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Doctoral thesis

**NTNU**
Norwegian University of Science and Technology
Thesis for the Degree of Philosophiae Doctor
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# Preface

Five years ago, I worked as a maintenance manager at a plant in the process industry. One of my challenges in this job was that we often had to base our maintenance decisions on experience and gut feeling because of a lack of data. One day, a colleague introduced me to a local firm that had started producing some wireless sensors for condition monitoring. We decided to test this product. These wireless sensors were so easy to install and harvest data from that I thought that "this really has the potential to change how we do maintenance".

In my experience, gathering real-time sensor data from equipment has traditionally been so expensive and cumbersome that this is mainly done for process control and for ensuring safe operation. Because installing traditional wired sensors requires cables for power supply and signals and engineers to make the data available in the SCADA system, implementing one new signal can take weeks and typically cost 10 000 EUR or more. Sometimes there is also a need for long production stops to install all the cables. With the new wireless sensors, technicians could install new sensors in minutes, and the data became immediately available from a cloud solution.

I was at this time unaware of concepts such as the fourth industrial revolution, Smart Maintenance, or prognostics and health management. Nonetheless, I decided that this was something I wanted to learn more about. I was fortunate to get a position as a Ph.D. candidate at the BRU21 program with the working title "Industry 4.0 and smart predictive maintenance" and set out to explore how the introduction of digital technologies can be used to improve maintenance performance. The Ph.D. project was carried out at the Department of Mechanical and Industrial Engineering (MTP) at the Norwegian University of Science and Technology (NTNU) in Trondheim, Norway, from November 2018 to September 2022. The work was accomplished under the supervision of Professor Jørn Vatn and Associate professor Per Schjølberg.

This thesis's target readers include researchers and practitioners interested in the digitalization of maintenance in the oil and gas industry, but also the process industry in general. It is assumed that the readers have basic knowledge of maintenance management, reliability, and maintenance optimization.

# Acknowledgments

During this Ph.D. project, I received a great deal of help from several people. I want to dedicate this section to everyone who has supported me over the last four years.

First, I want to express my gratitude to my supervisors, who guided me through this journey toward submitting my Ph.D. thesis. I thank my supervisor, Per Schjølberg, for giving me the opportunity to pursue this Ph.D. degree. I thank my supervisor, Jørn Vatn, for still being positive and encouraging even when I presented my umpteen concept for my first journal paper. I am grateful to both supervisors for giving me a large amount of academic freedom and enabling me to delve into research topics of my personal interest.

I thank Kim A. Jørgensen and the other employees at Lundin Norway AS for valuable discussion and for taking their time to answer my questions and explain the workings of maintenance in an offshore oil and gas context. I thank Emeritus Associate Professor Cecilia Haskins for our cooperation on Article III and your rigorous proofreading of my drafts of that paper. I thank postdoctoral researcher Xingheng Liu for our cooperation in paper VI. I really learned a lot from you during our cooperation.

Warm thanks to my fellow Ph.D. students and Post docks in the RAMS group and BRU21 program for seminars, coffee breaks, social events, and discussions over lunch. To Jon Martin, Harald, Haavard, Ewa, Ariful, Bahareh, Endre, Markus, and all the dear others.

Furthermore, I would like to thank the administrative staff for your help and assistance: Kari Elise Dahle, Monica Høgsten, Magnus Lyslo Haugskott, Linn-Cecilie Felle, and Øyvind Andersen.

Finally, I would like to express my gratitude to my dear Randi and my two kids, Magnus and Eivind. Thanks for your support and for putting up with me, even when I have been absent-minded and worked long hours on this thesis.

Tom Ivar Pedersen

# Abbreviations

AGAN – As Good As New
ARP – Age Replacement Policy
BRP – Block Replacement Policy
CBM – Condition-Based Maintenance
CMMS – Computerized Maintenance Management System
CPS – Cyber-Physical Systems
DC – Downstream Component
DM – Decision Maker
DT – Digital Twin
E&P – Exploration and production
ERP – Enterprise Resource Planning
EVA – Economic Value Added
HSEQ – Health, Safety, Environment, and Quality
ICT – Information and Communication Technologies
IG – Inverse Gaussian
IIC – Industrial Internet Consortium
IoS – Internet of Services
IoT – Internet of Things
IPV – Incremental Present Value
IR – Imperfect Repair
LP – Lean production
NCS – Norwegian Continental Shelf
NOK – Norwegian Kroner
NTNU – Norwegian University of Science and Technology
O&G – Oil and Gas
PdM – Predictive Maintenance
PR – Preventive Renewal
RUL – Remaining Useful Life
SCADA – Supervisory Control and Data Acquisition
SE – Systems Engineering
TBM – Time-Based Maintenance
UC – Upstream Component
VDM – Value Driven Maintenance

# Contents

# Summary


This Ph.D. project belongs to the BRU21 program. BRU21 stands for Better Resource Utilization in the 21st century and is NTNU's research and innovation program in digital and automation solutions for the Oil and Gas (O&G) industry.

The basis for the BRU21 research program is a series of facts findings meeting between NTNU and companies related to the Norwegian O&G industry conducted in 2016. In these meetings, the industry expressed a belief that digitalization is vitally important to secure the industry's competitiveness and that the O&G industry is lagging behind other industry sectors, such as manufacturing.

The most prominent concept for performance improvement in the manufacturing industry has in recent years been Industry 4.0. The main economic potential of Industry 4.0 lies in the ability to make faster and better decisions. This ability is facilitated by the recent development in sensor technology, combined with improvements in systems for collecting, storing, and analyzing large amounts of data. This technological development facilitates the introduction of digital twins, i.e., digital representations of physical assets, processes, or systems. Having digital representations of physical assets that are not developed for specific needs but instead can act as a single source of the truth, for all business area and use cases, help reduce the time and effort needed for collecting the necessary data for making high-quality data-driven decisions.

A large stream of papers proposing quantitative models for data-driven decision making in maintenance has been published in the last 50 years, but there is little empirical evidence of these models being used in the industry. Availability of the necessary data has traditionally been a challenge, but introducing concepts such as Industry 4.0 and digital twins may change this.

Six articles have been written in this Ph.D. project. The first three articles aimed to gain insight into the potential and current use of digitalization of maintenance in the O&G industry in the Norwegian Continental Shelf (NCS). In Article I, financial data from an example O&G production platform was analyzed to assess the economic value of improving maintenance. Articles II and III found indications that some Norwegian O&G companies have entered a virtuous circle of data collection and model development, increasing the benefits of data-driven decision making in maintenance.

The remaining three articles use the insights gained in the previous papers to propose how the industry can move forward with data-driven decision making in maintenance. Article IV proposes a framework for implementing Smart Maintenance that builds on elements from system engineering and lean production. Article V develops a CBM optimization model that accounts for the decision maker's risk aversion. Article VI presents a CBM optimizing model for a system subject to hard failure, imperfect repair, maintenance windows, and maintenance delay.

# Structure of thesis

This thesis is divided into two parts:

- Part I gives an overview of the background, scope, and objectives of this Ph.D. project and the research methods used. This part also presents the main results and the integrated nature of the work.
- Part II consists of the collection of articles that make up the main part of the work carried out in this Ph.D. project. The articles included in this thesis and my contribution to each of these are listed in Table 1.

Table 1. List of articles.

| No. | Article | Declaration of authorship |
|---|---|---|
| I | Pedersen TI, Schjølberg P. The Economic Dimension of Implementing Industry 4.0 in Maintenance and Asset Management. In: Y. W, K. M, T. Y, K. W, editors. Advanced Manufacturing and Automation IX IWAMA 2019. Plymouth; United Kingdom: Springer, Singapore; 2020. p. 299-306 | Pedersen and Schjølberg conceptualized the paper. Pedersen conducted the literature review, collected the data, and wrote the paper under the supervision of Schjølberg. |
| II | Pedersen TI, Vatn J, Jørgensen KA. Degradation Modeling of Centrifugal Pumps as Input to Predictive Maintenance. In: Baraldi P, Di Maio F, Zio E, editors. The 30th European Safety and Reliability Conference and the 15th Probabilistic Safety Assessment and Management Conference. Venice, Italy: Research Publishing, Singapore; 2020 | Pedersen conceptualized the paper and collected the data with the help of Jørgensen. Pedersen conducted the literature review, analyzed the data, and developed the methodology under the supervision of Vatn. Pedersen wrote the paper with feedback from Jørgensen and Vatn. |
| III | Pedersen TI, Størdal HG, Bjørnebekk HH, Vatn J. A Survey on the Use of Digital Twins for Maintenance and Safety in the Offshore Oil and Gas Industry. In: Castanier B, Cepin M, Bigaud D, Berenguer C, editors. 31st European Safety and Reliability Conference. Angers, France 2021. | Pedersen conceptualized the paper. Pedersen, Størdal and Bjørnebekk conducted the literature review. Pedersen developed the questionnaire together with Størdal and Bjørnebekk and with feedback from Vatn. Pedersen collected the data and wrote the paper with feedback from Vatn. |

Table 1. (continued)

| | | |
|---|---|---|
| IV | Pedersen TI, Haskins C. Framework for the Implementation of Smart Maintenance. In: Castanier B, Cepin M, Bigaud D, Berenguer C, editors. 31st European Safety and Reliability Conference. Angers, France 2021 | Pedersen conceptualized the paper and conducted the literature review. Pedersen created the framework and wrote the paper under the supervision of Haskins. |
| V | Pedersen TI, Vatn J. Optimizing a condition-based maintenance policy by taking the preferences of a risk-averse decision maker into account. Reliability Engineering & System Safety 2022 Vol. 228, 108775 | Pedersen: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing – original draft, Visualization. Vatn: Methodology, Supervision, Writing – review & editing. |
| VI | Pedersen TI, Liu X, Vatn J. Maintenance optimization of a system subject to two-stage degradation, hard failure, and imperfect repair. *Manuscript submitted to the journal Reliability Engineering and System Safety*. | Pedersen: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data Curation, Writing - Original Draft, Visualization<br>Liu: Methodology, Validation, Formal analysis, Writing - Original Draft, Writing - Review & Editing<br>Vatn: Methodology, Writing - Review & Editing, Supervision. |

# Part I – Main Report

# 1 Introduction

## 1.1 The BRU21 research project

Based on a drop in the oil price in combination with rising costs and an increasing focus on environmental factors, NTNU recognized in 2015 a need to update the university's strategy for education, innovation, and research related to the Norwegian oil and gas (O&G) industry (NTNU, 2017). In response to this, a series of fact-finding meetings with exploration and production (E&P) companies, service providers, authorities, and interest organizations was organized in 2016. In a report from 2017 that describes this process, the new strategy is presented as: "to identify technologies and solutions to assure future petroleum activities at low oil prices and build petroleum fields of the future that are environmentally friendly and have the highest standards of safety" (NTNU, 2017). One of the outcomes of this strategy process was the formation of a new research program called BRU21, which this Ph.D. project is a part of.

BRU21 stands for Better Resource Utilization in the 21st century and is a research and innovation program focusing on digital and automation solutions for the oil and gas industry (NTNU, 2019). The fact-finding meetings mentioned above revealed a consensus among the industry actors that digitalization is "critically important for future competitiveness" of the O&G industry on the Norwegian Continental Shelf (NCS) (NTNU, 2017,p.49). Based on this, the objective of the BRU21 program is defined as "to boost efficiency and enable new technologies for the oil and gas industry through digital and automation solutions" (NTNU, 2017,p.50). The BRU21 program is organized into six program areas:

- Exploration efficiency.
- Field development and economics.
- Drilling and well.
- Reservoir management and production optimization.
- Operations, maintenance, safety, and security.
- New business and operational models.

This Ph.D. project belongs to the program area of "Operations, maintenance, safety and security" and was funded by NTNU. The title of the Ph.D. project is "Industry 4.0 and Smart Predictive Maintenance".

By 2019, the research project consisted of 33 Ph.D. and PostDoc positions. NTNU funded ten positions, and 23 were funded by nine industry partners(NTNU, 2019). The Ph.D. projects are linked to industrial use cases. The motivation for this is to secure that the research meets the needs of the industry.

## 1.2 Background

### 1.2.1 Potential benefits of digitalization of maintenance

One way that digital solutions can help improve maintenance performance that has received much attention is the use of sensors to monitor the condition of equipment and, based on this, make predictions on when the equipment will fail (de Jonge, Teunter and Tinga, 2017). Online sensor-based condition monitoring has historically been very costly (Ahmad and Kamaruddin, 2012), and time-based maintenance has often been the best alternative for equipment with a defined wear-out period. In recent years, sensor technology developments and the falling cost of collecting and analyzing sensor data have allowed for wider use of online condition-based maintenance (CBM) (Alaswad and Xiang, 2017; Vrignat, Kratz and Avila, 2022).

Many papers on degradation modeling and maintenance optimization using condition monitoring data have been published in the last several decades. See, e.g., reviews by Alaswad and Xiang (2017), Lei *et al.* (2018), Zhang *et al.* (2018), or Olde Keizer, Flapper and Teunter (2017). The potential to improve maintenance performance by switching from time-based to condition-based maintenance policies has been demonstrated in several numeric examples in the academic literature. Examples are de Jonge, Teunter and Tinga (2017) and Van Horenbeek and Pintelon (2013). However, the quantitative models proposed in these papers are rarely tested on industrial data (de Jonge and Scarf, 2020), and studies on the use of these models in the industry are few (Fraser, Hvolby and Tseng, 2015).

On the other hand, several reports and white papers from consultancy and software companies present claims on the benefits of implementing digital solutions in maintenance. One example is a McKinsey report claiming that a 10 – 40 % maintenance cost reduction can be achieved by fitting products with sensors that monitor conditions and usage (Manyika *et al.*, 2011). Another report from the same company claims that “typically, predictive maintenance decreases the total machine downtime by 30 to 50 percent and increases machine life by 20 to 40 percent” (Baarup *et al.*, 2015, p. 24). Similar statements of the potential improvements have been presented in reports by the consultancy firms Accenture (Spelman *et al.*, 2017) and PwC together with Mainnovation (Haarman *et al.*, 2018). The software company Cognite states in a white paper that “in offshore environments, condition-based maintenance (and eventually, predictive maintenance) has the potential to revolutionize business models and reduce bottom lines” (Cognite, 2019, p. 13). Similar claims related to the potential benefits of introducing predictive maintenance in the upstream O&G industry are made by the software company Aspentech (Beck, 2017). However, these reports give few details on how the potential benefits are calculated.

But there are also those that paint a more moderate picture. An example is the software company Arundo which states that “true predictive maintenance is not immediately applicable for most equipment, due to the paucity of relevant data” (Dobson and Misra, 2019, p. 8). Another example is the consultancy firm Staufen, which, based on a survey of 450 German companies, states that the “added value of predictive maintenance is likely to be far lower than is often claimed” (Staufen, 2018, p. 35).

There is so far limited empirical evidence of the effect of data-driven maintenance in the asset-heavy industry (Bokrantz *et al.*, 2020b), but some studies have been found in the academic literature. In a case study from the Dutch process industry, Veldman, Klingenberg and Wortmann (2011, p. 49) found that "all the firms claimed to be struggling with prognostic condition-based maintenance tasks". In a later case study, also in the Dutch process industry, Van De Kerkhof, Akkermans and Noorderhaven (2015, p. 235) found that "many firms in the process industry struggle with systematically employing CBM activities in general and prognostic CBM approaches in particular". Based on interviews with maintenance experts from multiple industry sectors in the UK, Golightly, Kefalidou and Sharples (2018, p. 640) found that "full, predictive maintenance solutions were extremely challenging". A survey of practitioners in the Swedish automotive industry found that many respondents believed that transitioning their maintenance organization into being more data-driven has benefits (Savolainen *et al.*, 2020). However, the same study also found that most maintenance decisions were based on experience rather than data and concluded that because of "lack of competences, poor data quality, digitalized systems which are hard to use and inadequate approaches to implementing new systems, the organization has a hard time to transition towards a data-driven future" (Savolainen *et al.*, 2020, p. 99). A case study on the implementation of digital solutions to maintenance in a Swedish company within energy production found several hindering factors related to organizational and cultural aspects, such as: unclear aims, resistance to change, lack of cooperation between business functions, and lack of resources (Lundgren, Bokrantz and Skoogh, 2022). The long timeframes in maintenance were also identified as a challenge, as it may take years before the effects of initiatives can be measured. Another challenge was that the company was "determined to pursue development towards digitization and data-driven decision-making" (Lundgren, Bokrantz and Skoogh, 2022, p. 633), but management found it difficult to identify specific activities for achieving this goal.

Because of the many contradicting claims and few empirical studies, it is hard to assess the potential benefit of using condition monitoring data to improve maintenance performance. Another challenge when assessing the current state of the art in the digitalization of maintenance is a lack of coherent terminology among the different actors. An example is the terms CBM and predictive maintenance (PdM). While some understand these as synonyms, others understand these as different maintenance policies.

During this Ph.D. project, I have primarily followed the definitions given in EN 13306:2017 "Maintenance terminology" (CEN, 2017), and ISO 13372:2012 "Condition monitoring and diagnostics of machines — Vocabulary" (ISO, 2012b).

### 1.2.2 Making maintenance decisions

Two important ingredients when performing data-driven decision making are data and models. A model is a simplified version of a real system (Kossiakoff *et al.*, 2011). These models can be mental models based on intuition and previous experience that only exist in the decision maker's mind. Alternatively, these models can be formal quantitative models implemented in a computer program or a spreadsheet (Bratvold and Begg, 2009a). There are advantages and disadvantages to both these approaches.

An advantage of formally expressed quantitative models compared to mental models is that they make it easier for other people to examine the assumptions and elements that are included and excluded from the models. This makes the decision process more transparent (Bratvold and Begg, 2009a). A disadvantage of quantitative models is that they encourage a focus on only the aspects that are easy to quantify. Because of this, it will often be beneficial to combine data, quantitative models, and human judgment for decision augmentation (Bokrantz *et al.*, 2020c). However, humans are “imperfect information processors” (Bratvold and Begg, 2009a, p. 15), so in other situations, it may be preferable to use the data and quantitative models for decision automation without involving human intuition (Figure 1). Quantitative models can offer value when used both for decision automation and augmentation. In the remainder of this thesis, the term “model” is understood as a formal quantitative model unless described as a mental model.

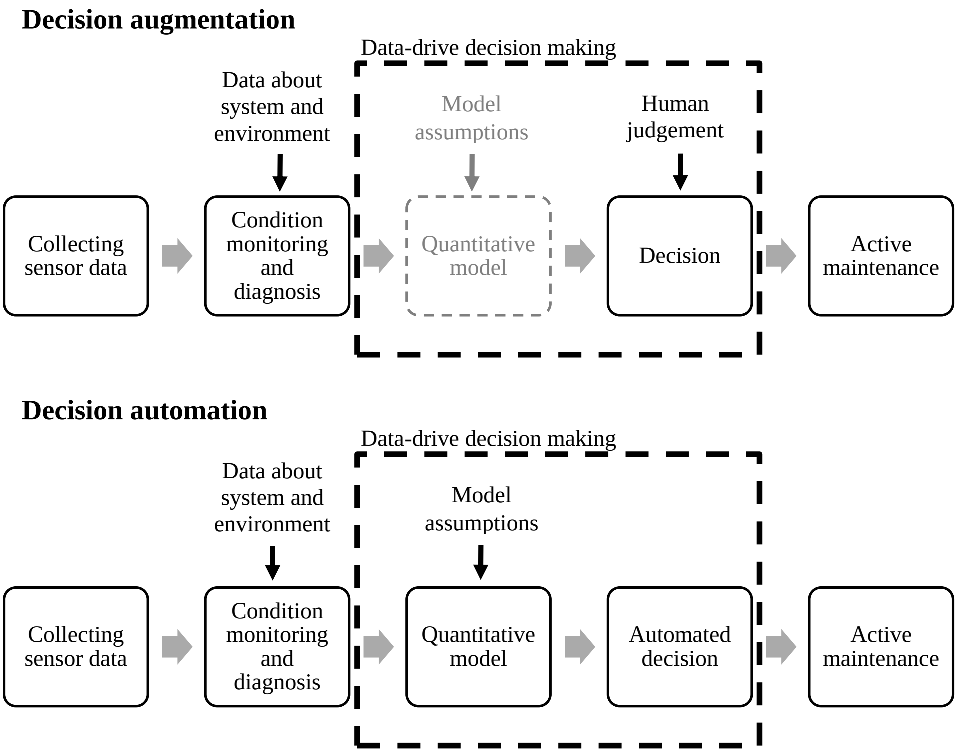


Figure 1. Illustration of decision augmentation and decision automation in maintenance. The quantitative model is shown in grey in the upper flowchart to illustrate that condition monitoring data can be used for decision augmentation without quantitative models. Inspired by (Bousdekis *et al.*, 2018) and (Bokrantz *et al.*, 2020c)

Decision analysis is a discipline that evolved in the 1950s and 1960s (Russell and Norvig, 2016). It offers procedures and tools for “transforming opaque decision problems into transparent decision problems by a sequence of transparent steps” (Howard, 1988, p. 680). A decision is within this discipline defined as a “choice between two or more alternatives that involve an irrevocable allocation of resources" (Howard and Abbas, 2016, p.30). This means that a mental commitment to follow a particular course of action is not counted as a decision (Bratvold and Begg, 2009b). While the primary focus of decision analysis in the early days where on guiding human decision makers in making decisions in line with their preferences, there has in recent years been an increasing focus on the use of decision analysis to ensure that automated decision processes behave as desired (Russell and Norvig, 2016).

A high-quality decision is "an action we take that is logically consistent with our objectives and preferences, the alternatives we perceive, and information we have" (Bratvold and Begg, 2009a, p.28). Howard and Abbas (2016) use a metaphor of a three-legged stool when depicting the elements that constitute a good decision. The basis for the decision is the three legs: the alternatives we perceive, "what we can do"; the information that we have, "what we know"; and our objectives and preferences, "what we want". If any of these three elements are missing, the stool tips over. For instance, if there is only one option, then there is no decision to make. The seat that holds these three legs together is the logic that decision analysis is based on. By using this logic, the best decision for a given decision basis, i.e., the three legs, can be found. The location of the stool symbolizes the frame of the decision. This determines what alternatives, information, and preferences are useful to that specific decision. For instance, if an operator wants to improve an asset's competitive strength, the operator may frame this as a decision to find the maintenance optimization model that minimizes the expected cost. Alternatively, the operator may use a larger frame that includes modifying the asset to eliminate failures or increase throughput.

The most important element in this metaphor is the person sitting on the stool. This is the decision maker who frames the decision and whose objectives and preferences should be considered when evaluating the alternatives. There is no decision without a decision maker that constructs the elements of the stool and assigns the necessary resources to implement the decision. Identifying the decision maker(s) can sometimes be challenging, especially for complex decisions in large organizations (Bratvold and Begg, 2009a). It is also important to be aware of agent-principal problems. For a corporation, such as an O&G company, the decision maker's objectives should be aligned with the shareholders.

Decision analysis and decision theory have seen little use in the maintenance literature, but de Almeida and Bohoris (1995) give an introduction to how decision theory can be used for maintenance decisions. Because maintenance decisions in the O&G industry can have severe consequences, it may be pertinent to account for the decision maker's attitudes towards risk when evaluating alternatives (Bratvold and Begg, 2009a). Expected utility theory (EUT) is a framework for taking attitudes towards risk into consideration when assessing alternatives with uncertain outcomes. The basis of EUT is axioms for describing the preferences of a rational decision maker faced with decisions under uncertainty (Clemen, 1991). Aven (2012) argues that EUT, as a normative theory for how to find the optimal decision in a mathematical framework, can be useful as a reference for assessing the quality of decisions.

For an introduction to decision analysis, see, e.g., Bratvold and Begg (2009a), who focus on application in the O&G industry. For a more comprehensive introduction, see, e.g., Clemen (1991), Keeney and Raiffa (1993), or Howard and Abbas (2016).

### 1.2.3 Digitalization of maintenance in the O&G industry

As mentioned in Chapter 1.1, there is a sentiment in the O&G industry that the implementation of digital solutions is important to improve the cost-efficiency of the industry (KonKraft, 2018; Settemsdal, 2019; Mogos, Eleftheriadis and Myklebust, 2019; DNV-GL, 2020; Larsen *et al.*, 2020; Hanssen, Myklebust and Onshus, 2021).

Devold, Graven and Halvorsrød (2017) claim that many O&G companies have invested in new technology but have failed to adapt the organizational structures and work process to realize this technology’s potential. According to a survey of the O&G industry conducted by DNV-GL (2020), the lack of standardization and integration of systems for collecting and storing data is a major obstacle preventing companies from realizing the potential of digitization. Because of this, already collected data require manual handling before it can be turned into information (KonKraft, 2018). A McKinsey report gives an example from an offshore oil and gas platform where only 1 percent of the collected data were analyzed. Even worse, the results of these analyzes were rarely used to “drive decision making” (Baarup *et al.*, 2015, p. 20).

In interviews by Machado (2019), industry experts from Norway and Brazil express that the offshore O&G industry is immature when it comes to the use of CBM and that data silos are a problem. Another obstacle is proving the economic potential of condition monitoring and CBM. In a survey by Mogos, Eleftheriadis and Myklebust (2019), suppliers to the O&G industry reported cost saving as an important motivation for digitalization. However, in the same survey, a high proportion of these respondents reported having “little knowledge” of concepts such as Industry 4.0 (46%) and cyber-physical systems (CPS) (70%) (Mogos, Eleftheriadis and Myklebust, 2019). Many respondents also reported a lack of knowledge and skills as barriers to implementing Industry 4.0.

In a study of six O&G companies operating on the NCS, Øien, Hauge and Grøtan (2020) found that all the companies had plans to implement predictive maintenance for both production equipment and safety barriers, but few of them had implemented this at the time of the survey. In a more recent study, Hanssen, Myklebust and Onshus (2021) found that suppliers and E&P companies in the Norwegian O&G industry are rapidly implementing digital solutions to achieve more effective operations. Nevertheless, they found that the level of digital maturity varies among the actors. When comparing the finding from Hanssen, Myklebust and Onshus (2021) with (Mogos, Eleftheriadis and Myklebust, 2019), data collected in 2017, and (Øien, Hauge and Grøtan, 2020), data collected in 2018, it seems that the digitalization of the O&G industry is happening at a rapid pace.

### 1.2.4 Industry 4.0

In the facts-finding meeting leading up to the formation of the BRU21 program, industry experts expressed a belief that the O&G industry is “lagging behind other industry sectors", like manufacturing, in adopting digital solutions (NTNU, 2017, p. 49). The most prominent concept for performance improvement in the manufacturing sector in recent years has been Industry 4.0 (Buer *et al.*, 2020). Inspired by this, there has been a focus on Industry 4.0 in this Ph.D. project.

The term Industry 4.0 or "Industrie 4.0" was coined by a working group created by the German government to strengthen the competitive position of the German manufacturing industry (Kagermann *et al.*, 2013). According to Kagermann *et al.* (2013), a fourth industrial revolution is coming as a result of the introduction of the Internet of Things (IoT) and Internet of Services (IoS) into the manufacturing sector.

Although most of the literature on Industry 4.0 so far has been conceptual, some empirical studies on the effect of this concept have started to emerge (Da Silva *et al.*, 2020; Buer, 2020). In a survey of Indian manufacturing companies, Kamble, Gunasekaran and Dhone (2020) found a significant positive effect of the implementation of Industry 4.0 on performance. In another survey conducted in Brazil, Dalenogare *et al.* (2018) found that some of the technologies related to Industry 4.0 are positively associated with improving operational performance (e.g., big data collection and analysis) and negative for some (e.g., additive manufacturing). However, these studies have been conducted on a high level (business units) (Ciano *et al.*, 2021) and have not focused on maintenance.

In recent years, concepts related to Industry 4.0 has started to emerge also in the oil and gas industry. Examples of these are "Oil and Gas 4.0" (Lu *et al.*, 2019) and "Topsides 4.0" (La Grange, 2018). However, according to Lu *et al.* (2019), Industry 4.0 is still in its infancy in this industry sector.

A challenge with Industry 4.0, as with many of the other emerging concepts related to digitalization, is that the academic community has not converged on the content of Industry 4.0 (Bokrantz *et al.*, 2020a). A large proportion of the literature on Industry 4.0 focuses on specific technologies (Silvestri *et al.*, 2020; Rüßmann *et al.*, 2015). However, according to Kagermann, Industry 4.0 is more than technology (Schuh *et al.*, 2017). While previous concepts for the digitalization of manufacturing, like Computer Integrated Manufacturing (CIM), had a vision of complete automation without human intervention (Schneider, 2018; Schmidt *et al.*, 2020), there is in Industry 4.0 an emphasis on the "interactive collaboration between human beings and technological systems" (Kagermann *et al.*, 2013, p. 16). However, this focus on the socio-technological aspect of Industry 4.0 appears to have been overlooked in much of the following literature (Davies, Coole and Smith, 2017).

The understanding of Industry 4.0 used in this Ph.D. project is based on a report by the German research organization Acatech (Schuh *et al.*, 2017). They define Industry 4.0 as "real-time, high data volume, multilateral communication and interconnectedness between cyber-physical systems and people" (Schuh *et al.*, 2017, p. 11). According to Acatech, the economic potential in Industry 4.0 lies mainly in the possibilities of faster and better decision making and adaptation. This is based on the following four factors (Schuh *et al.*, 2017):

- The ability to capture data and realize that something is happening.

- The ability to analyze the data and turn it into information that can provide insight into the implications.
- The presentation of the information, e.g., visualization, to decision makers for decision augmentation and use of data for decision automation.
- The integration of processes and systems to ensure that decisions are implemented and have the desired effect.

Acatech defines six stages of Industry 4.0 maturity. The first two stages, 1) Computerization and 2) Connectivity, are related to aspects needed for creating the basis for Industry 4.0. The third stage, 3) Visibility, is to make a digital twin of the factory that can act as a single source of the truth in the virtual world. An important point to note is that the efforts needed to develop models for analyzing online data often are small compared to the costs of securing that the input data remain valid over time (Sculley *et al.*, 2015). Unless a holistic approach to data collection and presentation is used, these costs will exceed the potential benefit for many use cases. This can be avoided by creating a digital twin, e.g., an up-to-date model of the entire production unit, that is “not tied to individual data analysis” (Schuh *et al.*, 2017, p. 17). The next stage is 4) Transparency, which is about analyzing the data in the digital twin using engineering knowledge and root cause analysis to improve the understanding of what happens in the production process. The insight gained in the fourth stage can be used to build 5) Predictive Capability. This can help companies implement proactive measures to avoid unvented events such as machine breakdowns. The final stage is named 6) Adaptability and is about implementing solutions that can act autonomously, i.e., without human assistance, to make decisions. Because it is demanding to succeed with the implementation of autonomous solutions, it is often best to carefully assess the risk and cost-benefit ratios on a case-by-case basis before moving to this stage (Schuh *et al.*, 2017).

### 1.2.5 Smart Maintenance

Several terms are used in the literature to describe maintenance concepts that exploit the possibilities offered by the fourth industrial revolution (Roda and Macchi, 2021). Examples are Maintenance 4.0 (Jasiulewicz-Kaczmarek and Gola, 2019), Prognostic and Health Management (PHM) (Sun *et al.*, 2012), E-maintenance (Márquez, 2007), Predictive Maintenance (PdM) (Golightly, Kefalidou and Sharples, 2018), and Smart Maintenance (Akkermans *et al.*, 2016).

In this thesis, the term Smart Maintenance is used. This is mainly because of the thorough conceptualization of Smart Maintenance by Bokrantz *et al.* (2020c). They define Smart Maintenance as “an organizational design for managing maintenance of manufacturing plants in environments with pervasive digital technologies”. Based on interviews with 110 industry experts, Bokrantz *et al.* (2020c) have identified four important dimensions of Smart Maintenance:

- data-driven decision making,
- human capital resource,
- internal integration, and
- external integration.

Of these four dimensions, data-driven decision making is the focus of this thesis. A recent literature review of Smart Maintenance and other maintenance concepts related to Industry 4.0 is presented in (Roda and Macchi, 2021).

### 1.2.6 Characteristics of the O&G industry relevant to maintenance.

The O&G industry has, together with other asset-intensive process industries, some characteristics that make it more challenging to implement digital capabilities compared to other industry sectors (ISO, 2019). For the process industry in general, Suzuki (1994) and Van De Kerkhof, Akkermans and Noorderhaven (2015) point to aspects such as:

- Complex processes and complex installations with many different equipment types and equipment-related problems.
- Higley integrated production processes where upstream and downstream equipment may affect each other.
- High financial and safety risks associated with breakdowns, making a "move fast and break things"-approach to innovation less suitable for this industry.
- The processes are often subject to change, making comparing data over time difficult.
- A large proportion of the equipment is custom-made, and every production context is slightly different, making comparisons between production units difficult.
- Long lifespans for assets and conservative maintenance programs results in limited failure data.

