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Jon Martin Fordal

Digitalization of the value chain

Improving value chain performance with prediction

Doctoral thesis

NTNU
Norwegian University of Science and Technology
Thesis for the Degree of
Philosophiae Doctor
Faculty of Engineering
Department of Mechanical and Industrial
Engineering

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Thesis for the Degree of Philosophiae Doctor

Trondheim, April 2023

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“We have a mantra in our team: well done is better than well said.”

- Karsten Warholm (athlete) and Leif Olav Alnes (coach)

Preface

This PhD thesis is submitted for the Degree of Philosophiae Doctor at the Department of Mechanical and Industrial Engineering at the Faculty of Engineering at the Norwegian University of Science and Technology (NTNU).

My interest in technology goes back as far as I can remember. This interest led me to a bachelor's degree in mechanical engineering with specialization in operation and maintenance. The bachelor’s thesis investigated standardization of maintenance and was written in cooperation with Equinor ASA (Statoil at that time). It gave me the opportunity to familiarize myself with the industry and how maintenance processes were operated.

After an MSc in Industrial Engineering, and master’s thesis written in cooperation with Elkem ASA, I started working as a maintenance engineer for Elkem Thamshavn AS. I learned a lot from Elkem employees about the challenging task of running a smelting process and performing maintenance at the same time. I was humbled by the opportunity to follow and learn from mechanics and electricians. Their experience and knowledge of the machines and critical production equipment was impressive. Moreover, the Elkem Business System (EBS) and its Maintenance in Business (MIB) concept showed me how the process industry could operate based on the principles from the Toyota Production System (TPS). In terms of digitalization, I saw a potential in utilizing new technology to a greater extent. This led me to the research project Cyber Physical System Plant Perspective (CPS-Plant). The opportunity to contribute to the Norwegian approach for the digital manufacturing industry and collaborate with a strong consortium motivated me.

Working on a PhD project during the Covid-19 pandemic has been an interesting journey. Overnight, working routines and lives had to change; communication and meetings that were once face-to-face were moved online. The duration of this PhD project was March 2018 – March 2022, meaning that nearly half of the PhD work was carried out under limitations brought by the Covid-19 pandemic. In the big picture, the consequences this pandemic has caused my PhD research are negligible compared to the much more critical consequences so many others have faced. According to the World

Health Organization, by the beginning of March 2022, more than six million deaths were due to Covid-19. I salute all healthcare workers for their heroic efforts.

Acknowledgments

For this PhD project, there are several people who deserve to be thanked, as the completion of the project would not have been possible without the massive support I have received.

My supervisor Per Schjølberg has a quote he often uses: *"A wise man learns by the experiences of others; an ordinary man learns by his own experience; a fool learns by nobody's experiences."* I am forever grateful and humble for the opportunity to learn from my fellow Stjørdaling. Per Schjølberg has taught me a lot about the field of maintenance, guided me through this PhD project, introduced me to several companies, and included me in industrial projects. He has also shown me how to build a bridge between academia and industry. Per is a people person, and maintenance is an area where people and culture are essential inputs. Thank you for leading the way.

Many thanks to my co-supervisors Odd Myklebust and Halvor Holtskog for being available for guidance and academic support. I would also like to thank my colleagues at NTNU and all my current and former PhD colleagues for their inspiration. My deepest gratitude also goes to Harald Rødseth, who has been an "informal co-supervisor" and showed great interest in the research work presented in this thesis. Harald has always been available for discussing ideas and concepts, contributing to articles, and providing helpful comments to improve my work.

A big thanks to the consortium in the research project CPS-Plant; it has been a pleasure to work with and learn from everybody involved. Special thanks to Arnt Johnsen in Norsk Hydro ASA for his interest and enthusiasm in discussing maintenance and digitalization, and for sharing his perspective on these areas within the process industry.

I am very appreciative to Knut Inge Fordal for introducing me to the process industry. He initiated my bachelor's thesis to be written in cooperation with Equinor ASA and connected me with Thor Inge Bernhardsen. Since then, Thor Inge has been a mentor, close associate, co-author, providing valuable support in many ways, for which I am very grateful. I would also like to thank the employees at Elkem Thamshavn AS for the way they met a newly graduated engineer with open arms. In addition, the employees at Elkem ASA Silicon Products Trondheim deserve many thanks for their generosity,

especially Morten Richardsen for sharing his knowledge and experience, as well as providing inspiration.

Many thanks to my friends for enriching my life and the support. Finally, I would like to express my gratitude to my parents, sister and two brothers. Thank you so much for everything you have given me. My mother has showed me what good-hearted means, and my father has taught me, in his own way, a lot about the importance of maintenance. Together, my parents have provided me with a set of values I am eternally grateful for and taught me the skills of hard work and perseverance.

Dere var vinden i ryggen.

Stjørdal, March 2022

Jon Martin Fordal

Summary

Industry has high expectations for the possibilities offered by increased use of digital data and digital technologies, often referred to as *digitalization*. Many have highlighted digitalization as a key element for succeeding in developing new green markets, solutions for handling emissions, and more sustainable manufacturing, as well as improving products to be in line with the circular economy and reducing waste through enhanced engineering and the application of new technology. Digitalization is also claimed to provide major competitive advantages, putting it high on the agenda for top manufacturing nations, companies, and academics.

However, there is still a need for more research in a wide range of fields to reap the promised benefits. This PhD thesis investigates how the fields of maintenance, value chain, and digitalization relate to this. Success in maintenance becomes increasingly important with the introduction of new technology and more complex value chains. The thesis objectives are to provide a better understanding and knowledge of the connection between maintenance and the value chain, how development of technology, maintenance and maintenance management can improve the value chain, and how to implement an integrated maintenance and value chain approach. The thesis addresses the following research questions (RQs):

- RQ 1: *What is the connection between maintenance and the value chain?*
- RQ 2: *How can the development of technology, maintenance and maintenance management improve industrialists' value chain and level of performance?*
- RQ 3: *How to implement an integrated maintenance and value chain approach in an industrial setting?*

The main contributions of this thesis can be summarized as follows:

- New knowledge and concepts within digitalizing the value chain, with a focus on how this relates to the maintenance function.
- Providing increased understanding of the connections between maintenance and the value chain, and how advancements in technology have increased the importance of acknowledging this in a contextual manner.

- Presentation of valuable insights into how Industry 4.0 technologies enable opportunities for improving existing maintenance practices and expanding the role of maintenance management into the value chain.
- New knowledge on how fundamental maintenance methods can be used as a basis for implementing new technology and ways of working.
- Presentation of new and existing indicators and their position in maintenance and value chain, and how the industrial development introduces a need for new indicators.
- A framework for qualification criteria for Operator 4.0 and identification of relevant Industry 4.0 technologies, and a discussion on the role of operators, maintenance personnel and other relevant job categories in an Industry 4.0 environment, and how this relates to the value chain perspective.

Overall, this thesis should provide a better understanding and new knowledge of the relationship between maintenance and the value chain, and how digitalization can strengthen them and be complementary integrated to improve value chain performance. The thesis aspires to support those who either manage or study these areas, individually or in combination.

Summary in Norwegian

Industrien har høye forventninger knyttet til muligheter introdusert ved økt bruk av digital data og digital teknologi, ofte omtalt som *digitalisering*. Mange har fremhevet digitalisering som et nøkkelelement for å lykkes med utvikling av nye grønne marked, løsninger for håndtering av utslipp, mer bærekraftig produksjon, forbedre produkter for å være i tråd med sirkulær økonomi, og redusere sløsing gjennom bedre ingeniørarbeid og anvendelse av ny teknologi. Det blir også hevdet at digitalisering vil gi store konkurransefortrinn, noe som har resultert i at ledende industriland, bedrifter, og forskere har plassert temaet høyt på sine agendaer.

