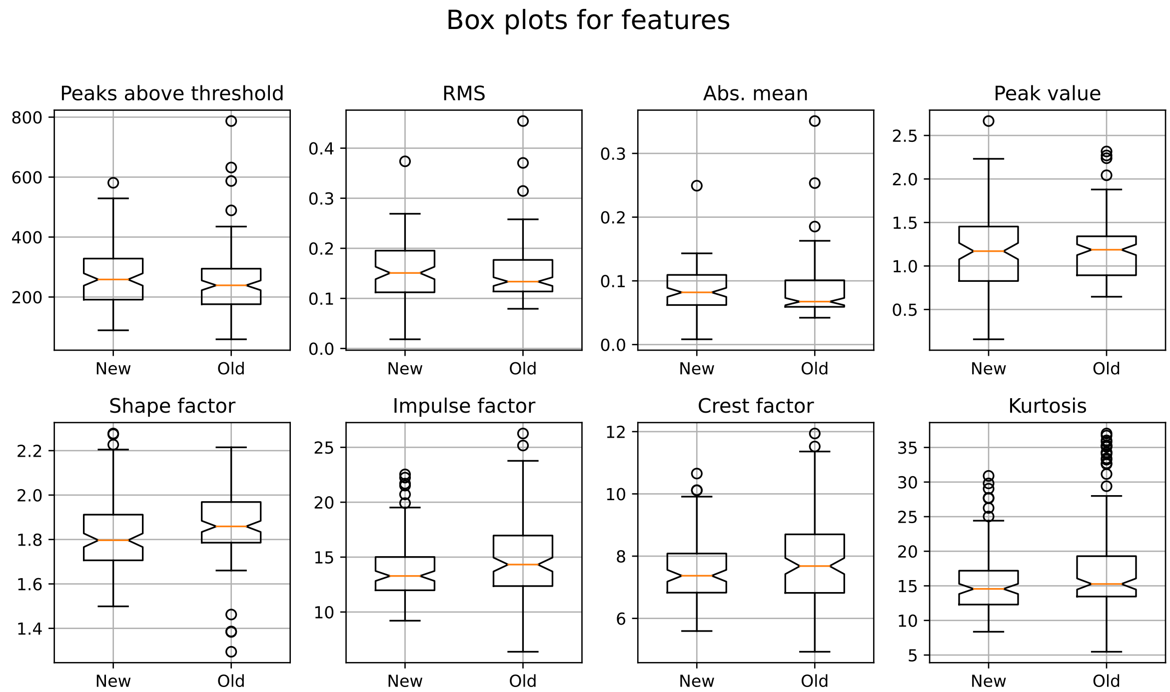


Figure 6.7: Various features extracted and box plotted from vibration signals of old and new mud pump valves.

known, since the data is labelled afterwards. A plausible cause might therefore be that the damage was not significant enough to obtain consistently higher RMS and peak values. However, a more likely reason for the insensitivity of peaks and RMS to valve condition might be the fact that the mud pump was operating at different speeds during measurement. From the sample database, it can be concluded that there is a correlation between mud pump operating speed and vibration level, RMS and peaks. Moreover, like mentioned earlier, the filtering on the signal may also give a distorted view on the RMS and peaks. To conclude, features that are in the dimension of acceleration are too dependent on the mud pump operating range.

This is substantiated by the second observation from the features box plots: dimensionless features like shape, impulse and crest factor, but also the kurtosis, all show an increase in value for the samples of old valves. Since they are dimensionless, they focus on the characteristics of the vibration signal instead of the value. Therefore, they are less dependent of the mud pump operating speed.

6.3.3. Fuzzy logic health condition classifier

The FL classifier utilises the numerical values of the vibration signal shape factor, impulse factor, crest factor and kurtosis to estimate a numerical value for the degradation of the valve. For each feature, membership functions are defined for low, average and high damage. The values of these membership functions are derived from the values of the sample groups in Figure 6.7. Damage is considered to be “Low” until the bottom end of the “New” sample group box is reached, from there the membership “Low” decreases to 0 at the median value of the “New” box plot. Vice versa, damage is considered to be “High” starting at 0 from the median of the “Old” box plot and is fully 1 at the top end of the box. The membership function for “Average” is in an equilateral triangular shape, where it is 0 at the bottom end of the “New” box plot and the top end of the “Old” box plot. The visual representation of the membership functions can be found in Figure 6.8. For the exact values, please refer to Appendix B.

The membership functions of the output state, the health condition, are three triangular shaped functions with values ranging from 0 - 100. This means the numerical output value will have the same range, describing the estimated level of degradation based on the extracted features. The membership functions are overlapping, so the output value is always member of two fuzzy values, which helps increasing robustness of determining the final numerical value. The output membership functions are visually represented in Figure 6.9 and exact values are given in Appendix B.

The fuzzy inference rules are formulated so that each possible combination of fuzzy values is cov-

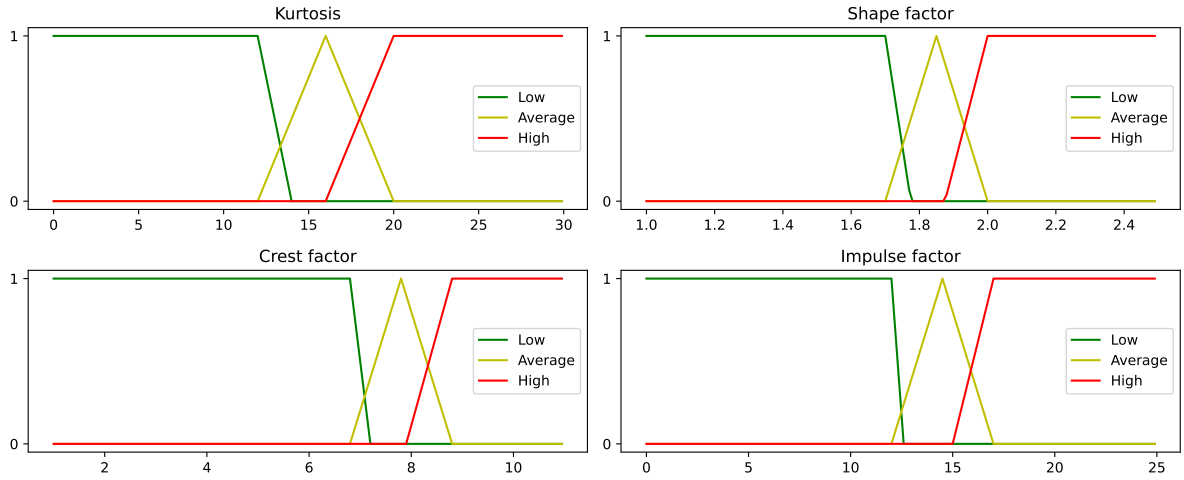


Figure 6.8: Fuzzy membership functions for the extracted feature kurtosis, shape factor, crest factor and impulse factor.

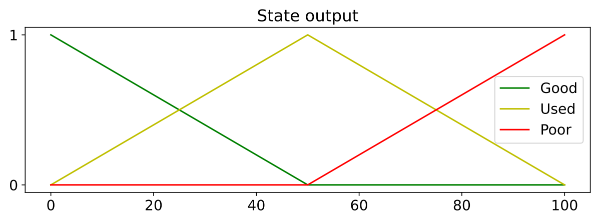


Figure 6.9: Fuzzy membership functions of the output state, corresponding to the estimated health condition of the valve.

ered and given a desired classification. In total, 21 rules were established which can be found in Appendix B.

To validate the method, the vibration features extracted in subsection 6.3.2 are classified per sample group and box plotted in Figure 6.10. From this figure, a distinction is visible between the FL classifier output value for the old and new samples. It can be concluded that the fuzzy health condition estimation module manages to successfully classify most old samples, however, there are some outliers.

6.3.4. Weibull AFT survival analysis

A Weibull AFT model is fitted to a dataset containing the running hours of mud pump valves before they were replaced. The dataset contains right-censored lifetime data and one covariate, where the latter was estimated per data point. The value of the covariate may change over time and can be considered as an accelerator for the time to failure. For the mud pumps it is assumed that the lifetime can be influenced by the currently measured condition. The health condition covariate x_{HC} is the direct output of the FL classifier, this means in practice it can take on a value between 0 - 100 where $x_{HC} = 100$ means the component is completely damaged. However, in the constructed dataset for the model

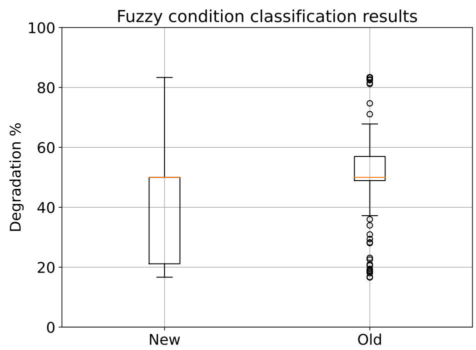


Figure 6.10: Results of the fuzzy classifier, box plotted for the old and new valve vibration samples.

fit, the exact value of x_{HC} was unknown. Therefore, the data entries for the damage covariates were generated synthetically. For this purpose, it is assumed that parts that were replaced due to failure have a random value between $37 \leq x_{HC} \leq 72$, and for parts that had not yet failed this range is $18 \leq x_{HC} \leq 55$, based on Figure 6.10. The dataset is quite diffused, with running times ranging from 20 - 450 hours. To increase the effect of a bad health condition on the RUL, and obtain a better model fit, parts that failed within 100 hours are assigned a random value between $60 \leq x_{HC} \leq 100$.

Weibull AFT fit

The Weibull AFT survival function with the health condition as covariate x_{HC} is formulated as:

$$S(t; x_{HC}) = \exp(-(\frac{t}{\exp(\beta_0 + \beta_{HC} x_{HC})})^{\exp(\rho)}) \tag{6.1}$$

After fitting this function to the dataset, the values of $[\beta_0, \beta_{HC}, \rho]$ are estimated to be $[6.839, -0.0246, 0.650]$. The partial effects on the survival functions of the health condition are plotted in Figure 6.11.

To validate the model, the goodness of fit on the used dataset is analysed using a Q-Q plot (Figure 6.11, right-hand side). The Q-Q plot plots the residuals of the model vs the quantiles of the normal distribution. It can show if the residuals are normally distributed, which is the case when they are on the red diagonal line $y = x$. Most residual points do not significantly deviate from the red line, except from outlier points where the absolute error is more than 200. Overall it can be concluded that the developed model meets the assumption that the dataset is normally distributed and is therefore appropriately selected. However, the value of the residuals is diffused. The root mean squared error is 96.948.

RUL prediction

For prediction of the RUL, it is decided that the unacceptable survival probability threshold $\tau = 0.125$, indicated with a red marked zone in Figure 6.11. This value is chosen as optimal balance between maximum parts usage and the risk of premature failure. Since the parameters of the survival function are known, the formula to determine the RUL based on the current time t and health condition x_{HC} can be constructed from Equation 5.17:

$$RUL(t; x_{HC}) = \exp(\beta_0 + \beta_{HC} x_{HC}) * (-\ln(\tau))^{(\frac{1}{\exp \rho})} - t \tag{6.2}$$

Where:

β_0	6.839
β_{HC}	-0.0246
$\exp(\rho)$	1.916
τ	0.125

The complete code for the developed mud pump agent is available in Appendix C.1.

6.4. Development of the system agent

From the RUL and operational states of the components, the system agent has to determine the current operational state and make maintenance decisions. The goal is to make maintenance decisions that

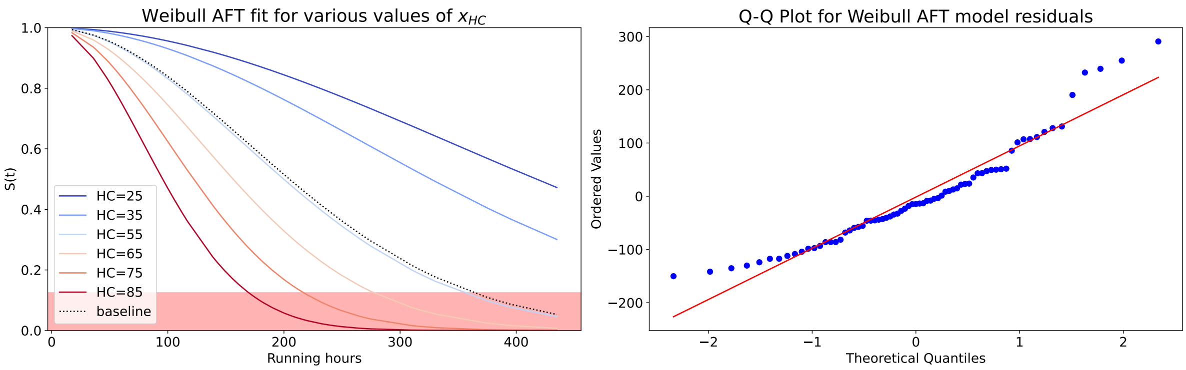


Figure 6.11: Result of the Weibull AFT fit. On the left, the partial effect of the health condition on the survival probability is plotted for various values of x_{HC}. The RUL threshold zone is marked in red. On the right is a Q-Q plot of the model residuals.

maximise uptime. The developed model will make maintenance decisions for the mud pump valves based on their RUL and the operational states of the mud pump, top drive and drawworks.

6.4.1. Rule-based state classification

Similar to the component agents, rule-based classification is used to determine the system operating state. The system agent first checks if there is circulation by analysing the states of the mud pumps. For drilling, the drawworks and top drive must be in drilling state while there is circulation. If the drawworks is in tripping state, the system is doing a tripping operation. Finally, all other states are determined as "not drilling".

if any $s = 1$ for s in [mudpumpstates] **then**
  circulation $\leftarrow 1$
else
  circulation $\leftarrow 0$
end if
if all $s = 1$ for s in [topdrivestate, drawworksstate, circulation] **then**
  $s_S \leftarrow 1$
else
  if drawworksstate $= 2$ **then**
    $s_S \leftarrow 2$
  else
    $s_S \leftarrow 0$
  end if
end if

To validate the rule-based state classification in the component and system agents, a 3-hour sample of operational parameters is used. The system classification is plotted, as well as the drillbit vertical distance from the surface in Figure 6.12. This allows to visually validate the state classification. In the green zones, which should indicate drilling operation, the drillbit moves away from the surface slowly, confirming the correct state is indeed drilling. In the red zones, it can be seen the drillbit is raised and subsequently lowered to the previous location at a faster rate, which confirms the drilling rig is tripping the drillstring. Concluding, the rule-based state classification system works appropriately and can be used for maintenance decision-making.

6.4.2. Expert reasoning system

The selected structure of the system agent's reasoning system is depicted in Figure 6.13. In the reasoning sytem, the inference engine deploys rules that analyse real-time updated input information and information from the knowledge base. In this context, real-time information includes the RUL of the components and the operational states of the components and the drilling rig system. Each entry in the knowledge base represents a component agent in the model with informative and updated status attributes. Component location, required maintenance actions and pre-set RUL and OM thresholds to trigger maintenance actions can all be considered as constant attributes. Status attributes are the

Figure 6.12: The result of the system operational state classifier. Green indicates drilling, red indicates tripping. The input for this classification are the parameter values in Figure 6.4. The drillbit location is plotted as well to validate the classification.

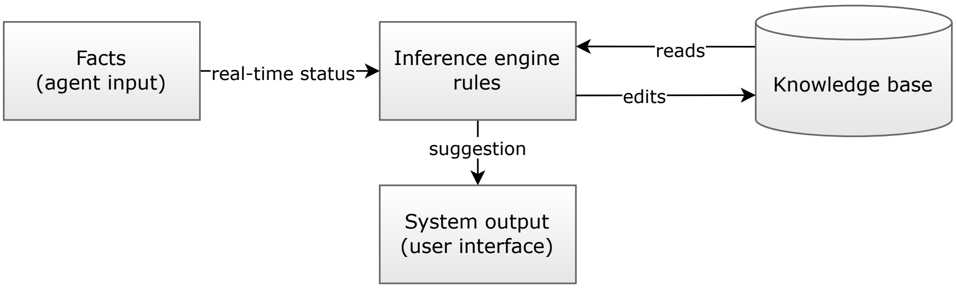


Figure 6.13: Schematic architecture of the reasoning system of the designed model.

RUL, if the component is in need of maintenance, or if it would be beneficial to conduct maintenance on the component when the opportunity arises.

The inference engine will first update the status attributes based on the new real-time RUL information. Components whose RUL drops below the set threshold for maintenance will trigger a maintenance suggestion. For example, in the knowledge base sample given in Table 6.1, the RUL of `mudpump2valve` almost fall below the set threshold of 8 hours, meaning it will become eligible for maintenance in a short notice. A maintenance suggestion will consist of the appropriate maintenance action linked to a maintenance window, which is the time until the component will fail: the RUL. If the drilling rig is not in drilling or tripping operation, the system agent will prompt to conduct maintenance immediately, since the system is already down. Only when there is a suggestion for immediate maintenance, OM will be suggested for adjacent components as well.

Components whose RUL is below the set threshold of OM, will become eligible for a maintenance action when a component on the same location fails as well, but will not trigger a system maintenance suggestion. In the example in Table 6.1, `mudpump3valve`, which is assigned to the same location as the other mud pumps, is eligible to receive OM. In a short notice, `mudpump2valve` will trigger a maintenance suggestion, and the system agent will then also suggest OM action to `mudpump3valve`. It is chosen to include OM suggestions in the system, since maintenance on the drilling rig will in most cases mean downtime of the rig. Since the aim is to maximise uptime, it might be useful to conduct maintenance on adjacent components anyway, since the system is down. This would be preferable over conducting maintenance on the same location on two separate successive occasions. The developed model of the system agent is available in Appendix C.2.

It is important to note that this expert system is easily modifiable and can be expanded with other options to improve drilling rig uptime. For instance, it would be possible to incorporate redundancy of components. Meaning, in case a failure is predicted to occur in a predetermined time window, the system can be programmed to suggest to switch to healthy machinery that is expected to not experience failure for a long time. It becomes clear that the expert system developed in this chapter is not the definite solution to provide advanced maintenance suggestions, however it is hard to determine what is the ideal decision-making solution since only the mud pump component agents could be fully developed. Furthermore, requirements and desired information for a decision-making process can vary based on the type of drilling rig and drilling project. By all means, the expert system method can be fit to achieve various decision-making objectives, even prescriptive maintenance actions could be suggested.