Because production units in offshore O&G are often made "one-off", they do not benefit from the programs for refinement and improvement that can be used for assets produced in long production series. Because of this, poor design and integration of different components is often a challenge in the process industry (Suzuki, 1994). Even if the system were correctly designed in the first place, changes to the production process, e.g., as the oil reservoir gets depleted, may cause systems to be operated outside optimal conditions, leading to accelerated wear.

These are all important aspects to consider when assessing the potential benefits of Smart Maintenance in the O&G industry and how concepts used in other industry sectors may be adapted.

### 1.2.7 Assessing the effect of maintenance.

A key barrier to implementing digital maintenance solutions is the difficulty of demonstrating the economic value of these solutions (Roda, Macchi and Fumagalli, 2018; Golightly, Kefalidou and Sharples, 2018). This is not surprising, as it is generally difficult to assess the effect of maintenance. There are mainly two reasons for this.

The first is related to the long timeframes in maintenance. This can lead to principal-agent conflicts if managers expect to leave the firm or get promoted to other positions before the effect of lacking maintenance appears (Young and O'Byrne, 2001; Zimmerman, 2011; Stewart, 2013; Brealey, Myers and Allen, 2017). Likewise, it is reasonable to assume that if a large backlog of maintenance has accumulated, there will be a corresponding delay from the allocation of additional maintenance resources until performance is fully restored.

Even without principal-agent conflicts, the long timeframes remain an issue when assessing maintenance performance. Adding to this is the asymmetry between the cost of performing maintenance and the potential cost of failures. The cost of performing maintenance is usually known while predicting the consequences of not performing a certain maintenance activity is harder. This is because the potential consequences may range from the asset working perfectly fine to a catastrophic failure. Because catastrophic events are rare, they will not appear in lagging performance indicators. Because of this, measuring the actual long-run performance of maintenance is challenging.

The other reason is that maintenance is a support function (Rosqvist, Laakso and Reunanen, 2009). Because of this, the direct cost of maintenance is easy to identify, while the benefits are shown in other areas, such as an increase in production, lower inventory levels, or better quality of the end product (Van Horenbeek and Pintelon, 2014). Because maintenance is so closely related to other business functions, both good and poor performance in maintenance can be hard to spot (Waeyenbergh and Pintelon, 2002).

In this Ph.D. project, two approaches for quantifying the effect of improvement in maintenance have been used. The first is the Value Driven Maintenance (VDM) sensitivity analysis used in Article I. This approach considers that maintenance is a support function by assessing how maintenance improvements can influence the business unit's economic performance (Haarman and Delahay, 2016). The VDM approach is explained further in Chapter 3.1 and Article I. The other approach is maintenance optimization models, which are treated in the next sub-chapter.

### 1.2.8 Maintenance optimization models

A maintenance optimization model is by Dekker (1996, p. 229) defined as: “a mathematical model in which both costs and benefits of maintenance are quantified and in which an optimum balance between both is obtained”. According to Dekker, maintenance optimization can be broken down into four steps (Figure 2).

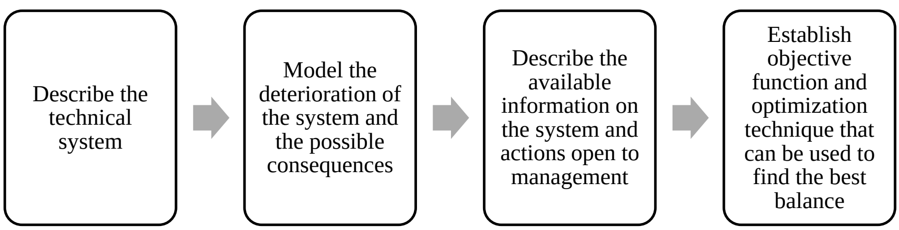


Figure 2. Four steps to establish a maintenance optimization model. Based on Dekker (1996).

Maintenance optimization can be used to find the optimal timing for active maintenance or inspections under a certain policy, e.g., the optimal renewal period under an age replacement policy, and to compare and rank alternative maintenance policies, e.g., by comparing the expected cost for an age and a block replacement policy (Dekker, 1996).

Several authors have, over the years, pointed out that despite the popularity of maintenance optimization models in the academic community, there is little evidence of these models being used in practice (Dekker, 1996; Fraser, Hvolby and Tseng, 2015; Veldman, Klingenberg and Wortmann, 2011; de Jonge and Scarf, 2020; Christer, 1999). With the assumption that maintenance managers want to maximize profit, the lack of use of the available maintenance optimization models can be seen as a paradox (Zio, 2009).

Based on a review of the application of maintenance optimization models, Dekker (1996) lists six aspects that can explain the gap between academia and industry when it comes to maintenance optimization models:

- Because of its stochastic nature, maintenance optimization models are challenging to understand and interpret for industry practitioners.
- Use of mathematical analysis and techniques as opposed to solutions to real problems is the focus of many published papers.
- Practitioners have little incentive to publish their results in the academic literature.
- Different technical systems deteriorate differently, and there is little knowledge on which models suit the different practical situations.
- The potential gains from developing optimization models are often insufficient to justify the development cost.
- Optimization models focus too much on planned revision and overhauls.

In some sense, this gap between academics and industry practitioners is natural because they have different incentives. Academics must be able to point to novelty in their proposed models to get published, giving them an incentive to make increasingly complex models. On the other hand, practitioners must balance the cost of developing, validating, and maintaining these models against the potential benefits of their use. Intuitively, making simpler models preferable to industry.

Another challenge that has been pointed to is the lack of data (Dekker and Scarf, 1998; de Jonge and Scarf, 2020; Scarf, 1997). Welte (2008, p. 62) describes this as a “vicious circle where missing data cause a lack of models, and missing models cause a lack of data”. See Figure 3.
Industry 4.0 and especially the concepts of digital twins can contribute to reducing the barrier related to the availability of relevant data. By implementing a digital twin that combines existing sources of data like enterprise resource planning (ERP) system and computerized maintenance management system (CMMS) with sensors from the shop floor in a single source of truth, the speed and cost of acquiring the necessary data can be improved (Schuh *et al.*, 2017; Malakuti *et al.*, 2020).

As pointed out by Agrawal, Gans and Goldfarb (2018), the economic theory of complementary goods says that when the cost of an input, e.g., condition monitoring data, is reduced, the value of complementing inputs, e.g., models used for data-driven decisions, will increase. The increase in value of data analytics and degradation models as condition monitoring data become more available are, for instance, pointed out in the Delphi studies conducted by Akkermans *et al.* (2016) and Bokrantz *et al.* (2017) on scenarios for the future of maintenance.

Based on this, it is reasonable to believe that, as data becomes more available, operators will leave the vicious cycle experienced by Welte (2008) and instead enter a virtuous cycle where the availability of data gives an incentive to make models, and models give an incentive to collect more data.

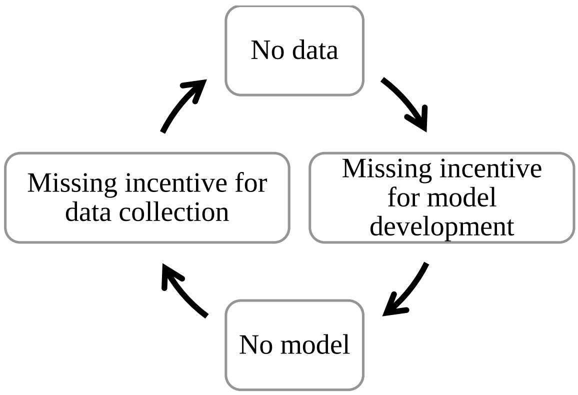


Figure 3. Vicious circle of data collection and model development. Figure is redrawn from (Welte, 2008, p. 63)

### 1.2.9 Degradation modeling approaches

The degradation modeling is an essential part of maintenance optimization (Zhang *et al.*, 2018). Degradation modeling approaches can be divided into five categories: physics-based, stochastic, knowledge-based, data-driven, or a hybrid approach which is a combination of the other approaches (ISO, 2015).

Physics-based models will often be impractical because of the complicity of industrial production systems (Wen *et al.*, 2018). Stochastic models are often better suited because the models are based on collected degradant data and can handle some unexplained randomness. Because of this, they do not require the same level of understanding of the system compared to a physics-based model (Wen *et al.*, 2018). Data-driven models, especially neural network models, have drawbacks in that they need a lot of data for training (Gorjian *et al.*, 2009; Vrignat, Kratz and Avila, 2022). As pointed out earlier, access to data can be an issue, especially in the O&G industry, because of a limited number of similar equipment.

Lack of interpretability and transparency is another issue with data-driven methods such as neural networks (Deng, Bucchianico and Pechenizkiy, 2020). Hanssen, Myklebust and Onshus (2021) point out that in the O&G industry, decisions that have safety implications must be explainable to comply with safety regulations. This makes data-driven models such as artificial neural networks challenging to use for decision automation for maintenance decisions in an O&G context. Compared with data-driven models, stochastic models are generally more explainable (Gorjian *et al.*, 2009) and better at quantifying the uncertainty in the output from the models (Deng, Bucchianico and Pechenizkiy, 2020).

Alaswad and Xiang (2017) group stochastic degradation models into three classes: discrete, proportional hazard models, and continuous degradation (Figure 4). In situations where the degradation is happening continuously, and the condition can be measured through sensors, the continuous degradation models are most relevant (Alaswad and Xiang, 2017). The Gamma and Inverse Gaussian (IG) processes are only suitable to model monotonically increasing degradation (Liu and Wang, 2020), while the Wiener process can be used to model non-monotonic degradation processes. This thesis uses variants of the Wiener process in Articles II, V, and VI. A review of Wiener process-based methods for degradation modeling is given in (Zhang *et al.*, 2018).

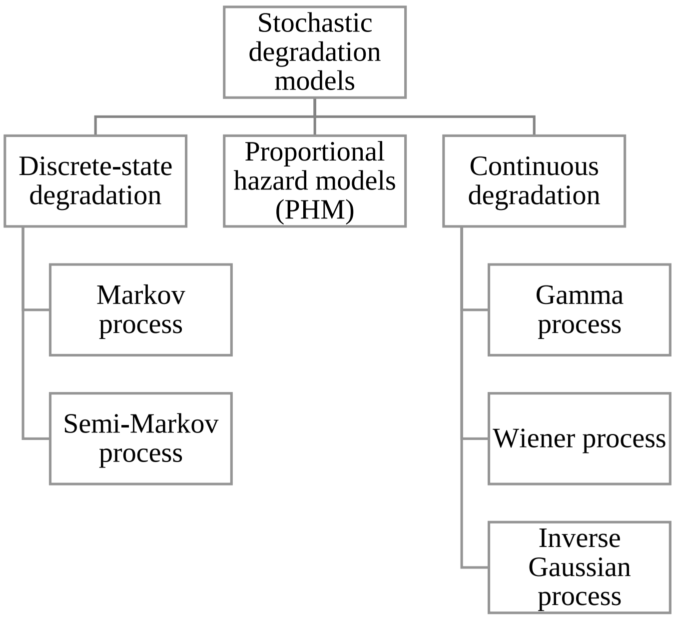


Figure 4. Overview of stochastic degradation models. Redrawn from (Alaswad and Xiang, 2017)

## 1.3 Objective and research questions

This thesis aims to explore if and how the introduction of elements from Industry 4.0 to maintenance can improve the competitiveness of the O&G industry on the Norwegian Continental Shelf (NCS).

The first three research questions are aimed at understanding the current situation in the Norwegian O&G related to potential benefits and current use of data-driven decision making in maintenance:

RQ1: How can implementing digital solutions in maintenance help improve the competitive position of the Norwegian O&G industry?

RQ2: Is the necessary data for breaking the "vicious circle of data collection and model development" available today in the Norwegian O&G industry?

RQ3: What types of quantitative maintenance models are preferred in the O&G industry on the NCS?

In the fourth research question, the focus is on how the industry should move forward when planning to implement quantitative models for data-driven decision making in maintenance:

RQ4: How should companies proceed when planning to implement Smart Maintenance?

The two final research questions are related to specific aspects of maintenance optimization models:

RQ5: How can CBM optimization models be developed, taking the preferences of a risk-averse decision maker into account?
RQ6: How can the principles from Industry 4.0 be utilized when developing CBM optimization models?

## 1.4 Delimitations

### 1.4.1 Boundaries related to industry sectors and equipment types

The focus of this thesis is limited to the maintenance of topside equipment in offshore oil and gas production on the NCS. However, a case from the process industry is used in Article VI because the O&G industry has many of the same characteristics (work practices, software, and hardware) as other asset-intensive process industries (ISO, 2019).

### 1.4.2 Technology and techniques related to Industry 4.0 and maintenance

Aspects of Industry 4.0 that are related to digital twins and data-driven decision-making have been explored. This means that technologies sometimes associated with Industry 4.0 and maintenance, such as augmented or virtual reality (Zheng *et al.*, 2018), additive manufacturing (Frank, Dalenogare and Ayala, 2019), or blockchain technology (Lu *et al.*, 2019), have not been considered.

### 1.4.3 Safety implications of digitalization of the O&G industry

Ensuring safe operation is essential in the O&G industry. The Norwegian Petroleum Safety Authority (PSA) has initiated studies on how digitization may impact safety, e.g., (Øien *et al.*, 2018; Øien *et al.*, 2019; Øien, Hauge and Grøtan, 2020). In one study commissioned by the PSA, Hanssen, Myklebust and Onshus (2021) point to challenges related to the rapid introduction of new IT systems for harvesting and analyzing data from production and safety-instrumented systems. Concerns on how increasing interconnectedness and complexity may affect safety are not new. For example, Perrow's (1999) "Normal accident theory" claims that increasing complexity makes failures inevitable.

Because the core idea of Industry 4.0 is to increase integration and interconnectedness, the safety implications of implementing Industry 4.0 is an important topic. However, safety has been studied in several other Ph.D. projects related to the O&G industry in recent years, for instance, in Ph.D. projects related to the SUBPRO program, e.g., (Srivastav, 2021; Zhang, 2021; Zikrullah, 2022; Xie, 2022). Because of this, the safety implications of digitalization are beyond the scope of this thesis.

# 2 Research approach

## 2.1 Introduction

The Oxford English Dictionary defines *research* as "a careful study of a subject, especially in order to discover new facts or information about it" (Oxford, 2022). When conducting this type of investigation, it is vital to follow a sound research methodology so others can scrutinize and evaluate the research. This chapter presents and discusses the research methodology and methods used in this Ph.D. project. The difference between research method and methodology is that the former describes a technique for data collection and analysis while the latter describes the general stance of the researcher (Evans, Gruba and Zobel, 2014).

The research work in this Ph.D. project is applied science. The aim is to generate new knowledge and insight that can help increase the cost-effectiveness of the O&G industry.

## 2.2 Research philosophy

The researcher is often regarded as a dispassionate outsider in the science, technology, engineering, and mathematics (STEM) disciplines (Evans, Gruba and Zobel, 2014). In these fields, researchers usually follow a positivistic research tradition where the researcher's worldview is not important. This applies to the part of the RAMS discipline dealing with mathematical modeling. A substantial part of the work conducted in this Ph.D. project is related to mathematical modeling, but methods for collecting empirical data have also been used. Examples are the survey in Article III and the archival research and interviews for the case studies in Articles I, II, and VI. Because of this, there is a need to make the reader aware of my philosophical position when conducting the research. This is because my beliefs and assumptions have influenced my research process (Bryman, 2016).

The term "research philosophy" refers to "a system of beliefs and assumptions about the development of knowledge" (Saunders, Lewis and Thornhill, 2019, p. 130). Three areas where philosophical positions in research differ are: ontology, "what is the nature of reality?"; epistemology, "how can we know what we know?"; and axiology, "what are the roles of values in research?". An overview of how five prominent philosophical positions differ in these three areas is presented in Table 2.

To improve the awareness of my own philosophical position as a researcher, I have used a reflexive tool called HARP (Heightening your Awareness of your Research Philosophy), presented in (Saunders, Lewis and Thornhill, 2019). This tool has helped me become self-aware of my worldview and how this may have influenced my research. The result of the HARP test is shown in Table 3.

Table 2. Comparison of five major philosophical positions in research and how ontology (researcher's view on reality), epistemology (researcher's view on what constitutes acceptable knowledge), and axiology (researcher's view on the role of values in research) are understood in these philosophies. Table is adapted from (Saunders, Lewis and Thornhill, 2019, pp. 144-5).

| Ontology | Epistemology | Axiology |
|---|---|---|
| | **Positivism** | |
| - Real, external, independent<br>- One true reality | - Observable and measurable facts<br>- Causal explanation and prediction as contribution | - Value-free research<br>- Researcher is detached, neutral, and independent of what is researched |
| | **Critical realism** | |
| - Layered understanding of reality (the empirical, the actual, and the real)<br>- External and independent | - Knowledge historically situated and transient<br>- Historical causal explanation as contribution | - Researcher acknowledges bias by world view, cultural experience, and upbringing<br>- Researcher is as objective as possible |
| | **Interpretivism** | |
| - Socially constructed through culture and language<br>- Multiple meanings, interpretations, and realities | - Theories and concepts are too simplistic<br>- New understandings and worldviews as contribution | - Researchers are part of what is researched (subjective)<br>- Researcher's interpretation is key to contribution |
| | **Postmodernism** | |
| - Social constructionism through power relations<br>- Some meanings, interpretations, and realities are dominated by and silenced by others | - What counts as "truth" and "knowledge" is decided by dominant ideologies<br>- Exposure of power relations and challenge of dominant views as contribution | - Researcher and research embedded in power relations<br>- Some research narratives are repressed and silenced at the expense of others |
| | **Pragmatism** | |
| - "Reality" is the practical consequence of ideas<br>- Flux of processes, experiences, and practices | - Practical meaning of knowledge in specific contexts<br>- Problem-solving and informed future practice as contribution | - Value-driven research<br>- Research initiated and sustained by the researcher's doubts and beliefs |

Table 3. Results from the HARP test taken by the author of this thesis. A researcher strongly agreeing (or disagreeing) with all statements related to a certain philosophy will reach a score of 18 (or – 18). The HARP is presented in (Saunders, Lewis and Thornhill, 2019).

| **Philosophy** | **SUM** |
|---|---|
| Pragmatism | 15 |
| Critical Realism | 10 |
| Post modernism | 9 |
| Interpretivism | 6 |
| Positivism | -4 |

According to the HARP test, pragmatism is the philosophical position I agree with most, while positivism is at the other end of the scale. According to pragmatism, "concepts are only relevant when they supports action" (Saunders, Lewis and Thornhill, 2019, p. 151). Theories, concepts, and ideas are to be evaluated based on their "practical consequences in a specific context" (Saunders, Lewis and Thornhill, 2019, p. 151). I am not surprised by this result, and although I only took this test at the end of my Ph.D. project, I believe that I had the similar preferences at the beginning of this Ph.D. project.

Because the researcher's philosophical position is usually not presented in the maintenance literature, it is hard to assess how much of the previous literature adheres to the various philosophical positions listed in Table 2. However, my impression is that many of the authors in this field favor a positivistic research philosophy. This is based on the focus on observable and measurable facts often found in the maintenance literature.

Nonetheless, some elements of pragmatism can be found. For example Fraser, Hvolby and Tseng (2015), state that researchers are obliged "to society to spend taxpayer funded research on addressing social needs and real-world problems". Another example is Scarf (1997, p. 493), which claims that maintenance models only have value as pure mathematics or to the extent they have an "impact upon the solution of real maintenance problems".

An effect of my preference for pragmatism is that I, throughout the Ph.D. project, have tried to understand how maintenance modeling can be used in specific contexts. Another effect is that I believe there are many ways of interpreting the world and that no single point of view can ever give the entire picture. This has motivated my use of mixed methods during this Ph.D. project.

## 2.3 The overall process of work

The Ph.D. project has gone through different phases. In the first semesters, completion of mandatory courses was the main activity. The focus then gradually shifted to writing articles. Literature was reviewed throughout the project period.

### 2.3.1 Literature review

According to Saunders, Lewis and Thornhill (2019), there are three reasons why conducting a critical review of the literature is important. Firstly, to help generate and refine research ideas at the beginning of the research project. Secondly, to provide context and frameworks for the research. Thirdly, to place the findings in relation to existing knowledge.

The literature review conducted in this Ph.D. project included academic articles from journals and conference proceedings on maintenance management, maintenance modeling, decision analysis, and Industry 4.0. Textbooks on relevant topics have also been used. In the initial phase of the Ph.D. project, standards, reports, and white papers from organizations and service providers such as consultancy firms were also reviewed. The motivation for including non-academic literature in the literature review was twofold. Firstly, to get an overview of the current knowledge and perceptions on digitalization of maintenance held by the actors in the industry. Secondly, because of the emergent character of the research topic, limited academic literature is available related to some of the aspects studied in this Ph.D. project, especially on the implementation and use of Smart Maintenance in the industry.

### 2.3.2 Research methods used

A mix of methods has been used in this Ph.D. project. Mixed methods research is often associated with the philosophical positions of pragmatism and critical realism (Saunders, Lewis and Thornhill, 2019). The research carried out during this Ph.D. project can be divided into two phases. The first phase focused on collecting empirical data answering RQ1, RQ2, and RQ3. The second phase emphasized using the insights from the first phase to propose solutions to the remaining research questions.

An abductive approach has been used in this Ph.D. project, moving back and forth between observations and theory as a better understanding of studied topics has emerged (Saunders, Lewis and Thornhill, 2019). The research method in the first phase can be characterized as sequential multi-phase and started with two studies where archival research was used (Saunders, Lewis and Thornhill, 2019). Financial statements, governmental documents, and company presentations were studied in Article I, while maintenance records and sensor reading from a data historian were studied in Article II. A quantitative study was used in the survey in Article III.

The choice of research methods has also been influenced by practical considerations such as timeline, available resources, my skills at the start of the project, and the research interests of my supervisors. When choosing the research methods and conceptualizing the different studies, I have tried to choose approaches where I have had some form of competitive advantage to make a scientific contribution. I have identified mainly three such advantages. Firstly, I have had access to industry experts and corporate computer systems from an O&G company through the BRU21 research program. This has been helpful when gathering the empirical data used in articles I, II, and V. Secondly, I have been part of a research group that is strong on maintenance modeling. This has been useful, especially for Articles II, V, and VI. Thirdly, my seven years of experience with maintenance in the process industry have made it easier for me to communicate with industrial practitioners.

The COVID19 pandemic, with lockdowns and other restrictions, limited the possibilities for company visits and collecting empirical data related to maintenance management from the industry in Norway in 2020 and 2021. In part because of this, I decided to shift the focus of this Ph.D. project from maintenance management to maintenance modeling halfway through the project. Because of this, a major part of the contribution in the second phase of the research carried out are the two maintenance optimization models proposed in Articles V and VI.

## 2.4 Assessing the quality of the research.

The understanding of how to judge and assess scientific quality differs between research traditions and philosophical positions (Saunders, Lewis and Thornhill, 2019). However, according to the Norwegian Research Council (NRC, 2000), there seems to be a general agreement that the following three aspects are important when assessing research quality:

- Originality: the extent to which the research represents a novelty in base research or innovative use of theory and methods in applied research.
- Solidity and rigor: in the form of good substantiation of claims and conclusions and fairness in argumentation and presentation of data. This is related to data quality, use of recognized scientific methods, good source referencing, consistency and coherence between claims made, and clear presentation of the research work.
- Relevance: both in an academic context and the extent to which the research has practical relevance. Academic relevance is judged by the extent the research help fill gaps in previous research and lays the foundation for future research. The practical relevance is judged based on the practical benefit to professional development in the studied field or benefits to society as a whole.

There can be contradictions between these aspects. For instance, a narrow focus on theoretical and methodological rigor may have an adverse effect on practical relevance (Saunders, Lewis and Thornhill, 2019). Because both aspects are important, the researcher must ensure that the research is valid and reliable and, at the same time, seen as relevant to practitioners so that they are interested in giving access to data and supporting the research. Because of this, tradeoffs must often be made when planning and executing applied research.

Different methods have been used to ensure the quality of the research carried out during this Ph.D. project. I have presented my findings at scientific conferences, seminars, and workshops, and received feedback from my peers. Books on research methods and methodology have been consulted. Industry representatives have also been consulted formally and informally throughout the Ph.D. project. In Articles I and II, participant validation (Saunders, Lewis and Thornhill, 2019) was performed by presenting the results to representatives from the organization where the data was collected during and at the completion of these studies. For both papers, the representatives from the organization gave feedback that the stated findings corresponded with their experience as practitioners.

# 3 Main results

This chapter serves three purposes. Firstly, to summarize the findings and discussions from the individual articles in this thesis. Secondly, to present how these separate pieces of work help answer the formulated research questions. Thirdly, to demonstrate the coherence of the thesis. The main results from the articles and their relation to the research questions are listed in Table 4. For the convenience of the reader, the research questions are restated below:

RQ1: How can implementing digital solutions in maintenance help improve the competitive position of the Norwegian O&G industry?
RQ2: Is the necessary data for breaking the "vicious circle of data collection and model development" available today in the Norwegian O&G industry?
RQ3: What types of quantitative maintenance models are preferred in the O&G industry on the NCS?
RQ4: How should companies proceed when planning to implement Smart Maintenance?
RQ5: How can CBM optimization models be developed, taking the preferences of a risk-averse decision maker into account?
RQ6: How can the principles from Industry 4.0 be utilized when developing CBM optimization models?

Table 4. The main results from each of the articles and link to the research questions.

| Article | Main results | Research question |
|---|---|---|
| I | The choice of digital solutions should be based on how maintenance improvements can contribute to economic value in that specific context. | RQ1 |
| II | A study of maintenance records and sensor data from an example O&G production platform found that quantitative models fed with online condition monitoring data were used. These models were mainly based on engineering first principles and used for anomaly detection. | RQ2, RQ3 |
| III | Respondents to a survey report to have achieved benefits from using digital twins in several areas, including cost and HSEQ. Results from the survey also indicate that some companies have broken the "vicious cycle", while others still see a lack of access to data as the main barrier. First principle / physics-based is the type of model that is most commonly used. | RQ1, RQ2, RQ3 |
| IV | A framework for the implementation of Smart Maintenance is proposed. | RQ4 |

Table 4. (continued)

| | | |
|---|---|---|
| V | A CBM optimization model that takes into account the decision maker's risk aversion is presented. A case study is used to demonstrate that using minimization of the long-run cost rate as optimization criteria may lead to decisions that are not in line with the preferences of a risk-averse decision maker. The case study also illustrates that the choice of modeling of the degradation process should be adapted based on the decision maker's risk preferences. | RQ5 |
| VI | A numerical procedure for maintenance optimizing of a system subject to two-stage degradation, hard failure, imperfect repair, maintenance windows, and maintenance delay is developed. A case study exemplifies the benefit of tailoring a maintenance policy for a specific system in a targeted manner. | RQ6 |

## 3.1 Article I: The economic dimension of implementing Industry 4.0 in maintenance and asset management

### 3.1.1 Introduction and motivation

As identified in the initial literature review, the prime motivation for the O&G industry to implement digital solutions is to secure the competitive position of this industry. Based on this, implementing Industry 4.0 is not an end, but a means to generate economic value.

In order to better understand how maintenance and asset management can be used to generate economic value in the offshore O&G industry, the sensitivity analysis tool from the Value Driven Maintenance (VDM) framework developed by Haarman and Delahay (2016) was used. Secondly, a literature review was performed to get an overview of how the digitalization of maintenance can be used to improve economic performance.

### 3.1.2 Method

The VDM sensitivity analysis builds on the Economic Value Added (EVA) framework developed by the Stern Stewart Corporation (Otley, 1999). The basic premise of this framework is that the primary goal of any corporation is to maximize shareholder value (Young and O'Byrne, 2001). In the EVA framework, a company generates value if operating profit is higher than the opportunity cost of capital employed (Zimmerman, 2011).

EVA is a metric based on accounting data and is, because of this, a lagging indicator. To counter this, the concept of value drivers is defined in the EVA framework as factors that can help create economic value in the future (Young and O'Byrne, 2001). Haarman and Delahay (2016) have defined six valued drivers related to maintenance and asset management in their VDM framework. These are: asset utilization; cost control; safety, health, environment, and quality (SHEQ) control; and capital allocation. Capital allocation is again divided into the value drives: investments, spare parts inventory, and lifetime extension.

According to (Haarman and Delahay, 2016), the different value drivers often conflict with each other. It is intuitively harder to increase availability and, at the same time, reduce maintenance costs and capital tied up in spare parts inventory. Based on this (Haarman and Delahay, 2016) argue that companies must prioritize which of the six value driver to focus on.

The VDM sensitivity analysis first calculates the change in cash flow from one percentage point improvement for each value driver. Then the Incremental Present Value (IPV) from the one percentage point improvement is calculated over the asset's remaining expected lifetime.

### 3.1.3 Results

The IPV for the six value drivers was calculated based on publicly available data from an example O&G offshore production platform (Figure 5). Because the forecasted production volumes for this O&G platform is expected to decline as the reservoir gets depleted, asset utilization is only the largest value driver when year 2 through 5 is used as the base year. Cost control becomes the value driver with the highest IPV from years 6 through 14. From year 15 and onwards, lifetime extension has the largest IPV.

The fact that the value drivers with the highest IPV is expected to change over the lifetime of this asset illustrates the importance of understanding the context of the specific O&G platform when planning to implement digital solutions to improve maintenance.

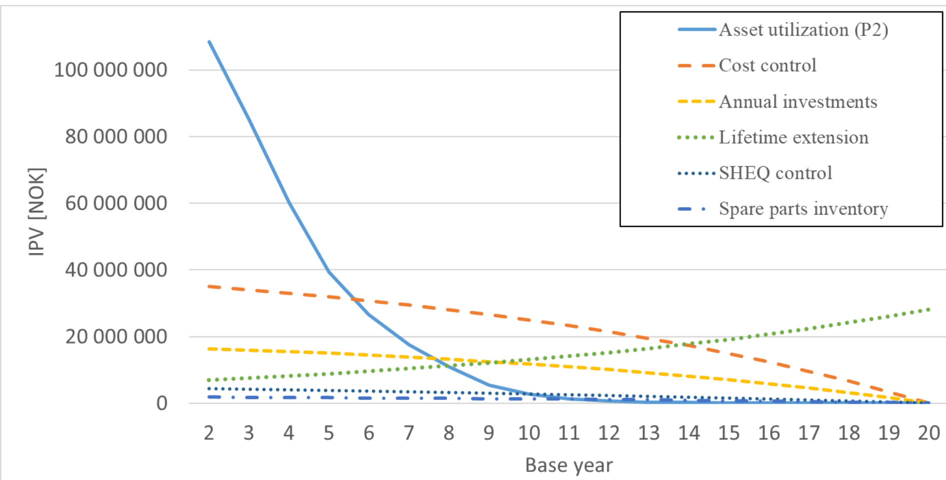


Figure 5. The relative size of the incremental present value (IPV) for the different value drivers as the base year of the VDM sensitivity analysis increases.

The next step was to conduct a literature review on how the introduction of Industry 4.0 and related concepts can help improve the six value drivers. The results are presented in Table 5. Inspired by Frank, Dalenogare and Ayala (2019) and Akkermans *et al.* (2016), we identified three dimensions of how digitalization can improve the six value drivers:

- **Smart maintenance** is related to deploying online sensors, collecting data, and using degradation models to develop better CBM policies, thereby reducing unplanned corrective maintenance and unnecessary preventive maintenance, resulting in increased asset utilization (Akkermans *et al.*, 2016).
- **Smart working** is related to using mobile devices, 3D, and augmented reality to make the execution of active maintenance more effective and efficient (Frank, Dalenogare and Ayala, 2019; Elia, Gnoni and Lanzilotto, 2016).
- **Smart products** are physical products with sensors that can exchange data with the operator, the manufacturer, and other products (Porter and Heppelmann, 2014). Smart products may facilitate new ways of cooperation between manufacturers, operators, and service providers that deliver value to all three parties. An example is servitization, where manufacturers sell the outcome of a product on a pay-as-you-go basis and not the product itself (Porter and Heppelmann, 2015; Grubic, 2018).

Table 5. The link between technology and value drivers based on the literature review. The + and – indicate whether the technology is expected to positively or negatively impact the corresponding value driver. Parentheses indicate less strong relationships.