Derimot er det fortsatt behov for mer forskning innen flere områder for å høste de lovede konkurransefortrinnene. Denne doktorgradsavhandlingen undersøker hvordan områdene vedlikehold, verdikjede, og digitalisering forholder seg til dette. Å lykkes med vedlikehold blir stadig viktigere ved innføring av ny teknologi og mer komplekse verdikjeder. Målet med avhandlingen er å gi en bedre forståelse og kunnskap om sammenhengen mellom vedlikehold og verdikjede, hvordan utvikling av teknologi, vedlikehold, og vedlikeholdsstyring kan forbedre verdikjeden, og hvordan implementere en integrert vedlikeholds- og verdikjedetilnærming. Avhandlingen tar for seg følgende forskningsspørsmål:

- Forskningsspørsmål 1: *Hvilken sammenheng er det mellom vedlikehold og verdikjeden?*
- Forskningsspørsmål 2: *Hvordan kan utvikling av teknologi, vedlikehold og vedlikeholdsstyring forbedre industrialister sine verdikjeder og ytelsesnivå?*
- Forskningsspørsmål 3: *Hvordan implementere en integrert vedlikeholds- og verdikjedetilnærming i en industriell setting?*

Denne avhandlingen presenterer bidrag til både teori og praksis, som kan oppsummeres som følger:

- Ny kunnskap og konsepter innen digitalisering av verdikjeden, med fokus på hvordan dette forholder seg til vedlikeholdsfunksjonen.

- Gitt økt forståelse for sammenhengen mellom vedlikehold og verdikjeden, og hvordan fremskritt innen teknologi har økt viktigheten av å anerkjenne dette på en kontekstuell måte.
- Presentert verdifull innsikt i hvordan digitale teknologier assosiert med Industri 4.0 gir muligheter for å forbedre eksisterende vedlikeholdspraksis og utvide rollen til vedlikeholdsstyring inn i verdikjeden.
- Ny kunnskap om hvordan grunnleggende vedlikeholdsmetoder kan brukes som grunnlag for implementering av ny teknologi og arbeidsmåter.
- Presentert nye og eksisterende indikatorer og deres rolle i vedlikehold og verdikjede, og hvordan den industrielle utviklingen introduserer behov for nye indikatorer.
- Et rammeverk for kvalifikasjonskriterier for Operatør 4.0 og identifisering av relevante digitale teknologier assosiert med Industri 4.0, og en diskusjon om rollen til operatører, vedlikeholdspersonell og andre relevante stillingskategorier i et arbeidsmiljø assosiert med Industri 4.0, og hvordan dette forholder seg til verdikjedeperspektivet.

Samlet sett bør denne avhandlingen gi en bedre forståelse og ny kunnskap om sammenhengen mellom vedlikehold og verdikjeden, og hvordan digitalisering kan styrke dem og integreres komplementært for å forbedre verdikjedens ytelse. Avhandlingen har som mål å støtte de som enten jobber med eller studerer disse områdende, individuelt eller i kombinasjon.

Abbreviations

AI	Artificial intelligence
AR	Augmented reality
CMMS	Computerized maintenance management system
CPS	Cyber-physical systems
EAM	Enterprise asset management
ERP	Enterprise resource planning
IIoT	Industrial Internet of Things
IoS	Internet of Services
IoT	Internet of Things
ICT	Information and communication technologies
IT	Information technology
KPI	Key performance indicator
MES	Manufacturing execution system
OEE	Overall equipment effectiveness
PDCA	Plan – Do – Check – Act
PdM	Predictive maintenance
RQ	Research question
TPM	Total productive maintenance
TPS	Toyota Production System
VCM	Value chain management
VCP	Value chain performance

Definitions

Maintenance [1]:

Combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function.

Required function [1]:

Function, combination of functions, or a total combination of functions of an item which are considered necessary to fulfill a given requirement.

Maintenance management [1]:

All activities of the management that determine the maintenance requirements, objectives, strategies and responsibilities, and implementation of them by such means as maintenance planning, maintenance control, and the improvement of maintenance activities and economics.

Availability [1]:

Ability of an item to be in a state to perform as and when required, under given conditions, assuming that the necessary external resources are provided.

Predictive maintenance [1]:

Condition-based maintenance carried out following a forecast derived from repeated analysis or known characteristics and evaluation of the significant parameters of the degradation of the item.

Value chain [2]:

A value chain is a set of activities that a firm operating in a specific industry performs in order to deliver a valuable product or service for the market.

Digitalization [3]:

The exploitation of digital opportunities.

Thesis Structure

This PhD thesis has two main parts:

- Part I – Main report: The first part provides a general background and introduction to the PhD project. The focus is on research objectives and questions, and limitations and scope for the research. Further, theoretical background on the research topic and a description of research methodology and the applied research design is also given. Finally, main results and discussions based on the articles and research findings are presented with concluding remarks and suggestions for further research.
- Part II – Articles: The second part is a collection of articles that represents the contributions of the research performed throughout this PhD project.

Appended Articles and Declaration of Authorship

Article 1:

Fordal J.M., Rødseth H., Schjølberg P. (2019) Initiating Industrie 4.0 by Implementing Sensor Management – Improving Operational Availability. In: Wang K., Wang Y., Strandhagen J., Yu T. (eds) Advanced Manufacturing and Automation VIII. IWAMA 2018. Lecture Notes in Electrical Engineering, vol. 484. Springer, Singapore. https://doi.org/10.1007/978-981-13-2375-1_26. Presented at *International Workshop of Advanced Manufacturing and Automation (IWAMA) 2018*, Changzhou, China, September 20-21, 2018.

Declaration of authorship:

Fordal conceptualized the article and created the concept with input from all co-authors. Fordal wrote the article, with contributions from Rødseth on the link between maintenance management and sensor management. Schjølberg provided feedback and relevant literature.

Article 2:

Fordal J.M., Bernhardsen T.I., Rødseth H., Schjølberg P. (2020) Balanced Maintenance Program with a Value Chain Perspective. In: Wang Y., Martinsen K., Yu T., Wang K. (eds) Advanced Manufacturing and Automation IX. IWAMA 2019. Lecture Notes in Electrical Engineering, vol. 634. Springer, Singapore. https://doi.org/10.1007/978-981-15-2341-0_39. Presented at *International Workshop of Advanced Manufacturing and Automation (IWAMA) 2019*, Plymouth, United Kingdom, November 21-22, 2019.

Declaration of authorship:

Fordal conceptualized the article and created the concept with input from Rødseth and Schjølberg, and industrial experience from Bernhardsen. Fordal wrote the article, with contributions from Rødseth on Smart Maintenance and from Bernhardsen on challenges in the process industry. Schjølberg provided feedback and relevant literature.

Article 3:

Fordal, J.M. (2019) Indicator for measuring performance of planned maintenance stops – an enabler for continuous improvement. In: Beer M., Zio E. (eds) Proceedings of the 29th European Safety and Reliability Conference (ESREL). https://doi.org/10.3850/978-981-11-2724-3_0237-cd. Presented at *European Safety and Reliability Conference (ESREL) 2019*, Hannover, Germany, September 22-26, 2019.

Declaration of authorship:

Fordal conceptualized the article and created the concept. Fordal wrote the article, conducted the literature review, and formalized the concept.

Article 4:

Fordal, J.M., Rødseth, H., Schjølberg, P., Santini, F. (2019) Enhancing value chain performance with maintenance indicators – an overview of advancements. In: Jyoti K. Sinha (ed), Proceedings of 4th International Conference on Maintenance Engineering (IncoME-IV 2019) (pp.113-122). Manchester, UK: University of Manchester. Presented at *International Conference on Maintenance Engineering, IncoME-IV 2019*, University of Manchester Middle East Centre Dubai UAE, April 24-25, 2019.