6.5. Finalised model overview

The model is developed in python, because of the availability of additional software packages that can be used for the various methods in the model, and because of the flexibility of dealing with data

Table 6.1: Example of the knowledge base used by the system agent. The last three columns are updated before the system agent checks thresholds and extracts relevant maintenance actions.

location	comp	action	RULth	OMth	Mstatus	Ostatus	**RUL**
mudpumps	mudpump1valve	Change fluid end component	8	24	FALSE	FALSE	**132.32**
mudpumps	mudpump2valve	Change fluid end component	8	24	FALSE	TRUE	**8.21**
mudpumps	mudpump3valve	Change fluid end component	8	24	FALSE	TRUE	**23.78**
mudpumps	mudpump4valve	Change fluid end component	8	24	FALSE	FALSE	**178.54**

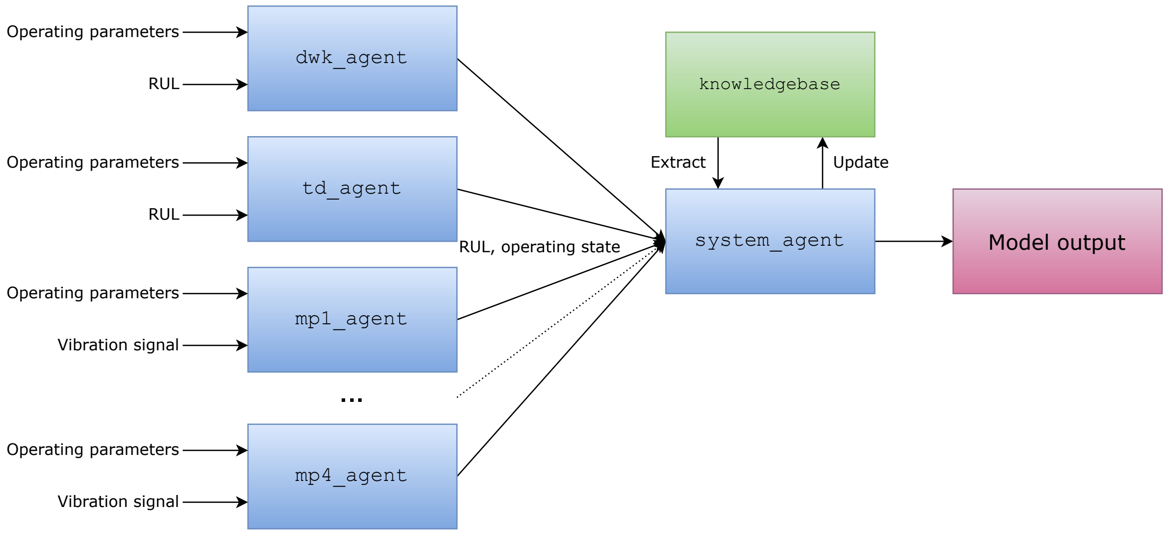


Figure 6.14: Structure of the realised software. Input parameters are depicted on the left and can be extracted from a dataset constructed from operational parameters extracted from SCADA and cleaned mud pump vibration signals.

frames. The developed model structure is depicted in Figure 6.14. Six medium-level component agents have been developed, one for the drawworks, one for the top drive and four for the mud pump valves. The drawworks and top drive agents have been included to assess the operational state of the system. Required operational parameters and a default value for the RUL can be used as input for these agents. The developed code for these agents is equal to the algorithms provided for the top drive and drawworks rule-based classification in subsection 6.3.1. Their RUL is a stationary default value because it is not of interest for the case study.

For the mud pumps, the required operational parameters are used as input as well. The complete code of the developed mud pump agent is given in Appendix C.1. It will run based on input of a cleaned vibration signal and operational parameters. Since the drilling rig in the field research could run four mud pumps simultaneously, four versions of the developed agent are used in the composed model. In this composed model, the system agent as given in Appendix C.2 is connected to the top drive, drawworks, four mud pump agents and a knowledge base. Based on their input, the system agent can schedule a maintenance decision based on system operations and component RUL. The actual implementation of this model for the case study will be discussed in chapter 7, which forms the beginning of the last part of this thesis.

6.6. Conclusion

The methods proposed in chapter 5 have been applied in a conceptual design. For application of the methods, data is used that was gathered during the field research. From collected vibration data, features could be extracted to establish a FL diagnostics model. By constructing a dataset from maintenance records and synthetic damage values, failure of valves can be predicted in a dynamic way. The developed expert reasoning system provides maintenance windows based on RUL and suggests opportunities for maintenance on adjacent locations to maximise uptime.

Although the used data has limitations both in terms of quality and quantity, these have been addressed in the model design. The applied methods have been validated individually, proving the chosen methods are indeed appropriate for their purpose. After application, the outline of the developed model did match the proposed framework in Figure 4.4 and the architecture in Figure 5.6. Concluding, this chapter has answered RQ4 by explaining how appropriate methods can be applied to develop a functioning drilling rig maintenance model using basic available data. The next chapter will use the developed model in a case study to research the model's behaviour in conditions partly similar to actual drilling operations.

7
Case study & Results

The case study uses the developed model as described in chapter 6. This model is able to simulate how the proposed architecture performs to analysee the RUL of component agents during operations. This chapter will first give the goal of the case study to elaborate what this case study will contribute to the overall research. Then, the simulated scenarios are given as well as their results. These results are discussed to finally answer how implementation can improve the operations of a drilling rig with respect to the uptime, which directly addresses RQ5.

7.1. Objective & scope of the case study

To answer the final research question, it has to be assessed how implementation of the proposed model can improve the reliability of a drilling rig, which can increase the availability and overall improve drilling rig operations. In this assessment, the model must be able to timely predict failure of parts, so that the system agent can schedule maintenance actions that will ultimately benefit the up-time of the drilling rig. Therefore, mainly the method of prediction of the components RUL will be validated. As described earlier in this thesis, the model can only be validated partially since condition monitoring data is acquired for the mud pumps. The case study will therefore assess the prediction of the mud pump valve RUL based on simulated valve failures and historical operational data. If the model is able to predict the failure time before the theoretical actual failure of the part, it can be validated that implementation in practice can improve operations. To test the performance, different scenarios are constructed to simulate some of the real-world situations that can occur during a drilling project.

7.1.1. Focus on RUL prediction

The choice to not incorporate the output of the system decision-agent in this case study has multiple reasons. First, the timing of suggestions by the system agent is fully dependent on its input, namely the operating state and predicted RUL of the components. If these functions are not accomplished accurately by the component agents, the system agent will not be able to give accurate suggestions either. Therefore one may argue it is not necessary to include the actions of the system agent in the case study simulations. Second, a more practical reason to exclude system agent suggestions from the case study is to increase simulation speed. Parsing and editing the knowledge base for each data point will significantly slow down the simulation iteration speed. Including the reasoning system can be considered if the outcome is worth a long simulation time. Third and final, it is important to realise that the output and actions of the system agent can be reasoned after simulation. Like already mentioned the RUL is the driving factor for accuracy of the reasoning system in the agent. By analysing the RUL prediction, we can argue at what point in time a maintenance action would be triggered by the agent and if that action is appropriate to the actual situation.

7.1.2. Model used for simulations

The model used in the case study simulations is developed in the previous chapter, however it is streamlined to optimise simulation time. This means that unnecessary modules in the developed agents will be removed. The drawworks and top drive component agents classify the operating state based

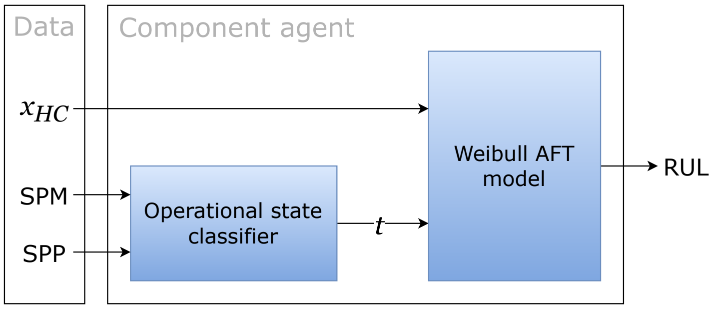


Figure 7.1: Schematic overview of the model and data used in the case study.

on historical parameters. Besides that, their RUL prediction module is left out of scope, they will not be altered.

However, the mud pump component agents will not incorporate a health condition assessment module. The input of the simulation will include the overall health condition in stead of vibration signal features. First, it is chosen to not use a vibration signal as input for the agent and then let it perform feature extraction, since there is not enough vibration data available, and moreover the available data points are measured with 30 minutes apart, which is not sufficient for the model. It was infeasible to simulate the model using vibration signals in the given time. Subsequently, it is chosen to not estimate the health condition based on artificial signal features, since the FL classifier requires a lot of processing time. For real-time classification this forms no problem, however it would drastically increase simulation time since the simulation will cover more than 140 operating hours. Performing FL classification for each data point would bring the total simulation time to little less than one day.

Finally, since the system agents decision-making output is not of interest for this case study, it will also not be included in the model. This will save some simulation time as well, since reading and editing the knowledge base for each data point can now be skipped. To summarise, the required input dataset will therefore consist out of operational parameters for the drawworks, top drive and four mud pumps, as well as synthetic health condition that can be changed over time to simulate an upcoming valve failure. Each row in the datasets corresponds to a second in historical operations and gives new values that all agents use in their functions. The model will then classify the mud pump operational state and predict the RUL per data point, as can be seen in Figure 7.1. An overview of the reduced code for the simulations can be found in C.3.

7.2. Case study scenarios

In the scenarios different variables are changed to mimic real-world situations. First, a failure is induced by artificially increasing the health condition x_{HC} that would ideally be classified by the FL model described in subsection 6.3.3. In these synthetic data sets, two different rates of deterioration are used. The second factor that is altered throughout the scenarios is the age of the component at the start of the simulation. This directly affects the outcome of the statistical RUL prediction. E.g., although a "new" component has a small chance to fail within a few days after installation, it might actually happen, and the model should then still be able to foresee the failure. Last, two different operating conditions of the land drilling rig system are used for the simulations, These operating conditions are derived from historical operational data collected during a drilling project.

7.2.1. Artificial failure

Two synthetic data sets are constructed to artificially mimic component failure in the simulations. As mentioned, in these data sets the health condition increases.

It is assumed that once failure has started, deterioration of the valves increases exponentially, since damage accumulates over time but severity of damage will influence the deterioration rate as well. x_{HC} starts at 21, which increases to 76 in either 50 or 100 hours. These values are chosen based on the results of the fuzzy classifier (refer to subsection 6.3.3). $x_{HC} = 21$ represents a healthy valve, and $x_{HC} = 76$ represents a valve that is already subject to significant wear. From that point, it increases at

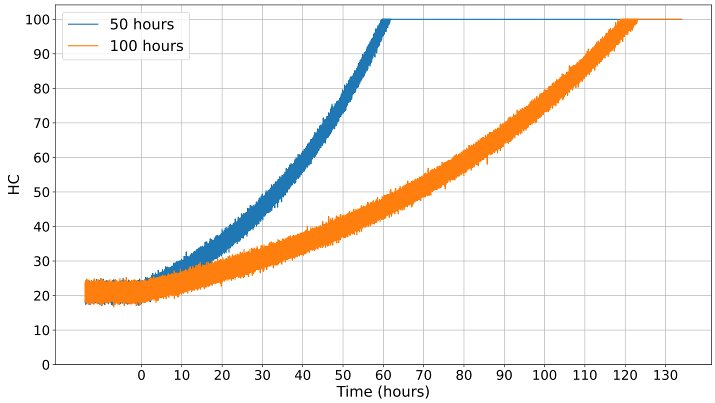


Figure 7.2: Plot of the artificially induced damage signal for the valves of a mud pump. At HC = 100 the valve has failed completely.

Table 7.1: Size of the two different operating condition data sets used in the case study. The minimum and maximum well depth reached during drilling operations in these datasets is given as well as the peak standpipe pressure, to indicate slight difference in conditions.

Dataset	Duration (hrs)	Data points	Min. well depth (m)	Max. well depth (m)	Max. SPP (bar)
A	164	590,400	818	1948	279
B	148	532,800	837	2269	265

the same exponential rate up to 100. The mathematical function used to construct the artificial failure:

$$x_{HC}(t) = 21(1 + \exp(\log(\frac{76}{21})\frac{t}{3600p})) \tag{7.1}$$

where t represents the time in seconds, p is the variable to determine the deterioration rate in hours and $x_{HC}(t) \leq 100$ for all values of t.

Since the fuzzy classifier can maximally output 100, it is assumed that it will not increase from there. The point of failure can be described as the first point in time where $x_{HC} = 100$. The model should trigger a maintenance action before that point in time is reached. To mimic the variance in CM signal, random noise is added to the health condition dataset to see how this noise propagates in the output.

7.2.2. Operating conditions

The developed model classifies the system operational state based on operational parameters from the top drive, drawworks and mud pumps. Available data collected during an actual drilling project is available for these components. The land drilling rig in this project completed the project with five 800hp mud pumps, where a maximum of four could run simultaneously and one was used as a backup. To simulate if the model can successfully comprehend system operations in real-time, this data is used in the case study. Two datasets are constructed, covering more than 100 hours each. The time period for extraction is selected to capture the drilling rig's operations mostly during continuous drilling. The information of the two data sets is given in Table 7.1.

7.2.3. Scenarios

Four scenarios are constructed to validate the RUL prediction of the model in different circumstances. The two different operating condition datasets are used, and for each operating condition dataset two different valve failures are simulated. Each scenario is run for component ages $t_0 = 0, t_0 = 100, t_0 = 200$. An overview of the scenarios is given in Table 7.2.

7.3. Results

The results are presented in a RUL vs time plot per scenario (Figure 7.3). In these plot, the actual RUL is represented by a straight red dashed line, starting from the point where the failure sets in and ending

Table 7.2: The scenarios that are simulated in the case study. Each scenario is simulated for each component age given in the last column.

Scenario	Op. conditions	p	Mud pump	t_0
1	A	100 hrs	MP2	0, 100, 200 hrs
2	A	50 hrs	MP4	0, 100, 200 hrs
3	B	100 hrs	MP4	0, 100, 200 hrs
4	B	50 hrs	MP3	0, 100, 200 hrs

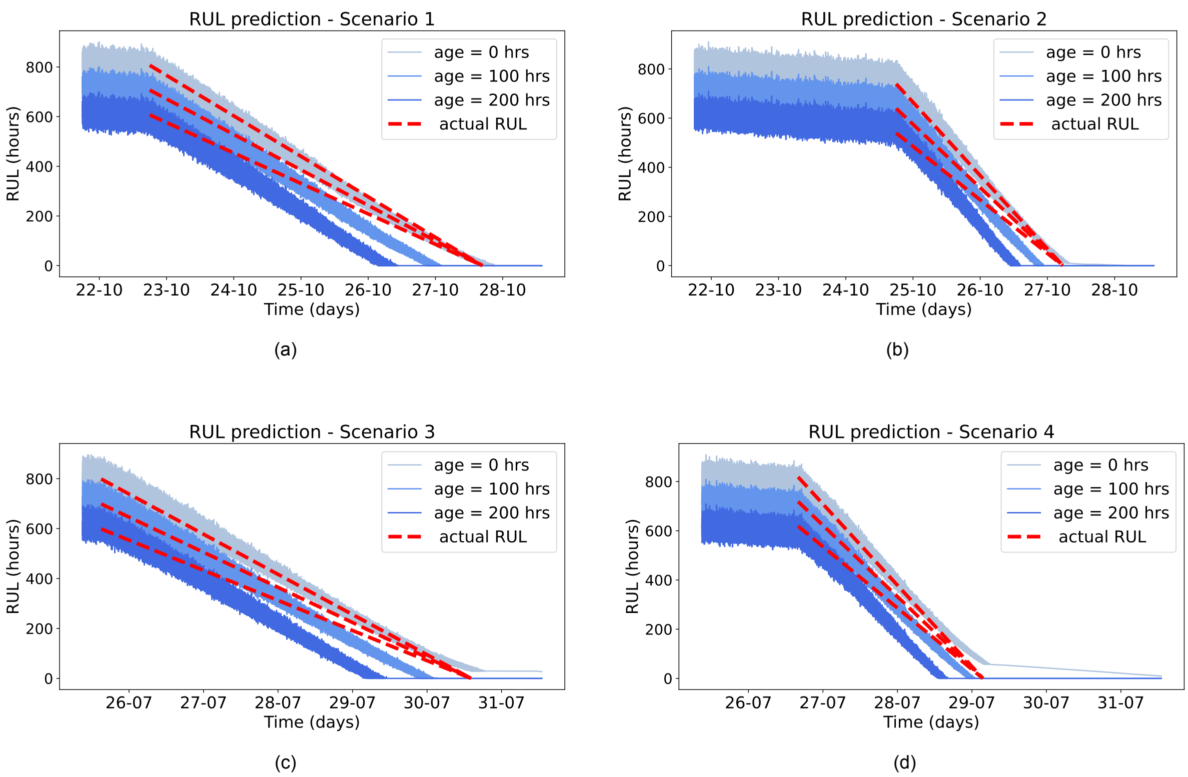


Figure 7.3: First results of case study simulations, plotted per scenario. The red lines represent the actual RUL curve.

Table 7.3: Actual and predicted time of failure for the case study simulations.

	Time of failure	t_0 (hrs)	T_L (hrs)	Predicted time of failure	Δt (hrs)	UF
Scenario 1	27-10 16:47	0	115.96	27-10 19:15	-2.47	1.02
		100	215.96	26-10 20:42	20.08	0.91
		200	415.96	26-10 03:15	37.53	0.91
Scenario 2	27-10 05:30	0	104.89	28-10 04:35	-23.08	1.22
		100	204.89	26-10 20:08	9.37	0.95
		200	404.89	26-10 10:51	18.65	0.95
Scenario 3	30-07 14:12	0	87.32	n.a.	n.a.	n.a.
		100	187.32	29-07 21:24	16.80	0.91
		200	287.32	29-07 04:30	33.70	0.88
Scenario 4	29-07 03:32	0	57.92	n.a.	n.a.	n.a.
		100	157.92	28-07 22:48	4.74	0.97
		200	257.92	28-07 13:17	14.25	0.94

at the point where the $x_{HC} = 100$. At this point, the failure will occur. Important information that can be deduced from these plots is presented in Table 7.3. In this table, the actual and predicted time of failure per simulation is given, as well as the actual lifetime T_L. Here, the predicted time of failure is the point in time where the RUL $= 0$. By calculating the difference between these timestamps, the residual Δt can be estimated. $\Delta t > 0$ means the failure is predicted in advance.