*Technology dimension*

| *Economic dimension* | **Front-end tech.** | Smart maintenance | Smart work | Smart products |
|---|---|---|---|---|
| | **Base technologies** | Sensors<br>Big data<br>IIoT | Mobile solutions<br>3D & VR | Same as<br>smart maint.<br>+ servitization |
| | **Income** | | | |
| | Asset utilization | + | (+) | (+) |
| | **- Cost** | | | |
| | Cost control | (+) | + | – |
| | SHEQ control | + | + | 0 |
| | **- Capital charge** | | | |
| | Investments | (–) | (–) | + |
| | Spare parts | 0 | 0 | + |
| | Lifetime extension | (+) | 0 | + |

### 3.1.4 Discussion and concluding remarks

This article helped shed light on RQ1. The O&G industry perceives implementing digital solutions as essential to ensure its competitive position. The VDM sensitivity analysis of an O&G production platform presented in this study exemplifies how the aspects of maintenance where an incremental improvement has the largest effect on economic performance may change over the platform's lifetime. However, the VDM sensitivity analysis only assesses incremental changes and is thus not suitable for assessing the economic potential of step changes. Examples of such step changes are the use of new technology and maintenance concepts allowing for the development of unmanned production platforms on the NCS. Nonetheless, this article exemplifies the importance of understanding the context when wanting to implement digital solutions to improve performance.

Another contribution from this article was to identify three areas where implementing digital maintenance solutions may contribute to improving maintenance performance. This study thus influenced the decision to focus on Smart Maintenance in the remainder of the Ph.D. project.

## 3.2 Article II: Degradation modeling of centrifugal pumps as input to predictive maintenance

### 3.2.1 Introduction and motivation

While we in Article I used financial data to get a bird’s eye view of the potential benefits of improving maintenance, we shifted to a bottom-up view in Paper II to get another angle on how digitalization can be used to improve maintenance performance in the O&G industry. At the time of writing this article, my focus was primarily on RUL prediction and predictive maintenance, while later in the Ph.D. project, the focus shifted to data-driven decision making maintenance in general. Because of this, the aspects of the study presented in this chapter differ from those presented in the article.

### 3.2.2 Method

Through the BRU21 program, I gained access to sensor data and maintenance records from an O&G production platform. This was a relatively new platform with a large number of sensors installed. The operating company had put much effort into developing health indicators for the equipment at the platform.

Because there were several thousand health indicators defined for the O&G platform, I could not study all of them. I chose to focus on the fixed-speed centrifugal pumps because this was a group of equipment with several similar units installed on the platform. Another advantage of fixed-speed centrifugal pumps is that this is relatively simple equipment where it is possible to monitor several important failure modes with condition monitoring techniques (Beebe, 2004).

Data from the first four years of production were collected. The dataset contained data from 232 sensors and health indicators describing the health and ambient condition of 15 pumps. All pumps but one was installed in pairs with one of the pumps operating at the time.

The data from last year was reserved as the test dataset. The training dataset, the sensor data from the first three years, was then explored for possible faults where predictive maintenance could have been used. This was done by examining all the work orders issued for these pumps and then examining the relevant sensor data for indications of degradation leading up to the failures. Of 248 work orders in the training dataset, 21 involved restoring the condition of a degraded or failed pump.

### 3.2.3 Results

In this study, it was observed that the operating company had implemented a large number of models based on engineering first principles and simple physical models that were used for decision augmentation. Alarm thresholds had been defined for many of these health indicators, and the model parameters and alarm thresholds were tuned and adjusted as the operator gained experience from using this system. A sign of increasing focus on these models where the introduction of a new work order category to identify incipient failures detected based on the condition monitoring data. Another sign of this was the introduction of a new position in the maintenance organization whose main responsibility was to monitor and continue developing the condition monitoring system.

When it comes to the 21 work orders on the centrifugal pumps, they were caused by the following faults:

- Damaged seals (10)
- Bearing damage (3)
- Oil leakage (3)
- Impeller damage (2)
- External shock (2)
- Sealing medium leakage (1)

In only three of these work orders, signs of degradation were visible in the condition monitoring data before the component had failed or the degradation had been discovered through other means, mainly visual inspections – these where one of the failures labeled as damaged seals, and both the failures labeled as impeller damage. The time from observable degradation in the condition monitoring data to failure was only three days for the instances of damaged seals. For faults where the time from observable degradation to failure is only a few days, the practical advantage of PdM over CBM is presumably small. Because of this, only the faults related to impeller damage were investigated further in Article II.

The pumps experiencing this failure were operated at a lower flow than anticipated in the design phase, only 20 to 30 % of the best efficiency point. This is known to cause cavitation and impeller wear (Karassik and McGuire, 1998). The degradation paths from the training dataset for these pumps are shown in Figure 6.

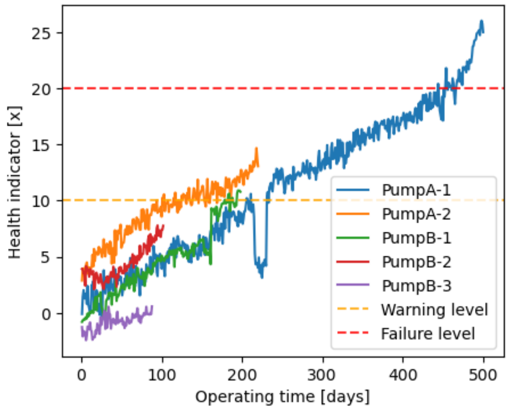


Figure 6. Degradation paths from the training dataset. The warning and failure levels marked in the plot were defined by the operating company.

Because the degradation increments appeared to be close to normally distributed, RUL predictions based on the assumption of a Wiener process were made. A comparison between this RUL prediction and the only degradation path in the training dataset going past the defined warning level is shown in Figure 7.

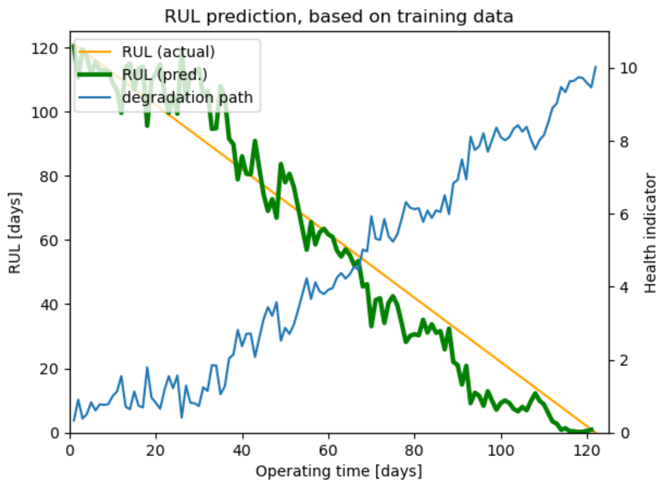


Figure 7. Comparison of the median RUL prediction (green line) based on the training dataset and the actual RUL (orange line) for a degradation path from the test dataset. The blue line shows the development of the health indicator for that degradation path.

No maintenance optimization model was developed in this paper, and the potential economic benefit was not quantified. However, as only one of the pumps needed to operate at the time and the pumps were located topside on a manned O&G platform, they were easily accessible for maintenance. Because of this, the added value of predicting the RUL was probably low in this case.

### 3.2.4 Discussion and concluding remarks

The archival research of condition monitoring data from the centrifugal pumps on the example O&G production platform shows that a large amount of data was collected and fed into models used for decision augmentation. Observations indicated that the operator company perceived the models as valuable and was working to improve the models as they collected more data. Based on this, Article II shows an example where the "vicious circle" described by Welte (2008) has been broken. Article II thus helps answer RQ2.

Article II also sheds light on RQ3. The operating company used mainly simple first principles, physics-based models, for anomaly detection. The data and models were used for decision augmentation and not decision automation. The use of maintenance optimization models or models for RUL predictions was not observed.

However, when writing Article II, my focus was on degradation modeling as input for predictive maintenance (PdM). The motivation for this was the extensive attention to PdM and degradation modeling in the literature. Article II illustrates some challenges when developing PdM optimization models. Assets such as centrifugal pumps have been used in industrial processes for more than a hundred years and are a well-known and reliable technology. Because of this, the necessary data for fitting prediction models will often not be available. The only failure mode where the degradation was observable in the health indicator well before the failure was caused by a design error when building the O&G platform. At the time of writing Article II, the operating company had ordered a set of smaller pumps to replace the pumps that had a problem with impeller wear. Based on a survey on the implementation of Industry 4.0 in the German manufacturing industry, the consulting firm Staufen reports similar findings: "companies have extensive experience with wear and tear on their machines as well as suitable on-site maintenance intervals, making the added value of predictive maintenance lower than is often asserted" (Staufen, 2019,p.34).

There are several limitations to the approach used in Article II to investigate whether the necessary condition monitoring data to implement PdM policies were available. For instance, vibration monitoring data were not available in this study. According to Beebe (2004), this is one of the most valuable sources of condition monitoring data for rotary machinery such as pumps. However, only three work orders in the dataset were related to bearing failures. Another limitation is that the pumps were regularly subject to visual inspections. Leakages caused by failure modes such as damaged seals and oil leakages might eventually have been observable in the condition monitoring data if they had not been identified and fixed based on visual inspection. Finally, because installing wired sensors have a high cost, when designing the O&G platform, the choice of sensors had been based primarily on process control and not on condition monitoring of the assets. If a larger amount of sensors had been installed and a method such as Failure Mode and Symptoms Analysis (FMSA) (ISO, 2012a) had been used to ensure early detection of all relevant failure modes, the situation might have been different.

Nonetheless, Article II still illustrates the challenge of collecting the necessary data to succeed with PdM policies. In this study, the only asset with enough degradation paths to fit an RUL model was subject to accelerated degradation caused by a design error. RUL models will be easier to develop for an operator of a large fleet of similar equipment because more data will be available. In addition, the cost of developing the models can be divvied over a much larger number of assets. This is in line with the category Smart Products and servitization as presented in Article I.

These last three paragraphs illustrate the importance of not starting with a specific technical solution, such as predictive maintenance, when wanting to improve maintenance performance but instead starting with the stakeholders' needs and a proper problem formulation. This is in line with the framework proposed in Article IV.

## 3.3 Article III: A survey on the use of digital twins for maintenance and safety in the offshore oil and gas industry

### 3.3.1 Introduction and motivation

An important barrier to realizing the potential of digitalization in the O&G industry is the use of proprietary software solutions and the lack of standardization which have led to data silos (Devold, Graven and Halvorsrød, 2017; Zborowski, 2018; ISO, 2019; DNV-GL, 2020). Because of this, manual work is needed to collect, convert, transfer, and validate the available data before it can be analyzed (KonKraft, 2018).

Digital Twin (DT) has been presented as an approach to reduce the data silo problem (Tao *et al.*, 2018; Schulte, Lheureux and Velosa, 2018; Malakuti *et al.*, 2020; van der Valk *et al.*, 2020). Because of this, DTs have been labeled a key enabler for succeeding with Industry 4.0 (Boss et al., 2020).

A challenge with the DT concept is the lack of a generally accepted definition (Uhlenkamp *et al.*, 2019; van der Valk *et al.*, 2020). There are generally two different views of the DT concept. Most academics focus on ultra-high fidelity models for accurate simulations of physical entities (van der Valk *et al.*, 2020). Industry practitioners, like the Industrial Internet Consortium (IIC) (Malakuti et al. 2020) and the advisory company Gartner (Schulte, Lheureux and Velosa, 2018), but also some academics (Grieves and Vickers 2017) assert that DTs are mainly about data handling.

To gain a better understanding of how DTs are used for maintenance and safety in the offshore oil and gas industry, we conducted a survey among O&G practitioners.

### 3.3.2 Method

Responses to the questionnaire were collected from industry practitioners invited to a seminar on the use of DT for maintenance, safety, and control in the offshore O&G industry. The seminar was organized in November 2020 by SUBPRO (2021), a research project focusing on technology innovation for subsea production and processing, and the BRU21 program.

Fifteen responses were included in the final sample giving a response rate of 22%. About half of the respondents (47%) assessed their organization as leading in digital maturity, which is higher than answers to similar questions in a survey of the global oil industry (DNV-GL, 2019). This is not surprising as a convenience sample of participants in a seminar on DT was used.

### 3.3.3 Results

Because of the sampling method (convenience sampling), a low number of respondents, and the bias among the respondents towards more digitally mature companies, results from this survey cannot be used for theory building. Nonetheless, Article III still sheds light on three of the research questions formulated for the thesis.

When it comes to how the implementation of digital solutions in maintenance can help improve the competitive position of the O&G industry on the NCS, the respondents report a benefit from the use of DT in several different areas, as shown in Table 6.

Table 6. Answers to the question: "Which of the following benefits have your organization or customers already achieved by using digital twin(s)?" (N/R = not relevant, *n* = 9)

| Benefits achieved | Yes | No | Don't know | N/R |
|---|---|---|---|---|
| Cost reduction. | 100 % | 0 % | 0 % | 0 % |
| Reduction of safety, health, environment & quality risks. | 78 % | 0 % | 22 % | 0 % |
| More effective operations. | 78 % | 0 % | 22 % | 0 % |
| Improved business decision making. | 67 % | 11 % | 11 % | 11 % |
| Improved energy efficiency. | 56 % | 0 % | 22 % | 22 % |
| Better product design. | 44 % | 22 % | 33 % | 0 % |
| Lifetime extension of aging asset. | 44 % | 11 % | 22 % | 22 % |
| New revenue streams. | 33 % | 11 % | 33 % | 22 % |

Regarding RQ2, when asked what they consider the most important barrier to using digital twins in the oil and gas industry in general, 33% answered "Lack of data / system integration". Based on this, lack of data or access to the data because of missing system integration is perceived as an issue by many respondents. However, among respondents who have already implemented digital twins, all reported having implemented models that monitor the current health of equipment and processes, while seven out of nine reported having implemented models that "predict future states of equipment or processes" (Table 7). Because of the poor formulation of these questions, the proportion of the respondents that have implemented models mainly for maintenance or production control is unknown. When asked whether automated decision making for maintenance is used, only one of the respondents answered yes. Even if more than half have answered "don't know" to this question, taken together with the other answers, this indicates that the data and models are mainly used for decision augmentation and not decision automation.

Table 7. Answers to the question: "What of the elements are currently part of the digital twin(s) used in your organization or in your products/services?" (*n* = 9).

| **Elements in digital twin** | **Yes** | **No** | **Don't know** |
|---|---|---|---|
| 3D representation of equipment / installations / plants. | 89 % | 11 % | 0 % |
| Real-time visualization of process/production status. | 89 % | 0 % | 11 % |
| Real-time visualization of equipment status. | 78 % | 0 % | 22 % |
| Real-time visualization of safety barriers. | 33 % | 0 % | 67 % |
| Simulations used for employee training. | 67 % | 11 % | 22 % |
| Simulations used for planning or production optimization. | 78 % | 0 % | 22 % |
| Models that monitor the current health of equipment or processes. | 100 % | 0 % | 0 % |
| Models that can identify cause-and-effect relationships between different process steps and/or equipment by combining data from different sources. | 44 % | 22 % | 33 % |
| Models that make predictions on future states of equipment or processes. | 78 % | 0 % | 22 % |
| Self-learning models (i.e. models that adapt as new data emerges). | 44 % | 33 % | 22 % |
| Automated decisions making related to process control. | 44 % | 11 % | 44 % |
| Automated decisions making related to maintenance. | 11 % | 33 % | 56 % |
| Automated decisions making related to safety. | 0 % | 33 % | 67 % |

Table 8. Answers to the question: "Which of the following types of models are used in the digital twin(s) in your organization or in your products/services?" (*n* = 9)

| **Types of models** | **Yes** | **No** | **Don't know** |
|---|---|---|---|
| White box (first principle / physics-based) | 78 % | 0 % | 22 % |
| Grey box (statistical / stochastic modeling) | 33 % | 22 % | 44 % |
| Black-box (machine learning, neural networks etc.) | 56 % | 11 % | 33 % |

The results from Article III also provide indications for answers to RQ3 on the types of models the practitioner prefers. Seven out of nine respondents use white box first principle physics-based models (Table 8). In response to the statement, “Reasonable estimations are normally sufficient to benefit from the use of digital twins,” 60 % of the respondents agree, while only 13% disagree. In response to the statement, “Ultra-high fidelity models are needed in order to give sufficient level of accuracy in digital twins,” only 20% agree.

Based on these responses, it seems that many industry practitioners prefer simple and understandable white box models. However, black-box models are also used, and some believe more complicated high-fidelity models are needed.

### 3.3.4 Discussions and concluding remarks

The survey in Article III illuminates the first three research questions defined for this thesis. Regarding RQ1, the respondents reported benefits from using DTs across several areas. Some respondents report missing access to data as the main barrier, but all the respondents who had implemented DT reported using models. This indicates that some companies have started breaking the vicious circle in RQ2. Regarding RQ3, a large proportion of the respondents use white box models and seem not to prefer the ultra-high fidelity models often associated with DTs in academic papers. The models seem to be used chiefly for decision augmentation and not decision automation.

Limitations to this study regarding the sampling method and the number of respondents have already been mentioned. Another limitation is that the size of the benefits from implementing DT has not been estimated, and we do not know if the reported results are achieved through small-scale pilots or full-scale implementations. We also do not know whether respondents from supplier companies refer to benefits achieved in their organization or by their customers.

However, the survey still indicates that some O&G companies have reached a level of digital maturity where they can utilize concepts such as DT to realize real business value.

## 3.4 Article IV: Framework for the implementation of Smart Maintenance

### 3.4.1 Introduction and motivation

As previously mentioned in Section 2, most of the research related to Industry 4.0 and maintenance has focused on technical aspects, and less attention has been given to how to organize and manage maintenance to take advantage of the new opportunities offered by the fourth industrial revolution. However, in empirical studies, organizational factors are often identified as a limiting factor in succeeding with data-driven maintenance (Savolainen *et al.*, 2020; Lundgren, Bokrantz and Skoogh, 2022; Golightly, Kefalidou and Sharples, 2018; Roda, Macchi and Fumagalli, 2018). Based on this, I wanted to propose a framework for implementing Smart Maintenance that addressed this as a socio-technical challenge.

Because integration and interconnectedness of IT systems, processes, and people are central aspects of Industry 4.0 (Schuh *et al.*, 2017), approaches to utilize the potential of this concept will require an interdisciplinary and holistic approach. Systems Engineering (SE) offers methods and proven industrial practices for managing this type of complexity (Kossiakoff *et al.*, 2011). Based on this, SE principles were used when formulating the framework in Article IV.

### 3.4.2 Background

Before Industry 4.0, Lean production (LP) was the most prominent concept for performance improvement in the manufacturing industry (MacKelprang and Nair, 2010; Buer, 2020; Schuh *et al.*, 2017). LP is here understood in line with Shah and Ward (2007, p. 791) as an "integrated socio-technical system whose main objective is to eliminate waste by concurrently reducing or minimizing supplier, customer, and internal variability". In a foreword to Schuh *et al.* (2017), Kagermann suggests that experience from LP implementation holds valuable lessons for how to succeed with the implementation of Industry 4.0. Recent empirical studies suggest that there are complementary effects between LP and Industry 4.0 (Tortorella and Fettermann, 2018; Rossini *et al.*, 2019; Kamble, Gunasekaran and Dhone, 2020; Buer *et al.*, 2020). However, these studies on the relationship between Industry 4.0 and LP have been conducted on a high level (Ciano *et al.*, 2021). Empirical studies that investigate the effect of Industry 4.0 and lean principles on maintenance have not been found in the literature, but in a conceptual paper by Sanders *et al.* (2017), Total Productive Maintenance (TPM) is postulated to be the LP tool that will benefit the most from Industry 4.0 technology.

### 3.4.3 Results

A framework was proposed in Article IV using contributions from LP, systems engineering, and maintenance management. The framework is shown in Figure 8.

The overall layout of the framework is inspired by a LP concept called *hoshin kanri* (HK), which is a tool for linking strategy with the operational level (Jolayemi, 2008). The influence of HK is illustrated with a Plan-Do-Study-Act (PDSA) loop at the tactical level.

Elements from System Engineering (SE) are included in the proposed framework by having the SPADE framework developed by Haskins (2008) at the strategic level. SE mainly uses a top-down approach that emphasize stakeholders needs and the broader context before focusing on specific solutions (Utne, 2007). This is based on the understanding that the whole is more than the sum of its parts. Another important feature in SE is a constant focus on iteratively evaluating the process. The processes at all levels in Figure 8 are circular to illustrate the iterative nature of continuous improvement.

The process at the operational level is illustrated with a variant of the PDSA cycle inspired by the steps for a successful CBM program defined by Van De Kerkhof, Akkermans and Noorderhaven (2015). At the core of this cycle is data-driven decision making. An essential part of this cycle is using the insight gained through data analysis to eliminate failures. This is in line with the LP principle of continual improvement. Maintenance does not have intrinsic value, so operators should focus on eliminating recurrent failures by identifying root causes and changing procedures or equipment design (Van De Kerkhof, Akkermans and Noorderhaven, 2015). This is especially important in the O&G industry because of the characteristics presented in Chapter 1.2.6.

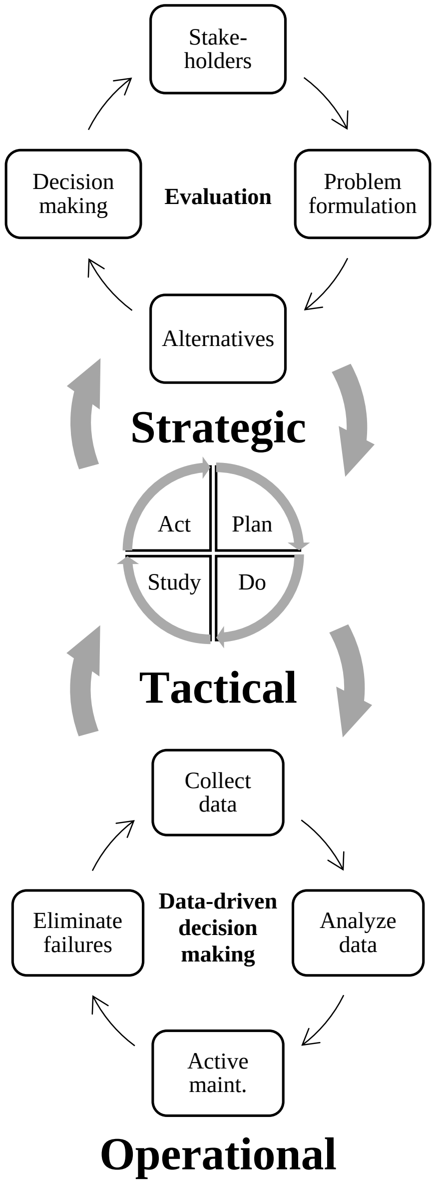


Figure 8. The proposed framework. The strategic level is based on the SPADE model by Haskins (2008), The four phases at the operational level are inspired by Van De Kerkhof, Akkermans and Noorderhaven (2015).

### 3.4.4 Discussion and concluding remarks

The connection between LP and Industry 4.0 has received much attention from the operations research community in the last five years (Buer, Strandhagen and Chan, 2018; Rossini *et al.*, 2019). Several authors have proposed that LP forms an important foundation for succeeding with Industry 4.0, and empirical evidence that support this has started to emerge (Ciano *et al.*, 2021). These studies have been done at a high level, and the links between specific principles from LP and Industry 4.0 and their effect on maintenance are still unclear. There are nonetheless compelling arguments that the introduction of lean principles such as standardization, focused improvement, and empowerment can provide a good basis for the successful implementation of Industry 4.0.

Implementation of Smart Maintenance requires performing a complicated set of activities, and no model or framework can cover all aspects. Because of this, there will be a need for different models and frameworks with different levels of abstraction to support this process (Rauzy and Haskins, 2019). The framework in Article IV was developed with the aim of making a simple model that is well suited for facilitating communication among all the stakeholders and that provides a holistic overview for implementing Smart Maintenance. Because of this, the illustration in Figure 8 has a high level of abstraction, and the labels are purposely generic so they can fit a wide range of organizations with different maturity levels regarding Industry 4.0 and maintenance management. There will be a need for several other models, frameworks, and tools for succeeding with the implementation of Smart Maintenance. Some of these have been mentioned in Article IV.

Article IV proposes an answer to RQ4. Empirically evaluating the proposed framework's effectiveness is challenging because of the long timeframes in maintenance and the high level of abstraction used in the framework. Interviews with industry representatives could have been used to assess the soundness of the proposed framework, but this was not done in this Ph.D. project. However, the framework's design was inspired by existing theory and proven industrial practices from SE and LP, in addition to findings from empirical studies on factors that characterize companies that succeed with Industry 4.0 and digital transformations.

## 3.5 Article V: Optimizing a condition-based maintenance policy by taking the preferences of a risk-averse decision maker into account

### 3.5.1 Introduction and motivation

According to established practice in System Engineering (Kossiakoff *et al.*, 2011; Haskins, 2008) and decision analysis (Bratvold and Begg, 2009a; Howard and Abbas, 2016), it is important to understand the preferences of the stakeholders and conduct a proper problem formulation in order to understand the current situation before diving into specific solutions. However, a recent literature review on maintenance optimization states that “most studies do not elaborate on the prerequisites for using their models in practice” (de Jonge and Scarf, 2020, p. 818).

When trying to conceptualize a study for my first manuscript targeted as a journal article, I wanted to use the degradation data found in Article II in an optimization model for predictive maintenance. I came up with the idea of introducing maintenance time as one of the decision variables. Maintenance time is here understood as the time needed for active maintenance together with administrative, technical, and logistic delay (CEN, 2017). The basis for this idea is the high cost of having maintenance personnel and spare parts readily available on offshore O&G platforms. If the operator has access to accurate RUL predictions, this facilitates the introduction of a maintenance concept where maintenance costs are reduced by only mobilizing the necessary resources on a just-in-time basis. If several different options for organizing the maintenance, with different cost and maintenance time, are available, there will be a certain response time that minimizes the overall cost, including downtime costs. The optimal threshold will depend on the characteristics of the degradation process and the cost structure.

I discussed this idea with a maintenance manager from an O&G company and learned that for some maintenance decisions with potentially severe economic consequences, they preferred more conservative options than the ones indicated as the most cost-effective in their analysis. In other words, this company sometimes deviated from using the minimization of expected cost as decision criteria because of risk aversion. Based on this discussion, I realized that a maintenance optimization model where a reduction in the long-run cost is traded with an increase in the variability of cost might not be accepted if the decision maker is risk-averse. Motivated by this, I set out to develop a CBM optimization model that considers the decision maker's risk preferences.

### 3.5.2 Background

The long-run cost rate is the most used criterion for optimizing CBM policies (van Noortwijk, 2009; Cherkaoui, Huynh and Grall, 2018; Zhang *et al.*, 2018; Vu *et al.*, 2021). One reason for this is that the long-run cost rate is relatively easy to calculate compared to the cost in a finite time (Rausand and Høyland, 2004; Cheng, Pandey and van der Weide, 2014). One must also keep in mind that the solution that minimizes the expected cost will result in the lowest costs in the long run, given the ability to absorb any losses (Welsh and Begg, 2008). Because of this, it is reasonable to assume risk neutrality and use expected cost as optimization criteria when the stakes involved are small compared to the decision maker’s total assets (Clemen, 1991; Russell and Norvig, 2016). However, even for large corporations, there will be some decisions where the potential consequences are so severe that minimization of expected cost is not desirable (Pratt, Raiffa and Schlaifer, 1995; Walls and Dyer, 1996).

Expected utility theory (EUT) is a framework for taking attitudes towards risk into consideration when assessing alternatives with uncertain outcomes. The basis of EUT is axioms for describing the preferences of a rational decision maker faced with decisions under uncertainty (Clemen, 1991).

An important concept in EUT is the certainty equivalent (CE). This is an amount such that the DM is indifferent between the consequences of an uncertain decision and receiving that amount for certain. As long as the utility function is monotonic (a large gain is always preferred to a smaller gain), the alternative with the highest CE will also be the alternative with the highest expected utility (Keeney and Raiffa, 1993). Because CE is in monetary terms, comparisons with the expected value can be made. As we are dealing with costs and not gains in Article V, the decision maker prefers the option that minimizes the CE in this paper.

### 3.5.3 Results

When calculating the expected utility of an option, the full probability distribution of potential outcomes must be found. In order to do this, we built on a procedure by Cheng et al. (2012). An exponential utility function was used to represent the preferences of the risk-averse decision maker. A numerical example and a case study were used to demonstrate that the preferred threshold for the decision variables changes when the decision maker is risk averse. A comparison of the expected cost and the certainty equivalent for a risk-averse decision maker from the example in Article V is shown in Figure 9 (b).

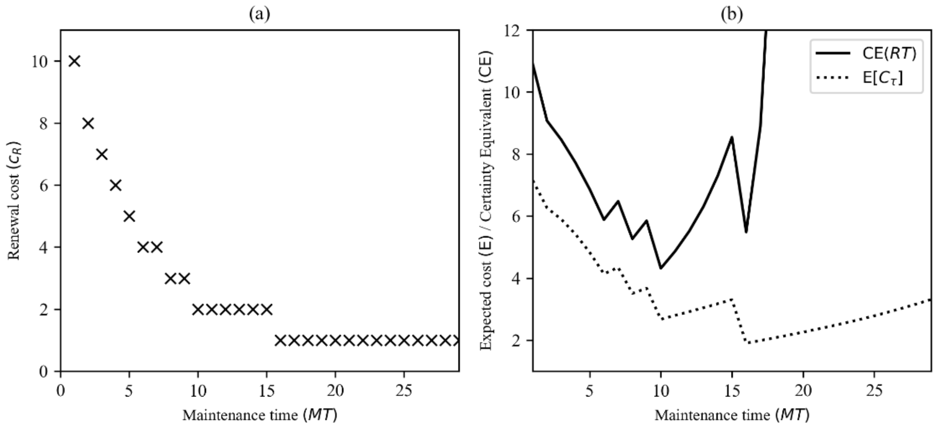


Figure 9. Plot (a) shows combinations of renewal cost ($c_R$) and maintenance time ($MT$) available to the decision maker (DM) in the example in Article V. Plot (b) shows the expected cost, $\mathrm{E}[C_\tau]$, and certainty equivalent of a decision maker with low risk-tolerance, $\mathrm{CE}(RT)$, depending on maintenance time. While a risk-neutral decision maker will prefer a maintenance time of 16 days in this example, the risk-averse decision maker prefers 10 days.

Another finding from Article V is that the decision maker's risk preferences should be considered when modeling the degradation process. The degradation increments in the case presented in Article V were close to normally distributed but with some excess kurtosis. The results in our paper showed that the assumption of a Wiener process was reasonable when optimizing the maintenance policy for a risk-neutral decision maker. However, using an alternative model that better represented the excess kurtosis of the degradation increments had a larger effect on the preferred thresholds for the decision variables when the decision maker was risk-averse.

### 3.5.4 Discussion and concluding remarks

Article V answers RQ5 on how a CBM optimization model can be developed so that the preferences of a risk-averse decision maker are taken into account. Expected utility theory (EUT) has previously seen little use in maintenance decision making, and to the best of my knowledge, an approach for optimizing a CBM policy for a risk-averse decision maker has not previously been presented.

For decisions where the potential outcomes are small compared to the overall economic resources of the organization, it is reasonable to assume risk neutrality and use minimization of the expected costs as the optimization criterion. Introducing EUT in maintenance optimization models may nonetheless be useful for two reasons.

The first reason is related to how a move from decision augmentation to decision automation will require different models. When models and data are used for decision augmentation, a human makes the final decision. The decision maker then uses his or her judgment and understanding of the limitations of the quantitative model in the specific context and either accepts the output from the quantitative model or makes an adjustment. EUT can be used to implement the stakeholders' preferences in the quantitative model and may thus facilitate the introduction of decision automation.

The other reason for incorporating utility theory into the optimization model is that different actors in the same organization may have different risk preferences. Explicitly formulating the risk tolerance in quantitative models may make it easier to achieve a coherent level of risk-taking throughout the organization. This can be useful in situations with principal-agent conflicts. For instance, the principal, e.g., company owners, might want to maximize the expected return from their investments, while agents, such as maintenance managers, might primarily want to avoid any incidents that can cause unpleasant focus from senior management. In studies of risk attitudes in O&G companies, Walls (2005) found that the most risk-averse companies generated a lower return on their assets. Based on this, Walls (2005, p.139) argues that "firms who can identify their appropriate risk tolerance level, and make allocation decisions based on that risk tolerance, will demonstrate significantly higher returns than those firms implementing lower and perhaps inappropriate risk tolerance levels."

## 3.6 Article VI: Maintenance optimization of a system subject to two-stage degradation, hard failure, and imperfect repair

### 3.6.1 Introduction and motivation

In the final paper in this Ph.D. project, I wanted to explore how principles from Industry 4.0 can be used when developing a maintenance optimization model. I also wanted to use data from an industrial case to gain insight into how data from an actual industrial environment can be used when developing such a model.