Declaration of authorship:

Fordal conceptualized the article and created the concept with input from all co-authors. Fordal wrote the article, with contributions from Rødseth on maintenance indicators and Smart Maintenance, and from Santini on advancements in the maintenance function. Schjølberg provided feedback and relevant literature.

Article 5:

Rødseth H., Fordal J.M., Schjølberg P. (2019) The Journey Towards World Class Maintenance with Profit Loss Indicator. In: Wang K., Wang Y., Strandhagen J., Yu T.

(eds) Advanced Manufacturing and Automation VIII. IWAMA 2018. Lecture Notes in Electrical Engineering, vol. 484. Springer, Singapore. https://doi.org/10.1007/978-981-13-2375-1_25. Presented at *International Workshop of Advanced Manufacturing and Automation (IWAMA) 2018*, Changzhou, China, September 20-21, 2018.

Declaration of authorship:

Rødseth conceptualized the article and created the concept with input from all co-authors. Rødseth wrote the article, with contributions from Fordal on maintenance management and value chain, including a focus diagram for maintenance indicators supporting the value chain.

Article 6:

Rødseth H., Eleftheriadis R., Lodgaard E., Fordal J.M. (2019) Operator 4.0 – Emerging Job Categories in Manufacturing. In: Wang K., Wang Y., Strandhagen J., Yu T. (eds) Advanced Manufacturing and Automation VIII. IWAMA 2018. Lecture Notes in Electrical Engineering, vol. 484. Springer, Singapore. https://doi.org/10.1007/978-981-13-2375-1_16. Presented at *International Workshop of Advanced Manufacturing and Automation (IWAMA) 2018*, Changzhou, China, September 20-21, 2018.

Declaration of authorship:

Rødseth conceptualized the article and created the concept with input from all co-authors. Rødseth wrote the article, with contributions from Fordal on the framework for evaluating Operator 4.0, Industry 4.0 technologies and evaluating the value chain perspective within these contributions.

Article 7:

Fordal J.M., Schjølberg P., Helgetun H., Skjermo T.Ø., Wang Y., Wang C. (2023) Application of sensor data based predictive maintenance and artificial neural networks to enable Industry 4.0. *Advances in Manufacturing*. https://doi.org/10.1007/s40436-022-00433-x.

Declaration of authorship:

Fordal conceptualized the article and created the concept with input from all co-authors. Fordal wrote the article, with contributions from Helgetun and Skjermo on the case and from Yi Wang and Chen Wang on the data model. Schjølberg provided feedback and relevant literature.

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Part I – Main report

Part II – Articles

Part I – Main report

1. Introduction

This chapter provides an introduction of the PhD project, with a focus on research objectives and questions as well as limitations and scope of the research. A general background on the research topic and a presentation of the Norwegian research project the Cyber Physical System Plant Perspective (CPS-Plant), which the PhD project has been a part of, is also given.

1.1 Background

Industry and the world are changing at a rapid pace. The former is raising the bar when it comes to resource and asset utilization in markets with increasingly demanding customers, while at the same time trying to incorporate new technology to gain a competitive advantage and increase profits. The latter is facing climate change and is currently in a race to prevent global warming. In this race, the industry can provide major support and be a part of the solution by developing new green markets, solutions for handling emissions, and more sustainable manufacturing, as well as improving products to be in line with the circular economy and reducing waste through enhanced engineering and the application of new technology. Succeeding in this race requires advances in research in a wide range of different fields.

Industry has high expectations for the possibilities offered by increased use of digital data and digital technologies, often referred to as *digitalization*. As a result, the concept *Industry 4.0* has been highlighted, and is on the lips of many industrialists and researchers. One definition of Industry 4.0, also known as the Fourth Industrial Revolution, is [4]: "*Industry 4.0 is the sum of all innovations derived and implemented in a value chain to address the trends of digitalization, autonomization, transparency, collaboration and the availability of real-time information of products and processes.*" In Germany, they have developed a German standardization roadmap for *Industrie 4.0*. In their 2030 vision for Industry 4.0, Autonomy, Interoperability and Sustainability are selected as strategic areas of action. Within the area of sustainability, the following has been presented on how this will support climate protection [5]: *"Industrie 4.0 makes it possible to tap additional potentials for resource efficiency. In combination with* *constructive and process-related approaches, material cycles can be closed over the entire product life cycle. Industrie 4.0 is thus a significant enabler for the circular economy and environmental and climate protection in general."* Industry 4.0 also introduces new opportunities for companies' maintenance function, and it is discussed how the field of maintenance, especially predictive maintenance (PdM), can contribute to reaping the promised benefits of Industry 4.0 [5, 6].

White paper no. 27 (2016-2017) "*A greener, smarter and more innovative industry"* from the Norwegian government was a milestone for industry in Norway. Here, the government's vision for an active industrial policy is presented [7]: *"Norway will be a world leader in industry and technology."* Further, the following is stated on how to achieve this vision [7]: *"Updated knowledge at all levels in enterprises is needed in order to achieve our visions. Increasing digitalisation and the development of new digital technologies affect how enterprises, logistics and value chains are organised, and how enterprises develop relationships with customers."* Finally, the focus on the need for new value chains and development towards more effective, more precise, and more automated production is discussed [7]: *"In parallel, we are facing technology advancements in the area of digitalisation and other enabling technologies which over time will transform Norwegian industry as we know it. This is occurring at a rapid rate. New materials are being used, and processes are being changed, automated and digitalised. It is a matter of more effective, more precise and more automated production, as well as of new products, new value chains and new business models."* Summarized, and based on the above, there is a need for development and research in these areas, from the perspective of society, industrial companies, government agencies, and academia.

The title of this PhD, *"Digitalization of the value chain - improving value chain performance with prediction"*, consists of several words requiring a definition. First, digitalization is defined as [3]: *"The exploitation of digital opportunities."* Thus, the use of digital technologies to change business processes and provide new revenue and value-producing opportunities is in focus. Second, a definition of value chain is [2]: *"A value chain is a set of activities that a firm operating in a specific industry performs in order to deliver a valuable product or service for the market."* Within value chains, there are three types of integration. Horizontal value chain integration is from suppliers to business partners, meaning inter-industry value chains and supply chains. Vertical value chain integration covers from productivity efficiency to added value, and linkage of production processes (inside manufacturing boundaries). Finally, end-to-end value chain integration is integration throughout the full life-cycle process (known as Smart Products). Further, the goal for any value chain is [2]: *"The overall goal is to deliver maximum value for the least possible total cost and create a competitive advantage."* Here, predictions based on value chain and maintenance data are assumed to provide significant competitive advantages and can reduce total cost [8, 9]. Prediction is defined as [10]: *"A thing predicted; a forecast."*

Based on the above-mentioned and possibilities introduced with emerging digital technologies, this PhD project brings a new view on the fields of maintenance and value chain, highlights their importance, and combines them to develop new frameworks, tools, and methodology to support process companies in increasing performance and resource utilization. The two fields are traditionally seen as independent, and there is a lack of knowledge on how maintenance can improve companies' value chains. The field of maintenance has for a long time been seen as a cost center, but findings prove that maintenance is a profit-generating function [11, 12]. Further, maintenance is said to have a significant impact on capacity, quality, costs, environment, and safety [11], and the introduction of Smart Maintenance (digitalization) is assumed to increase this impact [5, 13]. In [5, 11, 12, 14], they also suggest further investigation of the relationship between maintenance and overall organizational performance to provide a more holistic view of maintenance performance benefits. The original value chain concept presented by Michael Porter does not include maintenance [2]. Nor is maintenance included in more recent value chain frameworks presented by [15, 16]. The need for research within this area is underpinned by [17], where they claim there is a lack of developed literature within value chain management. Research on maintenance and value chain has mainly been carried out independently, and research on how these two fields can be combined and utilized to strengthen each other seems to have just launched from the start line.