7.3.1. Lifetime utilisation factor

For components with $t_0 = 100, t_0 = 200$, the model was able to timely predict failure. However, if this failure is predicted too early, it might lead to excessive maintenance, while this should actually be avoided. By calculating an utilisation factor, representing the percentage of time the equipment was in use while it could theoretically be used, it can be analyseed if the RUL prediction is not too early. The utilisation factor can be calculated using $T_L, \Delta t$:

$$\text{UF} = 1 - \frac{\Delta t}{T_L} \tag{7.2}$$

The UF is given in the rightmost column of Table 7.3. From these results, it can be concluded that components are predicted to fail when they are at around 90% of their theoretical lifetime, which is satisfactory and will not lead to excessive maintenance.

7.3.2. Early-life failure prediction

An obvious result is a negative failure prediction of new-installed components. In all four scenarios, failure of the component with $t_0 = 0$ is not predicted early enough. In scenarios 3 and 4, where the pumps experienced less running hours, it was not even possible to calculate Δt because due to the nature of the simulation the predicted RUL never reached 0. Based on the characteristics of the RUL prediction method (refer to subsection 6.3.4), it can be deduced that the survival model will struggle with predicting failure of items with a lifetime around 100 hours. This makes sense, because extreme conditions occur infrequently and can therefore not be represented correctly by a model with a statistical base. Calculating the RUL (Equation 6.2) with $x_{HC} = 100, t = 0$ yields 116.87, which is the lowest RUL the model can predict when $\tau = 0.125$. Therefore, components with $T_L \leq 116.87$ will not be handled well by the model.

However, since the RUL prediction module is dynamic, a simple improvement is to model the RUL threshold τ based on operating hours. Instead of a constant threshold value, modelling τ so it increases when $t \leq 100$ could improve prediction of early-life failure.

7.3.3. Resulting maintenance windows

The aim of the component's RUL prediction is to assist in maintenance decision-making, which is done by the system agent. To assess if the maintenance window suggested by the system agent is

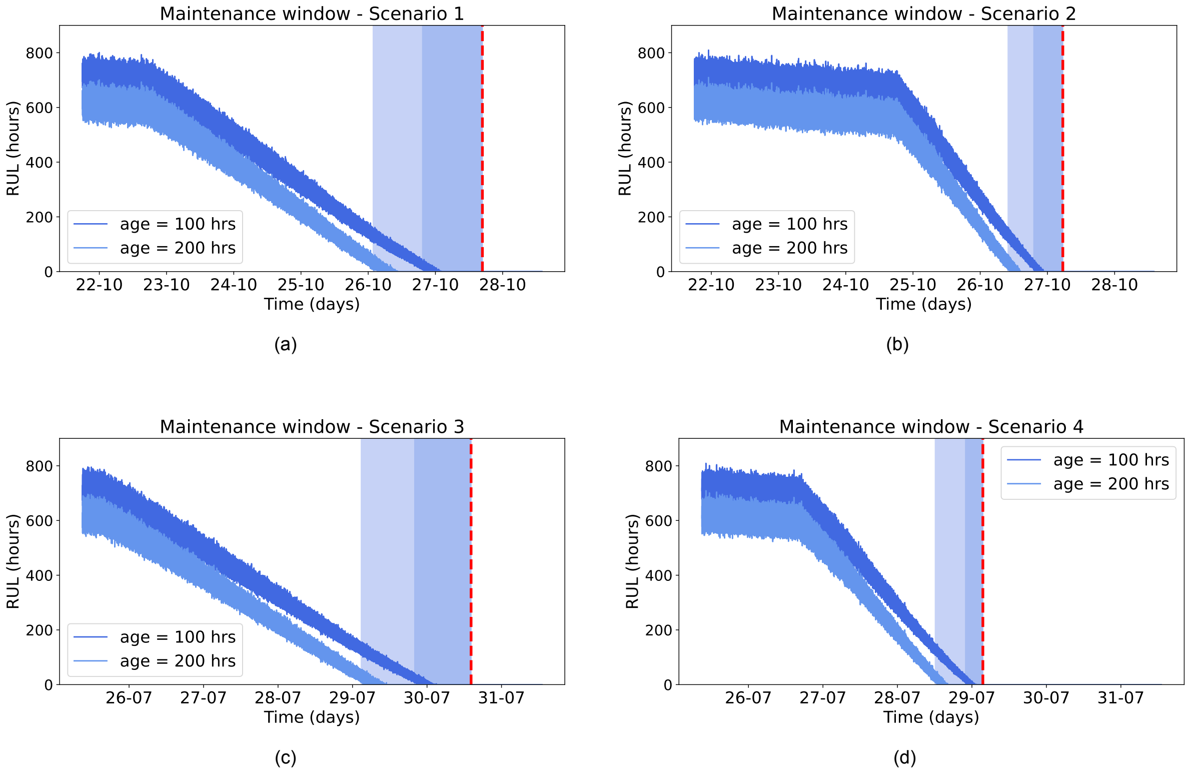


Figure 7.4: Maintenance windows suggested by the system agent when the RUL trigger for maintenance is 8 hours. Blue areas mark the maintenance window per component age. The red dashed line represents the theoretical moment of failure.

satisfactory, the moment this window will be triggered is plotted for the case study results in Figure 7.4. A maintenance window can be considered satisfactory if the maintenance window leaves enough time to schedule a maintenance action without disrupting operations. Since the simulation results for the components with a short lifetime were unsatisfactory, these are left out of the plots. Marked in blue, the maintenance windows are triggered when the predicted RUL first falls below 8 hours, since this is the set threshold in the system agent. The moment of failure is represented with a red, dashed vertical line.

In line with the lifetime utilisation factor calculated in the previous subsection, the suggested maintenance windows in the case study are sufficient to replace the component before failure, but will not result in excessive maintenance. In case of relatively quick evolving failures, the maintenance window should leave enough time to schedule a maintenance action. From Figure 7.4b & 7.4d, where the valve failure evolves in little more than 2 days, the provided maintenance window still leaves enough room to facilitate an optimal maintenance schedule.

7.3.4. Options for system decision-making

Towards implementation in practice, the system agent needs to be further developed to complete the generation of advanced maintenance actions. In section 6.4 it was already mentioned that the system agent may vary based on the type of drilling rig and drilling project. The design in this thesis consisted out of a expert reasoning system providing PdM and OM actions in order to maximise uptime. However, looking at the results in Figure 7.4, more options may be available. Over a long time period, a linear trend is visible in RUL predictions. The system agent may be expanded with trend analysis for scheduling maintenance up to 2 days in advance. Operational state trends can also be analyseed to determine future operations. Combining knowledge about future operations, upcoming maintenance and the service time for maintenance actions, the system agent can quantitatively calculate the best moment for maintenance with minimal loss of uptime. A system agent like this can be trained using reinforcement learning, to facilitate automated model improvement. One step further lies the option to find correlations between operational and RUL trends, which can lead towards a prescriptive maintenance solution.

7.4. Conclusion

This chapter has concluded the work in this thesis and now the answer to the final research question, RQ5, can be found. After selection of methods based on available data and realisation of the model, it was used in a case study to examine how the model can improve the drilling rig's uptime in practice. The approach of integrated maintenance was validated by assessing if the RUL prediction of the complete model is sufficient to improve the maintenance strategy and keep a high availability of components. From analysis of the case study results, it can be concluded that uptime of a drilling rig will be improved in three ways.

1. Unplanned downtime is minimised since unexpected failure can be predicted.
2. Excessive maintenance is avoided, because components are used up to 93% of their theoretical lifetime before replacement.
3. The resulting maintenance windows offer enough time for integrated scheduling of maintenance actions on the components, to find optimum moments for maintenance without significant disruption of operations.

To conclude, uptime of the drilling rig is improved by overall maximising the time between maintenance actions. The first results of implementing the proposed methodology look promising. After adopting a basic improvement the model will also be capable to predict early-life failure, resulting in a satisfactory model performance.

8

Conclusion & future work

This conclusion will first reflect on the research questions before providing the answer to the main research question. The limitations of this work will be discussed, followed by recommendations for future work, intended for both academics and industry professionals.

8.1. Conclusion

The objective of this research is to develop a maintenance method that can improve uptime of a land drilling rig. In contrast to previous research on drilling rig maintenance, the developed method should be an integrated approach, focusing on the operations of the whole drilling rig system.

RQ1: How are the core components of a drilling rig involved in the drilling process?
The operations of a land drilling rig are carried out by five subsystems that each complete an important function necessary for the land drilling process. In these subsystems, key components were specified that are in simultaneous operation during the standard operating states and procedures in a drilling project. The common failure modes of these components were determined, revealing hydraulic, electrical, or mechanical issues as the root causes of failure. When the key components are subject to failure, the drilling rig system will inevitably be subject to downtime since they are involved in all operations.

RQ2: What is the best strategy for maintenance on the components of a drilling rig?
From analysis of current application of maintenance on drilling rigs, it was concluded that these components receive maintenance in a mostly conventional way, meaning mostly corrective and PM policies. PM is undesirable for rig components, since it is based on generalised calculations and estimations, which means the actual component degradation is not taken into account. This will result in components unexpectedly breaking down before performance of maintenance, causing downtime and an urgent need for unscheduled maintenance. A drilling rig should receive maintenance that takes into account the actual degradation of key components to be able to adapt to the different harsh environments in which drilling rigs operate. Moreover, the best maintenance strategy for drilling rigs should actively assist in decision-making for the whole system. After surveying maintenance policies, a PdM strategy was selected as the best option for drilling rigs, using the available data on a drilling rig to enable dynamic and proactive maintenance scheduling.

RQ3: What is an applicable framework for the integration of component-level maintenance into a system-level decision-making model?
To apply PdM to a drilling rig in an integrated approach, a model framework was composed that would make maintenance decisions for the rig components based on the overall operational and conditional state of the drilling rig. The proposed framework is a hierarchical MAS, functional with real-time operational data from a rig's SCADA system and additional CM data. Since it only requires these data sources to function, it is applicable on land drilling rigs. It combines component-level diagnostics and prognostics with a single, centralised maintenance decision-making model. Because of the agent structure, the MAS framework allows to easily add components or CM methods to the model without the

need to reconfigure the complete software. Since there is automated data flow from the equipment to the model, the MAS can serve as the digital shadow of a drilling rig. Human users are integrated in the feedback loop to the physical equipment by acting on maintenance suggestions from the model. The framework is a first move to automated data insights and can be expanded with physical models to achieve an automated, accurate digital representation of the rig, taking a step towards DT for drilling rigs.

RQ4: How can appropriate methods be applied in the model to utilise available drilling rig data for condition assessment and generation of maintenance decisions?

The framework was further developed into a functioning model, by first defining the scope and functions of the agents. Bottom-level data agents form the connection for raw real-world data with the model. The data agents extract the relevant signals and clean this data to meet the requirements of higher-level agents. Component agents are responsible for classifying the operation and predicting RUL of their dedicated component, in real-time. This also requires assessment of component condition, which accompanies selection of an appropriate CM technique. Finally, the system agent is the module that centralises component operations and RUL, which are used to generate maintenance actions. For this matter, a knowledge base can be formulated by the user, which can be consulted by the system agent.

For the functions mentioned above, this research has identified and applied appropriate methods. The mud pump was the focus of the model development, more specifically the maintenance of the valves in the fluid end. Since vibration monitoring was chosen as CM technique, acceleration signals were acquired during an actual drilling project. After data preprocessing and feature extraction, an important result was the selection of dimensionless features for reliable diagnostics. A FL classifier was designed that was capable of detecting degradation of valves based on four extracted features. The Weibull AFT model was applied to design a RUL predictor with right-censored maintenance records and a synthetic result of the FL classifier. For accurate and dynamic prognostics, the rule-based classified component operational state and health condition were implemented in this predictor. The developed expert reasoning system in the system agent offers maintenance windows derived from components' RUL, along with recommendations for coordinating maintenance activities in nearby areas to maximise uptime.

RQ5: To what extent can implementation of this model in practice improve the uptime of a drilling rig?

To assess the result of implementation of the developed model in practice, it was partially validated, using mud pump valve failure as a case study. By analysis of the results, it was concluded that uptime of a drilling rig will be improved in three ways when the proposed model is implemented in practice. First, the case study proves the model is able to predict failure of components during operations, reducing the risk of sudden downtime. Second, excessive maintenance is avoided, since the model triggers maintenance actions when components have, on average, just 7% of their theoretical lifetime left. Third, partly due to the margin of the predictions, resulting maintenance windows offer enough time for the scheduling of maintenance actions on the components.

Using the findings to the research questions, the main research question can be answered:

How to achieve integrated maintenance for a drilling rig in a model making advanced maintenance decisions on system level, based on real-time data?

The novel methodology of a MAS model with a centralised decision-making process facilitates to take into account the status of the whole system, achieving an integrated perspective to drilling rig maintenance. The architecture of this model is constructed based on analysis of the core components in the drilling rig operations. This research has then demonstrated that PdM for drilling rigs can be enabled through analysis of readily available basic data and the selection of appropriate CM techniques. While the quality and availability of this data was limited, this research implements modelling methods that can still be able to give satisfactory results. Partial validation of the developed MAS model in the case study indicated that uptime of the drilling rig can be improved by maximising the time between maintenance actions, while preventing unexpected equipment breakdown.

8.2. Limitations of research

This research has successfully proposed a new integrated approach to drilling rig PdM, which was validated partially with a study on mud pump valve maintenance. After implementation of the proposed framework on this practical case, the first results looked promising. However, several limitations became apparent in this phase of the research. Application of real-world data played a key role in the development of the model. As mentioned throughout this work, the availability of this data was limited, and there was insufficient time and resources to address this issue. Consequently, the quality of the acquired data and the selection of methods were impacted. This section will briefly elaborate on this statement before recommendations for further work are given in the final section.

Availability of data
This thesis has emphasised the problem of the inefficient use and storage of data in the drilling industry, ironically this problem was encountered during the field research. While the drilling rig used for field measurements logged a wide range of operational parameters, there were few online CM sensors installed other than temperature switches and contamination switches in the HPU. Therefore it was necessary to temporarily install an online CM unit for the mud pumps. The installed CM unit had very limited measuring capacity, resulting in snippets of vibration signal, while continuous vibration monitoring would be preferable. Therefore the options of data analysis were quite constrained, since the data was unlabelled and the measurements could not be calibrated to find deviations to “normal” conditions. The method of dividing data into groups of “new” and “degraded” samples was therefore the only solution, but has resulted into a restricted insight on the actual degradation rate of the valves. Moreover, the acquired vibration data could not directly be used in the case study simulations. Continuous vibration measurements would allow for improved regression methods and more accurate deterioration assessment of the mud pump valves.

Quality of available data
Considering the Weibull fit of the maintenance records, some remarks can be made regarding the quality of these records. Firstly, it is important to note that during the drilling project downhole mud losses were experienced, prompting the decision to increase the coarse mud characteristics. This had noticeable effect on the wear of the valves, resulting in an increase of failures. Consequently, mud pump fluid end inspections increased and various valves were changed prematurely as a preventive measure. As a result, the maintenance records used in this thesis do not represent average valve conditions and will inevitably include many outliers. Furthermore, through comparison of the mud pump running hours in the maintenance records with operational hours from SCADA, it was concluded that in some instances a human error was made. Summarising, there are opportunities for improvement in the Weibull model, as the developed model might have some deviations from reality due to the issues mentioned.

8.3. Recommendations for future work

For future research towards achievement of PdM on land drilling rigs in practice, there are multiple opportunities and unexplored research gaps this thesis has introduced. From these options, recommendations for future work are offered, aimed at academic researchers and industry professionals.

8.3.1. Scientific recommendations

Field validation of proposed methodology
Since this thesis has mainly performed a proof of concept study, there is still a significant journey ahead until field validation of the proposed model. The model can be completed by implementing CM techniques and RUL prediction methods for the remaining core components in the system in the proposed architecture. After completion of the model, the applied methods need to be validated with continuous condition monitoring data during a drilling project. The results of this field validation can offer better insights in the effect of the integrated maintenance model on the uptime and operational performance of the drilling rig.

Enhancing functionality of the system agent
This research has not been able to develop and validate a autonomously functioning system agent, mainly because only the mud pump agents could provide real-time RUL prediction. However, the

system agent plays an important role in eventual success of this method, and therefore deserves a dedicated research. Extensive modelling of the complex drilling process can assist in enhancing the performance of the system agent's decision-making. For instance, reinforcement learning could be introduced to let the system agent "learn" the optimal moment of maintenance. Another option is to investigate how the system agent and its expert reasoning system can be utilised for prescriptive maintenance.

Progressing towards DT technology
As a final scientific recommendation, further expansion of the model towards a DT may be a valuable successive research. The proposed framework is a first step towards automated data analysis and offers room to implement physical models to gain highly detailed operational state insights. DT is a promising research topic, especially in the drilling industry were automation and smart use of data is still uncommon. The model now focuses on advanced maintenance, but also for operational performance and remote control developing the DT aspect of the model will be beneficial. In concrete terms, future research should focus on selecting the right methods that further enhance the model's hybrid approach in terms of accuracy. Academics should hereby lay emphasis on finding approaches that can deal with the constrained quality of data in the drilling industry.

8.3.2. Industry recommendations
Effective implementation of the proposed framework, as well as advanced maintenance practices in general, may still appear distant from current drilling operations. However, as emphasised before in this research, there is a great potential towards successful achievement of advanced maintenance for drilling rigs. It would require a joined effort from professionals in the industry to advance on the following recommendations.