In a meeting with a manager from the process industry, I was presented with a case they believed was a good candidate for data-driven decision making in maintenance. I was allowed access to that company's sensor data and maintenance records. I also interviewed employees and studied corporate documents to understand this industrial case. Inspired by this case, we developed the maintenance optimization model presented in Article VI.

### 3.6.2 Background

Core features of Industry 4.0 are the horizontal, vertical, and end-to-end integration of data streams, models, and processes (Kagermann *et al.*, 2013). Horizontal integration is related to exchanging information between the different functional units and steps in the production process. Vertical integration is related to the exchange of information between the different hierarchical levels, e.g., from sensors to the corporate planning level. End-to-end integration refers to the integration of the engineering process across the different lifecycle phases of an asset, e.g., between the design and use phases. The idea of potential benefits from better end-to-end integration is also often mentioned in literature on digital twins (Wuest, Hribernik and Thoben, 2015; Tao *et al.*, 2018; West and Blackburn, 2018; Liu *et al.*, 2021). Another important feature of Industry 4.0 is viewing the production environment as a social-technical system (Schneider, 2018). According to Kagermann *et al.* (2013), it is vital to ensure the involvement and commitment of employees in all parts of the production process in order to effectively utilize their knowledge and creativity to improve system performance.

We investigate in Article VI the optimization of a hybrid CBM policy for a two-component system, where the degradation level of the upstream component (UC) influences the failure rate of the downstream component (DC). The UC in the system is a cable supplying cooling water, whereas the DC is a component that needs cooling. The performance of the UC is gradually declining, which results in a drop in the water flow rate. Meanwhile, the demand for cooling of the DC fluctuates depending on several factors related to the production process and the ambient condition. Generally, the risk of hard failure in the DC increases as the flow rate in the UC decreases. Hard failure is in Article VI understood as a type of failure characterized by a sudden breakdown. This contrasts with soft failures, where a component is considered failed when the degradation reaches a predefined threshold (Zhu, Fouladirad and Bérenguer, 2016). Furthermore, the ability of the UC to fulfill its required function is easily monitored with online sensors, while the health of the DC cannot be revealed without prohibitively expensive inspections.

The degradation of the UC happens in a two-stage process. The component is healthy until the arrival of a shock that introduces a potential failure. The first phase is named the stable phase (S-phase). The second phase is named the degradation phase (D-phase). In the case study, the change from the S to the D-phase was defined as the first time the health indicator was found to be below a defined lower control limit (LCL) for the third time in a row. The datapoints used in the case study where the mean value per hour.

Maintenance actions for this system include imperfect repair (IR), a cleaning procedure that partially restores the performance of the UC, and preventive renewal (PR), which requires a shutdown of the system and causes an unavailability cost. Although IR can temporarily restore the flow rate, it does not influence the degradation rate. As the degradation rate increases with time, IRs are needed more and more often, and eventually, the system reaches a state where it is no longer economical to continue performing IRs. PR, on the other hand, brings both the UC and the DC to the as-good-as-new (AGAN) state. Figure 10 shows a sample degradation path.

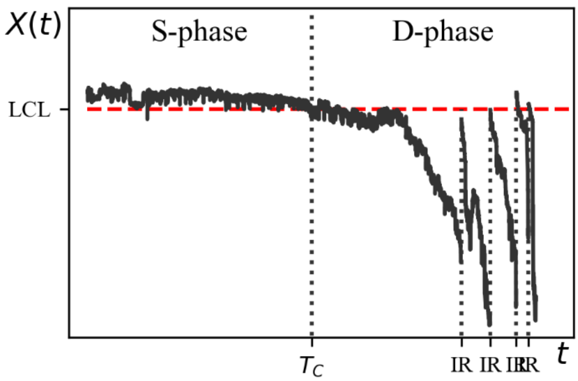


Figure 10. An example of a degradation path from the industrial dataset.

### 3.6.3 Results

Article VI presents four different maintenance policies. First, a procedure for finding the long-run cost rate for a simple preventive renewal (PR) policy without imperfect repair (IR) is presented. We then adjust the policy to include maintenance windows. Subsequently, the same is presented for IR policies with and without maintenance windows. Using parameters from the industrial case, we found that the hybrid maintenance policy with IR and PR resulted in only a 3% cost reduction compared to a pure PR policy when maintenance is performed immediately at the renewal threshold. However, when the PR is postponed to the first maintenance window after the PR threshold is reached, the hybrid policy achieved a 34% reduction in cost compared to the PR policy. This exemplifies the benefit of having the option to perform imperfect repairs so the performance of the UC can be kept in check while waiting for the next maintenance window to arrive.

### 3.6.4 Discussion and concluding remarks

Article VI aims to illuminate RQ6. A discussion on how the proposed model relates to the core features of Industry 4.0 is presented in the following.

An example of horizontal integration is that information from the maintenance function, i.e., the condition of the UC, and production function, i.e., planned maintenance windows, are combined in the model. Using IRs to postpone renewal to a preplanned maintenance window help reduce the disturbance to production.

An example of vertical integration is that information from different hierarchical levels of the organization is combined in the models. Examples are sensor data as input to the health indicator, data from the SCADA system on alarm limits to assess the maintenance delay for IR, and data from the ERP system as input to calculate the cost of performing maintenance and production loss.

End-to-end integration of engineering was not used in the case in Article VI as there was no exchange of information with the actors that had designed and produced the components in the maintained system. However, an example of how end-to-end integration of engineering might have been used to improve maintenance is presented below.

Operators in the process industry are generally reluctant to run equipment to hard failure and thus instead base maintenance decisions on defined failure thresholds. However, as the hard failure threshold is usually a random variable that depends on the characteristics of the operating condition and the characteristic of the component (Liu *et al.*, 2017), this may lead to unnecessarily conservative maintenance policies. Because the operators have limited experience of how the system behaves above these defined failure thresholds, it is challenging to accurately model the probability of hard failure and thereby assess whether the maintenance policy is unnecessarily conservative.

The company that designed the maintained component may have made models for assessing the probability of failure when making their design choices. Such information from the design phase may facilitate better modeling of the probability of hard failure in the use phase. Further, this may help the operator reduce the maintenance cost and help the designer by testing the assumptions from the design phase in the use phase. Achieving integration of the engineering processes in the design and use phases may thus contribute to an iterative improvement cycle for the component where the actors in both phases benefit from the exchange of information (Tao *et al.*, 2018).

The case study in Article VI also exemplifies the importance of the human-centered perspective of Industry 4.0. The ability to perform IR without disturbances to production resulted from a modification made by the mechanic in charge of maintaining the system. This exemplifies the potential for cost savings by combining maintenance modeling and optimization with the inventiveness of frontline personnel to develop maintenance policies tailored to the maintained system and maintenance capabilities at hand.

While the hybrid CBM model with maintenance windows achieved a smaller long-run cost rate compared to the other models, an apparent downside to a model with so many parameters is the efforts needed to develop, validate, and maintain the model. As operators in the process industry often use custom-made equipment or unique configurations of mass-produced components, there will often not be a large fleet of similar assets to share these costs on. This may make the cost of developing and maintaining such models higher than the potential gain.

Another aspect is the challenge of poorly designed and specified equipment often encountered in the process industry. There are indications that the failure mode studied in Article VI is caused by poor design. In addition to the two furnaces mentioned in Article VI, data were collected from four other furnaces. The gradual decline in cooling water flow was not found at these furnaces. Based on this, it is likely that the failure mode studied in Article VI could have been removed with some modifications to the system. Employees at the company had different theories on the root cause of this failure mode, but these theories were not investigated in the study leading up to Article VI.

From an academic perspective, this was an exciting dataset to use as inspiration for proposing a maintenance optimization model. From a business perspective, I believe that the primary objective of the operator should be to find the root cause of the failure mode and try to eliminate it through modifications before trying to implement a quantitative model for maintenance optimization.

This case and the example in Article II exemplify the importance of eliminating failures, as presented in the framework in Article IV.

# 4 Conclusions and further work

A widely held belief among industry actors in the Norwegian O&G industry is that the introduction of digital and automation solutions is vitally important to ensure the competitiveness of this industry sector. It is also believed that the upstream O&G industry is lagging behind industry sectors such as manufacturing in digitalization.

Maintenance, Industry 4.0, and digital transformations are broad fields that require knowledge in many areas. Because of this, a comprehensive answer to how the introduction of digital solutions can be used to improve maintenance performance is not possible within the limitations of a Ph.D. project. This thesis has focused on the use and development of quantitative models for maintenance decisions in the O&G industry on the Norwegian Continental Shelf (NCS). I have tried to shed light on this topic by approaching it from different angles and using a mix of methods.

There has been a lot of hype around predictive maintenance (PdM) based on online condition monitoring data. Companies that sell products and services related to the digitalization of maintenance have claimed that the potential benefits of CBM and PdM based on online condition monitoring data are substantial. On the other hand, empirical studies indicate that the industry is struggling with realizing this potential in practice, especially when it comes to PdM. Two key ingredients to data-driven decision making are data and models. Numerous quantitative maintenance models have been proposed in the academic literature in recent decades, but there is little empirical evidence that these models are used in the industry. Welte (2008) presents a vicious cycle where lack of data gives missing incentives to use models and vice versa. However, developments in sensor technology and the introduction of concepts such as digital twins make condition monitoring data increasingly available. The economic theory of complementary goods says that when one input becomes cheaper, demand for a complementary input increases. Assuming that condition monitoring data and maintenance models are complementary goods, increasing access to condition monitoring data will increase the value of quantitative models for data-driven decision making in maintenance.

## 4.1 Main conclusions

The research carried out in this Ph.D. project can be divided into two phases. The first three research questions and the first three articles focus on the potential benefits and current use of data-driven decision making for maintenance by O&G companies on the NCS.

The most important finding from this part of the thesis is that the Norwegian O&G industry is implementing digital solutions in a rapid phase, and there are indications that some companies in this industry have broken the vicious cycle described by Welte (2008). Articles II and III indicate that these companies have instead entered a virtuous circle where data collection gives incentives to develop model, leading to increasing use of data-driven decision making in maintenance.

These are, however, only exploratory studies. As there are signs that digital technologies are being adopted at a rapid pace, there is now a need for further empirical studies to understand how these technologies are adopted and their effects on performance.

The remaining three research questions and articles focus on how the insight gained from the first phase of the Ph.D. project can be used to develop further the use of data-driven decision making in maintenance. The main takeaway from this part of the thesis is the importance of understanding the context before starting to develop quantitative maintenance models. As Ron Howard, one of the founders of decision analysis has expressed: “the real problem in decision analysis is not making analyses complicated enough to be comprehensive, but rather keeping them simple enough to be affordable and useful” (from Bratvold and Begg, 2009b, p.21).

In order to understand when a quantitative model is “affordable and useful”, one must understand the needs of the stakeholders and how maintenance can contribute to economic value in the specific context. The framework in Article IV aims to give guidance on how this can be done by using established practices from systems engineering and lean management.

Further, the decision analysis discipline offers practical guidance for making decisions in line with the stakeholders’ objectives and preferences. Article V presents an approach for optimizing a CBM policy that considers the stakeholders’ risk aversion.

It is also important to understand that maintenance is a support function and that there should be a focus on using the insight gained from sensor data to find the root causes of recurring failures and eliminate them. This is especially important in the process industry, where custom-made equipment and unique configurations may lead to poor design, causing accelerated wear, as discussed in Articles II and VI.

## 4.2 Suggestions for further work

There is a need for further exploratory research on data-driven decision-making in maintenance to understand better the current use in the O&G industry. There is also a need for explanatory and evaluative studies to assess the benefits of introducing data-driven decision making, and digital maintenance solutions in general to the industry. Empirical studies should be developed to generate and disseminate useful knowledge to industry partitioners.

Relevant research methods are case studies, surveys, or grounded theory. Another approach is action research, which may be used to gain better insight and help with theory building on how to succeed with the implementation of Smart Maintenance. The instrument for measuring the four dimensions of Smart Maintenance developed in (Bokrantz *et al.*, 2020a) may be helpful in such empirical studies.

Possible topics to investigate are:

- Explore the types of quantitative models used in the industry and the gains achieved from using these models.
- Collect empirical data to quantify the potential benefits of using digital twins in maintenance.

- Identifying the most important enablers, barriers, and benefits of data-driven decision making in the industry.
- Explore the use of decision augmentation and decision automation and in the industry.
- Assess the potential benefits of decision augmentation versus decision automation and how quantitative models can support in realizing this potential.
- Collect empirical data on attitudes towards risk in maintenance decisions and evaluate the potential benefit of using expected utility theory in maintenance optimization models.
- Explore how the introduction of digital twins can facilitate better integration between design, production, and use phase of assets, and how this can be used to improve maintenance.

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# Part II – Articles

# Article I

Pedersen TI, Schjølberg P. The Economic Dimension of Implementing Industry 4.0 in Maintenance and Asset Management. In: Y. W, K. M, T. Y, K. W, editors. Advanced Manufacturing and Automation IX IWAMA 2019. Plymouth; United Kingdom: Springer, Singapore; 2020. p. 299-306

# Article II

Pedersen TI, Vatn J, Jørgensen KA. Degradation Modeling of Centrifugal Pumps as Input to Predictive Maintenance. In: Baraldi P, Di Maio F, Zio E, editors. The 30th European Safety and Reliability Conference and the 15th Probabilistic Safety Assessment and Management Conference. Venice, Italy: Research Publishing, Singapore; 2020

# Degradation Modelling of Centrifugal Pumps as Input to Predictive Maintenance

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The current development in sensor technology combined with improvements in systems for collecting, storing and analyzing large amounts of data, often associated with the term Industry 4.0, offers the opportunity to identify a larger proportion of faults before they turn into failures. A more proactive maintenance strategy has the potential to reduce maintenance costs by allowing maintenance organizations to focus resources on the right equipment at the right time, and to improve safety and availability by reducing the level of unplanned corrective maintenance. This paper explores the possibilities for predictive maintenance on a set of centrifugal pumps used at an offshore oil platform. As a basis for the analysis, sensor data and maintenance records for 15 centrifugal pumps collected over a period of four years is used. The data is split into a training and a test dataset. Causal tree diagnostic modelling is used to establish the link between failure mode and symptoms for one selected fault, impeller damage. Remaining useful life predictions (RUL) for impeller damage is developed based on a stochastic approach. The paper ends with a discussion of how the insights from the analysis can be used to improve maintenance performance.

*Keywords*: Degradation modelling, oil and gas industry, prognostics, Industry 4.0, predictive maintenance, causal tree diagnostic modelling, RUL, centrifugal pumps.

## 1. Introduction

In this paper the possibilities for predictive maintenance based on data from online monitoring is explored on a set of fixed speed centrifugal pumps installed on an offshore oil platform. The oil platform in question has an extensive system for online monitoring and is because of this considered as a good candidate for trying to apply predictive maintenance in practice.

In the next section of this paper theory related to Industry 4.0 and predictive maintenance is presented. In section three the example used in this paper is presented, followed by the result in section four. The paper ends with a discussion and conclusion in section five and six.

## 2. Industry 4.0 and Predictive Maintenance

### 2.1 *Industry 4.0*

The recent development in sensor technology and systems for collecting, storing and analyzing large amounts of data has the potential to bring big changes across business functions and industry sectors (Porter and Heppelmann 2015). When it comes to maintenance in the era of Industry 4.0, it is often predictive maintenance (PdM) that is highlighted as an application that can have a big impact (STAUFEN.AG 2019).

The falling cost of online monitoring has made it possible to monitor not only a handful of carefully selected critical equipment, but to monitor parameters throughout the whole process (Schuh et al. 2017, 16). In the offshore oil and gas industry this is an important technology in order to make remote-operated, unmanned production facilities possible. This can bring considerable savings in operating cost, but also in capital cost because platforms without living quarters can be made simpler and lighter, compared to manned installation (Offshore-technology 2019).

The disadvantage with unmanned platforms is that it will take longer time and cost more to mobilize for active maintenance. This calls for predictive maintenance in order to keep the number of visits to the platform at a minimum while at the same time obtaining acceptable availability.

### 2.2 *Predictive maintenance (PdM)*

PdM is in CEN 13306:2017 defined as "condition-based maintenance carried out following a forecast derived from repeated analysis or known characteristics and evaluation

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of the significant parameters of the degradation of the item" (CEN 2017).

Prognostics is a corresponding term that is used in the ISO standards, and is defined as "analysis of the symptoms of faults to predict future condition and residual life within design parameters" (ISO 2012b).

According to ISO 13381-1:2015 "The goal of prognostics is to provide the user with the capability to predict remaining useful life (RUL) with a satisfactory level of confidence" (ISO 2015,4). RUL is in the same standard defined as "remaining time before system health falls below a defined failure threshold".

The terms fault and failure will in this paper be used in line with ISO 13372:2012. Fault is in this standard defined as the "condition of a machine that occurs when one of its components or assemblies degrades or exhibits abnormal behavior, which may lead to the failure of the machine". While failure is defined as "termination of the ability of an item to perform a required function" (ISO 2012b). However, in practice often machines are shut down at a more conservative level than the level where failure is expected to occur, in order to avoid the hazards often associated with failures. This level will then be the defined failure threshold (ISO 2015, 7).

PdM can offer value compared with a more traditional CBM approach where one wait for measured condition to reach a defined level before active maintenance is executed. This is because PdM with RUL-predictions allow for longer mobilization times for spares and maintenance. This can bring considerable savings in remote locations like offshore oil platforms. Another advantage is that it can allow for grouping of maintenance jobs in a way that improve both availability and maintenance cost.

But for predictive maintenance to be possible one need a good overview of the relevant failure modes and one must have the capability to observe the progression of these failure modes. In addition, the rate of degradation or the PF-interval must have a level of consistency so that predictions can be made with a reasonable level of accuracy (ISO 2015).

Failure mode is here understood as the "observable manifestation of a system fault" (ISO 2012b) and PF-interval is the time from a fault is observable to failure occur (Rausand and Høyland 2004, 395).

### 2.3 *Failure modelling*

In order to make a RUL-prediction a model of the degradation until failure has to be made. According to ISO 13381-1:2015, failure modeling can be grouped into five different approaches: physics-based; statistical (or stochastic); heuristic (or knowledge based); data-driven; or hybrid modeling, which is a combination of the approaches above (ISO 2015,19).

In this paper a stochastic approach will be used to estimate the RUL.

## 3. Example from an Offshore Oil Platform

All the data in this section is collected from an offshore oil platform located on the Norwegian Continental Shelf (NCS).

The oil platform is continuously manned with internal maintenance personnel that are responsible for the daily maintenance, while contracted personnel and specialist are used for overhauls and modifications. A technical support organization located onshore supports the offshore organization with maintenance planning and advise.

There is a total of 22 fixed speed centrifugal pumps installed at the platform. Seven of the pumps have however seen very little use (less than one month) and have been excluded from further study.

For the 15 remaining pumps, sensor data from the four first years of production has been collected together with the maintenance records.

For the sensor data only one data point has been collected for each day (at 00:00:00). This has been considered as a high enough sampling rate for this application.

The data has been split into two datasets where the first three years has been labeled as the training dataset. This dataset has then been explored for possible faults where predictive maintenance can be used. The remaining one year of data has been labeled the test dataset. This dataset has been saved for validation of possible findings from the training dataset.

14 of the pumps are set up with two pumps in parallel, but only one pump running at the time. The remaining 15$^{th}$ pump has no redundancy. All pumps have sensors that measure pressure before and after the pump in addition to flow. Some of the pumps are fitted with additional sensors like temperature sensors. In total data from 123 sensors that monitor different aspects related to

the operation condition and performance of the 15 pumps has been collected.

To assist in the monitoring of the health of the pumps an asset monitoring software is used to present the sensor readings to the maintenance personnel. In addition, several health indicators are calculated as well. Among these are: Net Positive Suction Head deviation (NPSHd), pump efficiency and head deviation.

A set of symptoms of faults are defined for the pumps and warning, and alarm limits are set for all these symptoms.

### 3.1 *Maintenance records*

The maintenance records for the 15 pumps contains 248 corrective maintenance (CM) and preventive maintenance (PM) workorders in the time period of the training dataset. 21 of these workorders are corrective maintenance according to CEN 13306:2017 definition ("maintenance carried out after fault recognition and intended to restore an item into a state in which it can perform a required function") (CEN 2017). Workorders not related to active maintenance on physical parts (like software changes) has been excluded.

Grouped by the fault that caused the workorder to be initiated the list look like this:

- Damaged seals (10)
- Bearing damage (3)
- Oil leakage (3)
- Impeller damage (2)
- External shock (2)
- Sealing medium leakage (1)

Some of the faults in this list are clearly not possible to predict given the available data. One example is faults caused by external shock, where one of the workorders for instance was caused by someone stepping on a delicate part of the pump. Another is the category "bearing damage" given that vibration monitoring, or data from other sensors directed at bearings not have been collected.

The faults labelled oil leakage and sealing medium leakage has all been discovered by visual inspection before the faults have shown up in the sensor data. Visual inspection has also been used to discover nine of the ten instances of damaged seals. One of the instances of damaged seals was however discovered by online condition monitoring, but the time from observable fault to failure was only three days. For faults with this short PF-interval, predictive maintenance offers little practical advantage over CBM.

This leaves only the faults related to impeller damage as a good candidate for predictive maintenance in this dataset.

### 3.2 *Impeller damage*

The remainder of this section will focus on impeller damage.

To get a better understanding of this fault a causal three diagnostic model has been made. See figure 1 below.

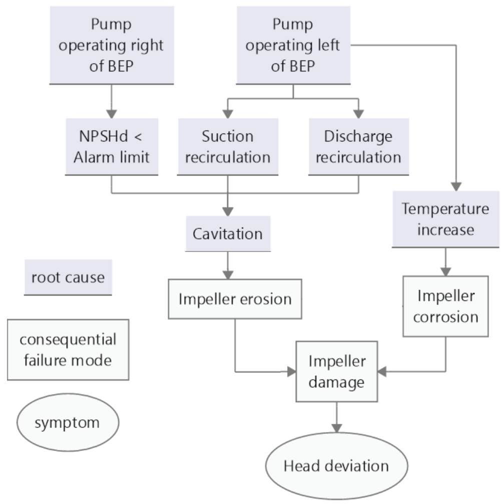


Fig. 1. Causal three diagnostic model based on (ISO 2012a). The causal links from root cause to symptom are based on Karassik and McGuire (1998). BEP = Best Efficiency Point. NPSHd = Net Positive Suction Head deviation.

From figure 1 one can see that head deviation is a symptom that one can expect as a result of the selected fault. Head deviation is here defined as:

$$Head_{dev} = \frac{100 * (Head_e - Head_a)}{Head_e} \tag{1}$$

The expected value of the head ($Head_e$) is based on the head-flow curve provided by the pump manufacturer. The value of the actual head ($Head_a$) is calculated based on the measured pressure before and after the pump. This is then converted into head based on the specific gravity of the pumping medium and adjusted based on coefficients for the system friction. These coefficients have been provided by the operator of the oil platform.

Both the two instances of impeller damage listed above are from two pumps that are installed in parallel and perform the same function. These pumps will be called the A and B pump. In addition, there is a third workorder (at the B pump), that was initiated because of an oil leakage, where a new impeller has been installed in the training data time period. Figure 2 a and b below shows the trend of the head deviation.

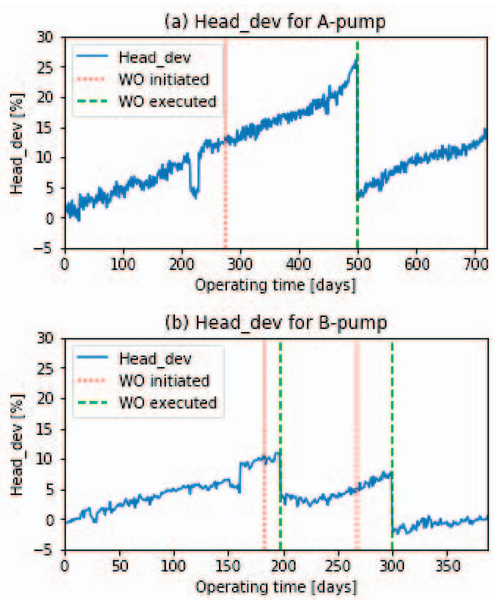


Fig. 2 a and b. The two figures above show how the degradation develop over time for the two pumps.

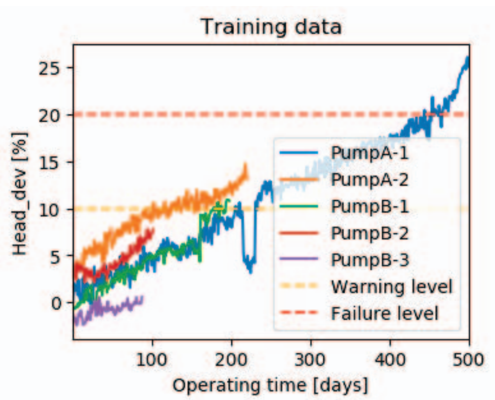


Fig. 3. The separate degradation paths in the training data split into separate lines. The dashed lines indicate the warning level of degradation and the defined failure threshold set by the operator of the oil platform.

In figure 3 one can see that the head deviation starts at different levels for the different degradation paths. This is most likely because not all the parts that has been subject to wear, like for instance impeller casing, has been replaced in the repairs.

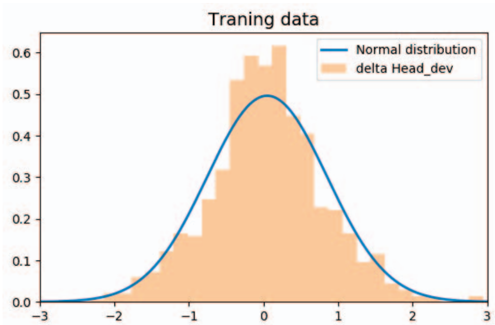


Fig 4. The change in head deviation from one sample to the next compared to the normal distribution.

The histogram in figure 4 show the change in head deviation from one sample to the next ($\Delta head_{dev}$). The mean is 0.049 and standard deviation is 0.804. The histogram appears similar to the normal distribution. However, based on D'Agostino's K-squared test the null hypothesis that the sample comes from a normal distribution is rejected with p-value $3*10^{-38}$.

Below in figure 5 is a plot of the test data. We will only use the degradation path that goes past the warning level in our testing.

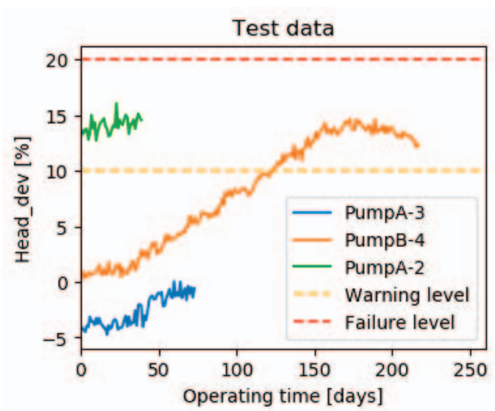


Fig. 5. The test data.

## 4. Prognosis for Impeller Damage

Based on the trend in head deviation and the fact that the pumps are running at flow of only 20 to

30 % of BEP the diagnostic model in figure 1 indicate that the pumps are subject to cavitation.

Closer inspection of one of the impellers removed from the pumps show damage to the outside of the impeller vanes and on the inside of the impeller inlet. Something that reinforces the assumption that the root cause of the impeller erosion is discharge and suction recirculation (Karassik and McGuire 1998,567).

After the diagnosis the next step in prognostics is to make a RUL-prediction.

### 4.1 *Predicting remaining useful life (RUL)*

In this section a stochastic approach based on the Inverse Gaussian distribution (IG) is used to predict RUL.

IG is a probability distribution that can be used to model the first passage time of a Wiener process. For a process to be a Wiener process each increment has to be independent and the difference between each consecutive step has to be normally distributed (Chhikara and Folks 1989, 23).

As shown in the previous section the requirement of normal distribution is not fulfilled in this example. But according to Chhikara and Folks: "[a]lthoug it is appealing to base the use of the IG distribution upon an underlying Wiener process, it is not at all critical". They make a comparison with the normal distribution which has become "acceptable to use (…) to describe all sorts of data" and that "[t]he situation with the IG distribution seems to be similar" (Chhikara and Folks 1989, 159-160).

We then formulate the degradation process as a Wiener process in line with Zhang et al. (2018):

$$X(t) = x_0 + vt + \sigma B(t) \qquad (2)$$

Where $x_0$ is the level of degradation at $t = 0$, $v$ is the drift parameter and $\sigma$ is the diffusion coefficient. Further on $x_t$ is the level of degradation at time t and $T$ is the first passage time of the failure threshold ($L$).

Because we have no degradation path in the test dataset that goes all the way to the failure threshold (20%), we will instead use the 10% warning level as our $L$ when predicting the RUL in this paper.

Next we assume that $T$ can be modelled by the Inverse Gaussian (IG) distribution with mean $\mu$ and shape $\lambda$ (Rausand and Høyland 2004,p 50):

$$T \sim IG(\mu_t, \lambda_t) \qquad (3)$$

Where $\mu_t = (L - x_t)/v$ and $\lambda_t = (L - x_t)^2/\sigma^2$.

In order to validate how well the IG distribution fits our data we have done a Monte Carlo (MC) simulation with $10^4$ runs. The MC has been done by drawing random samples of $\Delta x_t$ from the training dataset and counting the number of draws until $\sum \Delta x_t \geq L$.

In figure 6 a and b below the Probability Density Function (PDF) and Cumulative Density Function (CDF) of the IG distribution is compared with histograms based on the MC simulation. The MC simulation seems to fit reasonably well with the IG distribution. Something that reinforces the assumption that the IG distribution can be used in this case.

However, one weakness of using the MC simulation for validation in this case is that both the MC simulation and the IG distribution have the assumption that the degradation is happening in independent steps.

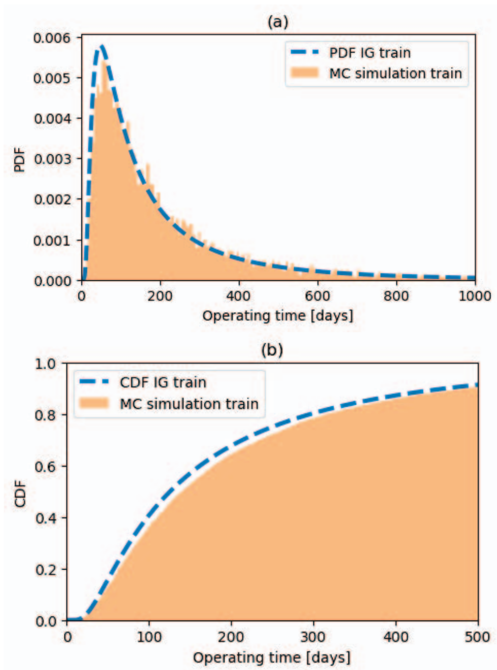


Fig. 6 a and b. Comparison of the PDF of the IG distribution (dashed line) and the MC simulation (histogram). Both are based on the training dataset.

The average RUL in the training data, and expected value based on the IG (E[T]) is 206 days. But based on the CDF of our IG-model, at this time the pump will already have failed in 69 % of the cases.

Because the cost associated with doing maintenance to late is often much higher than the other way around a more conservative measurement for the RUL prediction will normally be sensible to use.

This can be optimized if one knows the expected cost of PM and CM. But because we don't have access to this data, we have chosen the 10th percentile when estimating RUL. We then get RUL(IG,10) = 40 days at $x_0 = 0$.

The corresponding RUL based on the MC is RUL(MC,10) = 44 days, a 10% deviation against the IG.

### 4.2 *RUL prediction based on training data*

In the first approach for predicting RUL (RULtrain) we assume that $v$ and $\sigma$ are constant, and the parameters for Wiener process will be based on the training data ($v_{train} = \overline{\Delta x_{train}}$ and $\sigma_{train} = s_{\Delta x(train)}$).

Next we calculate the parameters for the IG: $\mu_t = (L - x_t)/v_{train}$ and $\lambda_t = (L - x_t)^2/\sigma^2_{train}$.

In figure 7 it is visualized how RULtrain at the median and 10th percentile perform against the actual RUL (RULa) as the degradation approaches $L$. RULa for the one degradation path that reaches 10% deviation in the test dataset is 121 days with $x_0 = 0{,}33$.