1.1.1 CPS-Plant

This PhD project is linked to the research project CPS-Plant. The CPS-Plant consortium consists of three Norwegian industry partners, Norsk Hydro ASA, Benteler Automotive Raufoss AS and Hycast AS, while SINTEF Digital and NTNU (Trondheim and Gjøvik) are the academic partners. SINTEF Manufacturing AS was the project leader. The project duration for CPS-Plant was 01 March 2017 – 28 February 2021. CPS-Plant received funding by The Research Council of Norway.

The overall goal for CPS-Plant was to improve and optimize production systems in Norwegian manufacturing and process industries targeting complex products and advanced materials by exploring the potential of digitalization. Industry 4.0 combines several major innovations in a wide spectrum of digital technologies necessary for transforming manufacturing and process industries. The methodology and knowledge foundation of the new digitalized manufacturing paradigm include the Internet of Things (IoT); Big Data technologies; cyber-physical systems (CPS) for manufacturing; advanced robotics; artificial intelligence; sophisticated sensors; cloud computing; zero-defect manufacturing. This new paradigm is in focus worldwide. However, in a high-cost country like Norway, it is essential to succeed in this realm for achieving improved competitiveness. Industries that lag in innovation tend to resort to outsourcing or lose their market share. Studies show that reduction of factor cost is the most common motive for manufacturing outsourcing. The observed increase in back-sourcing indicates effects of organizational learning in decision-making for international production. It is predicted that enterprises that neglect to address the above developments cannot remain competitive in the long term. Based on this, CPS-Plant aimed to develop a framework for the Norwegian approach for the digital manufacturing industry: A roadmap of new digital (Industry 4.0) technologies, and a demonstration and evaluation of new technologies for CPS where decision support through simulation capacities improves overall plant efficiency. Maintenance was an important element within the project, as improving the level of maintenance is linked to improvements in companies' performance. Figure 1.1 shows the project structure for the CPS-Plant project and the different work packages (WP). The PhD project was related to WP 5 – Digitalization over the value chain.

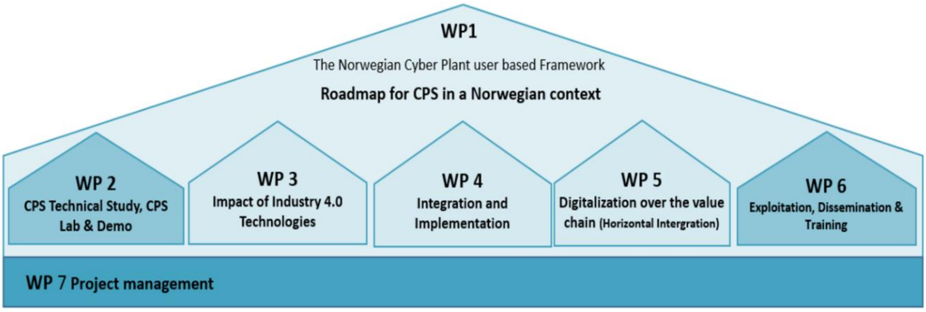


Figure 1.1: CPS-Plant project structure [18].

Further, digitalization in manufacturing, or Industry 4.0, has become the international strategy for manufacturing. This paradigm is built on CPS standing on a platform of embedded systems technologies as well as a strong and vital interaction between actors within production systems that can handle the complexity. The CPS-Plant project had a focus on the plant perspective (vertical value chain integration), within the factory or shop floor where finance, planning, constructions, and recycling are necessary. There was also an extension into the horizontal value chain, through the value network and the product and production life cycle, for a supplier-customer information flow. As an example of a value chain, Figure 1.2 presents the value chain for one of the industry partners, Norsk Hydro ASA.

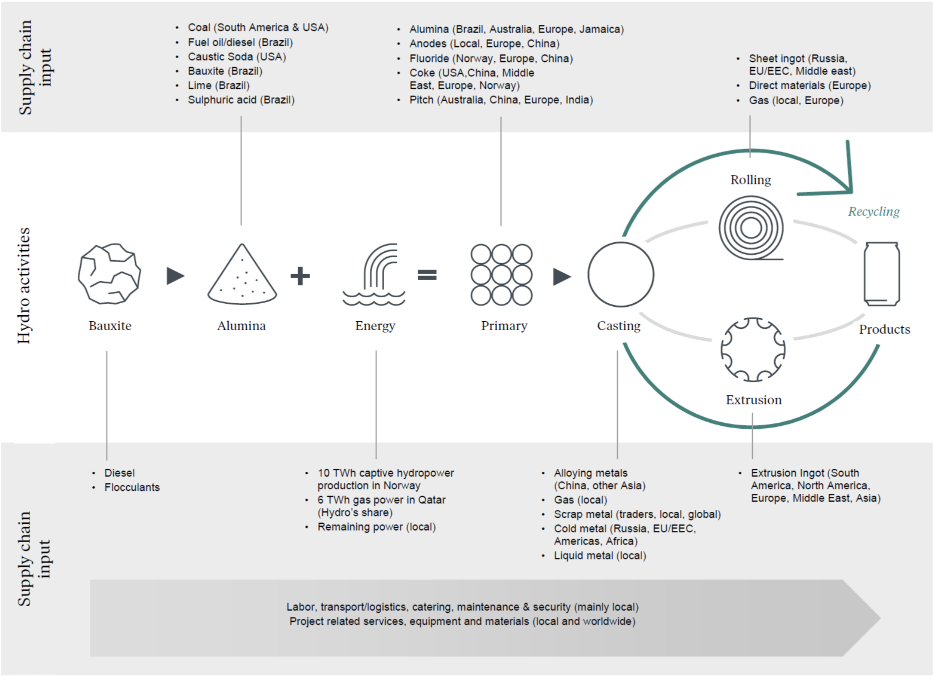


Figure 1.2: Hydro's value chain related to its supply chain [19].

1.2 Research motivation

It emerges clearly that there is a need for more research within maintenance and the value chain, and how digitalization can support these fields. Based on experience from the process industry, personal interest, and the research topic for CPS-Plant, the two points at issue, "*What is the problem*" and "*Why is it important*", were used to support defining the research for this PhD project. Figure 1.3 presents an overview of the problem statement and important outcomes of solving the problems.

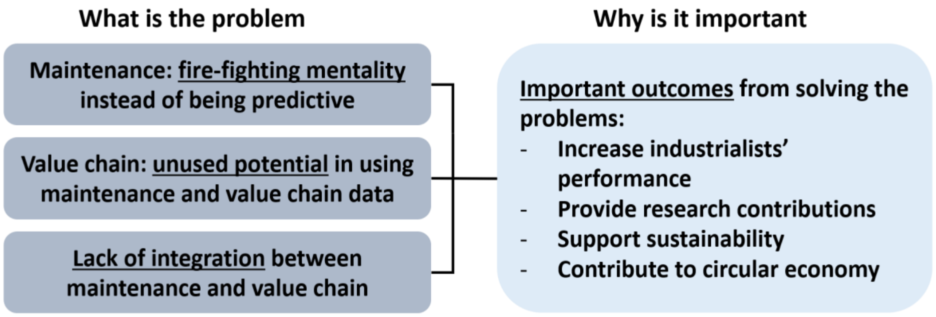


Figure 1.3: Overview of problem statement and important outcomes.

The above-mentioned problems are further discussed in the three following subchapters.