Improving data acquisition
The most apparent problem encountered in the drilling industry is the lack of data quality. To start, land drilling rigs should be equipped with SCADA systems for basic operational data acquisition and rig control. The SCADA system can form the base to implement relevant CM systems for the core components. For selection of CM techniques, academic literature can be consulted to identify relevant parameters for monitoring. It is important to note that effective CM can also mean to monitor process parameters, e.g. the mud pressure throughout the circulation system. Simultaneously, drilling operators need to dedicate more effort to offline data collection. This involves improvement in the logging of detail of maintenance records, as well as their level of detail. This data is very valuable to establish a reliable statistical base for prognostics.

Applying integrated PdM in practice
When drilling rig operators are able to collect relevant, qualitative CM and maintenance data, an effective PdM model can be developed. This thesis forms the framework for development, however it is important to incorporate real-time, continuous condition monitoring, something that was not possible in this work. Extensive field validation is necessary to identify opportunities of improvement. Eventually a model could be realised that enables PdM for land drilling rigs, with potential to be adopted by offshore drilling systems.

The initial goal for the drilling industry should be to realise software and additional sensor hardware that can be seamlessly integrated in the SCADA system of a drilling rig for an integrated maintenance approach. Integrated maintenance can then be taken to a superior level by expanding the framework with physics-based models and automated digital-physical connection. This will open the doors to implementation of DT technology in the drilling industry. The drilling industry will still have a long journey towards reaching full digitisation, but DT might be the technology that can bridge the current gap.

Bibliography

[1] Black Diamond Drilling Canada. *History of Drilling*. URL: https://www.bddrill.ca/drilling-school/history-of-drilling/#:~:text=100%20BC%20%2D%20Chinese%20Han%20Dynasty,gas%20in%20the%20Sichuan%20province. (visited on 04/09/2024).

[2] Bourgoyne Jr., A. T. et al. “Rotary Drilling Process”. In: *Applied Drilling Engineering*. Society of Petroleum Engineers, 1986. Chap. 1, pp. 1–40. ISBN: 978-1-55563-001-0.

[3] Schlumberger. *drillstring | Energy Glossary*. URL: https://glossary.slb.com/en/terms/d/drillstring (visited on 01/26/2023).

[4] Yazdi, M., Nedjati, A., and Abbassi, R. “Fuzzy dynamic risk-based maintenance investment optimization for offshore process facilities”. In: *Journal of Loss Prevention in the Process Industries* 57 (2019), pp. 194–207. DOI: 10.1016/j.jlp.11.014.

[5] Sattler, J. and Reed, B. “Avoiding Drilling Equipment Downtime - Four Case Studies”. In: IADC/SPE Asia Pacific Drilling Technology Conference and Exhibition (Kuala Lumpur, Malaysia, Sept. 13–15, 2004). 2004. DOI: 10.2118/87957-MS.

[6] Asad, M. M. et al. “Oil and Gas Disasters and Industrial Hazards Associated with Drilling Operation: An Extensive Literature Review”. In: International Conference on Computing, Mathematics and Engineering Technologies. 2019. DOI: 10.1109/ICOMET.2019.8673516.

[7] Dubey, S. “Sustainable Maintenance in Drilling Operations: New Risks, Changing Standards and Codes”. In: SPE/IADC Middle East Drilling Technology Conference and Exhibition (Abu Dhabi, UAE, Jan. 29–31, 2018). 2018. DOI: 10.2118/189407-MS.

[8] Zhan, S. et al. “Prognostics Health Management for a Directional Drilling System”. In: Prognostics & System Health Management Conference (Shenzhen, China, May 24–25, 2011). 2011. DOI: 10.1109/PHM.2011.5939543.

[9] Langlo, F. “Application of reliability centered maintenance on a drilling system”. MSc thesis. University of Stavanger, 2014. URL: https://www.scribd.com/document/274282443/Application-of-Reliability-Centered-Maintenance-on-a-Drilling-System (visited on 12/14/2022).

[10] Ismail, Z. et al. “Evaluating accidents in the offshore drilling of petroleum: Regional picture and reducing impact”. In: *Measurement* 51 (2014), pp. 18–33. DOI: 10.1016/j.measurement.2014.01.027.

[11] Tang, Y. et al. “A framework for making maintenance decisions for oil and gas drilling and production equipment”. In: *Journal of Natural Gas Science and Engineering* 26 (2015), pp. 1050–1058. DOI: 10.1016/j.jngse.2015.07.038.

[12] Shaipov, M. “Drilling and Well - Valve usage in changing environment”. MSc thesis. University of Stavanger, 2018. URL: https://uis.brage.unit.no/uis-xmlui/bitstream/handle/11250/2568594/Shaipov_Moslim.pdf?sequence=3%5C&isAllowed=y (visited on 01/19/2023).

[13] Omondi, P. K. “Impact of drilling equipment quality condition and expertise availability on well drilling cost - A case study of Olkaria geothermal field”. In: Proceedings, 6th African Rift Geothermal Conference (Addis Ababa, Ethiopia, Nov. 2–4, 2016). 2016. URL: https://www-semanticscholar-org.tudelft.idm.oclc.org/paper/IMPACT-OF-DRILLING-EQUIPMENT-QUALITY-CONDITION-AND-Otieno/536228b8ea59bb5ed248eb7ee181e9aa39230c54 (visited on 01/19/2023).

[14] Burrafato, S. et al. “Digital Disruption in Drilling & Completion Operations”. In: 14th Offshore Mediterranean Conference and Exhibition (Ravenna, Italy, Mar. 27–29, 2019). 2019. URL: https://onepetro-org.tudelft.idm.oclc.org/OMCONF/proceedings/OMC19/All-OMC19/OMC-2019-1236/1980 (visited on 01/20/2023).

[15] Dekker, M. and Thakkar, A. “Digitalisation - The Next Frontier for the Offshore Industry”. In: Offshore Technology Conference (Houston, Texas, USA, Apr. 30–May 3, 2018). 2018. DOI: 10.4043/28815-MS.

[16] Devold, H., Graven, T., and Halvorsrød, S. O. “Digitalization of Oil and Gas Facilities Reduce Cost and Improve Maintenance Operations”. In: Offshore Technology Conference (Houston, Texas, USA, May 1–4, 2017). 2017. DOI: 10.4043/27788-MS.

[17] Gooneratne, C. P. et al. “Drilling in the Fourth Industrial Revolution - Vision and challenges”. In: *IEEE Engineering Management Review* 48.4 (2020), pp. 144–159. DOI: 10.1109/EMR.2020.2999420.

[18] Kirschbaum, L. et al. “AI-Driven Maintenance Support for Downhole Tools and Electronics Operated in Dynamic Drilling Environments”. In: *IEEE Access* 8 (2020), pp. 78683–78701. DOI: 10.1109/ACCESS.2020.2990152.

[19] Ferket, J. “Asset Performance Management 4.0 Internet of Things iot Enabled Condition Monitoring, a Story from a Digital Maintenance Service Provider”. In: Abu Dhabi International Petroleum Exhibition & Conference (Abu Dhabi, UAE, Nov. 12–15, 2018). 2018. DOI: 10.2118/192636-MS.

[20] Nguyen, K., Do, P., and Grall, A. “Multi-level predictive maintenance for multi-component systems”. In: *Reliability Engineering & System Safety* 144 (2015). DOI: 10.1016/j.ress.2015.07.017.

[21] Tinga, T. and Loendersloot, R. “Physical Model-Based Prognostics and Health Monitoring to Enable Predictive Maintenance”. In: *Predictive Maintenance in Dynamic Systems*. Ed. by E. Lughofer and M. Sayed-Mouchaweh. Springer, Cham, 2019, pp. 313–353. DOI: 10.1007/978-3-030-05645-2_11.

[22] He, R. et al. “Condition-based maintenance optimization for multi-component systems considering prognostic information and degraded working efficiency”. In: *Reliability Engineering & System Safety* 234 (2023), p. 109167. DOI: 10.1016/j.ress.2023.109167.

[23] Simpson, D. A. “Well-Bore Construction (Drilling and Completions)”. In: *Practical Onshore Gas Field Engineering*. Gulf Professional Publishing, 2018. Chap. 2, pp. 85–134. DOI: 10.1016/B978-0-12-813022-3.00002-X.

[24] Oldenhuis, J. J. *State-of-the-art Maintenance on Land Drilling Rigs*. Unpublished literature review. 2023.

[25] Arnaout, A. et al. “Intelligent Real-time Drilling Operations Classification Using Trend Analysis of Drilling Rig Sensors Data”. In: SPE Kuwait International Petroleum Conference and Exhibition (Kuwait City, Kuwait, Dec. 10–12, 2012). 2012. DOI: 10.2118/163302-MS.

[26] Hilmawan, H. and Basri, H. “Reducing non-productive time of mud pump with acoustic emission monitoring techniques on fluid end parts”. In: *IOP Conference Series: Materials Science and Engineering* 1034 (2021), p. 012066. DOI: 10.1088/1757-899X/1034/1/012066.

[27] Reid, D. “The Development of Automated Drilling Rigs”. In: IADC/SPE Drilling Conference (Dallas, Texas, USA, Mar. 3–6, 1998). 1998. DOI: 10.2118/39373-MS.

[28] Richard, D. “The Next Major Step in Total Hands-Free Pipe Handling — No Derrickman in the Derrick Racking and Unracking Pipe”. In: SPE/IADC Drilling Conference (Amsterdam, The Netherlands, Feb. 20–22, 2007). 2007. DOI: 10.2118/105438-MS.

[29] Adams, D. A. “Improved CBM of Top Drives using Advanced Sensors and Novel Analysis Techniques”. MSc thesis. The University of Texas at Austin, 2015. URL: https://repositories.lib.utexas.edu/bitstream/handle/2152/41243/ADAMS-THESIS-2015.pdf?sequence=1%5C&isAllowed=y (visited on 01/11/2023).

[30] Ogidan, B. “Reducing Downtime Due to Top Drive: The $1000 Bet”. In: IADC/SPE Drilling Conference (Dallas, Texas, USA, Feb. 15–18, 1994). 1994. DOI: 10.2118/27512-MS.

[31] Manual, Drilling. *Top Drive in Drilling Components & Maintenance Steps*. 2021. URL: https://www.drillingmanual.com/top-drive-system-drilling-rig/ (visited on 10/05/2023).

[32] Capuano Jr., L. E. “Ch. 5 - Geothermal well drilling”. In: *Geothermal Power Generation. Developments and Innovation*. Woodhead Publishing, 2016. Chap. 5, pp. 107–139. DOI: 10.1016/B978-0-08-100337-4.00005-X.

[33] Schaaf, S., Pafitis, D., and Guichemerre, E. “Application of a Point the Bit Rotary Steerable System in Directional Drilling Prototype Well-bore Profiles”. In: SPE/AAPG Western Regional Meeting (Long Beach, California, USA, June 19–23, 2000). 2000. DOI: 10.2118/62519-MS.

[34] Islam, M. R. and Hossain, M. E. “State-of-the-art of drilling”. In: *Drilling Engineering. Towards Achieving Total Sustainability*. Gulf Professional Publishing, 2021. Chap. 2, pp. 17–178. DOI: 10.1016/B978-0-12-820193-0.00002-2.

[35] Guo, B. and Liu, G. “Equipment in Mud Circulating Systems”. In: *Applied Drilling Circulation Systems*. Gulf Professional Publishing, 2011. Chap. 1, pp. 3–18. DOI: 10.1016/B978-0-12-381957-4.00001-2.

[36] Guo, B. and Liu, G. “Mud Pumps”. In: *Applied Drilling Circulation Systems*. Gulf Professional Publishing, 2011. Chap. 3, pp. 61–79. DOI: 10.1016/B978-0-12-381957-4.00003-6.

[37] Lyons, W. C. et al. “Ch. 3 - Surface Equipment”. In: *Air and Gas Drilling Manual. Applications for Oil, Gas, Geothermal Fluid Recovery Wells, Specialized Construction Boreholes, and the History and Advent of the Directional DTH*. Gulf Professional Publishing, 2021. Chap. 3, pp. 37–65. DOI: 10.1016/B978-0-12-815792-3.00003-9.

[38] Noori, N. S., Waag, T. I., and Bianchi, F. M. “Condition Monitoring System for Internal Blowout Prevention (IBOP) in Top Drive Assembly System using Discrete Event Systems and Deep Learning approaches”. In: Proc. of the fifth European Conference of the Prognostics and Health Management Society (July 27–31, 2020). 2020. URL: https://munin.uit.no/handle/10037/19578 (visited on 12/15/2022).

[39] Verma, A. “Alternate Power and Energy Storage/Reuse for Drilling Rigs: Reduced Cost and Lower Emissions Provide Lower Footprint for Drilling Operations”. MSc thesis. Texas A&M University, 2009. URL: https://core.ac.uk/download/pdf/4279362.pdf (visited on 10/09/2023).

[40] King, G. *9.3: The Drilling Process. PNG 301 - Introduction to Petroleum and Natural Gas Engineering*. Penn State College of Earth and Mineral Sciences. URL: https://www.e-education.psu.edu/png301/node/729 (visited on 02/01/2023).

[41] Ruzhnikov, A. “Case study: Saving Days via Change of Connection Practices While Drilling”. In: SPE Russian Petroleum Technology Conference (Moscow, Russia, Oct. 22–24, 2019). 2019. DOI: 10.2118/196807-MS.

[42] Deighton, M. G. “Ch. 5 - Maintenance Management”. In: *Facility Integrity Management*. Gulf Professional Publishing, Boston, 2016. Chap. 5, pp. 87–139.

[43] Birolini, A. “Ch. 1 - Basic Concepts, Quality & Reliability (RAMS) Assurance of Complex Equipment and Systems”. In: *Reliability Engineering. Theory and Practice*. 7th ed. Springer, Berlin, 2014, pp. 1–24. DOI: 10.1007/978-3-642-39535-2.

[44] Tinga, T. *Principles of Loads and Failure Mechanisms. Applications in Maintenance, Reliability and Design*. Springer, London, 2013. ISBN: 978-1-4471-4917-0.

[45] Nowlan, F. S. and Heap, H. F. *Reliablity-Centered Maintenance*. Tech. rep. AD-A066579. Dec. 1978.

[46] Swanson, L. “Linking maintenance strategies to performance”. In: *International Journal of Production Economics* 70.3 (2001), pp. 237–244. DOI: 10.1016/S0925-5273(00)00067-0.

[47] Sheu, C. and Krajewski, L. J. “A decision model for corrective maintenance management”. In: *International Journal of Production Research* 32.6 (1994), pp. 1365–1382. DOI: 10.1080/00207549408957005.

[48] Wang, Y. et al. “A corrective maintenance scheme for engineering equipment”. In: *Engineering Failure Analysis* 36 (2014), pp. 269–283. DOI: 10.1016/j.engfailanal.2013.10.006.

[49] Motaghare, O., Pillai, A. S., and Ramachandran, K. I. “Predictive Maintenance Architecture”. In: IEEE International Conference on Computational Intelligence and Computing Research (ICCIC) (Madurai, India, Dec. 13–15, 2018). 2018. DOI: 10.1109/ICCIC.2018.8782406.

[50] Narayan, V. *Detective Maintenance*. Reliabilityweb. 2005. URL: https://reliabilityweb.com/articles/entry/detective_maintenance (visited on 01/12/2023).

[51] De, D. *Design Out For Reliability & Long Term Profitability*. 2003. URL: http://www.maintenanceworld.com/wp-content/uploads/2013/06/Design-Out-For-Reliability-Long-Term-Profitability.pdf (visited on 01/13/2023).

[52] Mughanyi, P., Mbohwa, C., and Madanhire, I. “Design-Out Maintenance as a Crucial Maintenance Facet”. In: Proceedings of the International Conference on Industrial Engineering and Operations Management (Bandung, Indonesia, Mar. 6–8, 2018). 2018, pp. 3406–3416. URL: http://ieomsociety.org/ieom2018/papers/677.pdf (visited on 02/08/2023).

[53] Venkatesh, J. *An Introduction to Total Productive Maintenance (TPM)*. Plant Maintenance Resource Center, 2005. URL: https://www.plant-maintenance.com/articles/tpm_intro.shtml (visited on 02/09/2023).

[54] Ab-Samat, H. and Kamaruddin, S. “Opportunistic Maintenance (OM) as a new advancement in maintenance approaches”. In: *Journal of Quality in Maintenance Engineering* 20.2 (2014), pp. 98–121. DOI: 10.1108/JQME-04-2013-0018.

[55] Basri, E. I. et al. “Preventive maintenance (PM) planning: a review”. In: *Journal of Quality in Maintenance Engineering* 23.2 (2017), pp. 114–143. DOI: 10.1108/JQME-04-2016-0014.

[56] Tinga, T. “Application of physical failure models to enable usage and load based maintenance”. In: *Reliability Engineering & System Safety* 95 (2010), pp. 1061–1075. DOI: 10.1016/j.ress.2010.04.015.

[57] Ahmad, R. and Kamaruddin, S. “An overview of time-based and condition-based maintenance in industrial application”. In: *Computers & Industrial Engineering* 63 (2012), pp. 135–149. DOI: 10.1016/j.cie.2012.02.002.

[58] Labib, A. “A decision analysis model for maintenance policy selection using a CMMS”. In: *Journal of Quality in Maintenance Engineering* 10.3 (2004), pp. 191–202. DOI: 10.1108/13552510410553244.

[59] Assis, R. and Marques, P. C. “A Dynamic Methodology for Setting up Inspection Time Intervals in Conditional Preventive Maintenance”. In: *Applied Sciences* 11.18 (2021), p. 8715. DOI: 10.3390/app11188715.

[60] Taheri, E., Kolmanovsky, I., and Gusikhin, O. *Survey of prognostic methods for condition-based maintenance in engineering systems*. Preview. arXiv. 2019. DOI: 10.48550/arXiv.1912.02708.

[61] Jardine, A. K. S., Lin, D., and Banjevic, D. “A review on machinery diagnostics and prognostics implementing condition-based maintenance”. In: *Mechanical Systems and Signal Processing* 20.7 (2006), pp. 1483–1510. DOI: 10.1016/j.ymssp.2005.09.012.