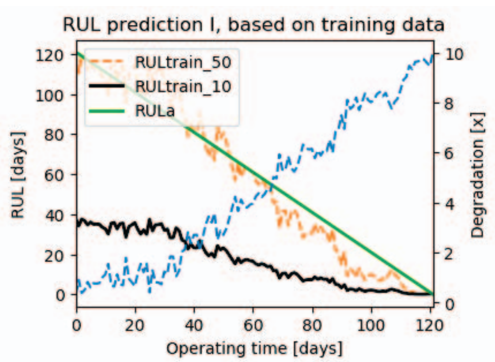


Fig. 7. Predicted RUL at the 10th percentile and median (RULtrain_10 and RULtrain_50) compared to the actual RUL (RULa), as RULa goes to 0 in the test degradation path. The degradation path is shown on the right y-axis.

As one can see from the plot in figure 7 the median RUL prediction (RULtrain_50) is within +/- 20 days of RULa throughout the degradation path. The RUL prediction at the 10th percentile is however much lower than RULa. This gives that if one chooses this as the measure for when to mobilize for active maintenance, the decision to mobilize will be made much earlier than is needed in the specific example in figure 7.

### 4.3 *RUL prediction with Bayesian inference*

In this section we open for the possibility that $v$ and $\sigma$ can change with new degradation paths. One rationale for this can be that for every repair, small differences in how the pumps are reassembled together with the state of parts that have not been repaired can affect the subsequent performance and degradation of the pumps.

If this assumption is true, we can never know the actual $v$ and $\sigma$ when predicting RUL for a future degradation path. One way to meet this challenge is to use Bayesian inference to update our prediction as data from the current degradation path becomes available.

In this paper we will perform the analysis first assuming that drift is unknown and that the diffusion coefficient is fixed, and then the other way around. Both these assumptions are admittingly not very realistic, but they simplify the problem of finding the posterior for the unknown parameters and make it possible find analytical solutions.

#### *4.3.1 Assuming v unknown and σ fixed*

In this approach we will use $v_0 = \sum v_i/N$ as our prior estimate for the drift, with precision $\tau_0^2 = 1\,/\,s^2_{v(i)}$. Where $v_i$ is the drift for the $i$-th degradation path and $N$ is the number of degradation paths in the training dataset.

We will use the degradation path in our test dataset to update our posterior distribution as the data becomes available. The estimate of the drift parameter based on the test data at time t will then be: $\overline{\Delta x_t}$ with precision $\tau_t^2 = 1\,/\,s^2_{\Delta x,t}$.

Based on Cowles (2013, 87) the posterior distribution for the drift at time $t$ ($v_t^*$) can be found with the following expression:

$$v_t^*|\boldsymbol{x} \sim N\left(\frac{t\tau_t^2\overline{\Delta x_t} + \tau_0^2 v_0}{t\tau_t^2 + \tau_0^2}, \frac{1}{t\tau_t^2 + \tau_0^2}\right) \quad (4)$$

Based on Eq. (4) we can find the expected value and 95% credible interval for the posterior of the drift. We then update the mean for our IG distribution: $\mu_{B,t} = (L - y_t)/v_t^*$. We keep the same shape parameter as in the previous approach: $\lambda_t = (L - y_t)^2/\sigma_{train}^2$.

As we can see from the graphs in figure 8 the RUL prediction at the 10th percentile is almost the same whether $v$ is based on the training data or the posterior from Eq. (4).

The reason for this is that the variance in the different trends of the degradation paths in the training dataset is so much smaller than the variance of $\Delta x$ in the test degradation path.

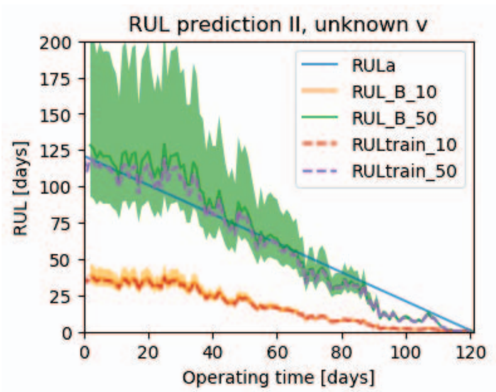


Fig. 8. The solid lines are the actual RUL (RULa) and RUL prediction based on Bayesian inference (RUL_B_10 and RUL_B_50) with shaded regions for the 95% credible interval for $v$. The dashed lines are the RUL predictions based on the training data.

#### 4.3.2 *Assuming v fixed and σ unknown*

In this approach we assume that the trend in the Wiener process is constant and the diffusion coefficient is changing. Based on Cowles (2013, 98) the posterior distribution for the precision of a normal distribution ($\tau^2$) can be expressed as:

$$\tau^2|\boldsymbol{x} \sim Gamma(\alpha + \frac{t}{2}, \beta + \frac{ts_{\Delta x,t}^2}{2}) \qquad (5)$$

We estimate the $\alpha$ and $\beta$ parameters for the gamma distribution for $\tau^2$ based on the following formulas:

$$\gamma = \ln\left(\frac{1}{N}\sum_{i=1}^{N}\tau_i\right) - \frac{1}{N}\sum_{i=1}^{N}\ln(\tau_i) \qquad (6)$$

$$\alpha \approx \frac{3-\gamma+\sqrt{(\gamma-3)^2+24\gamma}}{12\gamma} \qquad (7)$$

$$\beta = \frac{aN}{\sum_{i=1}^{N}x_i} \qquad (8)$$

Where $\tau_i^2$ in Eq. (6) is the precision of the $i$-th degradation path, and N is the number of degradation paths in the training dataset. Based on Eq. (6 – 8) we get $\alpha = 8.3$ and $\beta = 3.7$. Based on this we can estimate expected value and 95% credible interval for $\sigma^2 = 1/\tau^2$. We then use this to update the shape parameter for the IG distribution $\lambda_{B,t} = (L - y_t)^2/(\sigma^2)$, while the mean is kept the same: $\mu_t = (L - x_t)/v_{train}$.

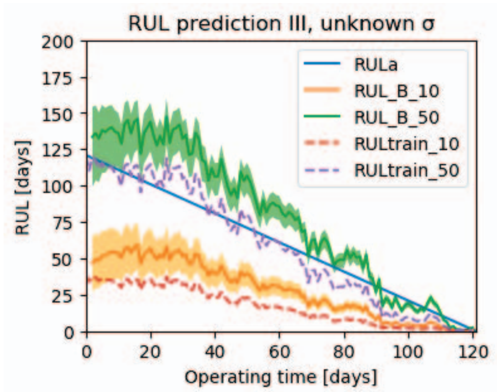


Fig. 9. RUL prediction based on Bayesian inference with 95% credible interval for $\sigma$ (solid lines with shaded region). The dashed lines are RUL the predictions based on training data.

Of cause a more realistic assumption would be to assume both $v$ and $\sigma$ as unknown at the same time. This is something that can be pursued in future work either by numerical integration or by using the Markov chain Monte Carlo method (Cowles 2013).

But the calculations in the two previous sub-section demonstrate that the uncertainties in $v$ and $\sigma$ have a considerable impact on the RUL-prediction.

## 5. Discussion

As presented in the introduction and section two, there are high expectations to the possibilities of PdM in relation to the fourth industrial revolution. However as seen in this paper there are several challenges related to successful employment of PdM.

One challenge met in this paper was that few of the faults of the pumps in question was observable with the available sensor data.

One possible solution to this challenge is to install more sensors. In order to find out what sensors to install and data to collect a method called Failure Mode and Symptoms Analysis (FMSA) can be used. This method offers a systematic approach to ensure that the installed sensors can monitor the relevant failure modes (ISO 2012a).

Another challenge met in this paper was that because of the limited time period and number of equipment in the dataset the number of identified faults was few. This contributes to the large uncertainty in the predicted RUL.

One possible approach to face this challenge is to get a bigger dataset in order to get better predictions. This could be in partnership with the equipment manufacturers or other operators of similar equipment.

The challenges related to successful implementation of predictive maintenance has also been recognized in a survey of 323 German companies in 2019. According to the consulting firm Staufen: “companies have extensive experience with wear and tear on their machines as well as suitable on-site maintenance intervals, making the added value of predictive maintenance lower than is often asserted.” (STAUFEN.AG 2019).

## 6. Conclusion

Given the complexity of implementing predictive maintenance the added value of this in traditional plants like the oil platform in this paper is probably limited.

However, in other settings where cost and/or mobilization time for active maintenance are considerable larger the kind of RUL prediction done in this paper can be an important contribution.

As pointed out in section two unmanned offshore platforms can offer considerable savings in terms of investment and operating cost, and unmanned solutions can be a necessity in order to make some marginal offshore oilfield in remote locations profitable.

But in order to secure the profitability of such a solution predictive maintenance with accurate RUL-predictions will be crucial in order to achieve acceptable availability and maintenance cost.

**Acknowledgement**

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# Article III

Pedersen TI, Størdal HG, Bjørnebekk HH, Vatn J. A Survey on the Use of Digital Twins for Maintenance and Safety in the Offshore Oil and Gas Industry. In: Castanier B, Cepin M, Bigaud D, Berenguer C, editors. 31st European Safety and Reliability Conference. Angers, France 2021.

# A SURVEY ON THE USE OF DIGITAL TWINS FOR MAINTENANCE AND SAFETY IN THE OFFSHORE OIL AND GAS INDUSTRY

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Companies in the oil and gas industry have, since the fall in oil price in 2014, been under pressures to cut costs and improve the effectiveness of their operations. Digitalization is generally considered as an important contributor to achieve this. One barrier to benefit from digitalization that is increasingly being recognized by the industry is data silos. Digital twin is a concept that has been proposed to alleviate this problem, but there is a lack of common understanding of what this concept entails and the potential benefits of this concept. To gain a better understanding of how digital twins are used for maintenance and safety in the offshore oil and gas industry, we have conducted a survey in the form of a web-based questionnaire among practitioners from this industry. 15 responses to the questionnaire was included in the final sample. Nine of these where from respondents that reported to have implemented digital twins in their own organization or in their products or services. Because of the low number of responses, the results cannot be used to draw conclusion on the current state of digital twins for maintenance and safety in the offshore oil and gas industry in general. But the results offer some insights that can be useful for further research.

*Keywords*: Industry 4.0, digital twin (DT), questionnaire, survey, Industrial Internet of Things (IIoT), offshore oil and gas, predictive maintenance, safety, Norwegian Continental Shelf (NCS), digitalization.

## 1. Introduction

After the fall in oil price in 2014, companies in the oil and gas (O&G) industry have been under pressure to cut costs and increase the efficiency of their operations (Aalberg et al. 2019; Wanasinghe et al. 2020; DNV-GL 2020b). There seems to be a consensus among the industry actors that digitalization is important to secure the future competitiveness of this industry (Mogos, Eleftheriadis, and Myklebust 2019; DNV-GL 2020b; KonKraft 2018; NTNU 2017).

The potential benefits of digitalization lie mainly in the ability to collect data; turn this data into information and then use this information to make faster and better decisions (Feder 2020; Wanasinghe et al. 2020; Schuh et al. 2020). Collecting and analyzing large streams of data is something that O&G industry have done for decades (Spelman et al. 2017) but the infrastructure has traditionally been built for specific purposes (DNV-GL 2020b). Data silos are increasingly been recognized as an important barrier for effective use of the collected data (KonKraft 2018; Zborowski 2018; Malakuti et al. 2020; Devold, Graven, and Halvorsrød 2017).

Digital twin (DT) is a concept that has been proposed to improve this situation and has been described as a “key enabler for the digital transformation” (Kritzinger et al. 2018, 1016). But “there is currently no common understanding of the term Digital Twin” (van der Valk et al. 2020, 2) and the understanding of DT has changed over time and vary depending on the application context (Boss et al. 2020).

To better understand the current use of this concept in the offshore O&G industry, a survey has been conducted. The survey was organized as a web-based questionnaire. Invitations to the survey was submitted to 69 practitioners from operator companies and service provides invited to a webinar on the current status and challenges related to the use of DT in the Norwegian O&G industry. 15 responses to the questionnaire was included in the final sample. Because the survey is based on a convenience sample (Bryman 2016) and have a low number of responses the results cannot be used to draw conclusions on the current state of DT for maintenance and safety in the offshore O&G industry in general. But the results still offer some insights that can be useful for further research.

The next section of this paper gives a presentation of the current challenges related to digitalization of the O&G industry and presents the DT concept. The method used in the survey is described in Section 3. Section 4 presents the results. The paper ends with a discussion in Section 5 and conclusions in Section 6.

## 2. Background

### 2.1. *Digitalization of the Oil and Gas Industry*

One of the barriers to realizing the potential of digitalization in the O&G industry is the use of proprietary software solutions and lack of standardization which have led to data silos (Zborowski 2018; ISO 2019; Devold, Graven, and Halvorsrød 2017; KonKraft 2018). Because of this, manual work is needed to collect, convert, transfer, and validate the available data before it can be analyzed. The problem of data siloes has also been recognized in other industry sectors (Tao, Cheng, et al. 2018; Grieves and Vickers 2017; van der Valk et al. 2020; Hoffmann et al. 2021).

DTs are presented as an approach to reduce the data silo problem (Malakuti et al. 2020; Schulte, Lheureux, and

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Velosa 2018; van der Valk et al. 2020; Tao, Cheng, et al. 2018). But how to design digital twins to best address this problem is a challenge that remains to be solved (Hoffmann et al. 2021; Tao, Zhang, et al. 2018). One of the challenges with the DT concept is the lack of a generally accepted definition (Uhlenkamp et al. 2019; van der Valk et al. 2020). This is in parts because the understanding of DT has evolved over time and vary between application areas (Boss et al. 2020).

According to Grieves and Vickers (2017) the basic concepts of DT have however been stable over time. The first of these is the idea of the DT as a virtual model of a physical asset that is an entity of its own (Sharma et al. 2018; Zborowski 2018). Another is that these two entities, the physical asset and its digital twin, are linked through the different life cycle phases of the asset (Grieves and Vickers 2017; Tao, Cheng, et al. 2018; Liu et al. 2021).

A key aspect of the DT is to establish a digital model that represents one universally accepted version of the truth that the different stakeholders can use to get the information they need of the physical object (Malakuti et al. 2020). The advantages of this is mainly twofold. Firstly, having the information on the physical object readily available in a digital format makes collecting the information much easier and faster (Schuh et al. 2020). The cost of collecting the information will also be reduced because redundant and overlapping work related to collecting and transferring data from the source is eliminated (Malakuti et al. 2020; Schulte, Lheureux, and Velosa 2018). The other main advantage is that it facilitates sharing of data between the different lifecycle phases of the asset, both backwards (e.g. sensor data from use phase as feedback to improve design), and forwards (e.g. simulation models developed in the design phase as decision support tools in the use-phase) (Wuest, Hribernik, and Thoben 2015; Tao, Cheng, et al. 2018).

One of the areas of controversy related to DT is the need for accuracy in the digital models (Liu et al. 2021; van der Valk et al. 2020). Academics, especially those related to aerospace and aviation (West and Blackburn 2018; Glaessgen and Stargel 2012) but also manufacturing (Tao, Cheng, et al. 2018), have focused on the modelling aspect of DT, and the need for ultra-high fidelity models in order to make accurate simulations of the physical entities. Industry practitioners like the Industrial Internet Consortium (IIC) (Malakuti et al. 2020), and some academics (Grieves and Vickers 2017) are focusing more on aspects related to data handling.

### 2.2. *Previous Surveys on the Digitalization of the Oil and Gas Industry.*

Previous surveys on the use of DTs in the O&G industry have not been found in the literature. But some surveys related to digitalization of this industry have been found and is presented in this subsection.

In a survey of 13 Norwegian supplies to the O&G industry Mogos, Eleftheriadis, and Myklebust (2019) found that the industry view digitalization as important to cut costs and increase efficiency in order to stay competitive. But they also found that a high proportion of the respondents reported to have little knowledge of concepts such as IoT, Industry 4.0 and CPS. When asked to rate important barrier for the implementation of digital strategies, categories related to knowledge and skills was most frequently chosen by the respondents.

Another source of information on the current use of digital solutions in the O&G industry is the annual survey of the global O&G industry conducted by DNV-GL. These surveys also report that the industry perceives digitalization as important to cut cost and increase production (DNV-GL 2019). In the most recent survey DNV-GL (2020b) reports that there is an increasing attention in the industry to secure that the collected data is available and have the right quality for analysis.

Øien, Hauge, and Grøtan (2020) have conducted a survey of six O&G operators on the Norwegian Continental Shelf (NCS). The focus of this survey was on the use of digital solutions for barrier management and potential vulnerabilities that can be introduced with digitalization.

Øien, Hauge, and Grøtan (2020) found that most of the operators use barrier panels to visualize the status of the safety barriers on the offshore O&G platforms. The barrier status is mainly based on manually collected data such as workorders and reports from the incident management systems. All the companies had examples of safety critical equipment subject to condition monitoring, but none of the operators had automatic updating of the barrier panels based on condition monitoring alarms. Several of the operators reported plans for implementing predictive maintenance (PdM), but few had implemented this maintenance concept. Most operators believe that vulnerabilities will arise from new digital solutions. But the operators do not regard digital security as a major concern when it comes to barrier management because of the limited interconnects between the barrier panels and physical objects (Øien, Hauge, and Grøtan 2020).

### 2.3. *The Application of Digital Twins*

In this paper we focus on the application of DT related to maintenance and safety.

Maintenance is the application of DT that has received the most attention in the academic literature (Liu et al. 2021). Potential benefits from introducing DT is the ability of combining data from several sources and use this to introduce predictive and prescriptive maintenance policies (Errandonea, Beltrán, and Arrizabalaga 2020). Another application is the use of high fidelity simulations to make synthetic failure data that that can be used to train algorithms for anomality detection and prediction of remaining useful life of equipment (Rao 2020). See Errandonea, Beltrán, and Arrizabalaga (2020) for a literature review on the use of DT for maintenance.

The use of DT for safety is much less prominent in the literature. But Grieves and Vickers (2017) states that the purpose of DT is to mitigate or eliminate unpredicted undesirable behavior from complex systems. They use the Deepwater Horizon disaster (BP 2010) as an example where better situational awareness and predictive capabilities offered by the DT could have helped alerted the operator of the potential consequences of their decisions and by that avoid the accident (Grieves and Vickers 2017).

### 2.4. *Frameworks for Classification of Digital Twins*

Several authors have proposed different frameworks for classifying DTs. One of these are Kritzinger et al. (2018) which defines three categories of DTs based on the level of integration between the digital and physical entities. Digital models are systems which only have manual data flow between the physical and digital object. Systems with automatic data flow from physical to digital object are labeled digital shadows. Systems with automatic dataflow in both directions are labeled digital twins.

DNV-GL (2020a) divide DTs into six stages based on capability: standalone, descriptive, diagnostic, predictive, prescriptive and autonomy. The first and last of these corresponds to the digital model and twin as defined by Kritzinger et al. (2018). DNV-GL (2020a) also categorizes the confidence levels that is needed of the output from the DTs. The required confidence level is calculated as the product of capability and potential consequences. DTs with high capability and high consequence have the highest requirements for confidence. DNV-GL (2020a) also offers procedures for assuring that the required confidence level of the DTs is met.

### 2.5. *Research Questions*

DT has become a popular concept but lacks a universally accepted definition. There is also a lack of agreement on how to create and deploy DTs (Liu et al. 2021).

Based on the literature review, we have formulated the following research questions:

- What do the practitioners in the offshore O&G industry perceive as the most important barriers and triggers for implementing DT?
- What are the potential benefits of DT, and is the offshore O&G industry able to realize these benefits?
- What are the capability levels of DTs used by the offshore O&G industry?
- What is the understanding of DT among the practitioners in the offshore O&G industry compared to the academic literature?

## 3. Research Method

### 3.1. *Sampling*

Responses to the questionnaire was collected from industry practitioners that was invited to a seminar on the use of DT for maintenance, safety, and control in the offshore O&G industry. The seminar was organized in November 2020 by SUBPRO (2021), a research project focusing on technology innovation for subsea production and processing, and BRU21 (2021), a research project focusing on the digitalization of the O&G industry. Both research projects are collaborations between the Norwegian University of Science and Technology (NTNU) and operators and service providers connected to the NCS. Because a convenience sample was used in the survey the results cannot be assumed to be generalizable to the offshore O&G industry in general (Bryman 2016).

The survey was organized as an anonymous web-based questionnaire using the service Nettskjema (2021). Invitations to the questionnaire was sent out by email to all the 69 participants from the industry, two days before the seminar. During the seminar a short presentation of the survey was given to all participants followed by a short break to complete the survey. No responses were collected after the seminar.

Table 1. Demographics of the final sample ($n$ = 15).

| | $n$ | % |
|---|---|---|
| **Primary industry** | | |
| Supplier / service provider | 8 | 53% |
| Operator company | 7 | 47% |
| **Primary role** | | |
| Engineering | 4 | 27 % |
| R&D | 3 | 20 % |
| General management | 2 | 13 % |
| IT | 2 | 13 % |
| Operations | 2 | 13 % |
| Risk management | 1 | 7 % |
| Sales | 1 | 7 % |
| **Digital maturity compared to peer** | | |
| Leading | 7 | 47 % |
| Average | 6 | 40 % |
| Lagging | 1 | 7 % |
| Don't want to disclose / Not relevant | 1 | 7 % |
| **Ability to profit from digitalization** | | |
| Leading | 4 | 27 % |
| Average | 5 | 33 % |
| Lagging | 2 | 13 % |
| Don't want to disclose / Not relevant | 1 | 7 % |
| Don't know | 3 | 20 % |

Of the 16 respondents that completed the survey, one respondent reported the education sector as primary industry and was removed from the final sample. This gives a final sample rate of 22%. The demographics of the final sample is presented in Table 1.

When asked to rate the digital maturity of their organization, about half of the respondents (47%) assessed their organization as being leading compared to their peers. In comparison only 21% reported to be “industry leaders in digitalization” in a survey by DNV-GL (2019, 26) of the global O&G industry, indicating that the sample in our survey probably are more digital mature than the average O&G company. This is not surprising given that the selected sample for the survey, participants to a seminar on DT.

### 3.2. *Survey Design*

Because of the immaturity of the DT concept an exploratory design has been chosen for the survey (Forza 2002). Previous measurement instruments for implementation of DT for maintenance and safety was not identified in the literature, so the questions for the survey was constructed based on previous surveys on use of PdM (Haarman et al. 2018), Industry 4.0 (Staufen 2019; Mogos, Eleftheriadis, and Myklebust 2019) and digital transformations (Kane et al. 2016).

One challenge when designing this survey is the lack of a commonly accepted understanding of the concept DT. In the introduction to the survey the term digital twin was defined as “a digital representation of a real-world entity or system”.

## 4. Results

The results of the survey are presented in a series of frequency tables in this section.

### 4.1 *General Questions Related to the use of Digital Twins in the Oil and Gas Industry*

All respondents were asked about their perception on the barriers and benefits of DT to the O&G industry in general. The answers in Table 2 through 4 are sorted based on frequency.

Table 2. Answers to the question: “What do you consider to be the most important benefit of using digital twins in the oil and gas industry in general?” ($n = 15$).

| The most important benefit | *n* | % |
|---|---|---|
| More effective operations | 7 | 47 % |
| Cost reduction | 3 | 20 % |
| Reduction of safety, health, environment & quality risks | 3 | 20 % |
| Improved business decision making | 1 | 7 % |
| Lifetime extension of aging asset | 1 | 7 % |
| Improved energy efficiency | 0 | 0 % |
| Better product design | 0 | 0 % |
| New revenue streams | 0 | 0 % |

The results in Table 2 are in line with the survey by Mogos, Eleftheriadis, and Myklebust (2019) on the motivation for implementing I4.0 in the O&G industry. But in contrast to the same survey few of the respondents reported skills and knowledge as the main barrier (Table 3).

When it comes to the most important trigger for the implementation of DT, 67% of the respondents regarded commercial factors, exemplified by higher demands for effectiveness and efficiency, as being the most important. Only 27% considered the technological development to be the most important trigger. This is in line with observations from the literature survey that the O&G industry regards digitalization as an important contributor to cut costs and increase effectiveness (DNV-GL 2020b).

Table 3. Answers to the question: “What do you consider to be the most important barrier to the use of digital twins in the oil and gas industry in general?” ($n = 15$).

| The most important barrier | *n* | % |
|---|---|---|
| Lack of data / systems integration | 5 | 33 % |
| Lack of business case | 3 | 20 % |
| Lack of organizational agility | 2 | 13 % |
| Lack of management understanding / commitment | 2 | 13 % |
| Too many competing priorities | 1 | 7 % |
| Insufficient technical skills | 1 | 7 % |
| Don’t know | 1 | 7 % |
| Security concerns | 0 | 0 % |
| None / no barriers exist | 0 | 0 % |

Table 4. Answers to the question: “Which of the following benefits has your organization or customers already achieved by using digital twin(s)?” (N/R = not relevant, $n = 9$).

| Benefits achieved | Yes | No | Don't know | N/R |
|---|---|---|---|---|
| Cost reduction. | 100 % | 0 % | 0 % | 0 % |
| Reduction of safety, health, environment & quality risks. | 78 % | 0 % | 22 % | 0 % |
| More effective operations. | 78 % | 0 % | 22 % | 0 % |
| Improved business decision making. | 67 % | 11 % | 11 % | 11 % |
| Improved energy efficiency. | 56 % | 0 % | 22 % | 22 % |
| Better product design. | 44 % | 22 % | 33 % | 0 % |
| Lifetime extension of aging asset. | 44 % | 11 % | 22 % | 22 % |
| New revenue streams. | 33 % | 11 % | 33 % | 22 % |

Table 5. Answers to the question: “Which of the following types of models are used in the digital twin(s) in your organization or in your products/services?” ($n = 9$).

| Types of models used | Yes | No | Don't know |
|---|---|---|---|
| White box (first principle / physics-based) | 78 % | 0 % | 22 % |
| Grey box (statistical / stochastic modelling) | 33 % | 22 % | 44 % |
| Black-box (machine learning, neural networks etc.) | 56 % | 11 % | 33 % |

Table 6. Answers to the question: "What of the elements are currently part of the digital twin(s) used in your organization or in your products/services?" ($n$ = 9).

| Elements in digital twin | Yes | No | Don't know |
|---|---|---|---|
| 3D representation of equipment / installations / plants. | 89 % | 11 % | 0 % |
| Real-time visualization of process/production status. | 89 % | 0 % | 11 % |
| Real-time visualization of equipment status. | 78 % | 0 % | 22 % |
| Real-time visualization of safety barriers. | 33 % | 0 % | 67 % |
| Simulations used for employee training. | 67 % | 11 % | 22 % |
| Simulations used for planning or production optimization. | 78 % | 0 % | 22 % |
| Models that monitor the current health of equipment or processes. | 100 % | 0 % | 0 % |
| Models that can identify cause-and-effect relationships between different process steps and/or equipment by combining data from different sources. | 44 % | 22 % | 33 % |
| Models that make predictions on future states of equipment or processes. | 78 % | 0 % | 22 % |
| Self-learning models (i.e. models that adapt as new data emerges). | 44 % | 33 % | 22 % |
| Automated decisions making related to process control. | 44 % | 11 % | 44 % |
| Automated decisions making related to maintenance. | 11 % | 33 % | 56 % |
| Automated decisions making related to safety. | 0 % | 33 % | 67 % |

Table 7. Answers to the question: "To what extent to do you agree with the following statements related to the use of digital twins in your organization" ($n$ = 15).

| Statements | Strongly agree | Agree | Neither agree nor disagree | Disagree | Strongly disagree | Don't know / Not Relevant |
|---|---|---|---|---|---|---|
| Digital twins are trusted when it comes to safety critical decisions. | 0 % | 20 % | 33 % | 33 % | 0 % | 13 % |
| Operators should only use solutions that are provided from one vendor in their digital twin. | 0 % | 7 % | 7 % | 33 % | 47 % | 7 % |
| Determining the source of inconsistencies between model and measurements is a major challenge in digital twins. | 13 % | 53 % | 27 % | 7 % | 0 % | 0 % |
| Reasonable estimations are normally sufficient to benefit from the use of digital twins. | 0 % | 60 % | 20 % | 13 % | 0 % | 7 % |
| A digital model is only a proper digital twin if there is automated dataflow in both direction between the two entities (i.e. the model can control the physical object). | 0 % | 7 % | 20 % | 53 % | 20 % | 0 % |
| Operators should combine elements from the suppliers that are best in their niche when organizing the digital twin for their assets. | 27 % | 33 % | 27 % | 7 % | 0 % | 7 % |
| Ultra-high fidelity models are needed in order to give sufficient level of accuracy in digital twins. | 0 % | 20 % | 40 % | 13 % | 13 % | 13 % |

### 4.2. *Company Specific Questions Related to the use of Digital Twins*

Nine of the respondents reported to have implemented DT in their own organization or products/services. Only one respondent considered the implementation of DT not relevant and reported no plans for implementing this in the future. Table 4 shows that the companies that have implemented DT report benefits over a wide range of areas. Table 5 shows that physics-based models are the modelling approach that is most widely used.

As can be seen from Table 6, several of the companies have a level of integration that corresponds to digital shadow as defined by Kritzinger et al. (2018). Only one respondent (11%) confirmed to have automated feedback from the digital model to the physical asset for maintenance and none when it comes to safety.

Another observation from Table 6 is that the capability level, as defined by DNV-GL (2020a) is higher for maintenance compared to safety. 78% reported predictive capabilities related to equipment status. On the other hand, only one third (33%) of the respondents reported that the DT have descriptive capabilities when it comes to safety.

### 4.3. *Statements Related to Digital Twins*

When it comes to the level of detail that is needed for the DT only 20% agreed that ultra-high fidelity models are needed, while 60% expressed that reasonable estimates normally are sufficient (Table 7). Only one respondent (7%) agreed that there must be automatic dataflow in both directions for a system to be labeled as a digital twin. Regarding implementation of DT more than half the respondents agreed that the operators should combine elements from several providers, while only one respondent disagreed to this statement.

## 5. Discussion

Several of the results in this survey are in line with previous surveys and literature on digitalization of the O&G industry. Commercial factors was reported to be the most important trigger for the implementation of DT and more effective operations and cost reductions was reported as the most importation benefits.

Among surprising results are the level of maturity when it comes to the use of DT compared to previous surveys on digitalization of the Norwegian O&G industry. Few respondents reported lack of technical skills and management commitment or understanding as the main barrier to DT implementation. This is in contrast to the survey conducted by Mogos, Eleftheriadis, and Myklebust (2019) in 2017 where lack of knowledge and skills was reported as important barriers by a majority of the respondents. Equally surprising is the high capability level of DTs related to maintenance that was found in our survey. While few of the operators was found to have implemented PdM in the survey by Øien, Hauge, and Grøtan (2020) conducted in 2019, about half (47%) of the total population in our survey reported to have implemented DTs with predictive capabilities for maintenance in their organization of products/services.

Both these results indicate that there has been a rapid development in the digital maturity of the O&G companies in the recent years. But this can also be a result of bias in our sample towards more digitally mature companies as indicated in Section 3.

This survey also provides some general insights on how to create and deploy DTs. The respondents report that the implemented DTs have contributed to improvements over a wide range of areas, but their understanding of this concept differs somewhat from the main tendencies in the literature. The first of these differences is related to the level of fidelity needed of the digital models. A majority of the respondents prefer reasonable accurate models over high-fidelity models. In comparison only 22% of papers in a literature review by van der Valk et al. (2020) refers to DTs as partial representations of their physical counterparts. Another area where the respondents in our survey disagree with the majority of publications is regarding the level of integration that is needed between the digital and physical counterparts (van der Valk et al. 2020). Only one respondent agree with the classification by Kritzinger et al. (2018) that require that there is automatic data flow in both directions between digital and physical entities in digital twins.

One possible explanation for this deviation from existing literature is that the need of DTs differs between application areas. Maintenance is one of the most human centric process within manufacturing (Brundage et al. 2019), and human judgement and knowhow is normally applied in addition to input from digital models (Bokrantz et al. 2020) when making maintenance decisions.

The need for fidelity in the digital models and the need for integration in order to profit from the use of DT for maintenance and safety may because of this be lower compared to other areas such as process optimization where existing models are more complex and decision cycles are faster.

This survey also shed some light on how to deploy DTs. A majority of the respondents preferred “best of breed” solutions over solutions from only one provider. This, together with the preference of reasonable accurate models, indicate that a gradual implementation strategy for DT that start with a minimum viable product and then improves from this can be a suitable option for the O&G industry. This is in line with recommendations for how to implement DT from the IIC (Malakuti et al. 2020) and the advisory firm Gartner (Schulte, Lheureux, and Velosa 2018).

## 5. Conclusion

In this study we have conducted an exploratory survey on the perception and use of DT among industry practitioners related to the Norwegian O&G industry. The contributions from this study can be divided into two parts.