1.2.1 Maintenance – traditionally seen as a costly unwanted necessity

A definition of maintenance is [1]: *"combination of all technical and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function."* The importance of maintenance is underpinned by Okoh et al., who state that a poor level of maintenance has caused several organizations significant losses in terms of production unavailability and damage to humans, the environment and physical assets [20]. Moreover, within the process industry, they claim that many accidents are connected to maintenance deficiencies in safety barriers [20]. Wilson [21] supports the above-mentioned, commenting that successfully performing maintenance is a comprehensive and resource-demanding challenging task for industrialists to handle.

Industry 4.0 has been on everyone's lips in recent years, and industrialists have been expecting substantial gains in productivity, significantly higher levels of automation, and drastic improvements in resource efficiency by putting Industry 4.0 on their agenda. The new technology and demands within the industry also require a significant increase in the level of maintenance [22], and, as a result, PdM has been highlighted. The work on PdM has contributed to changing the traditional view on maintenance, from being a costly unwanted necessity to seeing maintenance as a competitive advantage. PdM is defined as [1]: *"Condition-based maintenance carried out following a forecast derived* *from repeated analysis or known characteristics and evaluation of the significant parameters of the degradation of the item."*

PdM aims to maximize the life of equipment and reduce both planned and unplanned downtime, and, as a result, minimize maintenance costs. This is possible by analyzing data collected from components and equipment and using those analyses to precisely predict when a part will fail, enabling to perform maintenance actions at the right time. Although a lot of research and work has been done on PdM, succeeding with it and gaining the advantages has turned out to be challenging. In fact, the added value of stand-alone PdM machine projects is often lower than asserted, as companies have extensive experience with wear and tear on their machines. Thus, there is a need for an overall concept for using digitalization in an advantageous and holistic manner [23]. This underpins the importance of further investigating on how the field of maintenance can support industrialists in increasing their performance.

1.2.2 Value chain – lack of maintenance perspective

The concept of the value chain, as it is known today, was first introduced by Michael E. Porter in 1985 [2]. The value chain concept was originally aimed at identifying value activities, as these are the building blocks of competitive advantage, and focusing on these activities can be used to define improvement needs or opportunities for companies [2]. Porter identified two types of activities, namely, primary and support activities. First, the primary activities are inbound logistics, operations, outbound logistics, marketing and sales, and, finally, service. These are defined as activities within the main value creation process for a traditional and general manufacturer. Second, the support activities are procurement, technology development, human resource management, firm infrastructure. The role of these activities is to create a foundation for enabling and improving the function of primary activities [2].

Technological development, the competitive environment, and the way products are manufactured and sold, and their capabilities, have changed significantly since 1985. In a newer article from 2014, written by Michael E. Porter and James E. Heppelmann, they claim that [24]: *"Smart, connected products offer exponentially expanding* *opportunities for new functionality, far greater reliability, much higher product utilization, and capabilities that cut across and transcend traditional product boundaries. The changing nature of products is also disrupting value chains, forcing companies to rethink and retool nearly everything they do internally."* This underpins the rapid development of products and value chains, which is also connected to the field of maintenance. Smart and connected products enable real-time data being available for the manufacturer, supporting PdM and optimization of both the product and the value chain process [9, 24].

Even though a lot of research has been conducted within value chains [15, 17, 25-35], research on the link and integration to the field of maintenance seems lacking. However, within IoT and servitization there is research presenting how companies create value by improving operational reliability as well as through big data and business analytics, increased performance of equipment and optimized maintenance resulting in lower operating expense, and improved asset utilization [36]. Utilization of maintenance and value chain data in products, and, especially, in the value chain process for improving the maintenance function is an area to be further investigated.

1.2.3 Integrating the fields of maintenance and the value chain

Advancements in technology, increased competition, and customers demanding more bang for the buck require industrialists to continuously improve resource utilization and their products and services. The need for improvements goes for both the field of maintenance and the value chain, and, additionally, the integration between the two fields. Thus, there is a need to conduct research and work with the overall goal of further developing competence within the development of a digitalized and integrated value chain. Figure 1.4 presents three conceptual stages with coherent elements seen as important to success when moving towards a digitalized and integrated value chain.

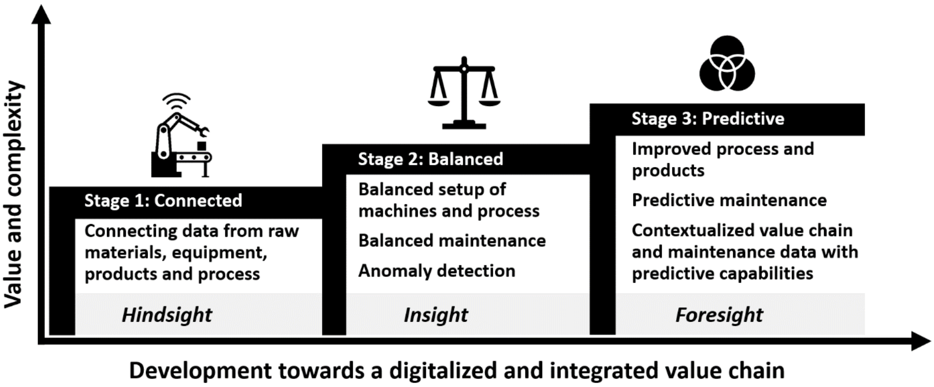


Figure 1.4: Three conceptual stages towards a digitalized and integrated value chain.

The three conceptual stages are divided into hindsight, insight, and foresight to indicate the way of working. Stage 1, “Connected”, targets creating a data foundation based on connected data gathered from raw materials, equipment, products, and process. This creates a foundation for decision support in stage 2, “Balanced”. Here, the data foundation is analyzed to provide an accurate and deep understanding of the current situation. Thus, setup of machines and process can be balanced based on need, anomalies, and managing variance to keep processes under control and stable. Finally, stage 3, “Predictive”, aims at predicting future need, setup and design of both value chain process and final products. Stage 3 should also enable PdM for critical equipment and utilize contextualized value chain and maintenance data with predictive capabilities for decision-making. Research has been carried out within elements related to the three stages presented above. However, there is still a need for more research and competence within such an extensive realm, especially regarding the maintenance perspective on horizontal and vertical system integration, which is underpinned by [37].

1.3 Research objectives and questions

Motivated by the challenges, potential, and overview of the problem statement outlined above, the research in this PhD focused on investigating the fields of maintenance and value chains. There are several unanswered questions and unexplored areas within each of these fields, but this PhD research mainly investigates the areas related to *how these* *fields can be integrated and their connection, how advancements in technology and the realm of maintenance can improve industrialists' value chain, and how to implement an integrated approach for the two fields in practice*. The objectives of this PhD research are to provide a better understanding and knowledge of:

- Understanding the connection between maintenance and the value chain.
- How can development of technology, maintenance and maintenance management improve the value chain?
- How to implement an integrated maintenance and value chain approach?

The following defined research problem for this PhD is:

How to integrate the fields of maintenance and value chain, in order to increase industrialists' level of performance?

Based on this, the following research questions (RQs) were defined to guide the research process:

RQ 1: *What is the connection between maintenance and the value chain?*

RQ 2: *How can the development of technology, maintenance and maintenance management improve industrialists' value chain and level of performance?*

RQ 3: *How to implement an integrated maintenance and value chain approach in an industrial setting?*

In addition to the research objectives, research problem, and research questions, two research goals were defined. Figure 1.5 presents the research questions and their link to the research goals.