[62] Ali, A. and Abdelhadi, A. “Condition-Based Monitoring and Maintenance: State of the Art Review”. In: *Applied Sciences* 12 (2022), p. 688. DOI: 10.3390/app12020688.

[63] Errandonea, I., Beltrán, S., and Arrizabalaga, S. “Digital Twin for maintenance: A literature review”. In: *Computers in Industry* 123 (2020), p. 10316. DOI: 10.1016/j.compind.2020.103316.

[64] Luo, W. et al. “A hybrid predictive maintenance approach for CNC machine tool driven by Digital Twin”. In: *Robotics and Computer Integrated Manufacturing* 65 (2020), p. 101974. DOI: 10.1016/j.rcim.2020.101974.

[65] Zonta, T. et al. “Predictive maintenance in the Industry 4.0: A systematic literature review”. In: *Computers & Industrial Engineering* 150 (2020), p. 106889. DOI: 10.1016/j.cie.2020.106889.

[66] van Dinter, R., Tekinerdogan, B., and Catal, C. “Predictive maintenance using digital twins: A systematic literature review”. In: *Information and Software Technology* 151 (2022), p. 107008. DOI: 10.1016/j.infsof.2022.107008.

[67] Coanda, P., Avram, M., and Constantin, V. “A state of the art of predictive maintenance techniques”. In: *IOP Conference Series: Materials Science and Engineering* 997 (2020), p. 012039. DOI: 10.1088/1757-899X/997/1/012039.

[68] Wu, B. and Tian, Z. “A Data Processing Method for CBM using PHM”. In: *International Journal of Performability Engineering* 8.4 (2012), pp. 389–398. DOI: 10.23940/ijpe.12.4.p389.mag.

[69] Kerschen, G. et al. “Sensor validation using principal component analysis”. In: *Smart Materials and Structures* 14 (2004), pp. 36–42. DOI: 10.1088/0964-1726/14/1/004.

[70] Chinnam, R. B. and Baruah, P. “A Neuron-fuzzy Approach for Estimating Mean Residual Life in Condition-based Maintenance Systems”. In: *International Journal of Materials and Product Technology* 20.1-3 (2004), pp. 166–179. DOI: 10.1504/IJMPT.2004.003920.

[71] He, Y. “Corrosion Monitoring”. In: *Reference Module in Materials Science and Materials Engineering*. Elsevier, 2016. DOI: 10.1016/B978-0-12-803581-8.03460-3.

[72] Nemeth, T. et al. “PriMa-X: A reference model for realizing prescriptive maintenance and assessing its maturity enhanced by machine learning”. In: *Procedia CIRP* 72 (2018). 51st CIRP Conference on Manufacturing Systems, pp. 1039–1044. DOI: 10.1016/j.procir.2018.03.280.

[73] Matyas, K. et al. “A procedural approach for realizing prescriptive maintenance planning in manufacturing industries”. In: *CIRP Annals - Manufacturing Technology* 66 (2017), pp. 461–464. DOI: 10.1016/j.cirp.2017.04.007.

[74] Choubey, S., Benton, R., and Johnsten, T. “Prescriptive Equipment Maintenance: A Framework”. In: IEEE International Conference on Big Data (Big Data) (Los Angeles, California, USA, Dec. 9–12, 2019). 2019. DOI: 10.1109/BigData47090.2019.9006213.

[75] National Research Council. *Research Directions in Computational Mechanics*. Washington DC, USA: The National Academies Press, 1991. ISBN: 978-0-309-04648-0. DOI: 10.17226/1909.

[76] Ran, Y. et al. *Survey of Predictive Maintenance: Systems, Purposes and Approaches*. Preview. arXiv. 2019. DOI: 10.48550/arXiv.1912.07383.

[77] Nakagawa, T. “Statistical Models on Maintenance”. In: *Springer Handbook of Engineering Statistics*. Ed. by H. Pham. Springer, London. Chap. 46, pp. 835–848. DOI: 10.1007/978-1-84628-288-1_46.

[78] Lee, D. and Pan, R. “Predictive maintenance of complex system with multi-level reliability structure”. In: *International Journal of Production Research* 55.16 (2017), pp. 4785–4801. DOI: 10.1080/00207543.2017.1299947.

[79] Van Horenbeek, A. and Pintelon, L. “A dynamic predictive maintenance policy for complex multi-component systems”. In: *Reliability Engineering & System Safety* 120 (2013), pp. 39–50. DOI: 10.1016/j.ress.2013.02.029.

[80] Pui, G. et al. “Risk-based maintenance of offshore managed pressure drilling (MPD) operation”. In: *Journal of Petroleum Science and Engineering* 159 (2017), pp. 513–521. DOI: 10.1016/j.petrol.2017.09.066.

[81] Bhandari, J. et al. “Risk analysis of deepwater drilling operations using Bayesian network”. In: *Journal of Loss Prevention in the Process Industries* 38 (2015), pp. 11–23. DOI: https://doi.org/10.1016/j.jlp.2015.08.004.

[82] Abdel-Aziz, I. H. and Helal, M. “Application of FMEA-FTA in reliability-centered maintenance planning”. In: Proc. of the 15th Int. AMME Coneference (Military Technical College Kobry El-Kobbah, Cairo, Egypt, May 29–31, 2012). 2012, pp. 72–82. URL: https://amme.journals.ekb.eg/article_37083_64c536832dbba53bcfd9cc2526f34a7c.pdf (visited on 12/15/2022).

[83] Peeters, J. F. W., Basten, R. J. I., and Tinga, T. “Improving failure analysis efficiency by combining FTA and FMEA in a recursive manner”. In: *Reliability Engineering and System Safety* 172 (2018), pp. 36–44. DOI: 10.1016/j.ress.2017.11.024.

[84] Valeev, S. and Kondratyeva, N. “Risk control and process safety management systems”. In: *Process Safety and Big Data*. 2021. Chap. 7, pp. 271–294. DOI: 10.1016/B978-0-12-822066-5.00005-4.

[85] Palau, A. S., Dhada, M. H., and Parlikad, A. K. “Multi-agent system architectures for collaborative prognostics”. In: *Journal of Intelligent Manufacturing* 30 (2019), pp. 2999–3013. DOI: 10.1007/s10845-019-01478-9.

[86] Rocha, A. D., Peres, R., and Barata, J. “An Agent Based Monitoring ARchitecture for Plug and Produce Based Manufacturing Systems”. In: IEEE 13th International Conference on Industrial Informatics (INDIN) (Cambridge, United Kingdom, July 22–24, 2015). 2015. DOI: 10.1109/INDIN.2015.7281926.

[87] Ruiz Rodríguez, M. L. et al. “Multi-agent deep reinforcement learning based Predictive Maintenance on parallel machines”. In: *Robotics and Computer-Integrated Manufacturing* 78 (2022), p. 102406. DOI: 10.1016/j.rcim.2022.102406.

[88] Meesublak, K. and Klinsukont, T. “A Cyber-Physical System Approach for Predictive Maintenance”. In: 2020 IEEE International Conference on Smart Internet of Things (SmartIoT) (Beijing, China, Aug. 14–16, 2020). 2020. DOI: 10.1109/SmartIoT49966.2020.00061.

[89] Parnianifard, A. and Wuttisittikulkij, L. *Digital-Twins towards Cyber-Physical Systems: A Brief Survey*. Unpublished. Preprints. 2022. DOI: 10.20944/preprints202208.0483.v1.

[90] Al-Najjar, B., Algabroun, H., and Jonsson, M. “Smart Maintenance Model using Cyber Physical System”. In: International Conference on ”Role of Industrial Engineering in Industry 4.0 Paradigm” (ICIEIND) (Bhubaneswar, India, Sept. 27–30, 2018). 2018, pp. 1–6. URL: http://urn.kb.se/resolve?urn=urn:nbn:se:lnu:diva-81912 (visited on 10/30/2023).

[91] Papa, G., Zurutuza, U., and Uribeetxeberria, R. “Cyber Physical System Based Proactive Collaborative Maintenance”. In: 2016 Internationcal Conference on Smart Systems and Technologies (SST) (Osijek, Croatia, Oct. 12–14, 2016). 2016. DOI: 10.1109/SST.2016.7765654.

[92] Jing, Y. and Wang, X. “Technical Research on Digital Twin of Oil Rig Winch”. In: Proc. of 7th International Conference on Intelligent Computing and Signal Processing (ICSP) (Xi’an, China, Apr. 15–17, 2022). 2022, pp. 1157–1160. DOI: 10.1109/ICSP54964.2022.9778817.

[93] Khosravanian, R. and Aadnøy, B. S. “Introduction to digital twin, automation and real-time centers”. In: *Methods for Petroleum Well Optimization*. Gulf Professional Publishing, 2022. Chap. 1, pp. 1–30. DOI: 10.1016/B978-0-323-90231-1.00006-6.

[94] Mihai, S. et al. “A Digital Twin Framework for Predictive Maintenance in Industry 4.0”. In: Proceedings of the 2020 International Conference on High Performance Computing & Simulation (Barcelona, Spain, Dec. 10–14, 2020). 2021. URL: https://eprints.mdx.ac.uk/31855/ (visited on 04/21/2023).

[95] Lu, Y. et al. “Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues”. In: *Robotics and Computer Integrated Manufacturing* 61 (2019), p. 101837. DOI: 10.1016/j.rcim.2019.101837.

[96] Parrott, A. and Warshaw, L. *Industry 4.0 and the digital twin*. Deloitte Insights. May 2017. URL: https://www2.deloitte.com/us/en/insights/focus/industry-4-0/digital-twin-technology-smart-factory.html (visited on 02/28/2023).

[97] Osinde, N. O. et al. “Process Modelling of Geothermal Drilling System Using Digital Twin for Real-Time Monitoring and Control”. In: *Designs* 3 (2019), p. 45. DOI: 10.3390/designs3030045.

[98] Zhang, R. et al. “Digital Twin and its Applications: A survey”. In: *The International Journal of Advanced Manufacturing Technology* 123 (2022), pp. 4123–4136. DOI: 10.1007/s00170-022-10445-3.

[99] Kritzinger, W. et al. “Digital Twin in manufacturing: A categorical literature review and classification”. In: *IFAC PapersOnLine* 51.11 (2018), pp. 1016–1022. DOI: 10.1016/j.ifacol.2018.08.474.

[100] Tune, N. *Beyond buzzwords: the true meaning and value of 'digital twins'*. SNC-Lavalin. Apr. 2019. URL: https://www.snclavalin.com/en/beyond-engineering/beyond-buzzwords-the-true-meaning-and-value-of-digital-twins (visited on 05/11/2023).

[101] Mauro, F. and Kana, A. A. "Digital twin for ship life-cycle: A critical systematic review". In: *Oceans Engineering* 269 (2023), p. 113479. DOI: 10.1016/j.oceaneng.2022.113479.

[102] Moyaux, T. et al. "An Agent-Based Architecture of the Digital Twin for an Emergency Department". In: *Sustainability* 15.4 (2023), p. 3412. DOI: 10.3390/su15043412.

[103] Wright, L. and Davidson, S. "How to tell the difference between a model and a digital twin". In: *Advanced Modeling and Simulation in Engineering Sciences* 7.13 (2020). DOI: 10.1186/s40323-020-00147-4.

[104] Palensky, P. et al. "Digital twins and their use in future power systems". In: *Digital Twin* (2022). Unpublished, version 2. DOI: 10.12688/digitaltwin.17435.2.

[105] Aivaliotis, P., Georgoulias, K., and Chryssolouris, G. "The use of Digital Twin for predictive maintenance in manufacturing". In: *International Journal of Computer Integrated Manufacturing* 32.11 (2019), pp. 1067–1080. DOI: 10.1080/0951192X.2019.1686173.

[106] Khan, M. E. and Khan, F. "A Comparative Study of White Box, Black Box and Grey Box Testing Techniques". In: *International Journal of Advanced Computer Science and Applications* 3.6 (2012), pp. 12–15. DOI: 10.14569/IJACSA.2012.030603.

[107] Aivaliotis, P., Georgoulias, K., and Alexopoulos, K. "Using digital twin for maintenance applications in manufacturing: State of the Art and Gap analysis". In: IEEE International Conference on Engineering, Technology and Innovation (Valbonne Sophia-Antipolis, France, June 17–19, 2019). 2019. DOI: 10.1109/ICE.2019.8792613.

[108] Wangsness, C. *What is a SCADA System and How Does It Work?* Online blog. OnLogic. 2023. URL: https://www.onlogic.com/company/io-hub/what-is-a-scada-system-and-how-does-it-work/ (visited on 01/11/2024).

[109] Archer, C. *How to export SCADA data into production software*. Online blog. WellAware. 2021. URL: https://blog.wellaware.us/blog/how-to-export-scada-data-into-production-software (visited on 01/11/2024).

[110] de Cheveigné, A. and Nelken, I. "Filters: When, Why, and How (Not) to Use Them". In: *Neuron* 102.2 (2019), pp. 280–293. DOI: 10.1016/j.neuron.2019.02.039.

[111] Ellis, G. "Filters in Control Systems". In: *Control System Design Guide (Fourth Edition)*. Butterworth-Heinemann, 2012. Chap. 9, pp. 165–183. DOI: 10.1016/B978-0-12-385920-4.00009-6.

[112] Levada, A. L. M. *Non-linear Adaptive Wiener Filter for Time Series Smoothing*. Preview. Research Square. 2022. DOI: 10.21203/rs.3.rs-2227854/v1.

[113] Hayes-Roth, F. "Rule-based systems". In: *Communications of the ACM* 28.9 (1985), pp. 921–932. DOI: 10.1145/4284.4286.

[114] Dernoncourt, F. *Introduction to fuzzy logic*. Massachusetts Institute of Technology. 2013. URL: https://www.researchgate.net/publication/267041266_Introduction_to_fuzzy_logic (visited on 02/17/2023).

[115] Gallab, M. et al. "Risk Assessment of Maintenance activities using Fuzzy Logic". In: *Procedia Computer Science* 148 (2019). Second International Conference on Intelligent Computing in Data Sciences (ICDS 2018), pp. 226–235. DOI: 10.1016/j.procs.2019.01.065.

[116] McCormick, S. *Survival Analysis, Part 1: The Weibull model*. 2018. URL: https://medium.com/utility-machine-learning/survival-analysis-part-1-the-weibull-model-5c2552c4356f (visited on 01/05/2024).

[117] Ragab, A. et al. "Remaining useful life predcition using prognostic methodology based on logical analysis of data and Kaplan-Meier estimation". In: *Journal of Intelligent Manufacturing* 27.5 (2014). DOI: 10.1007/s10845-014-0926-3.

[118] Liu, E., Liu, R. Y., and Lim, K. "Using the Weibull Accelerated Failure Time Regression Model to Predict Time to Health Events". In: *Applied Sciences* 13 (2023), p. 13041. DOI: 10.3390/app132413041.

[119] Kusiak, A. and Chen, M. "Expert systems for planning and scheduling manufacturing systems". In: *European Journal of Operational Research* 34.2 (1988), pp. 113–130. DOI: 10.1016/0377-2217(88)90346-3.

[120] Abdyukova, R. Ya. "Studies on operation and types of drilling pump valves". In: *IOP Conference Series: Materials Science and Engineering* 560 (2019), p. 012050. DOI: 10.1088/1757-899X/560/1/012050.

[121] Băltărețu Iancu, M., Hadăr, A., and Ulmanu, V. "Methods of Improving the Mud Pump Valve Life". In: *Annals: Series on Engineering Sciences (Academy of Romanian Scientists)* 7.2 (2015), pp. 103–112. URL: https://doaj.org/article/3f16b1ad44064e8d86bff502d944eb85 (visited on 04/05/2023).

[122] Spoerker, H. F. and Litzlbauer, C. H. "High-Frequency Mud Pump Pressure Monitoring Enables Timely Wear Detection". In: IADC/SPE Asia Pacific Drilling Technology (Jakarta, Indonesia, Sept. 9–11, 2002). 2002. DOI: 10.2118/77234-MS.

[123] Kyllingstad, Å. and Nessjøen, P. J. "Condition Based Maintenance: A New Early Leak Detection System for Mud Pumps". In: SPE/IADC Drilling Conference and Exhibition (Amsterdam, The Netherlands, Mar. 1–3, 2011). 2011. DOI: 10.2118/139888-MS.

[124] Yoon, D. et al. "Towards a practical, generally-applicable condition-based maintenance CBM system for mud pumps". In: IADC/SPE International Drilling Conference and Exhibition (Galveston, Texas, USA, Mar. 8–10, 2022). 2022. DOI: 10.2118/208741-MS.

[125] Yoon, D. et al. "Field Validation of Scalable Condition-Based Maintenance (CBM) of Mud Pumps". In: IADC/SPE International Drilling Conference and Exhibition (Stavanger, Norway, Mar. 7–9, 2023). 2023. DOI: 10.2118/212564-MS.

Appendix

A. Research Paper

An Integrated Approach for Advanced Maintenance on a Land Drilling Rig: a Mud Pump Case Study

J.J. Oldenhuis, Y. Pang, D.L. Schott and L.R.R. Holwerda

Abstract— **The drilling industry faces the challenge to move away from conventional maintenance strategies in order to maximise uptime. This paper introduces a holistic approach to land drilling rig Predictive Maintenance (PdM), integrating component maintenance into system-level decision-making. A hierarchical Multi-Agent System (MAS) framework is given, employing two layers of agents for the core components and one centralised system agent. Middle-level agents perform component diagnostics, prognostics and operational state classification, while the system agent uses expert reasoning for integrated maintenance scheduling. As a proof of concept, the model is partially validated. Vibration measurements from a mud pump during a drilling project are used to extract dimensionless features for a Fuzzy Logic (FL) classifier combined with Weibull Accelerated Failure Time (WAFT) for Remaining Useful Life (RUL) prediction. Case study inducing synthetic valve failure in historical operational data demonstrated the model is able to predict these failures on time. Maintenance actions were suggested when components reached 90% of their theoretical lifetime, preventing excessive maintenance and minimising disruption to drilling operations through integrated scheduling.**

I. Introduction

A. Research background

Land drilling rigs are complex machinery carrying out heavy operations, in an industry subject to high standards and requirements, where costs can run high during equipment downtime. Smooth progress during drilling operations is essential in this business, therefore reliable rigs are required [1]. One of the main challenges in the drilling industry is to implement efficient rig maintenance. Poor decision-making and too generic maintenance routines are currently contributing to ineffective repairs on drilling rigs, occasionally causing more equipment failure [2]–[5].