The first is related to the development in the digital maturity of the Norwegian O&G industry. The respondents report that benefits from use of DTs has been achieved across several areas, and few of the respondents consider lack of skills or knowledge as the most important barrier to the implementation of this concept. This indicates that the Norwegian O&G industry has reached a level of digital maturity where it can utilize concepts such as DT to realize real business value.

The other contribution is to shed light on the preferences for design and implementation of DTs for maintenance and safety in the O&G industry. The respondents report that benefit from DTs have been achieved over a wide range of areas even if they prefer simple models over high-fidelity models and lower level of integration between digital and physical entities than normally described in the literature.

There are several limitations to this study in addition to the ones already mentioned. One of them is that several of the questions have a high ratio of respondents that have chosen “don’t know”. A possible explanation for this is lack of clarity in the questionnaire. Closer examination of the data show that the background of the respondents that have chosen “don’t know” changes with the different questions. The number of samples are however too small to conduct quantitative analyses of differences based on the respondents’ backgrounds.

Another limitation is that the size of the benefits from implementing DT have not been estimated, and we do not know if the reported results are achieved through small scale pilots or full-scale implementations. We also do not know if the respondents from the suppliers are referring to benefits achieved in their own organizations or by their customers.

Further research should continue to investigate the use of DT, the potential benefits associated with this concept and different perceptions among suppliers and operators in the O&G industry.

Our survey indicates that the use of DTs offers real business value for the O&G industry. An interesting topic for further research is to investigate more in detail the magnitude of these benefits and how these has been achieved, either through interviews or case studies. Such a study could also investigate if and how the introduction of DTs affects the relationship between operators, suppliers and, third party service providers.

Because of the low number of respondents in our survey, quantitative analysis to identify correlations between the achieved results and the methods and capability level of the implemented DTs was not possible to conduct. A new survey with a sample size large enough to allow for such an analysis might provide valuable information on how to best implement DT.

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# Article IV

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# FRAMEWORK FOR THE IMPLEMENTATION OF SMART MAINTENANCE

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Recent developments in sensor technology and systems for connecting digital and physical systems, often associated with the terms Industry 4.0 and cyber-physical systems, are expected to bring substantial changes to how maintenance and asset management will be conducted in the coming years. Most of the research related to Industry 4.0 and maintenance have focused on technical aspects, and less attention has been given to how to organize and manage maintenance in order to take advantage of the new possibilities offered by the fourth industrial revolution. While many claims have been made about the potential improvements related to maintenance that can be achieved from implementing Industry 4.0, empirical studies suggest that industry practitioners are struggling to realize these improvements. There are also signs that there exists overall a poor understanding of how to implement Industry 4.0. The contribution of this paper is to address these socio-technical challenges with a multidisciplinary framework for the implementation of Smart Maintenance. The framework is divided into three levels: strategic, tactical, and operational, and is influenced by lean production, systems engineering and maintenance management.

*Keywords*: Industry 4.0, Predictive Maintenance (PdM), Plan-Do-Study-Act (PDSA), systems engineering, SPADE, Smart Maintenance, cyber-physical systems (CPS), Prognostics and Health Management (PHM), maintenance management, Lean Production (LP), Hoshin Kanri (HK).

## 1. Introduction

The notion of a fourth industrial revolution instigated by the introduction of internet technology into the manufacturing industry has been popularized under the term Industry 4.0 (I4.0) (Schneider 2018). The introduction of I4.0 is believed to have the potential for large improvements across industry sectors and business functions, including maintenance and asset management (Zio 2016).

Several manufacturing companies have started or are planning to implement I4.0 (Staufen 2019), but according to Oztemel and Gursev (2020, 166) “there is still a high uncertainty and fuzzy understanding among the manufacturers with respect to the way to implement Industry 4.0 philosophy”. They further claim that “it is now main responsibility of the research community to develop technological infrastructure with physical systems, management models, business models as well as some well-defined Industry 4.0 scenarios in order to make the life for the practitioners easy” (Oztemel and Gursev 2020, 127).

The increase in complexity and interconnectivity associated with the introduction of I4.0, has elevated the importance of maintenance and Smart Maintenance has been defined as “the enabler of Industry 4.0” (DIN/DKE 2018, 59). Predictive maintenance (PdM) based on online condition monitoring is often the first specific application of I4.0 mentioned (Bokrantz et al. 2020; Staufen 2019). But empirical studies suggest that industry are struggling with the implementation of data-driven PdM (Golightly, Kefalidou, and Sharples 2018; Veldman, Klingenberg, and Wortmann 2011; Van De Kerkhof, Akkermans, and Noorderhaven 2015).

This paper will address these socio-technical challenges by offering a framework for the implementation of concepts related to I4.0 in maintenance in the manufacturing industry. Because integration and interconnectedness of IT-systems, processes and people are central aspects of I4.0 (Schuh et al. 2017), approaches to utilize the potential of this concept will require an interdisciplinary and holistic approach. Systems engineering methods have proven useful in managing this type of complexity (Kossiakoff et al. 2011). Based on recent empirical studies that suggest that there are complementary effects between Lean Production (LP) and I4.0, the suggested framework also uses principles from LP.

The next section presents a brief literature review of I4.0 and Smart Maintenance. A framework for the implementation of Smart Maintenance in an I4.0 context is proposed in Section 3. The paper ends with a discussion in Section 4 and conclusions in Section 5.

## 2. Literature Review

### 2.1. *Industry 4.0 - overview*

The term Industry 4.0 or “Industrie 4.0” was first coined by a working group sponsored by the German government with the aim of strengthening the competitive position of the German manufacturing industry. According to Kagermann et al. (2013) a fourth industrial revolution is inevitable as a result of the introduction of Internet of Things and Internet of Services into the manufacturing sector.

As noted by Drath and Horch (2014), I4.0 is the first industrial revolution to be announced before it happens. The research on I4.0 has so far mostly been conceptual (Buer 2020) and there is still no commonly accepted definition of I4.0 (Oztemel and Gursev 2020).

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Previous concepts for the digitalization of manufacturing, like Computer Integrated Manufacturing (CIM) had a vision of complete automation without human intervention (Schneider 2018; Schmidt et al. 2020). In Kagermann et al. (2013) there are several references to the need for considering the socio-technological aspect in order to take full advantage of I4.0, but this appears to have been overlooked in much of the following literature (Davies, Coole, and Smith 2017).

The understanding of I4.0 that will be used in the remainder of this text is based on a report by the German research organization Acatech. Acatech defines I4.0 as "real-time, high data volume, multilateral communication and interconnectedness between cyber-physical systems and people" (Schuh et al. 2017, 11). This definition clearly places I4.0 in the category of socio-technical challenges.

### 2.2. *Industry 4.0 and lean production*

Lean production (LP) has for several decades been the most prominent concept for performance improvement in the manufacturing industry (MacKelprang and Nair 2010). There are however several examples of LP implementation projects that have failed to improve performance (Bortolotti, Boscari, and Danese 2015), and Schuh et al. (2017) suggest that experience from LP implementation holds valuable lesson for how to succeed with the implementation of I4.0. According to lean literature these failures are often caused by insufficient attention to organizational culture and too much focus on hard lean practices (tools and techniques) (Liker 2004; Rother 2010). In a survey on organizational culture and lean implementation Bortolotti, Boscari, and Danese (2015) found that plants that succeed are characterized by an organizational culture that focus on high institutional collectivism, future orientation, and humane orientation alongside the lean soft practices: problem solving, employee training, supplier partnership, customer involvement and continuous improvement.

There are still disagreements among academics and practitioners of what comprises LP (MacKelprang and Nair 2010). In this paper LP is understood in line with Shah and Ward (2007, 791) as an "integrated socio-technical system whose main objective is to eliminate waste by concurrently reducing or minimizing supplier, customer, and internal variability."

The notion that LP and I4.0 complement each other is popular among industry practitioners (Staufen 2015) and academics (Buer, Strandhagen, and Chan 2018), and the connection between these two concepts is a topic that has received increasing attention in operations research literature in the last 5 years (Ciano et al. 2021).

Surveys of European (Rossini et al. 2019) and Brazilian manufacturers (Tortorella and Fettermann 2018) has shown that there is a significant association between implementation of I4.0 technologies and LP practices among high performing companies.

In a survey of Indian manufacturing companies Kamble, Gunasekaran, and Dhone (2020) found a significant positive effect from implementation of I4.0 on performance, but when controlling for implementation of LP the effect became negative and insignificant. In contrast to this Buer et al. (2020), in a survey of Norwegian companies, found that companies that have implemented both I4.0 and LP performed better than can be explained by their individual effects.

Common to all these studies is that the relationship between I4.0 and LP has been studied on a high level. There is a need for further research on the relationships between the specific elements of I4.0 and LP to increase the understanding of how to succeed with implementation of both I4.0 and LP (Rossini et al. 2019; Ciano et al. 2021).

Empirical studies that investigate the effect of I4.0 and lean principles on maintenance have not been found in the literature, but in a conceptual paper by Sanders et al. (2017) Total Productive Maintenance (TPM) is postulated to be the LP tool that will benefit the most from I4.0 technology, while LP principles such as standardization, quick changeover and value-stream mapping are presented as LP tools that can support the implementation of I4.0.

### 2.3. *Industry 4.0 and maintenance*

There is an abundance of reports and white papers from consultancy and software companies related to the potential benefits to maintenance by implementing I4.0. One example is a report from McKinsey where it is estimated that a 10 – 40 % reduction in maintenance cost can be achieved from fitting products with sensors that monitor both condition and usage (Manyika et al. 2011). In another report from the same company it is claimed that "typically, predictive maintenance decreases the total machine downtime by 30 to 50 percent and increases machine life by 20 to 40 percent" (Baarup et al. 2015, 24). Similar statements of the potential improvements have been presented in reports by the consultancy firms Accenture (Spelman et al. 2017) and PwC together with Mainnovation (Haarman et al. 2018). However, all these reports offer few details on how the potential benefits are achieved.

Other sources paint a more moderate picture. One example of this is the software company Arundo that claims that "true predictive maintenance is not immediately applicable for most equipment, due to the paucity of relevant data" (Dobson and Misra 2019, 8). Another example is the consultancy firm Staufen that based on a survey of 450 German companies states that the "added value of predictive maintenance is likely to be far lower than is often claimed" (Staufen 2018, 35).

The potential for improvement by implementing data-driven PdM and related maintenance concepts are also presented in the academic literature, with claims of the potential to reduce maintenance costs, improve availability, reduce risk and provide valuable information to the design process of new equipment (Zonta et al. 2020; Porter and Heppelmann 2014; Lee et al. 2014; Sun et al. 2012). But the focus in the academic literature on maintenance optimization is mainly on developing new models with few examples of the use of data-driven PdM available in the literature (de Jonge and Scarf 2020). There are empirical studies that suggest that it is hard to succeed with the implementation of data-driven PdM in practice. In a multiple case study of Dutch process industry Veldman, Wortmann, and Klingenberg (2011, 49) found that "all the firms claimed to be struggling with prognostic condition-based maintenance tasks." In a later case study of Dutch process industry Van De Kerkhof, Akkermans, and Noorderhaven (2015, 236) found that "many firms in the process industry struggle with systematically employing CBM activities in general and prognostic CBM approaches in particular." Based on a series of interviews of maintenance experts from UK industry, Golightly, Kefalidou, and Sharples (2018, 640) found that implementing "full, predictive maintenance solutions were extremely challenging."

### 2.4. *Smart Maintenance*

Several terms are being used in the academic literature for describing maintenance concepts that can exploit the possibilities offered by the fourth industrial revolution (Bokrantz et al. 2020). Examples are Maintenance 4.0 (Jasiulewicz-Kaczmarek and Gola 2019), Prognostic and Health Management (PHM) (Sun et al. 2012), E-maintenance (Márquez and Pham 2007), Predictive Maintenance (PdM) (Golightly, Kefalidou, and Sharples 2018), and Smart Maintenance (Akkermans et al. 2016).

In this paper we use the term Smart Maintenance because we believe that this term best describes the distinct characteristics of maintenance in an I4.0 context. Smart Maintenance is defined by Bokrantz et al. (2020, 11) as "an organizational design for managing maintenance of manufacturing plants in environments with pervasive digital technologies." Based on interviews with 110 industry experts Bokrantz et al. (2020) analyzed the elements that constitute Smart Maintenance. These have been grouped into the four categories: data-driven decision-making, human capital resource, internal integration, and external integration (Bokrantz et al. 2020).

According to Golightly, Kefalidou, and Sharples (2018), one important contribution to the complexity of data-driven maintenance is that knowledge and competence are needed on a wide range of topics: the equipment that is monitored; the sensor technology to collect the data; the ICT-system to log and transmit the data; methods to analyze the data and make predictions; understanding of the operational context; visualizations to present the information to the decision makers, and a thorough understanding of the actions the maintenance department can take based on this information. This diversity of elements makes collaboration within and across different organizations necessary.

Roda, Macchi, and Fumagalli (2018) conducted interviews with 20 maintenance experts from Italian companies and concluded that the most important barriers are lack of a culture for data-based decisions making, lack of cooperation internally and between organizations, and lack of skills in digital technology accentuated by the difficulty of calculating the payback of the digital transformation of maintenance.

## 3. The Proposed Framework

This section proposes a framework for the introduction of Smart Maintenance, based on the challenges identified in the literature review. The proposed framework is built using contributions from LP, systems engineering, and maintenance management, as illustrated in Figure 1.

In accordance with Tsang, Jardine, and Kolodny (1999) the framework has been split into three different levels: strategic, tactical, and operational. Strategic decisions are understood as long-term decisions, for instance the selection of the maintenance management system. The tactical level is related to the use of available resources to realize the strategy in an effective and efficient way. The operational level is concerned with the execution of the daily maintenance activities. The different stages of the framework are explained in the rest of this section.

### 3.1. *The overall layout*

The overall layout of the framework is inspired by a LP concept called *hoshin kanri* (HK) which is a tool for linking strategy with the operational level (Jolayemi 2008). HK is more participative than traditional western approaches for strategy deployment, which makes management more process minded and is considered more effective to manage change (Witcher and Butterworth 2001).

The use of HK in connection with I4.0 has previously been explored by Villalba-Diez et al. (2018) and Schmidt et al. (2020) but these studies are rather conceptual and do not mention maintenance. Empirical studies on use of HK in connection with I4.0 and maintenance has not been found in the literature, but there are compelling arguments that the HK process is well suited for implementation of Smart Maintenance.

The first of these arguments is the focus in HK of having a thorough process for establishing the values, mission, and vison of the organization in order to establish the direction for the organization (Jolayemi 2008). Golightly, Kefalidou, and Sharples (2018) have found that because of the large number of stakeholders and lengthy time frames involved, a clear strategy is vital to succeed in a project with the aim of implementing data-driven PdM.

The next aspect is the process of vertical and horizontal integration when deploying this strategy (Jolayemi 2008). The approach for achieving this integration in HK often is referred to as catchball, which refers to a game of throwing a ball back and forth between players. In a corporate environment it can be defined as a facts-based dialog, up, down, and horizontally in the organization to align objectives and iterate towards the vision (Jolayemi 2008). This fits well with the need for internal and external integration that are central aspects of Smart Maintenance (Bokrantz et al. 2020). The use of PDSA is important to structure the catchball process (Jolayemi 2008).

The influence of HK is illustration in Fig. 1 by having a strategy and operational process that are connected by a PDSA-loop at the tactical level. Between all three levels are arrows to illustrate the constant dialogue and feedback between the different levels (the catchball process). The processes at all levels are circular to illustrate the iterative nature of continuous improvement.

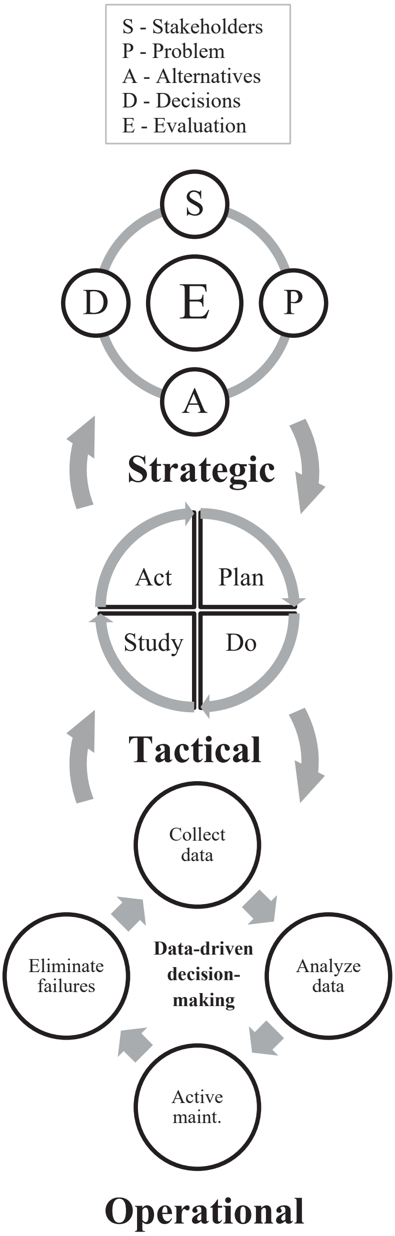


Fig 1. The proposed framework. The strategic level is based on the SPADE-model by Haskins (2008). The four phases at the operational level are inspired by Van De Kerkhof, Akkermans, and Noorderhaven (2015).

**3.2.** ***The Strategic level***

The basic idea of I4.0 is to improve performance by combining many elements onto one system by vertical, horizontal, and end-to-end integration (Kagermann et al. 2013). Systems engineering is a discipline that offers principles and practices for how to handle such complex systems (Kossiakoff et al. 2011). At the same time, the introduction of I4.0 will affect large parts of the organization, and the framework must be easy to communicate to people who are not familiar with I4.0 or systems engineering. The SPADE-framework developed by Haskins (2008) was created to support this kind of situation and embodies the essential aspects of systems engineering in a simple and jargon-free way.

**3.2.1.** ***Stakeholders***

Because of the importance of internal and external integration in Smart Maintenance (Bokrantz et al. 2020) it is essential to identify all the stakeholders involved. This is normally the starting point in the SPADE-model and involves finding all the relevant stakeholders, understanding their roles, and resolving conflicting interests among them (Haskins 2008).

**3.2.2.** ***Problem formulation***

The important factors in this part of the SPADE framework are (Haskins 2008):

- to understand the current situation and the problem that needs to be solved,
- to imagine possible alternative futures,
- to establish measures of effectiveness that solutions developed at later stages can be measured against.

For a maintenance strategy to be effective it must be consistent with the manufacturing and business strategy (Pintelon, Pinjala, and Vereecke 2006). It is also important to assess the maturity of the maintenance organization (Suzuki 1994) and the digital maturity of the organization as a whole (Schumacher, Schumacher, and Sihn 2020) to be able to later set realistic targets for its implementation. Finally, in the problem formulation one must develop measures of effectiveness (Sproles 2000). See Lundgren, Skoogh, and Bokrantz (2018) for a review of models for quantifying the effect of maintenance.

**3.2.3.** ***Alternatives***

There are several different alternative strategies available when implementing Smart Maintenance (Pedersen and Schjølberg 2020). The viewpoints collected during the problem formulation will be natural starting points for development of solutions to solve the problems (Haskins 2008).

**3.2.4.** ***Decision-making***

When making decisions about the strategy for implementing a new technology one needs to consider not only technological aspects but also commercial aspects and organizational culture (Phaal, Farrukh, and Probert 2004). Among the choices the organization must make is what capabilities to develop internally and what to outsource (Porter and Heppelmann 2014).

A specific example related to Smart Maintenance is the recent development in remote sensing technology which has opened new possibilities for servitization of physical assets (Grubic 2018). One potential benefit of servitization is better alignment of operators and manufacturers when both have an incentive to maximize availability (Grubic and Jennions 2018). But relying heavily on an external service provider will reduce the possibility to develop the maintenance capability as a source of competitive advantage (Pintelon, Pinjala, and Vereecke 2006).

#### 3.2.5. *Evaluation*

This is an activity that must be done continuously in order to secure that all relevant stakeholders are included; that the problem formulation is still relevant; and that feedback is used to make improvements (Haskins 2008).

### 3.3. *The Tactical level*

This level is related to the process of implementing the strategy. In other words, putting the strategy to work. According to a study by Kane et al. (2016) one of the main characteristics of the organizations that are successful in their digital transformation is a culture that emphasizes risk-taking and rapid experimentation. Based on this the Plan-Do-Study-Act cycle (PDSA), which is a tool for iterative improvement by testing ideas in practice (Hayes 2010), is chosen to illustrate the process at the tactical level.

#### 3.3.1. *Plan*

In order to implement new maintenance concepts in a controlled way they must be segmented into manageable parts. Waeyenbergh and Pintelon (2002) have developed a framework for developing and implementing maintenance concepts that are suited to the needs of the organization. Several authors have proposed to use financial measures, such as return on investments, when prioritizing and planning for the implementation of Smart Maintenance and related maintenance concepts (Zio 2016). Calculating the return from the implementation of Smart Maintenance can however be hard in practice (Roda, Macchi, and Fumagalli 2018). According to the experience of Waeyenbergh and Pintelon (2004), in a manufacturing environment normally it is sufficient to elicit the most important system from the operators and begin there to implement any new plan.

#### 3.3.2. *Do*

This is the point where the ideas and concepts from the strategic level meets the real world. Running pilots can be an effective way of testing out the new digital solutions and learn how to use them (Hayes 2010, 254). But it is important to keep in mind that a major part of the potential of I4.0 is the integration of data, processes and organizational infrastructure, and that certain benefits only can be achieved when implementation has reached a certain scale (Schuh et al. 2017; Schneider 2018).

#### 3.3.3. *Study*

Because activities normally do not go as planned it is important to study and compare the actual results against the expected results (Hayes 2010). This stage is often referred to as the check-stage, but Deming, who is one of the most important contributors to the development of the PDSA-cycle, has argued that study is a better word because it better indicates the importance of learning (Moen and Norman 2006) from the real-world feedback.

#### 3.3.4. *Act*

Based on the results and lessons learned, together with feedback from the strategic levels, actions are taken and adjustments are made. A new plan informed by the accumulated learning is developed, and the PDSA-cycle is restarted (Moen and Norman 2006).

### 3.4. *Operational level*

This is the level where the digital solutions are used to achieve improved maintenance performance. Maintenance decision have traditionally been dominated by experience and intuition (Van De Kerkhof, Akkermans, and Noorderhaven 2015). The aim of Smart Maintenance is to improve performance by data-driven decision-making. The process that is needed to achieve this is illustrated with a variant of the PDSA-cycle that is inspired by the steps for a successful CBM program defined by Van De Kerkhof, Akkermans, and Noorderhaven (2015).

#### 3.4.1. *Collect data*

Maintenance optimization models have been a popular topic for research for several decades (de Jonge and Scarf 2020), but lack of data has traditionally been a barrier for using these models in practice (Dekker and Scarf 1998; Bokrantz et al. 2020; Sikorska, Hodkiewicz, and Ma 2011). The increase in availability of data from recent technological developments offers the possibility to lower this barrier (Zio 2016).

#### 3.4.2. *Analyze data*

This step is about making assessments of equipment health and estimating remaining useful life based on the collected data. A large number of review papers for prognostics models for maintenance are available in the literature. See for instance Lee et al. (2014), Sikorska, Hodkiewicz, and Ma (2011), Si et al. (2011), Carvalho et al. (2019) or Zhang, Yang, and Wang (2019).

#### 3.4.3. *Active maintenance*

Data collection and analysis have value only to the extent that it contributes to better decisions (Bokrantz et al. 2020). These decisions have been split into two groups: decisions related to when and how to perform active maintenance and decisions related to improvements that eliminates the causes of failures.

#### 3.4.4. *Eliminate failures*

PdM will fail in an environment with too much variability (Suzuki 1994). It is important to continuously improve procedures and equipment design to reach sufficient level of stability (Van De Kerkhof, Akkermans, and Noorderhaven 2015).

## 4. Discussion

It is a widely held belief among both academics and industry practitioners that I4.0 and CPS have the potential to bring large changes to manufacturing environments and maintenance is one of the business functions that will be affected. But there is no consensus definition of what I4.0 entails or how to implement this concept. The large number of overlapping and sometimes poorly defined concepts for describing maintenance in a I4.0 context has contributed to the confusion.

The technological development and falling cost of sensors and systems for collecting and analyzing data have led to an increasing interest in CBM, and several claims have been made on the potential for improving maintenance by using condition monitoring data to estimate remaining useful life of assets. But empirical studies indicate that the manufacturing industry struggles with the implementation of data-driven PdM in practice.

The connection between LP and I4.0 has received much attention from the operations research community in the last 5 years. Several authors have proposed that LP forms an important foundation for succeeding with I4.0 and empirical evidence that support this has started to emerge. These studies have been done at a high level and the links between specific principles from LP and I4.0 and their effect on maintenance are still unclear. There are however compelling arguments that the introduction of lean principles such as standardization, focused improvement and empowerment can form a basis for successful implementation of I4.0.

We propose in this paper a framework for the implementation of Smart Maintenance to help alleviate the challenges related to the introduction of I4.0 and data-driven PdM identified in the literature study. The implementation of Smart Maintenance is a complicated set of activities and no model or framework can cover all aspects. Because of this there will be a need for different models and frameworks with different levels of abstraction to support this process (Rauzy and Haskins 2019). The framework in this paper has been developed with the aim of making a simple model that is well suited for facilitating communication among all the stakeholders and that provides a holistic overview for implementing Smart Maintenance. Because of this, the illustration in Fig. 1 has a high level of abstraction and the labels are purposely generic so it can fit a wide range of organizations with different levels of maturity when it comes I4.0 and maintenance management. There will be a need for several other models, frameworks, and tools for succeeding with the implementation of Smart Maintenance and some of these have been mentioned in Section 3.

## 5. Conclusion

As reported in this paper there are indications that industry is struggling with the implementation of I4.0 and data-driven predictive maintenance, and that there is a need for models and frameworks for alleviating this situation. The framework proposed in this paper, which combines the underlying principles of I4.0 with existing models and frameworks from systems engineering, maintenance management and lean production is intended to inspire other researchers and offer pragmatic assistance to industry practitioners.

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# Article V

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# Optimizing a condition-based maintenance policy by taking the preferences of a risk-averse decision maker into account

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A B S T R A C T

Reasonably accurate remaining-useful-life (RUL) predictions allow for the introduction of maintenance policies where resources, such as spare parts and personnel, are only acquired based on the predicted need. For some assets, such a policy will help reduce the cost of renewals but will also increase the probability of renewal cycles with long downtime and associated large losses. From a decision theoretical point of view decision makers are often risk-averse and therefore their financial risk tolerance should be considered. This paper presents a procedure based on expected utility theory for the optimization challenge. To calculate the expected utility the characteristic function is used to find the full probability mass function of the maintenance cost in a finite time interval. A numerical example and a case study, based on data from an offshore oil and gas platform, are presented to illustrate the proposed model. These examples show that using the long-run cost rate to optimize the presented maintenance policy may lead to decisions that are not in line with the preferences of a risk-averse decision maker.

## 1. Introduction

### 1.1. Background

Technological developments in the last few decades related to condition monitoring and systems for collecting, storing, and analyzing large amounts of data have the potential to considerably improve the maintenance of industrial assets [1–10]. Condition monitoring data can be used to discover degradation at an early stage, so that measures can be implemented to avoid the potential safety issues and production disturbances associated with unplanned corrective maintenance [11]. This information can also be used to reduce maintenance costs by helping maintenance organizations to focus their resources on the right equipment at the right time [12–16].

Examples of how predictions of remaining useful life (RUL) based on degradation models can be used to reduce maintenance costs are for instance provided in a number of studies on grouping of maintenance for multi-component systems with dependencies [17]. Examples of these studies are [18–22]. Other studies have combined degradation models with information on fluctuations in the cost related to maintenance over time to improve timing of active maintenance and by this reduce the overall costs. These temporal changes can be related to the direct cost of performing maintenance, for instance through changes in the price of spare parts [23] or related to unavailability losses. Unavailability loss caused by maintenance can be reduce by timing active maintenance with externally induce production stops [24] or periods when the production rate or marked prices are low [25].

The potential benefit of degradation models that is the focus of this paper is the use of RUL predictions to reduce the need for having a short maintenance time. In line with the European standard for maintenance terminology, maintenance time is in this paper understood as the combination of the time needed for active maintenance together with administrative, technical, and logistic delay [26]. Logistic delay is the time needed to mobilize the necessary resources, such as personnel and spare parts, to complete the active maintenance [26] and will for some assets constitute a large part of the total maintenance time. In a literature review on logistics and supply chain management for maintenance of offshore wind farms [27] presents several trade-offs between logistic delay and cost that managers must make on a strategic, tactical, and operational level. Examples are location of spare parts, e.g., central or distributed warehouses, or means of transport for maintenance personnel, e.g., boat or helicopter. In a study by [28] of maintenance in an electrical power company the cost of repair contracts fall exponentially as the specified response time is increased. In a review of benefits

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and challenges of prognostics for maintenance [16] presents several examples of how RUL predictions can be used to reduce costs, for example by purchasing spare parts "just-in-time" based on the RUL prediction. Comparted to a traditional spare parts policy of having spare parts in stock, such a spare parts policy will increase the time from maintenance decision is made to renewal can be completed.

The potential for using RUL predictions for cost reductions can be particularly large for assets in remote locations [15,29,30]. An example of this is offshore oil and gas production, where the costs of having personnel and spare parts readily available are high. Settemsdal [31] presents a case study of an oil and gas platform where remote condition monitoring and predictive maintenance were used to achieve cost reductions by reducing the level of personnel and spare parts offshore and at the same time achieve high availability. On the Norwegian continental shelf, unmanned production platforms are assumed to have the potential to achieve as much as 50% reduction in operating cost and 30% reduction in capital cost compared with traditional concepts [32]. An important contribution to this cost reduction is that unmanned platforms can be made much simpler. Unmanned oil and gas platforms are however rare on the Norwegian continental shelf. A challenge with such concepts is longer maintenance time, which may result in downtime losses that offset the savings [32]. In [33] unmanned platforms are grouped in five categories based on complexity. Different platform designs will affect not only the logistic delay for maintenance, but may also influence the technical delay, administrative delay, and active maintenance time. When developing the design and operating concept for such an oil and platform, several tradeoffs must be made between maintenance time and cost.

With a reasonable accurate RUL prediction, one can implement a maintenance policy with long logistic, administrative, and technical delay, while ensuring high availability. With improvements in technology for remote condition monitoring and degradation modeling, maintenance policies with longer maintenance time becomes more attractive for assets where the cost of performing maintenance can be reduce by increasing maintenance time. A disadvantage of a maintenance policy with a long maintenance time is that this increases the probability of renewal cycles with long downtime. Because of this, assuring the robustness of such a maintenance policy is important. Cherkaoui et al. [34] defines two types of robustness for maintenance policies. The first is related to imperfect modeling and parameter estimation of the degradation or failure and the extent to which miss-specification in these factors lead to higher maintenance cost. The second is related to the variability in cost from one renewal cycle to the next. The latter of these two is the focus of this study.

The variability of the cost is usually not considered when evaluating maintenance policies, and most of the existing literature on maintenance optimization uses the long-run cost rate as the objective function to minimize [23,34–36]. Because choosing the alternative with the lowest expected cost will minimize costs in the long run, this is the best course of action for a risk-neutral decision maker (DM) who can endure any losses [37]. However, most managers are not risk-neutral and even large corporations can be harmed by single events with major consequences [38]. Based on this, it may be beneficial to take the decision maker's risk tolerance into consideration when evaluating a maintenance policy where one trades a reduction in the expected cost with an increase in the variability of the costs between renewal cycles.

### 1.2. Objectives

The first objective of this paper is to propose a condition-based maintenance (CBM) policy with maintenance threshold ($M$) and maintenance time ($MT$) as the decision variables. The second objective is to present a procedure that takes into account the decision maker's financial risk tolerance when optimizing such a maintenance policy.

### 1.3. Contributions

The first contribution of this paper is the presentation of an approach to minimize the long-run cost rate, including downtime costs, of a CBM policy by optimizing the maintenance threshold ($M$) and maintenance time ($MT$). A CBM policy with maintenance time as one of the decision variables has, to the best of our knowledge, not previously been presented in the maintenance literature.