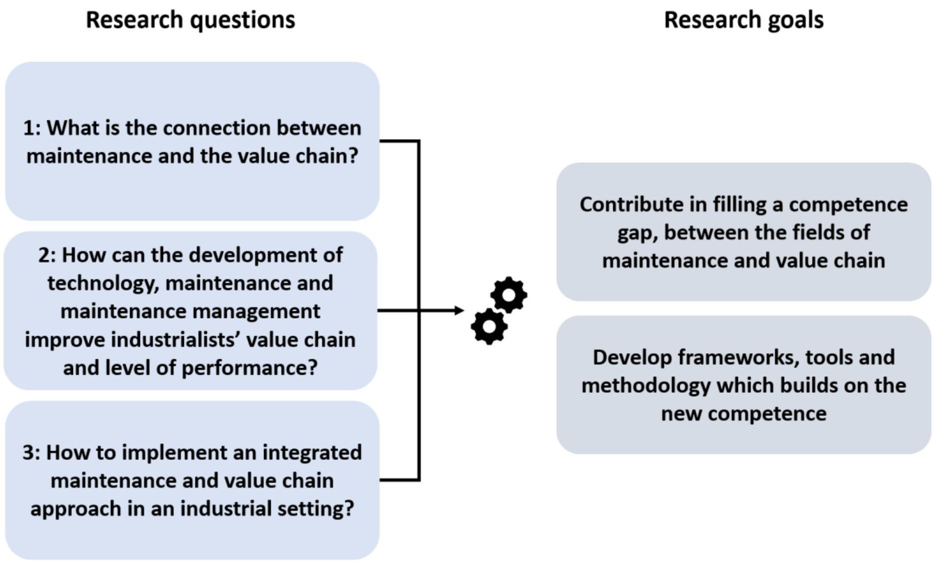


Figure 1.5: Research questions and research goals.

1.4 Limitations and scope

This PhD project covers three main topics. The first main topic is maintenance, which includes maintenance frameworks, maintenance management, and PdM. The second main topic is value chains, which includes value chain performance, value chain management, and value chain frameworks. The third main topic is digitalization, which includes Industry 4.0 and the development towards a digitalized and integrated value chain.

This PhD is part of the Norwegian research project CPS-Plant. The goal of the CPS-Plant project is to improve and optimize production systems in Norwegian manufacturing and process industries, targeting complex products and advanced materials by exploring the potential of digitalization. The findings of the research in this PhD will mainly be targeting applications within the manufacturing and process industry, applicable to both stand-alone machines and complete production lines. The findings are not limited to Norwegian industry.

The PhD project will be focused on the topics identified as part of the scope. In addition, as the first main topic, maintenance has different perspectives, generally said to be the maintenance optimization perspective (focusing on predicting remaining useful life (RUL) and optimizing maintenance intervals) and the organizational perspective (focusing on a holistic view of the maintenance function and value creation), this PhD will focus more on the organizational perspective. The research in this PhD is complementary rather than competing.

When planning the PhD project, it was not expected that a global pandemic would spread midway into the project. The Covid-19 pandemic introduced some unplanned limitations. The rapid expansion of Covid-19 led to travel restrictions and social distancing, and many companies shut their gates to reduce risk. Both CPS-Plant and this PhD project have faced challenges due to these restrictions. Yet it is difficult to imagine how different the final result would have turned out compared to the original plan. Evaluation of research quality is further described in Chapter 3.3.

1.5 Outline of thesis

This thesis is structured in two parts: Part I constitutes the main report of the thesis and Part II is the collection of appended articles. Part I is based on the research that has been presented in the articles. It presents relevant theory, provides an overview of the research process and integrates the contributions of the independent articles in a coherent argument.

Part I is organized as follows:

Chapter 1 introduces the general background and the PhD project, followed by a presentation of CPS-Plant. Further, Chapter 1 focuses on research motivation, research objectives and questions, and limitations and scope for the research.

Chapter 2 presents the theoretical background relevant to the research topic of maintenance, value chain, and digitalization. It includes relevant theory within maintenance management, predictive maintenance, value chain performance and indicators, Industry 4.0 and reference architectures from top manufacturing nations.

Chapter 3 provides a description of research methodology and the applied research design. Evaluation of research quality and ethical aspects of the research is also given.

Chapter 4 presents the main results and the contribution from the appended articles is presented and discussed. Implications for practitioners are also given.

Chapter 5 marks the end of the thesis, presents concluding remarks and proposes suggestions for further research.

Figure 1.6 illustrates the thesis outline and links the chapters with the commonly used structure in scientific writing, namely, introduction, methods, results, and discussion (IMRaD).

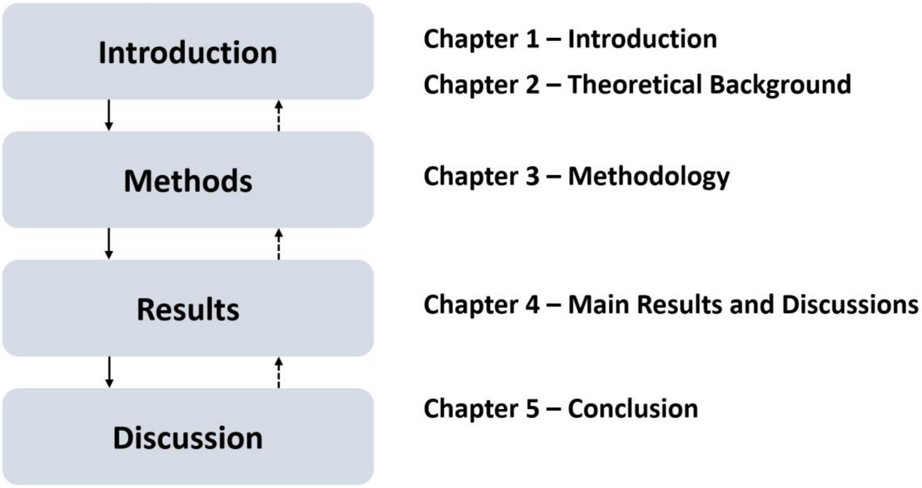


Figure 1.6: Outline of thesis according to the commonly used IMRaD structure.

Part II includes the articles that were written to disseminate the results of this PhD project. It contains the following seven articles:

1. Fordal J.M., Rødseth H., Schjølberg P. (2019) Initiating Industrie 4.0 by Implementing Sensor Management – Improving Operational Availability. In: Wang K., Wang Y., Strandhagen J., Yu T. (eds) Advanced Manufacturing and Automation VIII. IWAMA 2018. Lecture Notes in Electrical Engineering, vol. 484. Springer, Singapore.