B. Problem statement

Experts have widespread belief that the recent digitisation of the drilling industry can lead to informed maintenance decision making based on insight, knowledge and forecasting [6]–[11]. By applying data techniques in a dedicated system to determine the best maintenance options, advanced maintenance is achieved. However, most research focuses on individual components. It is preferable to provide an integrated solution for a drilling rig, gaining a holistic view of the rig's health condition and maintenance needs. This is also recognised in the broad field of maintenance optimisation research [12], [13]. It is simultaneously acknowledged that system level strategies would require prognostics of all components, but in practice, this is often not possible [13], [14]. While these academic sources do provide general solutions towards the general problem, to the author's knowledge, there have been no efforts to find a solution for a drilling rig system yet. A lack of integrated maintenance methods for drilling rigs is identified. A complex structure consisting of critical components calls for a holistic maintenance strategy and raises the need for integration between component level maintenance strategies and the overall drilling rig operations.

C. Research scope

This paper proposes a strategy to integrate advanced maintenance of drilling rig components at a system level. The main result will be a method for the integration of already available operational data with additional condition monitoring (CM) methods in a single model. This model generates maintenance actions that are beneficial to the drilling rig's uptime. Development requires selection and application of appropriate methods to achieve real-time maintenance decision-making. To partially validate the method, the model will be realised and used in a case study on the mud pump valve system of a drilling rig. The main research question of this paper is formulated as:

How to achieve advanced maintenance of mud pump valves in a model making integrated maintenance decisions on drilling rig system level, based on real-time data?

The research work consists of three phases. In the first phase, through literature review a thorough understanding of mud pump operations, maintenance theory and system modelling is gained. These three fields of knowledge are merged to establish a framework for the maintenance model. The second phase is a field research, conducted concurrently with the literature review. Vibration signal data is gathered by placement of sensors on a mud pump's fluid end that is operational during a drilling project. Combined with logged operational data from the drilling rig SCADA system and mud pump maintenance records, data is acquired to use in the model development. The field research also offers insights into the actual operations during a drilling project, enhancing understanding about the drilling rig as a system and exposing opportunities for maintenance improvement. In the third and final phase of the research the proposed model is developed and (partially) validated. Historical operational data is merged with synthetic failure data sets to validate and test the effectiveness of the complete model in various different cases of simulated mud pump failure. The accuracy of upcoming failure prediction will serve as performance indicator to test the improvement of the drilling rig maintenance and reliability.

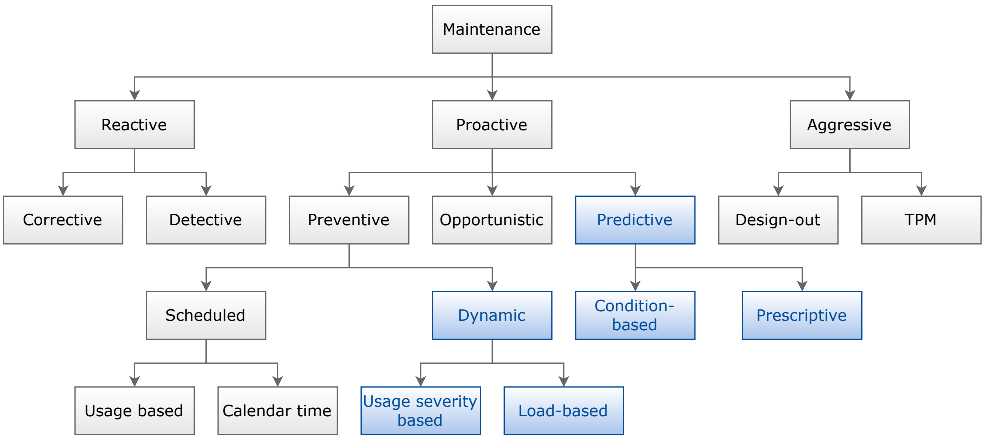


Fig. 1. Overview and classification of different maintenance policies, based on [15]–[17]. The advanced maintenance policies are highlighted in blue.

II. Literature Review

A. Mud pump operations analysis

Drilling rig functionality is divided in five sub-systems: the (i) rotary, (ii) circulation, (iii) hoisting, (iv) blowout prevention and (v) power supply system [18], [19]. These systems are in continuous operations during drilling projects. In the circulation system, mud pumps are required to ensure minimal pressure of drilling fluid (mud). They are considered as the heart of the drilling rig. [20]. Mud is essential during the drilling process, as it (i) removes cuttings from the wellbore, (ii) lubricates and cools the drillbit and (iii) controls downhole pressure to prevent other fluids and gasses from entering the wellbore [21]. Triplex piston pumps with reciprocating positive-displacement mechanisms have become the prevailing choice in contemporary drilling. More than often drilling rigs use multiple mud pumps in series.

In a triplex mud pump two main sections are distinguished: the power end and the fluid end. The power end is driven by a powerful motor, either mounted directly on the drive shaft or via a belt drive. Torque and rotation is translated to a huge crankshaft driving three pistons. Valves in the fluid end open and close, moving mud from the inlet to the pressure chamber and from there to the outlet. One can deduce triplex mud pumps have six valves: one suction and one discharge valve per piston.

B. Failure mode of the valves

Mud pump valves are subject to different types of wear, particularly mechanical or sliding wear, erosion and corrosion [22], [23]. Despite various attempts to improve reliability of the valves, their lifetime at a pressure between 16-18MPa still does not exceed 100 hours [24]. For the drilling of deeper wells, mud pump pressure can be increased up to 32MPa, reducing the lifetime of hydraulic parts in twofold [22]. It is evident that valves are replaced regularly during drilling due to these conditions. Timely changing a damaged valve is important since a washout will quickly damage the fluid module inside due to the coarse characteristics and high pressure of the mud. A leaking valve is detected by placing a random metal tool against the fluid end and the other end to the human ear, like a kind of simple stethoscope, to detect an odd noise that indicates leakage. These checks are conducted frequently, but they often give little time to prepare for replacement of the valve.

C. Maintenance theory

Maintenance management aims to (i) maximise equipment availability and (ii) ensures maintenance resources are optimised [17]. A successful maintenance strategy should improve equipment reliability while reducing cost of ownership. Reliability is the probability that equipment will perform its required function under given operating conditions for a stated time interval [25]. When equipment stops performing its required function, this is defined as a failure. The point availability of equipment can be assessed using the following formula:

$$A = \frac{\text{MTBF}}{\text{MTBF} + \text{MTTR}} \tag{1}$$

where MTBF is the mean operating time between failures and MTTR is the time to repair the equipment [15], [25]. From Equation 1, it can be concluded that maintenance plays a decisive role in assuring a high availability level. Therefore a dedicated, effective and efficient way to conduct maintenance on equipment must be decided: a maintenance strategy [15]. Selecting a maintenance strategy strongly depends on the object of interest. There is no perfect maintenance strategy to suit all equipment in all circumstances. A broad overview of maintenance policies is given in Figure 1.

D. Conventional drilling rig maintenance

Land drilling rig operators adopt conventional approaches to maintenance. These are mostly reactive (RM) or preventive maintenance (PM) policies based on inspection intervals and replacement cycles, often applied to equipment classes [3], [8]. Undesirable effects of these policies are that (i) equipment with different failure rates unjustly receive equal maintenance, (ii) to avoid failures as much as possible short inspection intervals are used, leading to high maintenance costs and (iii) excessive maintenance leads to more chance of human error, resulting in even more equipment failure. RM and PM could actually decrease the reliability of a system. This can be substantiated by looking at the failure patterns

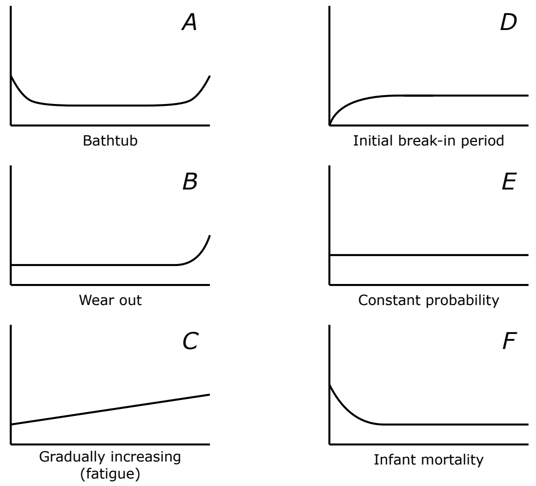


Fig. 2. Pattern curves of failure probability over time. Patterns A,B and C show a probability of failure related to equipment age. The failure probability patterns D, E and F are mostly constant, therefore they do not relate to age. (based on [11], [26])

of aircraft parts [26], depicted in Figure 2. These failures were divided into age-related failures (A,B,C) and non-age related failures (D,E,F). 89% of the components analysed fell in the latter group. This exposes a weakness of scheduled maintenance: it assumes equipment condition will degrade with age, posing the risk of performing maintenance on equipment that is still in good condition [8], [11]. Nowadays, data could be used to achieve informed decision making based experience and forecasting [6], [11]. However, most rig operators lack to convert data into useful information that can be used for decision making or fail to retain important data that could be of future use [8], [27].

E. Predictive Maintenance (PdM)

PdM is an advanced proactive maintenance strategy that determines the optimal moment for maintenance through model or data analysis. The goal of PdM is maximisation of the time interval between maintenance tasks without the occurrence of equipment failure. Using the actual operating condition of the equipment, PdM can predict the future state of equipment, also depending on historical operation or degradation behaviour data [28]. PdM basically involves three tasks: CM, diagnostics and prognostics.

1) Condition Monitoring (CM): CM techniques focus on monitoring a critical condition parameter through deployment of sensors on the equipment. Common techniques are vibration, acoustic, lubrication oil, particle, corrosive, thermal and performance analysis [29]. Based on the CM technique, three types of data can be gathered: (i) single *Value type* data collected at a specific time, (ii) *Waveform type* time series data collected over an interval of time and (iii) *Multidimensional type* data, e.g. thermographs [30].

2) Diagnostics: Diagnostics is conducted to detect, isolate and identify potential faults and failure modes [31]. Diagnostic methods can use pattern recognition or modelling techniques to detect and classify a failure or fault. But just monitoring a condition parameter until it exceeds a critical value that requires immediate action, will not improve reliability of the system. Therefore a prognostic method is required to determine the best future moment of maintenance [15]. While prognostics might seem superior to diagnostics, as it can prevent failure, it cannot replace diagnostics. Diagnostics is still needed to give accurate maintenance decision support when a sudden fault is occurring [30].

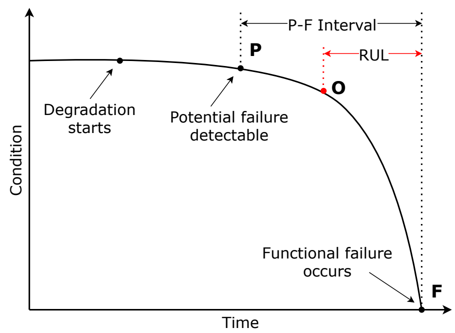


Fig. 3. A general P-F curve: relation between observance of a potential failure (P) and the actual failure (F). The RUL from a certain observation (O) is highlighted as well. (Image based on [15])

3) Prognostics: Prognostics rely on fault indicators and degradation rates, which are in the outputs of diagnostics [31]. The aim of a prognostic method can be shown with a P-F curve as illustrated in Figure 3. Degradation starts from the moment of installation and is noticeable in an early stage, where it will not affect the performance of the system. However, from a certain point in time **P**, a CM system will be able to detect an anomaly that points to an upcoming failure, **F**. The P-F interval, also called delay time of equipment, is very essential for the success of a PdM strategy, since small delay times require flexible maintenance strategies while large delay times allow for broad opportunity windows for the clustering of maintenance [15]. Prognostics are needed to estimate the RUL, which is the time to failure F, measured from any point on the P-F curve [31], [32], depicted in Figure 3 at observation time **O**. A PdM strategy revolves around achieving the most precise forecast of equipment RUL.

III. System model framework

A. Requirements for the model

The goal of the research is to find a holistic approach to the application of PdM on a drilling rig. For this purpose, it is necessary to first identify an applicable framework for the system model. The requirements for the system model are defined as:

- Integration of component-level maintenance solutions to system-level decision-making.
- Functional based on available data. It is assumed that this data consists of operational parameters gathered by the rig operational control system, CM data and maintenance records of the commonly maintained components on the rig.

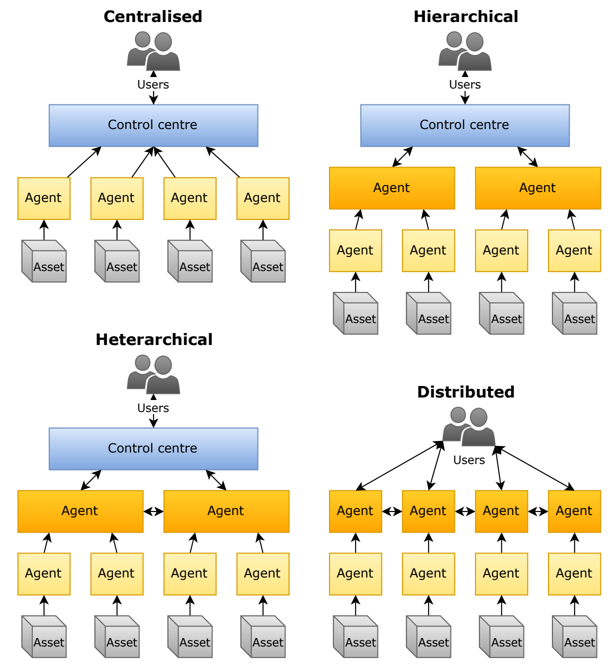


Fig. 4. Four types of MAS in PdM (Image based on [33])

- Easily modifiable model structure. Reasons to modify the model are to change, add or remove a component or CM method.

B. Multi-Agent Systems (MAS)

In MAS, a decision-making system is constructed from multiple "agents". Agents are entities in the system that can independently make decisions to achieve their own goal. Agents may cooperate with each other or a "collective mind" to exchange information or resources [34]. MAS architectures for PdM are commonly classified in four types [33] (see Figure 4):

- *Centralised:* a control centre has full control over system decision-making. Agents communicate with this centre by sending data and receiving maintenance recommendations. The control centre can be considered as the "main agent" as it is the only one that actually analyses the data and does the decision-making.
- *Hierarchical:* lower-level agents perform simple tasks and provide information to intermediate agents, who account for most of the decision-making in the system. The control centre has full control of the communications in the system, assigning groups and tasks to the intermediate agents.
- *Heterarchical:* in addition to a hierarchical architecture, it allows for horizontal communication between agents. The control centre lets agents communicate with each other by a clustering algorithm.
- *Distributed:* all intermediate agents are in the same level of hierarchy, and take independent decisions without supervision of a higher-level control centre. The agents therefore have peer-to-peer connections and are stimulated to establish collaborations.

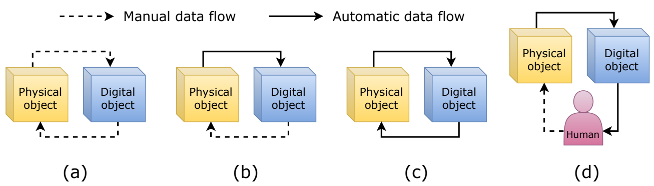


Fig. 5. Classification of DT based on level of data integration: (a) Digital model, (b) Digital shadow, (c) DT and (d) DT with human integrated in the decision loop. (Image based on [36]–[39])

MAS can be very agile and adaptive to the situation of the physical equipment. An advantage of MAS, is that the work of processing and analysing parts of the data can be distributed among various levels of agents, reducing the workload on top-level parts of system. Additionally, MAS allow to (de)attach components without the need to reconfigure the whole software [35].

C. Digital Twin (DT)

DT is a popular concept in recent technology, merging physical modelling with real-time data analysis [40]–[42]. DT technology consists of a virtual model, a physical system, and a data interface facilitating an automated interaction between the physical world and the virtual space. This automated connection is what distinguishes a DT from a digital model, which is often overlooked in the industry [37]. To help understand the concept of DT, models are classified based on data integration in Figure 5, here DT involves a bidirectional and automatic data interaction [36]. Other criteria that define a DT are that it should be sufficiently (i) physics-based, (ii) accurate, and (iii) quick in decision-making [43]. For maintenance strategies, human integration in DT decision loops is proposed since in practice automated actions can be undesirable and are mostly still unfeasible [39]. When a DT gives real-time updated suggestions to the user, the user can decide to follow up the suggestions and 'close the loop'. In PdM, DT plays a crucial role by combining physical models with data-driven approaches for RUL prediction, as a hybrid approach [37], [42]. DT can be used for real-time data acquisition, historical data analysis, and what-if analyses to optimise PdM strategies [41], [44], [45].

D. Proposed model framework

To meet the requirements in subsection III-A, this research proposes a hierarchical MAS depicted in Figure 6. This model will schedule maintenance actions, based on SCADA and CM data representing the physical environment. The lowest level contains data agents that pre-process the raw data from the environment, by means of data selection and filtering. Utilising the cleaned data, component agents give an assessment of the operation status and RUL of the physical component and communicate their conclusion to the system-level agent, the controller. The controller will give a real-time classification of the rig operating state and consults a knowledge base to suggest upcoming maintenance actions in the system. Since the MAS gives an automated interpretation of the physical equipment, it represents a

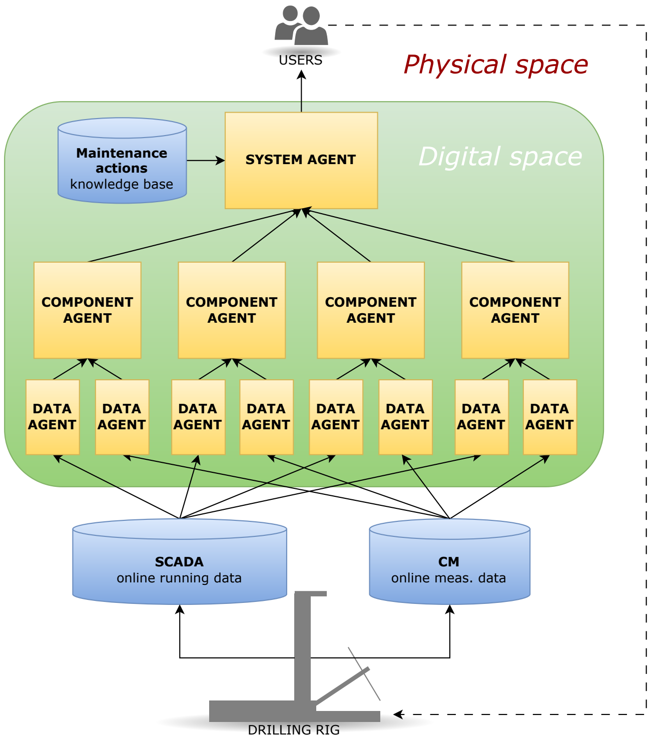


Fig. 6. The centralised MAS-DT framework proposed in this work.

digital shadow (Figure 5c). The operator is the link to the physical system: they can decide to follow up the suggestions and alter the system, by conducting maintenance.