The second contribution of this paper is to demonstrate how such a CBM policy can be optimized based on the decision maker's financial risk tolerance using expected utility theory (EUT). To achieve this, we build on an approach previously offered by Cheng et al. [39] to find the full probability mass function of maintenance costs in finite time for a system that is subject to a stochastic degrading process. We expand on Cheng et al. [39] in three areas:

- Degradation process: While Cheng et al. [39] models the degradation as a gamma process, we propose a more general procedure that can handle non-monotonic degradation processes such as the Wiener process.
- Maintenance policy: Cheng et al. [39] present a CBM policy where the inspection interval is the decision variable to optimize and the costs of preventive and corrective maintenance are fixed. In our paper, we assume a CBM policy with online monitoring and maintenance threshold ($M$) and maintenance time ($MT$) as the decision variables. The cost of corrective maintenance is in our model not fixed but depends on the length of the downtime.
- Optimization criteria: While Cheng et al. [39] use value-at-risk (VaR) as optimization criteria, we use expected utility theory to find the maintenance policy that is best in line with the preferences of a risk-averse decision maker.

### 1.4. Limitations

Among the limitations of this paper are the following aspects:

- We have not collected empirical data on the risk tolerance related to maintenance decisions. In the case study, a simple utility function based on empirical studies of financial risk tolerance in the oil and gas industry [40,41] was used to demonstrate the proposed maintenance policy. Any use of expected utility theory must be based on the preferences of the relevant DM for that specific case [42].
- An important factor to consider when eliciting the decision maker's preferences is the existence of agency problems [43]. Agents, such as maintenance managers, may have incentives to be more, or less, risk-averse than the organization's principals, and because of this make choices that are not in line with the organization's overall objectives [38,40,41]. Such considerations are however not in the scope of this paper, and we have assumed that the DM represents the preferences of the relevant stakeholders.
- In this study, we have assumed that the maintenance time is deterministic. This is probably not the case in most actual situations and a more realistic model with stochastic maintenance time can be developed in further work.
- It is important to evaluate the prognostic accuracy when implementing a CBM policy that is optimized based on a degradation model [44]. This was however not the focus of this paper, and evaluation of model and parameter accuracy was not performed for the case study.
- A simple grid search was used to find the optimal thresholds for our decision variables. A more sophisticated optimization method would have improved the speed and accuracy of the proposed approach [45], but this was not the focus of this paper.

### 1.5. Organization

The remainder of this paper is organized as follows. In Section 2, we review some of the existing literature on approaches for taking the variability of the cost into account when evaluating maintenance policies. In Section 3, we present the maintained system and the proposed maintenance policy. Section 4 introduces a numerical example, followed by a case study based on data collected from two pumps operated at an offshore oil and gas platform in Section 5. A discussion and conclusions are presented in Sections 6 and 7. The notations used in this paper are listed in Table 1.

## 2. Alternatives to long-run cost rate as optimization criteria

The long-run cost rate is the most used criterion for optimization of CBM-policies [23,34–36]. One reason for this is that the long-run cost rate is relatively easy to calculate compared to the cost in finite time [46,47]. Use of the long-run cost rate is well suited for less expensive components and when the mean life is short compared to the planning horizon of the maintenance program [39]. One must also keep in mind that the solution that minimizes the expected cost will result in the lowest costs in the long run, given the ability to absorb any losses [38]. Because of this, it is reasonable to assume risk neutrality and use expected cost as optimization criteria when the stakes involved are small compared to the decision maker's total assets [48,49]. However, even for large corporations there will be some decisions where the potential consequences are so severe that minimization of expected cost is not desirable [41,50]. Empirical studies on attitudes towards risk normally finds that managers are risk-averse [40,51]. An effect of risk-averse behavior is the insurance industry [49,52]. Without risk aversion, the insurance industry would not be able to charge premiums that are greater than the expected costs from insurance claims, and thus would not be able to make a profit [48].

Most maintenance decisions will not have probable outcomes so severe that they can cause bankruptcy. Large fluctuations in costs may still be undesirable because they lead to inconveniences when preparing budgets [34] and can affect the organization's terms for external financing [53]. Large losses can also cause side effects such as loss of management focus and reduced reputation among suppliers and customers [43].

**Table 1**
Notation.

| | |
|---|---|
| $Y(t)$ | Degradation at time $t$. |
| $L$ | Defined failure threshold. |
| $M$ | Maintenance threshold, (threshold where mobilization for renewal is started). |
| $T_M, T_L$ | First hitting time (FHT) of the thresholds $M$ and $L$. |
| $T_D$ | Length of downtime for one renewal cycle. |
| $MT$ | Maintenance time, (total time from $T_M$ to renewal is completed including logistic delay). |
| $T_R$ | Length of one renewal cycle ($T_R = T_M + MT$). |
| $c_R(MT)$ | Cost of renewal as a function of the maintenance time ($MT$). |
| $c_F(MT,\tau)$ | Fixed maintenance cost for the period $(0,\tau]$ as a function of the maintenance time ($MT$). |
| $\theta$ | Shape factor for $c_R$ and $c_F$. |
| $c_D$ | Downtime cost per unit of time. |
| $RT_H$, $RT_L$ | High and low risk tolerance coefficient. |
| $\nu,\ \sigma_B$ | Drift and diffusion coefficient of the Wiener process. |
| $B(t)$ | Standard Brownian motion. |
| $\lambda,\ \mu$ | Shape and mean parameter for the inverse Gaussian (IG) distribution. |
| $\tau$ | The time horizon for which maintenance cost is evaluated. |
| $\mu_T,\ \mu_M$ | Mean time to failure (E[$T_L$]), mean time between $T_M$ and $T_L$ (E[$T_L - T_M$]). |
| $\rho$ | Unit cost (greatest common divisor of costs). |
| $C(\tau)$ | Maintenance cost in the time interval $(0,\tau]$. |
| $\phi(\omega,\tau)$ | The characteristic function of $C(\tau)$. |
| $c_\infty$ | Long-run cost rate. |
| $q_M(k)$ | Probability of mobilization for maintenance starting at time $k$. |
| $q_{D,k}(a)$ | Probability that both $T_D = a$ and $T_M = k$ occurs. |
| $q_C(c,\tau)$ | Probability of maintenance cost $c$ in time interval $(0,\tau]$. |
| $n_C$ | An integer such that $n_C\rho$ is the upper bound for $C(\tau)$. |
| $u(\cdot), l(\cdot)$ | Utility function, loss function. |

Few papers in the maintenance literature have presented approaches for taking the variability of the cost into account when evaluating maintenance policies [34,35]. One exception is Pandey et al. [54] which presents a method for finding the variance of the cost of a CBM policy in finite time. This is further developed by the same authors in Cheng et al. [39] where a method for finding the full probability mass function of the maintenance cost in finite time is presented. The Value-at-Risk (VaR) at the 95th percentile, which is the level of cost that it is only 5% probability of exceeding, is then used to evaluate the optimal inspection interval. Use of measures such as variance and VaR gives a better understanding of the variability of the cost and VaR is widely used for managing financial risk [53]. A challenge with both these approaches is that they tell nothing about the possibility of extreme values above the defined threshold [53]. This is not a large problem if the distribution of the cost is normally distributed, and the tail risk quickly goes to zero [55], but this is not always the case. As show in [56] the skewness and kurtosis of maintenance cost in finite time can vary considerably as the decision variables are changed.

Another approach for taking the variability of cost into account when optimizing maintenance policies are presented in [34,57]. Both builds on the concept of portfolio selection from Markowitz [58], where the basic idea is to minimize the sum of the expected cost and variance depending on some weighting coefficient. A challenge with this approach is that experience has shown that decision makers may have preferences between alternatives with the same expected value and variance [42, Ch. 4]. This is especially the case if there are potential outcomes among the alternatives with severe consequences and low probability. The reason for this is that the decision maker's preferences may be influenced by attitudes towards risk [37]. When the decision maker has an aversion to potential large losses, this will influence the preference in ways that cannot be captured by using the expected value or the other methods presented above in this section [42].

Expected utility theory (EUT) is a framework for taking attitudes towards risk into consideration when assessing alternatives with uncertain outcomes. The basis of EUT is axioms for describing the preferences of a rational decision maker faced with decisions under uncertainty [49]. EUT has previously seen little use in maintenance decisions [59], but some use of multi-attribute utility theory has been presented in the maintenance literature [60]. Examples are [61] who find the optimal inspection interval for a CBM-policy considering both preferences for cost and downtime and [28] for selecting the repair contract that offers the best tradeoff between cost and response time.

Cumulative prospect theory (CPR) is another approach for taking the decision maker's preferences for risk into account. CPR has been used in some studies related to optimization of the design and maintenance of civil infrastructure [62–64]. The CPR theory was first proposed by [65] and is more descriptive than EUT when modeling the preferences of the decision makers [66]. For comparisons between the use of EUT and CPT for maintenance decisions, see [63,67].

This paper applies a unidimensional expected utility theory approach and demonstrates how EUT can be used to take into account the preferences of a risk-averse DM. For an introduction to EUT see for instance Clemen [49] or Keeney and Raiffa [42].

## 3. Maintenance policy

### 3.1. Description of the maintained system

To reap a benefit from having a degradation model there must be some way of using the predictions of future states of the component to improve availability or reduce costs [13]. In this paper it is assumed that the RUL-predictions from the degradation model can be used to achieve cost reductions by increasing the maintenance time ($MT$). Maintenance time is in this paper understood as the time interval from a decision to mobilize for maintenance is made to the renewal is completed (Fig. 1). It is assumed that changing the $MT$ can affect costs in two ways. The first is that the cost of renewal, $c_R(MT)$, is reduced when the required maintenance time is increased. As an example, if a short response time is required from a maintenance contractor, the contractor will likely charge a higher price for each renewal than if the required response time is extended [28]. The other assumption is that ensuring a short maintenance time may require costs that are not related to a specific renewal. This may for instance be the cost of having a service vessel on call so maintenance personnel can be transported to the site at short notice. This is referred to as fixed cost as a function of maintenance time: $c_F(MT)$. An increase in maintenance time can be adjusted for by setting a more conservative threshold on the health indicator for when the decision to mobilize for maintenance is made. If the RUL prediction has a reasonable level of accuracy, this adjustment can be made without having an increase in downtime costs that offset the savings from increasing the maintenance time.

There are two decision variables in this policy. The first is the maintenance threshold ($M$). When the health indicator passes $M$ for the first time, a decision to mobilize for maintenance is made. This time is labeled $T_M = \inf[t : Y(t) \geq M]$. Maintenance time ($MT$) is the other decision variable. This is the time from mobilization for maintenance is started to renewal is completed and includes active maintenance time together with logistic, technical and administrative delay [26]. Fig 1 illustrates the parts that make up maintenance time. $MT$ is assumed deterministic.

The length of one renewal cycle ($T_R$) is $T_M + MT$. The asset is considered failed and taken out of production if the health indicator passes the failure threshold $L$. This time is labeled $T_L = \inf[t : Y(t) \geq L]$. If $T_L < T_R$ there is a downtime ($T_D$) of length $T_R - T_L$. The cost rate of downtime is $c_D$. If failure happens in the time increment that mobilization is completed ($T_L = T_R$) there is no downtime. Fig 2 shows an illustration of a sample degradation path. Renewal is assumed to bring the asset back to "as-good-as-new" condition.

### 3.2. Long-run cost rate when assuming a Wiener process

In cases where active maintenance brings the component back to as-good-as-new condition, renewal theory can be used to find the expected maintenance cost [46]. The long-run cost rate, the expected average cost per unit of time in an unbounded timeframe, can be found by dividing the expected renewal cycle cost by the expected renewal cycle length [36].

$$\lim_{\tau\to\infty}\frac{\mathrm{E}[C(\tau)]}{\tau} = \frac{\mathrm{E}[C(T_R)]}{\mathrm{E}[T_R]} = c_\infty \tag{1}$$

The Wiener process can be used to model the degradation when the degradation increments are independent and normally distributed [68]. The Wiener degradation model is often expressed as [35]:

$$Y(t) = y_0 + \nu t + \sigma_B B(t) \tag{2}$$

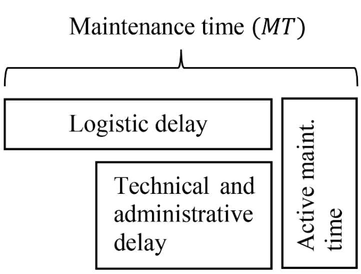


**Fig. 1.** Maintenance time consists of logistic, administrative, and technical delay in addition to active maintenance time. Illustration is inspired by [26].

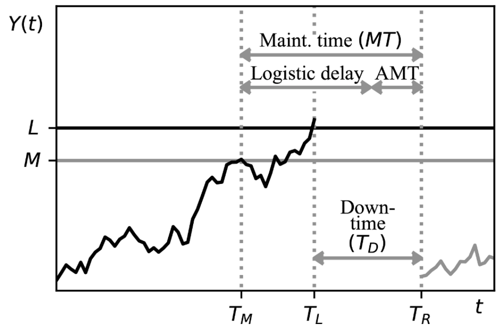


**Fig. 2.** Illustration of a sample degradation path. Mobilization for maintenance is started the first time the health indicator passes the maintenance threshold $M$. This time is labeled $T_M$. Maintenance time ($MT$) is the sum of logistic delay and active maintenance time ($AMT$), i.e., time from $T_M$ to renewal is completed. The total time for one renewal period is thus: $T_M + MT = T_R$. If the failure threshold $L$ is passed before $T_R$ there will be a downtime ($T_D$) with duration $T_R - T_L$.

where $y_0$ is the level of degradation at time $t = 0$, $\nu$ is the drift and $\sigma_B$ is the diffusion coefficient. $B(t)$ represents the standard Brownian motion. If degradation data is available the parameters $\nu$ and $\sigma_B$ can be estimated by maximum likelihood estimation (MLE) [35]. One convenient property of the Wiener process is that the first passage time to a fixed threshold follows an inverse Gaussian (IG) distribution [68]. If no maintenance is performed $T_L \sim \mathrm{IG}(\mu, \lambda)$, with $\mu = (L - y_0)/\nu$ and $\lambda = (L - y_0)^2/\sigma_B^2$ [69]. The probability density function (PDF) of $T_L$ can be written as [46]:

$$f_T(t;\mu,\lambda) = \sqrt{\frac{\lambda}{2\pi t^3}}\exp\left(-\frac{\lambda(t-\mu)^2}{2\mu^2 t}\right) \tag{3}$$

Based on this the long-run cost rate can be found by the following expression:

$$c_\infty(M, MT) = \frac{c_R(MT) + c_D\int_0^{MT} f_T(t;\mu_M,\lambda_M)(MT-t)dt}{M/\nu + MT} + c_F(MT), \quad M \in [0, L - \nu MT] \tag{4}$$

with $\mu_M = (L - M)/\nu$, and $\lambda_M = (L - M)^2/\sigma_B^2$. Further on, $c_R(MT)$ is the cost of renewal as a function of maintenance time, $c_D$ is the downtime cost rate and $c_F(MT)$ is the part of fixed costs affected by the maintenance time.

Using Eq. (4) the combination of $M$ and $MT$ that minimizes the long-run cost rate, including downtime cost, can be found by performing a grid search. For some assets, depending on the variance of the degradation process and reduction in $c_R$ and $c_F$ as $MT$ is increased, there will be some value larger than the minimum value of $MT$ that minimize the long-run cost rate. However, as described in the introduction and Section 2 it is not always appropriate to use only the expected cost when optimizing a maintenance policy. Especially in this policy, where by increasing the maintenance time we trade a reduction in the expected cost by increasing the variability of costs between renewal cycles, it can be argued that the decision maker's financial risk tolerance should be considered. Because of this, an alternative approach to optimizing this maintenance policy, which considers the preferences of a risk-averse DM, is presented Section 3.3.

### 3.3. Taking the preferences of a risk-averse decision maker into account

This Section presents how expected utility theory (EUT) can be used to take into account the preferences of a risk-averse decision maker (DM). It has been shown that if one can assign an appropriate utility to every possible outcome for a range of decision, then choosing the decision with the highest expected utility is the best course of action [42]. Because the range of possible outcomes can be large, it is often convenient to model the preferences with a utility function [49]. The shape of the utility function indicates the DMs preferences towards risk. If the utility function forms a straight line the DM is defined as risk-neutral. For the risk-neutral DM, the decision the maximizes the expected value will also maximize the expected utility. If the utility function is concave the DM is defined as risk-averse. A risk-averse DM is willing to pay more to avoid an uncertain situation with potential large losses than the expected cost of the outcome [64]. Due to this, the use of expected cost as optimization criterion for a risk-averse DM may lead to decisions that are not in line with the preferences of this DM.

There are several different techniques for defining utility functions, and the choice of utility function must be based on the preferences of the relevant DM and the context for the decision [42]. The exponential function is however often a good first choice because of its simplicity and interpretability [70]. This is often written as $u(x) = -\exp(-x/RT)$, where $RT$ is the risk tolerance coefficient and $x$ is the variable of interest, for instance net present value [40,42]. The $RT$-coefficient can be estimated by asking the DM to choose between doing nothing and entering a lottery with an equal probability of receiving $RT$ or $-RT/2$. The $RT$ where the DM is indifferent between entering the lottery or doing nothing indicates the risk tolerance [40,42,49].

In this paper we are dealing with maintenance cost and thus it is more appropriate to use the term loss function ($l$) [59]:

$$l(C_\tau) = \exp\left(\frac{C_\tau}{RT}\right), 0 \le C_\tau \le c_u \tag{5}$$

A challenge with using an exponential loss function is that if the probability of the outcomes does not go to zero fast enough, there will be some consequences so undesirable that it becomes challenging to make meaningful comparisons of alternatives [49]. Due to this, the loss function must have an upper bound [50] denoted $c_u$ in Eq. (5).

An important concept in EUT is the certainty equivalent (CE). This is an amount such that the DM is indifferent between the consequences of an uncertain decision and receiving that amount for certain, i.e. $l(\mathrm{CE}) = \mathrm{E}[l(C_\tau)]$ [42]. As long as the loss function is monotonic (a small loss is always preferred to a larger loss) the alternative with the smallest CE will also be the alternative with the smallest expected loss (conversely the highest expected utility) [42]. Because CE is in money terms, comparisons with the expected value can be made [49]. The difference between the expected value and the CE is called the risk premium [64]. When the CE is related to a loss, this is often referred to as an insurance premium [50]. This is the amount a DM would pay to avoid the financial responsibility of the possible outcomes of an uncertain condition [42]. Based on the loss function specified in Eq. (5) the CE can be found by the following expression:

$$\mathrm{CE}(RT) = \ln(\mathrm{E}[l(C_\tau)])RT = \ln\left(\sum_{c=0}^{c=c_u} q_C(c,\tau)\exp\left(\frac{c}{RT}\right)\right)RT \tag{6}$$

To solve Eq. (6), the probability mass function of the maintenance cost in a finite time horizon $(0,\tau]$ must be found: $q_C(c,\tau) = \Pr[C(\tau) = c]$. This is the topic of the next Section.

### 3.4. The probability mass function of maintenance cost in finite time

This Section is based on a method by Cheng et al. [39] for finding the probability mass function (PMF) of maintenance cost in a finite time interval with use of the characteristic function. We have made some adjustments to this method to fit with our assumptions of a non-monotonic degradation process and varying downtime length.

In line with Cheng et al. [39] cost and time have been discretized for practical reasons because this simplifies the computation of the distribution of the maintenance cost in finite time. Discretization of time can be justified because maintenance decisions are often made at fixed intervals, for instance at daily planning meetings. Discretization of time can however cause distortions when calculating the downtime cost if the evaluated downtime length is short compared to the time increments. This should be considered when setting the intervals when discretizing time.

#### 3.4.1. The characteristic function of the maintenance cost in finite time

According to Cheng et al. [39] the PMF of the maintenance cost in a finite time interval can be found by the following discrete Fourier transform (DFT):

$$q_C(c,\tau) = c_F + \frac{1}{n_c+1}\sum_{m=0}^{n_C}\phi(\omega_m,\tau)e^{-i\omega_m c} \tag{7}$$

where $\phi(\omega,\tau) = \mathrm{E}[\exp(i\omega C(\tau))]$ is the characteristic function of $C(\tau)$, $i = \sqrt{-1}$ is the imaginary number and $\omega$ is the angular frequency [71]. Since the method for finding the characteristic function of $C(\tau)$ used in this paper is based on [39], only the key formulas are presented here. The reader is directed to [39] for a more detailed description of this part of the method. For simplicity we omit the fixed cost ($c_F$) in the remainder of this section.

We discretize the maintenance cost, $C(\tau)$, in steps $0, \rho, 2\rho, \ldots, n_C\rho$. Where $n_C\rho$ is an upper limit of the cost such that $\Pr[C(\tau) > n_C\rho] \sim 0$. The angular frequency, $\omega$, is discretized in the quantities: $0, \Delta\omega, 2\Delta\omega, \ldots, n_C\Delta\omega$. The unit frequency is defined as [39]:

$$\Delta\omega = \frac{2\pi}{(n_C+1)\rho} \tag{8}$$

If the level of $n_C$ is set too low, the probability mass outside the range $[0,(n_C+1)\rho]$ is arbitrarily moved inside this range when the DFT is performed, thus distorting the results [71]. Setting a too high level for $n_C$ will on the other hand give a long computational time because Eq. (10) must be solved $\tau(n_c+1)$ times. Because the length of maintenance time has a large effect on the upper bound for maintenance cost, we propose the following adjustment to Eq. (19) in [39] which offers a pragmatic tradeoff between accuracy and computational effort when calculating $n_C$:

$$n_C(MT) = \left\lceil \frac{10\sqrt{MT}c_D\tau}{\mu_T\rho} \right\rceil \tag{9}$$

where $\lceil . \bullet \rceil$ is an integer ceiling function and $\mu_T$ is the mean time to failure ($L/\nu$).

The initial value of the characteristic function is $\phi(\omega,0) = 1$ for all values of $\omega$ since $C_\tau(0) = 0$. As show in Eq. 27 in Cheng et al. [39] the characteristic function of the maintenance cost for the time interval $(0,\tau]$ can be found by the following renewal type equation:

$$\phi(\omega,\tau) = \sum_{k=1}^{\tau}\phi(\omega,\tau-k)q_\phi(\omega,k) + G_\phi(\omega,\tau) \tag{10}$$

where $q_\phi(\omega,\tau)$ represents the characteristic function of a first renewal cycle, $T_1$, and $G_\phi(\omega,\tau)$ represents a not completed renewal cycle at the end of the time interval $(0,\tau]$. The cost of one renewal cycle is: $c_D T_D + c_R$, where $T_D = [0, 1, \ldots, MT]$ is the length of downtime and $c_D$ and $c_R$ are the costs of downtime and renewal. Based on this, $q_\phi$ at time $k + MT$ can be expressed as:

$$q_\phi(\omega,k+MT) = \sum_{a=0}^{MT} e^{i\omega(c_D(MT-a)+c_R)}q_{D,k}(a), \quad k \in [0,\tau-MT] \tag{11}$$

Where $a = MT$ is preventive maintenance (i.e., that $T_M + MT \le T_L$) and no downtime cost is incurred. To solve Eq. (11) we need to find the

PMF for the length of downtime ($q_D$) when the mobilization time $T_M = k$. This is treated in the next two Sections.

#### 3.4.2. The distribution of the first hitting time (FHT) of the maintenance threshold ($T_M$)

We now relax the assumption that the degradation follows a Wiener process. We keep the assumption that the degradation follows a Lévy process with the following properties [72]:

1 The starting point is known: $\Pr[Y(t=0)=0]=1$.
2 Increments are independent: For any $0 \le t_1 < t_2 < \ldots < t_n < \infty$, $Y_{t_2} - Y_{t_1}, \ldots, Y_{t_n} - Y_{t_{n-1}}$ are independent.
3 Increments are stationary: $Y(t) - Y(s)$ has the same distribution as $Y(t-s), \forall s \le t$.
4 $Y(t)$ is continuous in probability, for any $\varepsilon > 0$ and $t \ge 0$, it holds that $\lim_{h\to 0} \Pr[|Y_{t+h} - Y_t| > \varepsilon] = 0$.

Because the increments are independent and stationary (property 2 and 3), the degradation in any time increment is a random variable $Y(t+dt) - Y(t) = S(dt)$, with the PDF $g(s)$. Because the starting point is known (property 1), the level of the health indicator at the first time-increment is: $Y(k=1) = Y(k=0) + S(dt)$.

In the numerical approach both the time and health indicator are discretized. $k = 0, 1, \ldots, \infty$ is a time index corresponding to $t = 0, dt, 2dt, \ldots$, and $n$ is an index for the health indicator. To discretize the health indicator, equally sized intervals of length $\Delta y$ are used. By setting the increment $\Delta y$ sufficiently small, we can approximate the continuous degradation process arbitrarily close. A vector $f_k$ is used to hold the PMF of $Y(k\cdot dt)$, where $f_k[n] = \Pr([n-0.5]\Delta y \le Y(k\cdot dt) < [n+0.5]\Delta y)$. The range of $n$ is limited by a lower value $n_l$ such that $\Pr(Y(k\cdot dt) \le [n_l - 0.5]\Delta y)$ is sufficiently small to be ignored.

The PMF of the degradation in one time increment $dt$ is discretized with the same interval $\Delta y$. In the numerical procedure $g$ is a vector to hold the PMF bounded by some lower and upper values $s_l$ and $s_u$ such that almost all probability mass is within these values. Typically, the bounds are defined by +/- 5 to 10 standard deviations from the expected degradation in one time increment, depending on the desired accuracy.

An upper value of the vector $f_k$ is pragmatically set to $n_u = n_L + s_u$, where $n_L$ represents the failure threshold ($L$). Further $n_M$ is the index corresponding to the maintenance threshold ($M$), thus we have $(n_L - 0.5)\Delta y = L$ and $(n_M - 0.5)\Delta y = M$. Note that $n_l < 0$, such that if our programming language does not allow negative indexes, we may shift all indexes to the right.

From the law of total probability, a discrete convolution may be used to update the PMF of the health indicator at the first time increment ($k = 1$):

$$f_{k=1}[n] = (f_{k=0} * g)[n] = \sum_{m=s_l}^{s_u} f_{k=0}[n-m]g[m] \tag{12}$$

where $*$ is the convolution operator. As time evolves, i.e., for $k = 2, 3, \ldots$ the PMF is similarly updated by letting $f_k[n] = (f_{k-1} * g)[n]$.

Special treatment is required when we search for the first hitting time of $M$, i.e., $T_M$. A new vector $f_{k,M}$ is introduced to represent the first hitting time, i.e.,

$$f_{k,M}[n] = \left(f_{k-1,M}(k-1 | Y(t\cdot dt) < M, \forall t < k) * g\right)[n] \tag{13}$$

The probability that $T_M$ occurs at time $k$ is thus:

$$q_M(k) = \Pr[T_M = k | Y(t\cdot dt) < M, \forall t < k] = \sum_{n=n_M}^{n_u} f_{k,M}[n] \tag{14}$$

After the calculation of $q_M(k)$ we set $f_{k,M}[n] = 0, n \ge n_M$ to account for the condition that $Y(t\cdot dt) < M, \forall t < k$.

#### 3.4.3. The PMF of the downtime length ($T_D$)

To find the distribution of the cost associated with one renewal cycle, the PMF of the downtime length, $T_D$, must be found for all values of $k$:

$$\begin{aligned} q_{D,k}(a) &= \Pr[T_D = MT - a \cap T_M = k] \\ &= \Pr[Y((k+a)dt) \ge L \cap T_M = k | Y(t\cdot dt) < L, \forall t < (k+a)], a \in [0, MT] \end{aligned} \tag{15}$$

The probability that the health indicator passes both the maintenance ($M$) and defined failure threshold ($L$) in a single time increment ($T_D = MT$) can be found by the following expression:

$$\begin{aligned} q_{D,k}(a=0) &= \Pr[T_D = MT \cap T_M = k | Y(t\cdot dt) < L, \forall t < k] \\ &= \sum_{n=n_L}^{n_u} f_{k,M}[n] \end{aligned} \tag{16}$$

A vector $f_{a,L,k}$ is introduced to hold the probability mass of the health indicator that enters the interval $[n_M, n_L)$ at time increment $k$. The evolution of this probability mass can be updated by using a recursive routine similar to the one used in the previous Section:

$$\begin{aligned} &f_{a,L,k}[n] \\ &= \left(f_{a-1,L,k}(a-1 \cap T_M = k | Y(t\cdot dt) < L, \forall t < (k+a)) * g\right)[n] \end{aligned} \tag{17}$$

The probability of a downtime length of $a = j$, $j \in [1, MT)$ when $k = T_M$ can be found by,

$$q_{D,k}(a=j) = \sum_{n=n_L}^{n_u} f_{a=j,L,k}[n] \tag{18}$$

Similar to the previous Section, we set $f_{a,L,k}[n] = 0, n \ge n_L$ at the end of each iteration to account for the condition that $Y(t\cdot dt) < L, \forall t < (k+a)$.

If the FHT of the failure threshold, $L$, has not occurred before $T_M + MT$ there is no downtime, and the renewal cycle is ended with preventive maintenance. The probability of preventive maintenance, i.e., $a = MT$, is:

$$\begin{aligned} q_{D,k}(a=MT) &= \Pr[T_D = 0 \cap T_M = k | Y(t\cdot dt) < L, \forall t < (k+MT)] \\ &= \sum_{n=n_l}^{n_u} f_{a=MT,L,k}[n] \end{aligned} \tag{19}$$

#### 3.4.4. The cost of the last renewal cycle

This Section presents calculation of the cost of the last renewal cycle in the time interval $(0,\tau]$. If mobilization for maintenance is started in the time interval: $(\tau - MT, \tau]$, downtime costs may be incurred from an incomplete renewal cycle. To take account of this, the probability of all combinations of $T_M$ and $T_D$ for an incomplete renewal cycle at the end of the defined time horizon must be calculated. The cost of renewal does not accrue for the last renewal cycle if $T_M + MT > \tau$. The last term in Eq. (10) can thus be expressed as:

$$G_\phi(\omega,\tau) = \sum_{a=0}^{MT}\sum_{b=1}^{MT}\left[e^{i\omega c_q(a,b)} q_{D,k}(T_D = MT - a, T_M = \tau - (MT - b))\right] + \overline{Q}_M(k) \tag{20}$$

Where $c_q(a,b)$, is the downtime costs from a renewal cycle that is not completed before $\tau$:

$$c_q(a,b) = \begin{cases} (MT - a - b + 1)c_D & \text{if } (a+b) \le MT \\ 0 & \text{otherwise.} \end{cases} \tag{21}$$

If the mobilization threshold is not reached in the time interval $(0,\tau]$, i.e.: $T_{M,1} > \tau$, there is no costs related to downtime or renewal (i.e., $C_\tau = 0$). The last part of Eq. (20) is thus:

$$\overline{Q}_M(k) = 1 - \sum_{j=1}^{k} q_M(j) \tag{22}$$

If we want to include the downtime and renewal costs from the last renewal cycle that accrue after $\tau$ this can be done by substituting Eq.

(20) by Eq. (22) and calculating Eq. (11) for $k \in [0, \tau]$. This may in some cases be more appropriate if the asset is to remain in operation after the defined time interval $(0, \tau]$.

## 4. Illustrative example

This section presents an example of how the proposed policy can be applied. The parameters are given in Table 2. Units have not been specified because they have no practical relevance.

We assume that the degradation increments are normally distributed: $g(s) \sim \mathrm{N}(\nu, \sigma_B^2)$. This gives a mean time to failure of: $L/\nu = 100$. We further assume that the cost of performing renewals decreases exponentially when the maintenance time ($MT$) is increased. An example of this cost structure could be the price a maintenance contractor requires to enter a contract for performing a renewal, given the maintenance time required. We remind the reader that the maintenance time in this study is defined as the total time from the decision to mobilize for maintenance is made and until the renewal is completed. If the required maintenance time is short, the contractor may need to use an expensive means of transportation for maintenance personnel, e.g., a helicopter, to ensure a short enough logistic delay to complete the renewal in the required time. If the required maintenance time is increased, the need for expensive measures to ensure that the renewal is completed within the required time is reduced, and the costs of such measures approach zeros as the $MT$ is further increased. A similar cost structure for repair contracts has previously been presented in [28]. In practice, the decision maker will probably have a discrete number of combinations of renewal cost and maintenance time to choose from. In this example the equation $c_R(\mathrm{MT}) = c_{\mathrm{R1}} + c_{\mathrm{R2}}\exp(-(MT-1)/\theta),\ \mathrm{MT} \geq 1$ is used to represent combinations of renewal cost and maintenance time ($MT$) available to the decision maker (Fig 3). Because cost is a discrete variable, as specified in Section 3.4, $c_R(MT)$ is rounded to the nearest multiple of the unit cost ($\rho$). The fixed cost, $c_F$, is in this example assumed to not change with $MT$ and can thus be removed from the equation. The health indicator has been discretized with increments $\Delta y = 0.01$.