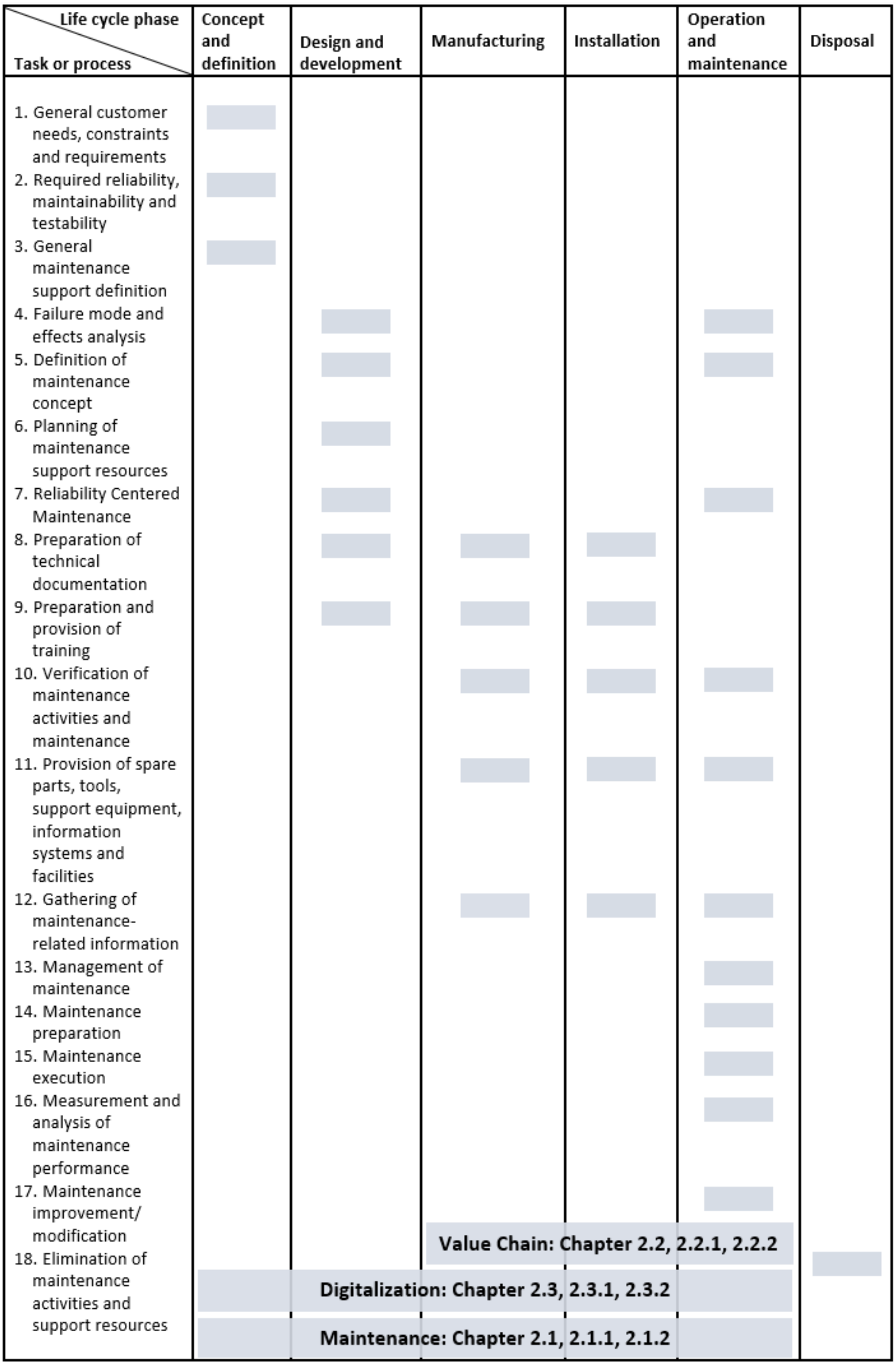
2. Fordal J.M., Bernhardsen T.I., Rødseth H., Schjølberg P. (2020) Balanced Maintenance Program with a Value Chain Perspective. In: Wang Y., Martinsen K., Yu T., Wang K. (eds) Advanced Manufacturing and Automation IX. IWAMA 2019. Lecture Notes in Electrical Engineering, vol. 634. Springer, Singapore.
3. Fordal, J.M. (2019) Indicator for measuring performance of planned maintenance stops – an enabler for continuous improvement. In: Beer M., Zio E. (eds) Proceedings of the 29th European Safety and Reliability Conference (ESREL).
4. Fordal, J.M., Rødseth, H., Schjølberg, P., Santini, F. (2019) Enhancing value chain performance with maintenance indicators – an overview of advancements. In: Jyoti K. Sinha (ed), Proceedings of 4th International Conference on Maintenance Engineering (IncoME-IV 2019) (pp.113-122). Manchester, UK: University of Manchester.
5. Rødseth H., Fordal J.M., Schjølberg P. (2019) The Journey Towards World Class Maintenance with Profit Loss Indicator. In: Wang K., Wang Y., Strandhagen J., Yu T. (eds) Advanced Manufacturing and Automation VIII. IWAMA 2018. Lecture Notes in Electrical Engineering, vol. 484. Springer, Singapore.
6. Rødseth H., Eleftheriadis R., Lodgaard E., Fordal J.M. (2019) Operator 4.0 – Emerging Job Categories in Manufacturing. In: Wang K., Wang Y., Strandhagen J., Yu T. (eds) Advanced Manufacturing and Automation VIII. IWAMA 2018. Lecture Notes in Electrical Engineering, vol. 484. Springer, Singapore.
7. Fordal J.M., Schjølberg P., Helgetun H., Skjermo T.Ø., Wang Y., Wang C. (2023) Application of sensor data based predictive maintenance and artificial neural networks to enable Industry 4.0. Advances in Manufacturing. https://doi.org/10.1007/s40436-022-00433-x.

2. Theoretical Background

This chapter presents the relevant theoretical background for this research study. It will focus on the fields of maintenance, value chain, and digitalization. First, the development of maintenance, emphasizing PdM, and maintenance indicators are introduced. Maintenance management and maintenance management models are also presented. Second, the area of value chains, value chain performance and indicators, and continuous improvement in the value chain is discussed. Third, digitalization is described with a focus on Industry 4.0 and moving towards a digitalized and integrated value chain. Figure 2.1 positions the next chapters and the three fields in the context of maintenance and maintenance support during the life cycle, as presented in IEC 60300-3-14:2004 [38]. In addition to scientific articles, books, reports, and national industrial strategic documents, the following standards have supported the foundation for this theoretical background:

- EN 13306:2017 Maintenance – Maintenance terminology
- EN 15341:2019 Maintenance – Maintenance Key Performance Indicators
- EN 15628:2014 Maintenance - Qualification of maintenance personnel
- EN 16646:2014 Maintenance - Maintenance within physical asset management
- EN 17007:2017 Maintenance process and associated indicators
- EN 50126-1:2017 Railway applications - The Specification and Demonstration of Reliability, Availability, Maintainability and Safety (RAMS) Part 1: Generic RAMS Process
- IEC 62264-1:2013 Enterprise-control system integration Part 1
- IEC 60300-3-14:2004 Dependability management - Part 3-14: Application guide - Maintenance and maintenance support
- IEC PAS 63088:2017 Smart manufacturing – Reference architecture model industry 4.0 (RAMI 4.0)
- ISO 13374 family - Condition monitoring and diagnostics of machines – Data processing, communication and presentation
- ISO 13379-1:2012 Condition monitoring and diagnostics of machines — Data interpretation and diagnostics techniques — Part 1: General guidelines

- ISO 13381-1:2015 Condition monitoring and diagnostics of machines — Prognostics — Part 1: General guidelines
- ISO 14224:2016 Petroleum, petrochemical and natural gas industries — Collection and exchange of reliability and maintenance data for equipment
- ISO 17359:2018 Condition monitoring and diagnostics of machines — General guidelines
- ISO 18095:2018 Condition monitoring and diagnostics of power transformers
  - ISO/TC 108 – several standards on condition monitoring
- ISO 55000 family - Asset management
- Maintenance baseline study - The Norwegian Petroleum Directorate May 1. 1998
- NORSOK Z-008:2017 Risk based maintenance and consequence classification



Life cycle phase / Task or process	Concept and definition	Design and development	Manufacturing	Installation	Operation and maintenance	Disposal
1. General customer needs, constraints and requirements	▨					
2. Required reliability, maintainability and testability	▨					
3. General maintenance support definition	▨					
4. Failure mode and effects analysis		▨			▨	
5. Definition of maintenance concept		▨			▨	
6. Planning of maintenance support resources		▨				
7. Reliability Centered Maintenance		▨			▨	
8. Preparation of technical documentation		▨	▨	▨		
9. Preparation and provision of training		▨	▨	▨		
10. Verification of maintenance activities and maintenance			▨	▨	▨	
11. Provision of spare parts, tools, support equipment, information systems and facilities			▨	▨	▨	
12. Gathering of maintenance-related information			▨	▨	▨	
13. Management of maintenance					▨	
14. Maintenance preparation					▨	
15. Maintenance execution					▨	
16. Measurement and analysis of maintenance performance					▨	
17. Maintenance improvement/ modification					▨	
18. Elimination of maintenance activities and support resources						▨

Value Chain: Chapter 2.2, 2.2.1, 2.2.2

Digitalization: Chapter 2.3, 2.3.1, 2.3.2

Maintenance: Chapter 2.1, 2.1.1, 2.1.2

Figure 2.1: Positioning body of knowledge in this thesis within IEC 60300-3-14:2004 [38].