IV. Mud pump PdM design

A. CM technique selection for field research

In literature, various efforts have been made for the CM of mud pump valve wear. Early attempts focus on pressure monitoring, as slight loss of pressure can indicate the start of leakage, however this would require intrusive sensors with a very high accuracy [46], [47]. Accelerometers are a better alternative, measuring high frequency vibrations that indicate leakage of the valves [47], [48]. So far, there is one example of a field validated tool that uses acoustic sensors in combination with accelerometers for the prediction of valve leakage [49].

In the field research, accelerometers are chosen as sensors in an online vibration monitoring system. Six accelerometers are placed on the side of the fluid end, each in the proximity of a discharge or suction valve. The sensors are connected to a data acquisition (DAQ) unit that is located at the side of the mud pump. This unit is then connected to a power supply and a laptop, fitted with software and a database to store the acquired vibration signals (Figure 7). This is a temporary setup for the research, however, this kind of setup could also easily be integrated into the drilling rig for constant CM, by connection the DAQ unit to the SCADA system via modbus protocol.

B. Data preprocessing

The vibration data acquired during field research was analysed. The mud pumps were mounted in container-sized

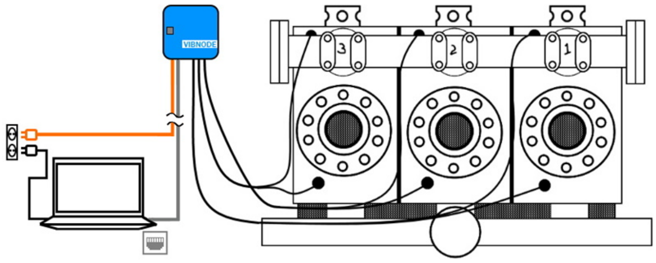


Fig. 7. Schematic depiction of sensor setup

frames, connected in a line, so there was clear inference of structure-borne vibrations from other mud pumps. Two signal filters were applied to pre-process the acceleration data.

From Figure 8, one can notice a dominant band in the lower frequencies, around 50Hz to 250Hz. Therefore, first a fourth order Butterworth high-pass filter with a cutoff frequency off 240Hz is applied to obtain a time series signal containing the higher frequencies, which are of interest.

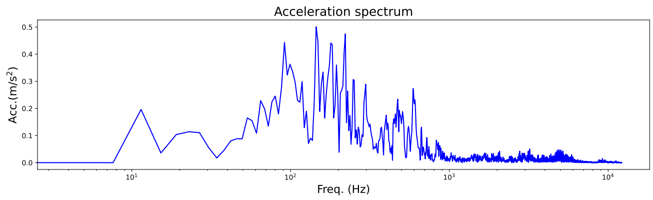


Fig. 8. Example of acceleration FFT spectrum acquired from mud pump vibrations

To remove the random noise still present in the signal, a Wiener filter is designed and applied because of its good characteristics for removing random noise. The algorithm used is the adaptive linear Wiener filter, that point-wise calculates the filtered output signal for sample n:

$$y(n) = \mu_x + (x(n) - \mu_x)\frac{\sigma_x^2}{\sigma_x^2 + \sigma_n^2} \tag{2}$$

Here μ_x is the local mean of the input signal, $x(n)$ is the noisy input, σ_x^2 and σ_n^2 are the local variance of the input signal and the noise, respectively [50]. A window size $n = 3$ is used to form local neighbourhoods for the mean and variances. The results of the filters are depicted in Figure 9.

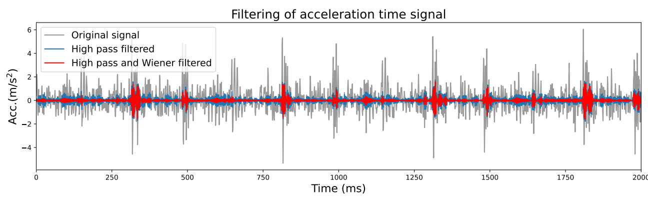


Fig. 9. Results after application of high-pass and Wiener filtering

C. Classification of operational state

The component agents and system agent are charged with classification of the operational state, which plays a critical role in maintenance decision-making. From operational parameters, the component agents classify the component state, and based on these states the system agent will determine

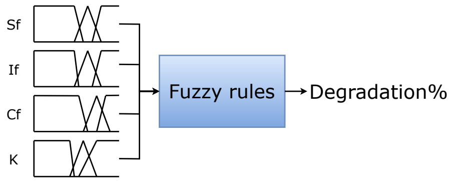


Fig. 10. Schematic overview of FL classifier for the condition of component health

the operation of the whole drilling rig. Looking at various equipment parameters, an experienced driller will effortlessly recognise the rig's operation. A rule-based system (RBS) is used to translate human data interpretation into a model that can accurately classify component state based on certain SCADA parameters. Various conditional 'if x then y' rules are used to cover all possible operating modes of the components. The same method is applied for the system agent to classify if the rig is in drilling operation or not.

D. Fuzzy logic (FL) diagnostics

In diagnostics, various features are extracted and selected to be used in a FL degradation classifier. The exact dependencies of equipment health based on these features is unknown, so to deal with this uncertainty fuzzy rules can be applied. FL provides flexibility in reasoning since inaccuracies, uncertainties and subjectivities can be taken into account [51] For the design of the FL classifier, various features were extracted from samples recorded 24 hours before and after replacement of a valve, to identify deviation between the vibration of new and degraded valves. The precise level of degradation of these samples was unknown. In the end, four dimensionless features describing the shape of the signal were selected: (i) shape factor, (ii) impulse factor, (iii) crest factor and (iv) kurtosis of the signal. Other features like RMS, number of peaks, absolute mean showed no difference between the two test groups, presumably because the pump speed was of too great influence.

Membership functions were established for the features and fuzzy terms for each feature are used in a fuzzy inference engine, were rules are deployed to obtain the output state. The numerical value of the output state is the degree of degradation between 0 and 100, were 100 represents a completely failed part.

The FL classifier in Figure 10 was validated using the analysed signal samples. Results indicated that on average it was able to successfully classify the estimated degradation (Figure 11).

E. RUL prediction using WAFT

From available maintenance records, a survival analysis can be conducted to find the survival function $S(t)$ that represents the probability of survival at time t. To achieve this, a probability distribution has to be found that fits the maintenance data. The right-censored maintenance data consists of running hours of parts and a binary variable representing if the parts has failed at that point or not. However, using this data would make a solely statistical model based on just on variable (t). Therefore, a WAFT model was designed, using the FL classified degradation rate as the covariate x_{HC}. The dataset was expanded with a column containing values of x_{HC}, were it was assumed parts replaced due to failure had $37 \leq x_{HC} \leq 72$ and preventively replaced parts had $18 \leq x_{HC} \leq 55$. Due to the sparsity of running hours in the maintenance dataset, parts that failed within 100hrs were assigned $60 \leq x_{HC} \leq 100$ to increase the effect of the health covariate on the RUL. The Weibull distribution was used to fit the data and find the survival function

$$S(t; x, y) = \exp(-(\frac{t}{\lambda(x)})^{\rho(y)}) \tag{3}$$

Where $\lambda(x) = \exp(\beta_0 + \beta_{HC} x_{HC})$ determines the scale of the function and $\rho(y) = \exp(\alpha_0)$ indicates the shape of the function, meaning the failure rate. Therefore the set of parameters that are determined by fitting the dataset are $[\beta_0, \beta_1, \alpha_0]$. Finally, by establishing τ as a threshold value for S, the RUL can be determined by calculating $t_\tau - t$ where t_τ represents the first time were $S = \tau$. Since we can use the WAFT survival function to calculate this time, the equation for the RUL is:

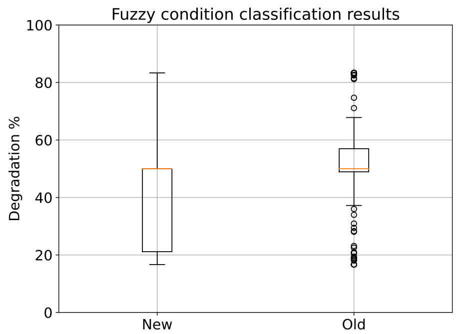
$$\mathrm{RUL}(t; x_{HC}) = \exp(\beta_0 + \beta_{HC} x_{HC}) * (-\ln(\tau))^{(\frac{1}{\exp \alpha_0})} - t \tag{4}$$

The resulting functions of the WAFT fit for some values of x_{HC} can be seen in Figure 12.

V. Results

A. Case study setup

To validate the methods in section IV and the overall model framework in Figure 6, the model is developed and used in a case study of historical operational records combined with synthetic failure data. The case study will assess the prediction of the mud pump valve RUL, since



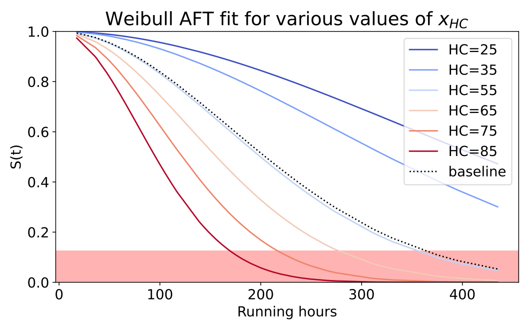


Fig. 12. WAFT survival functions, RUL threshold indicated in red.

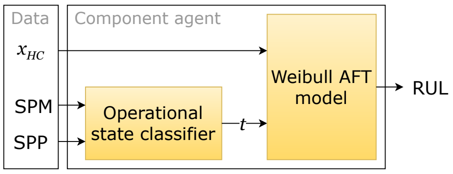


Fig. 13. Scheme of model used in case study simulations

the component RUL is the decisive factor for the maintenance decision-making of the system agent. A dataset is constructed combining historical mud pump operational parameters (SPM, SPP) and an artificially induced valve failure. The model used in the case study simulation is a simplified version of the developed component agent, where the FL classifier is excluded to save time. As depicted in Figure 13, the model will classify the operational state of the mud pump to calculate t, and predict the RUL based on t and x_{HC}, the theoretical output of the FL classifier. To mimic the failure, x_{HC} increases exponentially from 21 to 76:

$$x_{HC}(t) = 21(1 + \exp(\log(\frac{76}{21})\frac{t}{3600p})) \tag{5}$$

Here p is the desired pace of deterioration and the valve has completely failed when $x_{HC} = 100$. Four scenarios are constructed, combining two different operational conditions and two different failure evolutions ($p = 50$, $p = 100$). Each scenario is simulated for component ages $t_0 = 0, t_0 = 100, t_0 = 200$.

B. Results

The results of the case study simulations are presented in Table I. Here, T_L is the actual lifetime of the component, Δt is the time between failure prediction and actual failure and UF is the lifetime utilisation factor, to represent the proportion of time the equipment was in use compared to the time it could theoretically be used:

$$\text{UF} = 1 - \frac{\Delta t}{T_L} \tag{6}$$

VI. Discussion

From Table I, it can be concluded that the model timely predicts failure of used components ($t_0 \geq 100$). The UF for these predictions has satisfactory values: with an average utilisation of 0.93, implementation of the model in practice

TABLE I
RESULTS OF CASE STUDY SIMULATIONS.

Op. Cond.	p(hrs)	t_0(hrs)	T_L(hrs)	Δt(hrs)	UF
A	100	0	115.96	-2.47	1.02
		100	215.96	20.08	0.91
		200	415.96	37.53	0.91
A	50	0	104.89	-23.08	1.22
		100	204.89	9.37	0.95
		200	404.89	18.65	0.95
B	100	0	87.32	n.a.	n.a.
		100	187.32	16.80	0.91
		200	287.32	33.70	0.88
B	50	0	57.92	n.a.	n.a.
		100	157.92	4.74	0.97
		200	257.92	14.25	0.94

will not cause excessive maintenance. A shortcoming of the model is identified, since the model fails to timely predict early-life failures. This is in line with expectations since the statistical range of the WAFT will struggle with outliers. To tackle this problem, the RUL threshold τ can be dynamically modelled so it increases for components with $t \leq 100$hrs in order to accurately handle $T_L \leq 100$. To see how maintenance windows will be suggested by the system agent, the results are plotted in Figure 14.

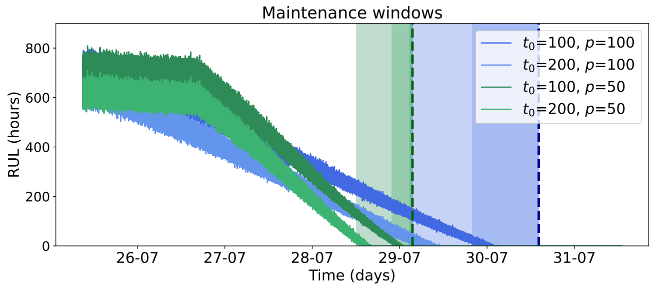


Fig. 14. Plot of the RUL predictions and maintenance windows suggested by the system agent.

VII. Conclusion & Future Work

A MAS for the integration of component diagnostics and prognostics to system-level maintenance decision-making was developed for a land drilling rig. While limited real-world data for this purpose was available, the method is partially validated by developing the proposed framework into a functioning model for PdM of mud pump valves. Dimensionless features extracted from mud pump vibration were used in a FL classifier to assess the health condition of the valves. This parameter was used in a WAFT model to dynamically predict the RUL. From case study results, it can be concluded that the methodology can improve drilling rig uptime in three ways: (i) unforeseen equipment failure is mitigated, (ii) components are maintained at 93% of their lifetime, avoiding excessive maintenance and (iii) holistic perspective on the resulting maintenance windows can be used to find the optimum moment of maintenance without disruption of rig operations. Further research is needed to field validate the model using continuous monitoring data. Remaining component agents can be designed and implemented, combined with further advancements for the system agent in order to develop a complete drilling rig PdM model.

References

[1] F. Langlo, “Application of reliability centered maintenance on a drilling system,” Master’s thesis, University of Stavanger, 2014. [Online].
[2] Z. Ismail, K. K. Kong, S. Z. Othman, K. H. Law, S. Y. Khoo, Z. C. Ong, and S. M. Shirazi, “Evaluating accidents in the offshore drilling of petroleum: Regional picture and reducing impact,” *Measurement*, vol. 51, pp. 18–33, 2014.
[3] Y. Tang, Z. Zou, J. Jing, Z. Zhang, and C. Xie, “A framework for making maintenance decisions for oil and gas drilling and production equipment,” *Journal of Natural Gas Science and Engineering*, vol. 26, pp. 1050–1058, 2015.
[4] M. Shaipov, “Drilling and well - valve usage in changing environment,” Master’s thesis, University of Stavanger, 2018. [Online].

[5] P. K. Omondi, "Impact of drilling equipment quality condition and expertise availability on well drilling cost - a case study of olkaria geothermal field," *Proceedings, 6th African Rift Geothermal Conference*, 2016. [Online].

[6] S. Burrafato, A. Maliardi, S. Spagnolo, P. Cappuccio, and R. Poloni, "Digital disruption in drilling & completion operations," *14th Offshore Mediterranean Conference and Exhibition*, 2019. [Online].

[7] M. Dekker and A. Thakkar, "Digitalisation - the next frontier for the offshore industry," *Offshore Technology Conference*, 2018.

[8] H. Devold, T. Graven, and S. O. Halvorsrød, "Digitalization of oil and gas facilities reduce cost and improve maintenance operations," *Offshore Technology Conference*, 2017.

[9] C. P. Gooneratne, A. Magana-Mora, W. Contreras Otalvora, M. Affleck, P. Singh, G. Zhan, and T. E. Moellendick, "Drilling in the fourth industrial revolution - vision and challenges," *IEEE Engineering Management Review*, vol. 48, no. 4, pp. 144–159, 2020.

[10] L. Kirschbaum, D. Roman, G. Singh, J. Bruns, V. Robu, and D. Flynn, "AI-driven maintenance support for downhole tools and electronics operated in dynamic drilling environments," *IEEE Access*, vol. 8, pp. 78 683–78 701, 2020.

[11] J. Ferket, "Asset performance management 4.0 internet of things iot enabled condition monitoring, a story from a digital maintenance service provider," *Abu Dhabi International Petroleum Exhibition & Conference*, 2018.

[12] K. Nguyen, P. Do, and A. Grall, "Multi-level predictive maintenance for multi-component systems," *Reliability Engineering & System Safety*, vol. 144, 2015.

[13] T. Tinga and R. Loendersloot, *Physical Model-Based Prognostics and Health Monitoring to Enable Predictive Maintenance*. Springer, Cham, 2019, pp. 313–353.

[14] R. He, Z. Tian, Y. Wang, M. Zuo, and Z. Guo, "Condition-based maintenance optimization for multi-component systems considering prognostic information and degraded working efficiency," *Reliability Engineering & System Safety*, vol. 234, p. 109167, 2023.

[15] T. Tinga, *Principles of Loads and Failure Mechanisms*. Springer, London, 2013.

[16] L. Swanson, "Linking maintenance strategies to performance," *International Journal of Production Economics*, vol. 70, no. 3, pp. 237–244, 2001.