The PMF of the maintenance cost was calculated using Eq. (7) over a grid with combinations of the decision variables. The maintenance time ($MT$) was varied from 1 to 29 with a step size of 1 and the maintenance threshold ($M$) from 0 to 9.9 with a step size of 0.1. Two examples of the PMF for the maintenance cost with different threshold for the decisions variables are shown in Fig 4. A drawback of using discrete Fourier transform to find the probability distribution of maintenance cost is that some distortions are introduced [73]. The distortions are so small that they do not affect the calculation of the expected cost but can pose a challenge when calculating the loss function. This is because of the rapid rise of the exponential function in Eq. (5) when the cost becomes large. We introduce a cutoff level at $10^{-15}$ and remove all probabilities below this level. This will also remove some of the actual probability distribution of $C_\tau$. Different cutoff levels where tested and it was found that as long as the level is below $10^{-7}$, the choice of decision variables in this example is not affected.

**Table 2**
Parameters used in the example.

| Parameter | Value |
|---|---|
| Failure threshold | |
| $L$ | 10 |
| Evaluation horizon | |
| $\tau$ | 100 |
| Degradation process | |
| $\nu, \sigma_B$ | 0.1,0.5 |
| Cost structure | |
| $c_D, c_{R1}, c_{R2}, \theta$ | 10,1,9,5 |
| Unit cost: | |
| $\rho$ | 1 |
| Risk tolerance | |
| $RT$ | 5 |

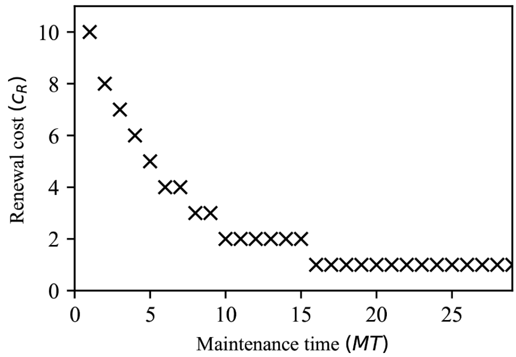


**Fig. 3.** Plot of combinations of renewal cost ($c_R$) and maintenance time ($MT$) available to the decision maker (DM). We assume that a part of the renewal cost is fixed ($c_{R1}$) while the rest of the cost decrease ($c_{R2}$) with increasing $MT$. Maintenance time is the time from a maintenance decision is made until renewal is completed.

Fig 5 shows a surface plot of the expected cost, $\mathrm{E}[C_\tau]$, for combinations of $M$ and $MT$. The expected cost based on the long-run cost rate, the expected cost based on the finite time approach, and the certainty equivalent (CE) for a risk-averse DM are compared in Fig 6 and Table 3. The optimal decision for a risk-neutral DM is to choose the combination of decision variables that gives the lowest expected cost. The two approaches based on the long-run cost rate and the expected cost in a finite time horizon both result in practically the same optimal decision variables in the example. Based on this, a risk-neutral DM has little to gain from using the more involved procedure specified in Section 3.3 and 3.4 to find the cost in finite time compared to using only the long-run cost rate in Eq. (4).

As expected, a more conservative maintenance threshold, $M = 3.4$, and a shorter maintenance time, $MT = 10$, is preferred when the minimization of the CE for a risk-averse DM is used as decision criterion. We remind the reader that, as presented in Section 3.3, the CE represents an amount such that the DM is indifferent between the consequences of an uncertain decision and receiving this amount for certain. The preferred thresholds for the decision variables for the risk-averse DM give an expected cost of 3.6. This is almost twice as high as the expected cost when choosing the thresholds for the decision variables preferred by a risk-neutral DM (1.9).

On the other hand, a risk-averse DM facing the PMF of the maintenance cost when the decision variables are based on the minimization of the long-run cost rate ($MT = 16,\ M = 3.2$) would be willing to pay up to 100.0 to be relieved of this uncertainty. This means that the insurance premium ($\mathrm{CE} - \mathrm{E}[C_\tau]$) that the risk-averse DM would be willing to pay would be very high and demonstrates that using the long-run cost rate as decision criterion will give a choice of decision variables not in line with the preference of that DM. If minimization of CE is used as decision criterion, this will give a $\mathrm{CE} = 4.3$ for the risk-averse DM. This is less than one twentieth of the CE when the minimization of the expected cost is used as decision criterion. This shows that the minimization of the CE is a better choice of decision criterion for the risk-averse DM in this example.

The circular markers in Fig 6 show results of Monte Carlo (MC) simulations with $10^6$ sample paths. The MC simulations was performed on the NTNU IDUN computing cluster [74]. Even with this large number of samples, there are some deviations from the results of the numerical routine for the CE when $MT > 10$. This is because the exponential form of the loss function in Eq. (5) puts a large weight on outcomes with high cost when the risk tolerance is low.

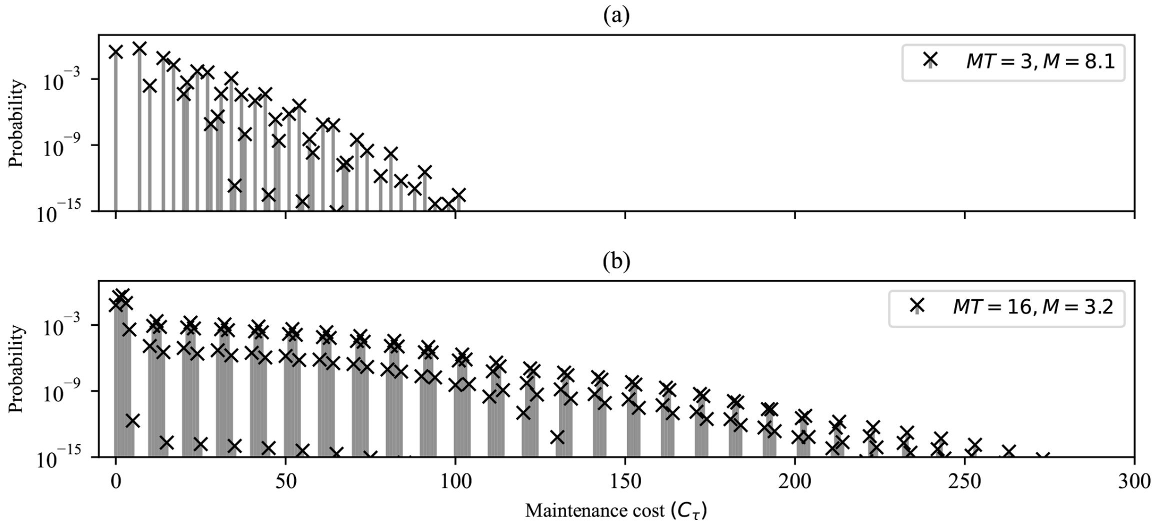


**Fig. 4.** Plots of the probability mass function of the maintenance cost in finite time with decision variables (a): $MT = 3$, $M = 8.1$ and (b): $MT = 16$, $M = 3.2$. When the $MT$ is increased, the cost of performing renewal is reduced, but the possibility of renewal cycles with long downtime is introduced, resulting in a long tail of possible outcomes with high costs but low probability in (b).

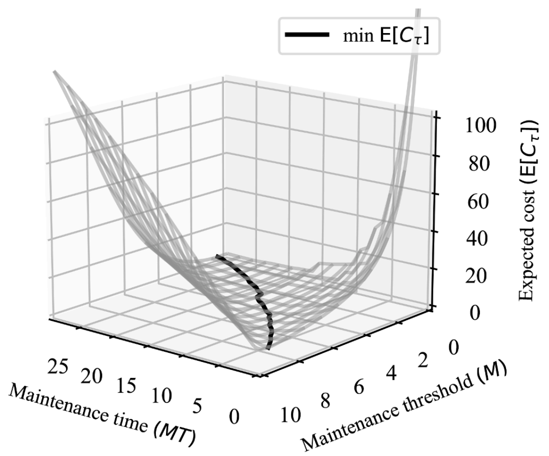


**Fig. 5.** A gridplot of the decision variables and the resulting expected cost. The solid line shows the maintenance threshold ($M$) which minimize the expected cost depending on the maintenance time ($MT$).

## 5. Case study

### 5.1. Background

The case study is based on data collected from two pumps operated at an offshore oil and gas platform. These pumps have previously been described in [75] and more information on the pumps can be found in that paper. Both pumps have a problem with cavitation. This leads to degradation of the impeller. A health indicator based on the deviation between the expected and actual head delivered by the pumps has proven to be a good indicator of the condition of the impeller. The operating company has defined a 20% deviation on this health indicator as the failure threshold for these pumps. It is assumed that the pumps are shut down when the health indicator exceeds the defined failure threshold, and that this cause a loss of production until renewal of the failed pump is completed. It is further assumed that low output because of impeller wear is the only failure mode.

In contrast to the example in Section 4, we assume in the case study that the cost of performing renewals, $c_R$, is not affected by a change in maintenance time, i.e., $c_R$ is constant in this section. Instead, we assume that having a short maintenance time requires costs that are not related to a specific renewal. For example, if the required maintenance time on an offshore oil and gas platform is very short, this can only be achieved if the necessary resources, such as maintenance personnel, are permanently stationed on the platform. Having personnel stationed offshore will incur costs regardless of whether renewals are performed or not. An alternative with lower fixed costs, but longer maintenance time is to have maintenance personnel on call onshore and then transport them to the site when needed. Along the same line of reasoning, several different combinations of cost and maintenance time can be thought of based on factors such as spare parts policy, means of transport, or available tools. Data on costs and maintenance time for specific alternatives have not been collected for the case study, instead the equation $c_F(\mathrm{MT}) = c_{F1}\exp(-(MT-1)/\theta),\ \mathrm{MT} \geq 1$ is used to represent a tradeoff between maintenance time ($MT$) and fixed maintenance cost ($c_F$) available to the DM. Fig 7 shows degradation paths and renewal times from the case study.

### 5.2. Assuming normally distributed degradation increments

The autocorrelation plot in Fig 8 indicates that the degradation process has independent increments. Fig 9(a) shows that the histogram of the degradation increments has a bell-shaped curve with both positive and negative increments. Of the three most popular stochastic models for continuous degradation (Wiener, gamma and, inverse Gaussian [9]), the Wiener process fits best with this dataset. When assuming a Wiener process the MLE for the drift parameter is $\hat{\nu} = 0.0459$, and the estimate for the diffusion coefficient is $\hat{\sigma}_B = 0.3050$.

### 5.3. Alternative model of the degradation increments

As can be seen in Fig 9(b), the tails of the case data do not fit well

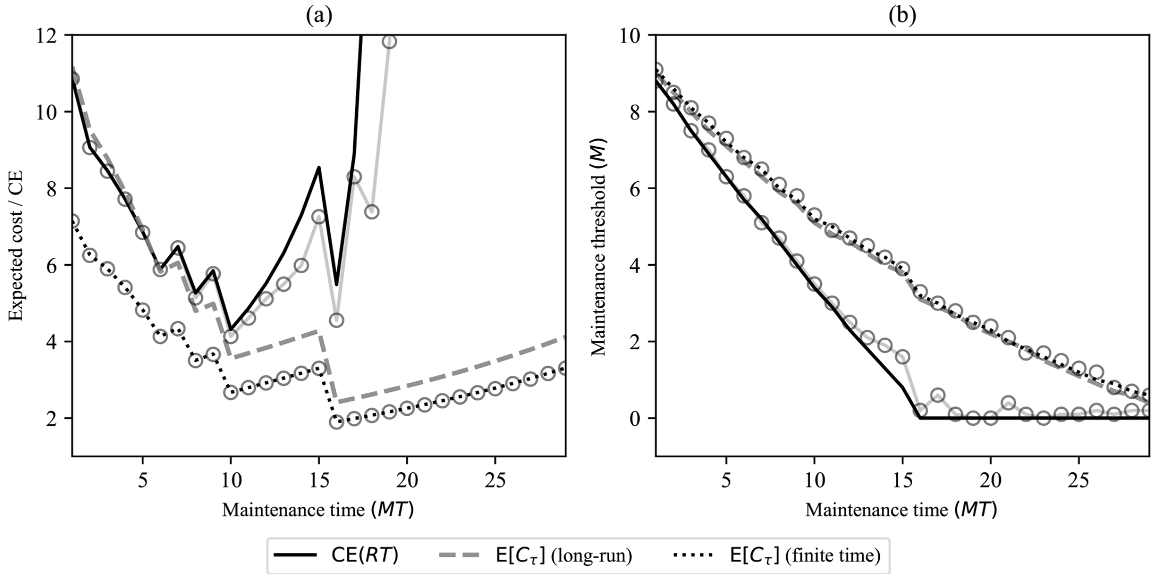


**Fig. 6.** Comparison of the expected cost (E$[C_\tau]$) and certainty equivalent (CE) depending on risk tolerance, shown in (a), and the optimal maintenance threshold (b) depending on maintenance time ($MT$). As show in (b), a risk-averse decision maker will prefer a more conservative maintenance threshold. The circular points represent the Monte Carlo simulations.

**Table 3**
The optimal decision variables based on the preferences of the decision maker (DM). A risk-averse DM prefers a more conservative maintenance threshold ($M$) and maintenance time ($MT$), resulting in an expected cost almost twice as high.

| Decision criteria | Optimal decision variables | E$[C_\tau]$ | CE$(RT)$ |
|---|---|---|---|
| E$[C_\tau]$ (long-run) | $MT = 16, M = 3.1$ | **1.9**[a] | 96.2 |
| E$[C_\tau]$ (finite time) | $MT = 16, M = 3.2$ | **1.9** | 100.0 |
| CE$(RT = 5)$ | $MT = 10, M = 3.4$ | 3.6 | **4.3** |

[a] The expected cost in the interval $(0, \tau]$ when the choice of decision variables is based on the minimization of the long-run cost rate. The estimated cost when using Eq. (4) is: $c_\infty \tau = 2.4$.

with the assumption of normally distributed degradation increments. To better represent the excess kurtosis of the historical data, a second approach for modeling the degradation increments was introduced. In this approach, the degradation increments were assumed to come from a combination of three different normal distributions. The GaussianMixture model, from the Python library Scikit-learn [76], was used to estimate the mean, variance and weight of the three distributions (Fig. 4). This gives a representation of the degradation increments that are closer to the historical data, especially in the tails (dotted line in Fig 9). This is labeled the GaussMix-degradation increments.

### 5.4. *Risk tolerance in the case study*

The operating company's risk tolerance related to maintenance decisions was not investigated in this case study. In an empirical study of capital allocations to petroleum exploration projects, Walls found the risk tolerance of US-based oil companies to range between 1 and 100 MUSD. We have used these values to represent risk-averse decision makers with low and high risk tolerance in the case study, labeled as $RT_L$ and $RT_H$, respectively. The rest of the parameters used in the case study are shown in Table 5.

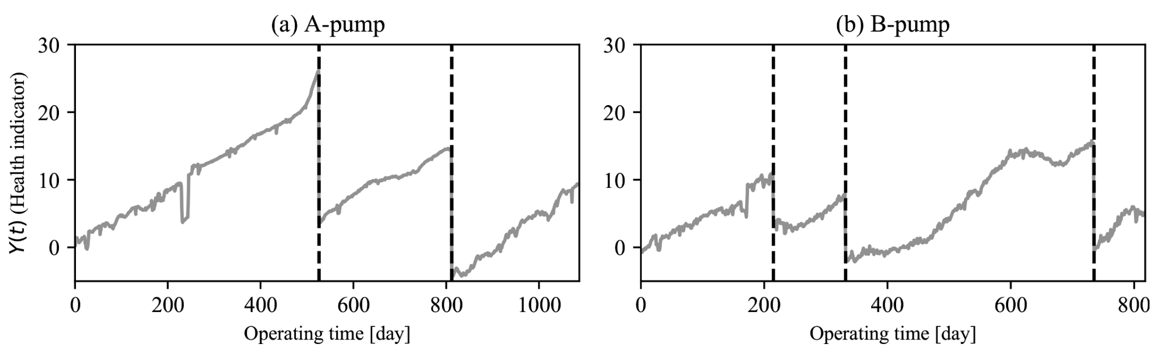


**Fig. 7.** Degradation paths for the two pumps used in the case study. The data used in the analysis is the mean value of each day. The vertical dashed lines represent times when the impellers have been renewed.

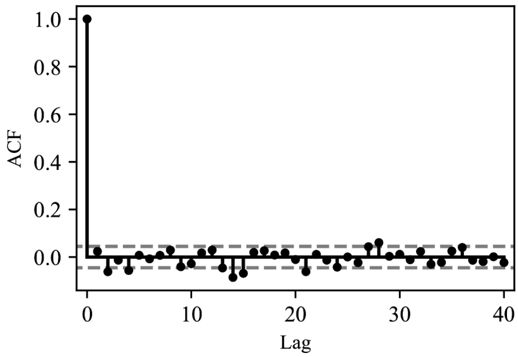


**Fig. 8.** Plot of the autocorrelation function (ACF) of the degradation increments in the case study. The dashed lines illustrate the 95% confidence interval ($1.96/\sqrt{n}$), assuming an i.i.d. normal random variable [72].

### 5.5. Results

A grid search for the optimal decision variables was performed for both models of the degradation increments. Monte Carlo simulations with $10^5$ sample paths were performed for validation. As in the example in Section 4, the cutoff level was set to $10^{-15}$, removing all instances of $C_\tau$ with probabilities less than this level. Again, the results were not affected as long as the cutoff level was kept below $10^{-7}$.

The results of the grid search based on normally distributed degradation increments are shown in Table 6 and Fig 10. As in the example in Section 4, the optimal thresholds for the decision variables are practically the same for both approaches based on minimizing the expected cost. The risk-neutral DM will thus come to practically the same decision by using minimization of the long-run cost rate compared with the more involved approach of calculating the expected cost in finite time.

**Table 4**
The parameters of the three normal distributions that constitutes the Gaussian mixture model.

| Distribution | Mean | Std. | Weight |
|---|---|---|---|
| 1 | $\sim 0$ | 0.724 | 0.09 |
| 2 | 0.054 | 0.053 | 0.42 |
| 3 | 0.048 | 0.006 | 0.48 |

**Table 5**
Parameters used in the case study.

| Parameter | Value |
|---|---|
| $L$ | 20 |
| $\tau$ | 730 days |
| $\nu, \sigma_B$ | 0.0459, 0.3050 |
| $c_D$ | 800 kUSD/day |
| $c_R$ | 200 kUSD |
| $c_{F,1}$ | 200 kUSD |
| $\theta$ | 7 days |
| $\rho$ | 200 kUSD |
| $RT_L$ | 1 MUSD |
| $RT_H$ | 100 MUSD |

**Table 6**
The optimal decision variables based on the preferences of the decision maker (DM), assuming normally distributed degradation increments.

| Decision criteria | Optimal decision variables | $\mathrm{E}[C_\tau]$ | $\mathrm{CE}(RT_H)$ | $\mathrm{CE}(RT_L)$ |
|---|---|---|---|---|
| $\mathrm{E}[C_\tau]$ (long-run) | $M = 15.7, MT = 16$ | **346**[a] | **346** | 422 |
| $\mathrm{E}[C_\tau]$ (finite time) | $M = 15.8, MT = 16$ | **346** | **346** | 454 |
| $\mathrm{CE}(RT_H)$ | $M = 15.7, MT = 16$ | **346** | **346** | – |
| $\mathrm{CE}(RT_L)$ | $M = 15.5, MT = 14$ | 355 | – | **367** |

[a] The expected cost in the interval $(0, \tau]$ when the choice of decision variables is based on the minimization of the long-run cost rate. The estimated cost when using Eq. (4) is: $c_\infty \tau = 440$ kUSD.

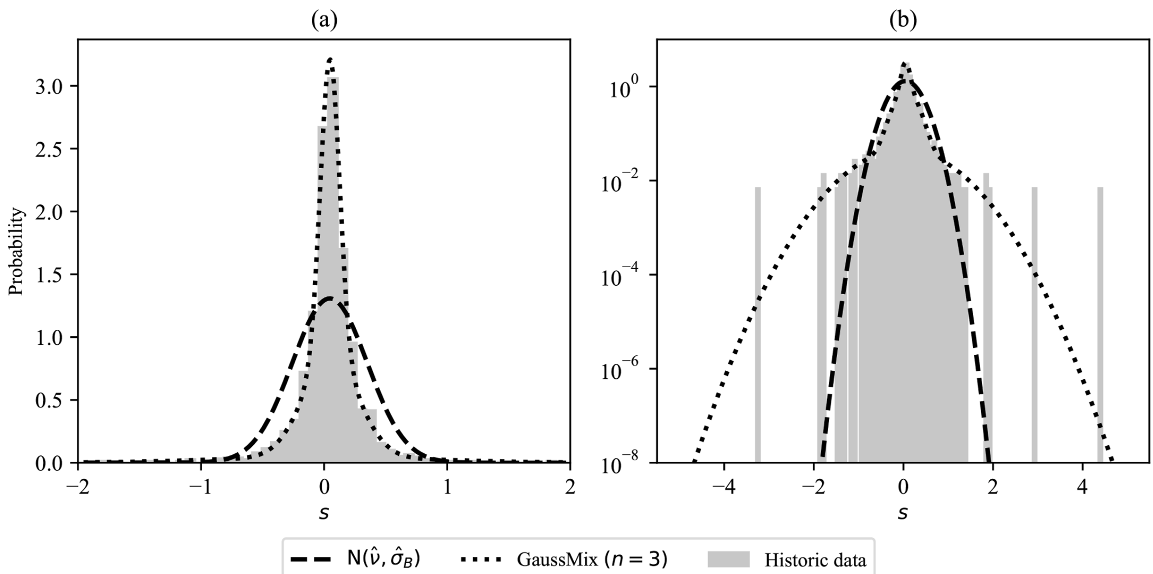


**Fig. 9.** Two approaches have been used to model the degradation increments. The first approach assumes that the degradation increments are normally distributed: $\mathrm{N}(\hat{\nu}, \hat{\sigma}_B)$ (dashed lines). The second approach, labelled GaussMix, assumes that the degradation increments are a combination of three different normal distributions (dotted lines). The second approach gives a better representation of the excess kurtosis of the case data.

Introducing minimization of the CE as decision criteria does not affect the optimal choice of decision variables when the high risk tolerance coefficient, $RT_H$, is used. If the DM has a low risk tolerance, $RT_L$, the optimal thresholds for the decision variables becomes slightly more conservative ($M = 15.5,\ MT = 14$). This gives a $(355 - 346)/346 \approx 3\%$ increase in expected cost.

Table 7 and Fig 11 show the results when using the GaussMix model for the degradation increments. The long-run cost rate based on Eq. (4), which assumes a Wiener degradation process, no longer gives the same result as the approach based on the expected cost in finite time. But the difference in expected cost between these two approaches is only $(372 - 364)/364 \approx 2\%$. The optimal thresholds for the decision variables for a DM with high risk tolerance are still the same as for a risk-neutral DM.

Because the GaussMix-distribution has heavier tails, the optimal thresholds for the decision variables for a DM with low risk tolerance becomes more conservative ($M = 15.0,\ MT = 10$). This choice of decision variables gives an increase in expected cost of $(395 - 364)/364 \approx 9\%$ compared to the optimal decision variables for a risk neutral DM. On the other hand, a DM with a low risk tolerance would be willing to pay up to 1985 kUSD to be relieved of the uncertainty caused by use of the decision variables preferred by the risk-neutral DM ($M = 15.2,\ MT = 16$). If minimization of the CE is used as decision criteria for the DM with low risk tolerance, this gives an CE of 412 kUSD which is considerable smaller than the CE if the two other decision criteria are used.

**Table 7**
The optimal decision variables based on the preferences of the decision maker (DM) using the GaussMix model of the degradation increments with heavier tails.

| Decision criteria | Optimal decision variables | $E[C_\tau]$ | $CE(RT_H)$ | $CE(RT_L)$ |
|---|---|---|---|---|
| $E[C_\tau]$ (long-run) | $M = 15.7, MT = 16$ | 372[a] | 373 | 3844 |
| $E[C_\tau]$ (finite time) | $M = 15.2, MT = 16$ | **364** | **364** | 1985 |
| $CE(RT_H)$ | $M = 15.2, MT = 16$ | **364** | **364** | – |
| $CE(RT_L)$ | $M = 15.0, MT = 10$ | 395 | – | **412** |

[a] The expected cost in the interval $(0, \tau]$ when the choice of decision variables is based on the minimization of the long-run cost rate. The estimated cost when using Eq. (4) is: $c_\infty \tau = 440$ kUSD.

## 6. Discussion

Minimization of the long-run cost rate is often used as optimization criterion for maintenance policies [23,34–36,39]. In this paper we have found that such an approach is reasonable when the decision maker is risk-neutral. Use of the more involved procedure for finding the complete probability distribution of cost in finite time had practically no impact on the optimal decision variables for a risk-neutral decision maker for the maintenance policy presented in this paper. This was found to change if the decision maker has a low risk tolerance compared to the potential outcomes of the maintenance policy. If this is the case, using minimization of the long-run cost rate as the decision criterion may lead to decisions that are not in line with the preferences of the decision maker. Based on this, it is important to consider the financial risk tolerance of the decision maker when developing an optimization model for maintenance.

Another assumption often made when modeling continuous stochastic degradation processes is that the degradation increments follow either the gamma, Wiener, or inverse Gaussian distribution [9,35,77]. In the case study in Section 5, the degradation increments were close to normally distributed, but with some excess kurtosis. The results in our paper show that the assumption of a Wiener process is reasonable to make when optimizing the maintenance policy for a risk-neutral decision maker. However, for a decision maker with low risk tolerance, accurate modeling of the degradation process becomes more important. This is in our paper exemplified by using an alternative probability distribution with heavier tails to represent the degradation increments. This demonstrates the need to consider both types of robustness as specified by Cherkaoui et al. [34] when the decision maker is risk-averse.

Maintenance decision have traditionally been based on gut feeling and intuition [15,78–80]. Besides [62], little empirical data on the

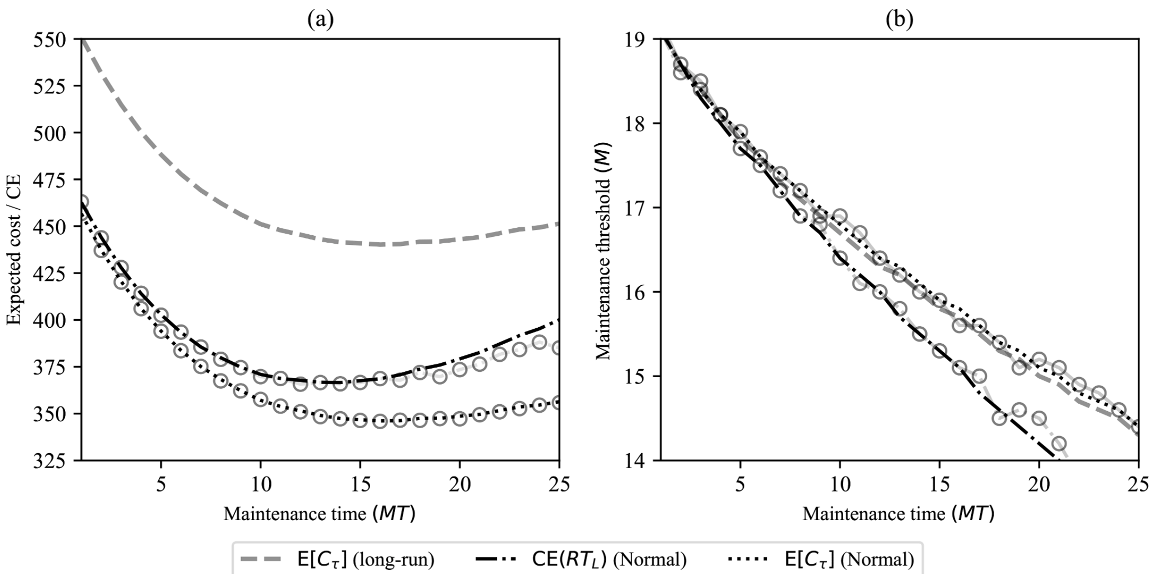


**Fig. 10.** Comparison of the expected cost and the certainty equivalent (CE) when normally distributed degradation increments are assumed (a). Optimal maintenance threshold ($M$) given maintenance time ($MT$) is shown in (b). When the high risk tolerance coefficient ($RT_H$) is used, the results are practically the same as for the expected cost in finite time. These results are therefore not shown in the figure. The circular points represent the Monte Carlo simulations.

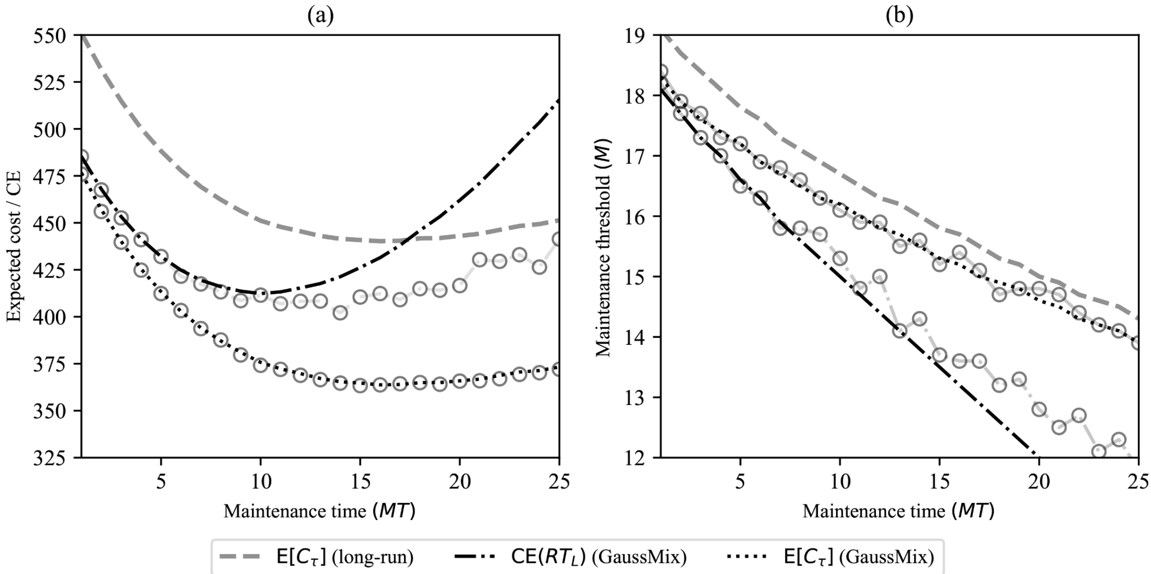


**Fig. 11.** Comparison of the expected cost and certainty equivalent (CE) when GaussMix degradation increments are assumed (a). The optimal maintenance thresholds ($M$) given maintenance time ($MT$) are shown in (b). When the high risk tolerance coefficient ($RT_H$) is used, the results are practically the same as for the expected cost in finite time. These results are therefore not shown in the figure. The circular points represent the Monte Carlo simulations.

financial risk tolerance for maintenance decisions is available in the literature, but it is reasonable to assumed that maintenance managers are risk-averse, as is normally the case for managers in general [42,49,70]. As developments in sensor technology and maintenance models enable the introduction of decision automation [80] and prescriptive maintenance policies, with models that prescribe which maintenance measures to conduct at what time [81], it becomes important that the outputs from the models are in line with the preferences of the decision makers [78]. This can be ensured by including elements from expected utility theory in the models [48,59].

## 7. Conclusion

The decision maker's risk tolerance may affect the preferred thresholds for the decision variables for the CBM policy proposed in this paper. For decisions where the potential outcomes are small compared to the overall economic resources of the organization, it is reasonable to assume risk neutrality and use the minimization of the expected costs as the optimization criterion. Most maintenance decisions probably fall into this category, and minimization of the long-run cost rate is normally used as optimization criterion for maintenance policies. This changes when the risk tolerance of the decision maker is small compared to potential outcomes of the maintenance policy. Because of this, it is important to assess the risk tolerance of the relevant decision makers when developing maintenance policies.

An approach for finding the expected utility of a CBM policy for a single unit system has been presented in this paper. This has been done by using the characteristic function to find the probability mass function of the maintenance cost in finite time, and an exponential utility function to calculate the expected utility. The numerical procedure in this paper was found to be more efficient than Monte Carlo simulations.

Further research can be done along several axis. The maintenance model can be made more realistic by changing the variable mobilization time, $MT$, from deterministic to stochastic. Another possible expansion of the model is to introduce sequential decisions in the maintenance policy. For example, by introducing one or several thresholds where measures are taken to shorten the maintenance time as the degradation progresses.

Another possible direction of further research is to collect more empirical data on the risk tolerance related to maintenance decisions. This may clarify the need for approaches that take into account the variability of the cost when optimizing maintenance policies.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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