[17] M. G. Deighton, *Ch. 5 - Maintenance Management*. Gulf Professional Publishing, Boston, 2016, ch. 5, pp. 87–139.

[18] A. Arnaout, R. Fruhwirth, B. Esmael, and G. Thonhauser, "Intelligent real-time drilling operations classification using trend analysis of drilling rig sensors data," *SPE Kuwait International Petroleum Conference and Exhibition*, 2012.

[19] H. Hilmawan and H. Basri, "Reducing non-productive time of mud pump with acoustic emission monitoring techniques on fluid end parts," *IOP Conference Series: Materials Science and Engineering*, vol. 1034, p. 012066, 2021.

[20] B. Guo and G. Liu, *Mud Pumps*. Gulf Professional Publishing, 2011, ch. 3, pp. 61–79.

[21] D. A. Simpson, *Well-Bore Construction (Drilling and Completions)*. Gulf Professional Publishing, 2018, ch. 2, pp. 85–134.

[22] R. Y. Abdyukova, "Studies on operation and types of drilling pump valves," *IOP Conference Series: Materials Science and Engineering*, vol. 560, p. 012050, 2019.

[23] M. Băltăretu Iancu, A. Hadăr, and V. Ulmanu, "Methods of improving the mud pump valve life," *Annals: Series on Engineering Sciences (Academy of Romanian Scientists)*, vol. 7, no. 2, pp. 103–112, 2015. [Online].

[24] P. A. Kulakov, I. H. Y. Apparov, and V. G. Afanasenko, "Improvement of mud pump valve," *IOP Conf. Series: Materials Science and Engineering*, vol. 451, p. 012201, 2018.

[25] A. Birolini, *Ch. 1 - Basic Concepts, Quality & Reliability (RAMS) Assurance of Complex Equipment and Systems*, 7th ed. Springer, Berlin, 2014, pp. 1–24.

[26] F. S. Nowlan and H. F. Heap, "Reliablity-centered maintenance," Tech. Rep. AD-A066579, 12 1978.

[27] S. Dubey, "Sustainable maintenance in drilling operations: New risks, changing standards and codes," *SPE/IADC Middle East Drilling Technology Conference and Exhibition*, 2018.

[28] O. Motaghare, A. S. Pillai, and K. I. Ramachandran, "Predictive maintenance architecture," *IEEE International Conference on Computational Intelligence and Computing Research (ICCIC)*, 2018.

[29] P. Coanda, M. Avram, and V. Constantin, "A state of the art of predictive maintenance techniques," *IOP Conference Series: Materials Science and Engineering*, vol. 997, p. 012039, 2020.

[30] A. K. S. Jardine, D. Lin, and D. Banjevic, "A review on machinery diagnostics and prognostics implementing condition-based maintenance," *Mechanical Systems and Signal Processing*, vol. 20, no. 7, pp. 1483–1510, 2006.

[31] E. Taheri, I. Kolmanovsky, and O. Gusikhin. (2019) Survey of prognostic methods for condition-based maintenance in engineering systems. arXiv. Preview.

[32] A. Ali and A. Abdelhadi, "Condition-based monitoring and maintenance: State of the art review," *Applied Sciences*, vol. 12, p. 688, 2022.

[33] A. S. Palau, M. H. Dhada, and A. K. Parlikad, "Multi-agent system architectures for collaborative prognostics," *Journal of Intelligent Manufacturing*, vol. 30, pp. 2999–3013, 2019.

[34] S. Valeev and N. Kondratyeva, *Risk control and process safety management systems*, 2021, ch. 7, pp. 271–294.

[35] A. D. Rocha, R. Peres, and J. Barata, "An agent based monitoring architecture for plug and produce based manufacturing systems," *IEEE 13th International Conference on Industrial Informatics (INDIN)*, 2015.

[36] W. Kritzinger, M. Karner, G. Traar, J. Henjes, and W. Sihn, "Digital twin in manufacturing: A categorical literature review and classification," *IFAC PapersOnLine*, vol. 51, no. 11, pp. 1016–1022, 2018.

[37] I. Errandonea, S. Beltrán, and S. Arrizabalaga, "Digital twin for maintenance: A literature review," *Computers in Industry*, vol. 123, p. 10316, 2020.

[38] F. Mauro and A. A. Kana, "Digital twin for ship life-cycle: A critical systematic review," *Oceans Engineering*, vol. 269, p. 113479, 2023.

[39] T. Moyaux, Y. Liu, G. Bouleux, and V. Cheutet, "An agent-based architecture of the digital twin for an emergency department," *Sustainability*, vol. 15, no. 4, p. 3412, 2023.

[40] Y. Jing and X. Wang, "Technical research on digital twin of oil rig winch," *Proc. of 7th International Conference on Intelligent Computing and Signal Processing (ICSP)*, 2022, pp. 1157–1160.

[41] R. Khosravanian and B. S. Aadnøy, *Introduction to digital twin, automation and real-time centers*. Gulf Professional Publishing, 2022, ch. 1, pp. 1–30.

[42] S. Mihai, W. Davis, D. V. Hung, M. Karamanoglu, B. Barn, R. V. Prasad, H. Venkataraman, and H. Nguyen, "A digital twin framework for predictive maintenance in industry 4.0," *Proceedings of the 2020 International Conference on High Performance Computing & Simulation*, 2021. [Online].

[43] L. Wright and S. Davidson, "How to tell the difference between a model and a digital twin," *Advanced Modeling and Simulation in Engineering Sciences*, vol. 7, no. 13, 2020.

[44] W. Luo, T. Hu, Y. Ye, C. Zhang, and Y. Wei, "A hybrid predictive maintenance approach for CNC machine tool driven by digital twin," *Robotics and Computer Integrated Manufacturing*, vol. 65, p. 101974, 2020.

[45] P. Aivaliotis, K. Georgoulias, and K. Alexopoulos, "Using digital twin for maintenance applications in manufacturing: State of the art and gap analysis," *IEEE International Conference on Engineering, Technology and Innovation*, 2019.

[46] H. F. Spoerker and C. H. Litzlbauer, "High-frequency mud pump pressure monitoring enables timely wear detection," *IADC/SPE Asia Pacific Drilling Technology*, 2002.

[47] Kyllingstad and P. J. Nessjøen, "Condition based maintenance: A new early leak detection system for mud pumps," *SPE/IADC Drilling Conference and Exhibition*, 2011.

[48] D. Yoon, S. Gul, P. Ashok, and E. van Oort, "Towards a practical, generally-applicable condition-based maintenance CBM system for mud pumps," *IADC/SPE International Drilling Conference and Exhibition*, 2022.

[49] D. Yoon, P. Ashok, E. van Oort, P. Annaiyappa, and S. Abe, "Field validation of scalable condition-based maintenance (cbm) of mud pumps," *IADC/SPE International Drilling Conference and Exhibition*, 2023.

[50] A. L. M. Levada. (2022) Non-linear adaptive wiener filter for time series smoothing. Research Square. Preview.

[51] F. Dernoncourt. (2013) Introduction to fuzzy logic. Massachusetts Institute of Technology. [Online].

B

Fuzzy logic classifier design

Features membership functions

	Kurtosis	**Shape factor**	**Crest factor**	**Impulse factor**
μ['low'] =	1 if $x < 12$ $\frac{14-x}{2}$ if $12 \leq x \leq 14$ 0 if $x > 14$	1 if $x < 1.7$ $\frac{1.775-x}{0.075}$ if $1.7 \leq x \leq 1.775$ 0 if $x > 1.775$	1 if $x < 6.8$ $\frac{7.2-x}{0.4}$ if $6.8 \leq x \leq 7.2$ 0 if $x > 7.2$	1 if $x < 12$ $\frac{12.6-x}{0.6}$ if $12 \leq x \leq 12.6$ 0 if $x > 12.6$
μ['avg'] =	$\frac{x-12}{4}$ if $12 \leq x \leq 16$ $\frac{20-x}{4}$ if $12 < x \leq 20$ 0 if $12 < x > 20$	$\frac{x-1.7}{0.15}$ if $1.7 \leq x \leq 1.85$ $\frac{2-x}{0.15}$ if $1.85 < x \leq 2$ 0 if $1.7 < x > 2$	$x - 6.8$ if $6.8 \leq x \leq 7.8$ $8.8 - x$ if $7.8 < x \leq 8.8$ 0 if $6.8 < x > 8.8$	$\frac{x-12}{2.5}$ if $12 \leq x \leq 14.5$ $\frac{17-x}{2.5}$ if $14.5 < x \leq 17$ 0 if $14.5 < x > 17$
μ['high'] =	0 if $x < 16$ $\frac{x-16}{4}$ if $16 \leq x \leq 20$ 1 if $x > 20$	0 if $x < 1.875$ $\frac{x-1.875}{0.125}$ if $1.875 \leq x \leq 2$ 1 if $x > 2$	0 if $x < 7.9$ $\frac{x-7.9}{0.9}$ if $7.9 \leq x \leq 8.8$ 1 if $x > 8.8$	0 if $x < 15$ $\frac{x-15}{2}$ if $15 \leq x \leq 17$ 1 if $x > 17$

Output state membership functions

	Output state
μ['good'] =	1 if $x < 0$ $\frac{50-x}{50}$ if $0 \leq x \leq 50$ 0 if $x > 50$
μ['used'] =	$\frac{x}{50}$ if $0 \leq x \leq 50$ $\frac{100-x}{50}$ if $50 < x \leq 100$ 0 if $0 < x > 100$
μ['poor'] =	0 if $x < 50$ $\frac{x-50}{50}$ if $50 \leq x \leq 100$ 1 if $x > 100$

Fuzzy rules

Kurtosis	Crest factor	Shape factor	Impulse factor	Output state
high	high	high	high	poor
high	avg	avg	high	poor
high	avg	avg	avg	used
high	high	avg	avg	poor
high	avg	high	avg	used
avg	avg	avg	avg	used
avg	high	high	high	poor
avg	high	high	avg	poor
avg	high	avg	avg	used
avg	avg	high	avg	used
avg	low	avg	low	used
low	low	low	low	good
low	avg	avg	low	used
low	low	avg	avg	used
low	low	avg	low	good
low	avg	low	low	good
low	low	low	avg	good
low	avg	low	avg	good
high	avg	high	high	used
avg	high	avg	high	used
avg	low	high	avg	used

C

Pseudo code

C.1. Mud pump component agent code

Listing C.1: Pseudo code of the python script developed for mud pump agent.

```
# Developed mud pump component agent
# INPUT:
# - Operational parameters
#    - strokes per minute (spm)
#    - standpipe pressure (spp)
# - Filtered vibration time series signal (x)

# ----- Operational state -----
Define MP_classifier(spm, spp) function:
  if spp < 50:
    return 0
  else:
    if spm > 20:
      return 1
    else:
      return 2

mp_state = MP_classifier(spm,spp)

# ----- Health condition assessment -----
Define feature_extractor(x) function:
  rms = sqrt(mean(x^2))
  absmean = mean(abs(x))
  krs = mean((x - mean(x))^4) / mean((x - mean(x))^2)^2  # Kurtosis
  shf = rms / absmean                                   # Shape factor
  crf = max(abs(x)) / rms                               # Crest factor
  imf = max(abs(x)) / absmean                           # Impulse factor
  return krs, shf, crf, imf

(krs, shf, crf, imf) = feature_extractor(x)

Define FL_classify(krs,shf,crf,imf) function:
  # Fuzzification
  Define krs membership functions ...
  Define shf membership functions ...
  Define crf membership functions ...
  Define imf membership functions ...

  Define HC membership functions ...

  # Fuzzy rules
  rules = [rule1 ... rule21]

  # Start fuzzy classification process
  fuzzify_input = membership_values[krs,shf,crf, imf]
  Evaluate rules ...
  Compute numerical output ...
  HC = num_output
  return HC

HC = FL_classify(krs,shf,crf,imf)
```

```
# ----- RUL prediction -----
Define RT_counter(mp_state) function:
  if mp_state == 1:
    rt := rt + (1/3600)   # Take old running hours value and add 1 time unit, then store as new value
  return rt

rt := RT_counter(mp_state)   # Set start value of current running hours

Define RUL_predictor(rt, HC) function:
  lifetime = exp(6.839 - 0.0246 * HC) * (log(0.125)) ^ (1/exp(0.65))
  RUL = lifetime - rt
  return RUL

# OUTPUT:
# - Operational state (mp_state)
# - Health condition (HC)
# - current running hours (rt)
# - RUL (RUL)
```

C.2. System agent code

Listing C.2: Pseudo code of the python script developed for system agent.

```
# Developed system agent
# INPUT:
# - Component operating states
#  - top drive (td_state)
#  - drawworks (dwk_state)
#  - mud pumps (mpx_state)
# - Component RUL
#  - top drive (td_RUL)
#  - drawworks (dwk_RUL)
#  - mud pumps (mpx_RUL)
# - knowledge base

# ----- Operational state -----
Define SYSTEM_classifier(td_state, dwk_state, mp1_state, mp2_state, mp3_state, mp4_state) function:
  # Check circulation
  if any state == 1 for state in [mp1_state, mp2_state, mp3_state, mp4_state]:
    circ = 1
  else
    circ = 0

  # Check drilling
  if all state == 1 for state in [td_state, dwk_state, circ]:
    return 1        # Drilling
  else:
    if dwk_state == 2:
      return 2      # Tripping
    else:
      return 0      # Not drilling or tripping

system_state = SYSTEM_classifier(td_state, dwk_state, mp1_state, mp2_state, mp3_state, mp4_state)

# ----- Maintenance decision-making -----

# First read and edit the knowledge base
knowledge_base = read(knowledgebase.xlsx)
system_RUL = (td_RUL, dwk_RUL, mp1_RUL, mp2_RUL, mp3_RUL, mp4_RUL)

Define kb_updater(row, RUL) function:
  row[RUL] = RUL   # Update the RUL with new RUL
  if row[RUL] < row[OMth]:
    row[OMstatus] = true  # Trigger for OM
  if row[RUL] < row[RULth]:
    row[Mstatus] = true  # Trigger for PdM
  return row

# Use temporary knowledge base
temp_knowledgebase := kb_updater(row, system_RUL) for row in knowledge_base

# Create empty set for components requiring maintenance
maintenance_set = set()

# Go through maintenance sequence
```

```
Define maintenance_sequence(row, maintenance_set, system_state) function:
  if row[Mstatus] == true:
    if system_state == 0:
      # Trigger immediate maintenance actions
      # Create a suggestion message for immediate maintenance
      suggestion = 'Conduct maintenance on {row[location]}:'
      # Query the knowledge base for immediate maintenance actions on the same location
      immediate_maint = query temp_knowledgebase
                        where location == row[location]
                        and OMstatus == true
                        and component ≠ in maintenance_set
      if immediate_maint is not empty:
        for each other_row in immediate_maint:
          # Add OM components and actions to the suggestion message
          suggestion := suggestion + other_row[component] + other_row[action]
          add other_row[component] to maintenance_set
    else:
      # Trigger maintenance window
      # Create a suggestion message for maintenance window
      suggestion = 'Maintenance required on {row[component]}: {row[action]} in {row[RUL]} hours.'
  else:
    suggestion = 'No maintenance required.'
  return suggestion

for row in temp_knowledgebase:
  maintenance_sequence(row, maintenance_set, system_state)

# Generate output of model
print(suggestion)
save temp_knowledgebase as knowledge_base

# OUTPUT:
# - maintenance suggestion to user
# - updated knowledge base
```

C.3. Case study simulation code

Listing C.3: Pseudo code of the python script used for the case study simulations.

```
# Model developed for case study simulations
# INPUT:
# - dataframe containing:
#  - component operational parameters
#  - artificial health condition of mud pump (mpx_HC)

# ----- Top drive component agent -----
Define TD_classifier(tdtorque, tdspeed) function:
  if tdtorque > 1000 and tspeed > 12:
    return 1
  else:
    return 0

# ----- Drawworks component agent -----
Define DWK_classifier(dwkload, dwkspeed) function:
  if -0.1 < dwkspeed < 0.1:
    return 0            # Holding
  else:
    if dwkspeed ⩽ -0.1:
      if dwkspeed < -1:
        if dwkload ⩾ 20:
          return 2      # POOH
        else:
          return 0      # TD up mast
      else:
        return 0        # Reaming up, adjusting TD position
    else:
      if dwkspeed > 1:
        if dwkload ⩾ 20:
          return 2      # RIH
        else:
          return 0      # TD down mast
      else:
        if dwkload ⩾ 20:
          return 1      # Drilling
        else:
          return 0      # adjusting TD position

# ----- Mud pump component agent -----
```

```
Define MP_classifier(spm, spp) function:
  if spp < 50:
    return 0
  else:
    if spm > 20:
      return 1
    else:
      return 2

Define RUL_predictor(rt, mpx_HC) function:
  lifetime = exp(6.839 - 0.0246 * mpx_HC) * (log(0.125)) ^ (1/exp(0.65))
  RUL = lifetime - rt
  return RUL

# ----- System agent -----
Define SYSTEM_classifier(td_state, dwk_state, mp1_state, mp2_state, mp3_state, mp4_state) function:
  # Check circulation
  if any state == 1 for state in [mp1_state, mp2_state, mp3_state, mp4_state]:
    circ = 1
  else
    circ = 0

  # Check drilling
  if all state == 1 for state in [td_state, dwk_state, circ]:
    return 1       # Drilling
  else:
    if dwk_state == 2:
      return 2     # Tripping
    else:
      return 0     # Not drilling or tripping


# ----- Simulation code -----

# Load simulation dataset and make results database
dataset = read(dataset.csv)
results = []

# Set start component age
rt = 0

# Simulation cycle, iterate through rows in dataset
for row in dataset:
  # First classify component operating states
  td_state = TD_classifier output
  dwk_state = DWK_classifier output
  [mp_states] = MP_classifier output for each mud pump

  # For mud pump of interest (mpx), calculate RUL
  # First update running hours with one second if the pump is running
  if mpx_state == 1:
    rt := rt + (1/3600)

  mpx_RUL = RUL_predictor output

  # Finally determine system state
  system_state = SYSTEM_classifier output

  # Store the iteration results
  row(results) = [t, system_state, mpx_RUL, mpx_HC, rt]

OUTPUT:
- results: dataframe containing all simulation results
```

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