2.1 Maintenance

The field of maintenance is broad both in terms of industrial and social applicability, and research area. While there are many different definitions and viewpoints on this field, it is clear that the importance of succeeding in maintenance has increased with the introduction of digitalization and more complex production systems [5]. As an example, acatech – German Academy of Science and Engineering has estimated that machinery availability and productivity gains enabled by industrial maintenance translate into a saving of one trillion euros a year for German industry, and that maintenance can serve as a driver of innovation by analyzing large volumes of data relating to machines and systems introduced with Industry 4.0 technologies [39].

The importance of maintenance is also highlighted in the perspective of asset management, and in [40], part of the reason is presented as follows: *"Ever-increasing competition caused by factors such as globalization puts more pressures on the effectiveness, efficiency and productivity of the production equipment in question and as a consequence forces companies to make early replacements or to increase the OEE, availability or dependability of the production system."* Increased environmental and safety requirements also demand similar improvements, underpinning maintenance as a key area for companies. Maintenance is further discussed in the context of asset management in [41-43], and a definition of physical asset management is given in the standard EN 16646:2014 Maintenance – Maintenance within physical asset management [44]: *"the optimal life cycle management of physical assets to sustainably achieve the stated business objectives."*

A common understanding and use of maintenance terminology, and an advantageous selection and implementation of maintenance types supports a successful maintenance function. Figure 2.2 gives an overview of some of the main maintenance types.

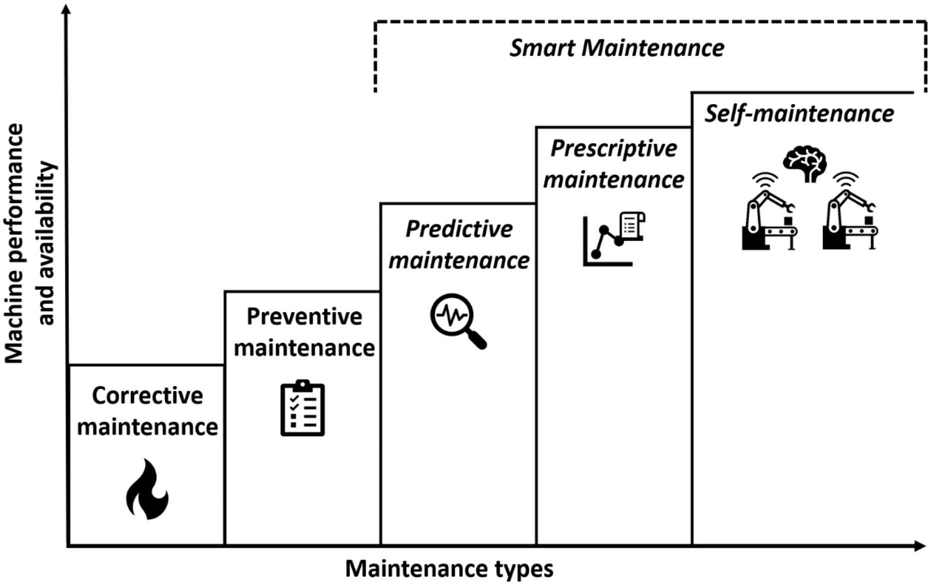


Figure 2.2: Development of maintenance types [37, 45-48].

The first way of performing maintenance is known as fire-fighting, or reactive maintenance, and was the most common way of performing maintenance in the first years of industrialization [49]. This is named corrective maintenance and is defined by EN 13306:2017 as follows [1]: *"Maintenance carried out after fault recognition and intended to restore an item into a state in which it can perform a required function"*. Thus, this is maintenance carried out when the ability of an item to be in a state to perform as and when required is already lost. On the other hand, preventive maintenance emerged as experience and understanding of the value in avoiding breakdowns was gained with the introduction of more advanced machinery and assembly lines [49]. Corrective maintenance can further be subdivided into immediate and deferred corrective maintenance [1]. Preventive maintenance is defined as [1]: *"Maintenance carried out intended to assess and/or to mitigate degradation and reduce the probability of failure of an item."* Preventive maintenance can further be categorized into predetermined maintenance or condition-based maintenance, where the latter can be divided into PdM and non predictive condition based maintenance [1].

PdM, also known as Maintenance 4.0 [49], has received a lot of attention with the introduction of Industry 4.0, and many industrialists have had this term on their agenda [6]. A definition of PdM is [1]: *"Condition-based maintenance carried out following a forecast derived from repeated analysis or known characteristics and evaluation of the significant parameters of the degradation of the item."* It is claimed that reactive and periodic preventive maintenance strategies will increasingly be replaced by PdM strategies moving towards Industry 4.0 [5]. PdM is further presented in Chapter 2.1.2. Moreover, development in technology and research has resulted in introducing prescriptive maintenance, which adds a new dimension to PdM by including a prescribed recommendation, or a course of action, for the predicted failure [49]. As an example, PdM aims to answer [50]: *"What will happen when?"*, while prescriptive maintenance aims to answer [50]: *"How can we control the occurrence of a specific event? (How should it happen?)"*. Finally, self-maintenance has also been introduced and a definition is given in [51]: *"Self-maintenance refers to the ability to carry out regular quality and safety checking by the machine itself, to detect anomaly, and to make immediate repairs when needed by using stocked spare parts to avoid potential catastrophic loss."* Thus, the aim for self-maintenance is to have self-maintaining machines which can monitor and diagnose themselves, and when any failure or degradation occurs, it can still maintain the required function for a while [51]. This maintenance type can be seen as part of the top level in the CPS 5C architecture presented in [46], which is further discussed in Chapter 2.3.1. Combined, PdM, prescriptive maintenance, and self-maintenance can be seen under the umbrella of Smart Maintenance, which can be defined as [52]: *"an organizational design for managing maintenance of manufacturing plants in environments with pervasive digital technologies."* According to [52], Smart Maintenance is a multidimensional concept consisting of the dimensions data-driven decision-making, human capital resource, internal integration, and external integration.

Summarized, there are many different definitions of the above-mentioned and a lack of common ground, especially regarding the Smart Maintenance umbrella. However, agreement on a set of functional capabilities for characterizing maintenance in smart factories is starting to be established. As an example, five capabilities in this regard are presented as follows in [50]:

- *Prediction capability to monitor, analyze and anticipate hidden patterns and anomalies and accordingly predict critical and unexpected events (i.e., moment of failure)*
- *Optimization capability to achieve an optimal point in maintenance planning through economically efficient use of human and physical resources as well as knowledge assets*
- *Adaptation capability to conform to (unexpected) changes and reconfigurations in work-orders and production plans*
- *Learnability to continuously learn from former experiences (i.e., failure events and former decision-making instances)*
- *Capability of intelligent actions and self-direction to (completely) automatise maintenance workflow and decision-support systems (i.e., autonomous maintenance management)*

Germany has started several initiatives for guiding companies on their digital transformation process and towards smart factories, e.g., acatech Industrie 4.0 Maturity Index [53], Platform Industrie 4.0 [54], German Standardization Roadmap Industrie 4.0 [5], and The Standardization Roadmap of Predictive Maintenance for Sino-German Industrie 4.0/Intelligent Manufacturing [6]. Six maturity stages for Industrie 4.0, with their objectives, and their position within digitalization, Industry 4.0, and predictive maintenance in the development towards Smart Maintenance are given in Figure 2.3 [53, 55, 56].

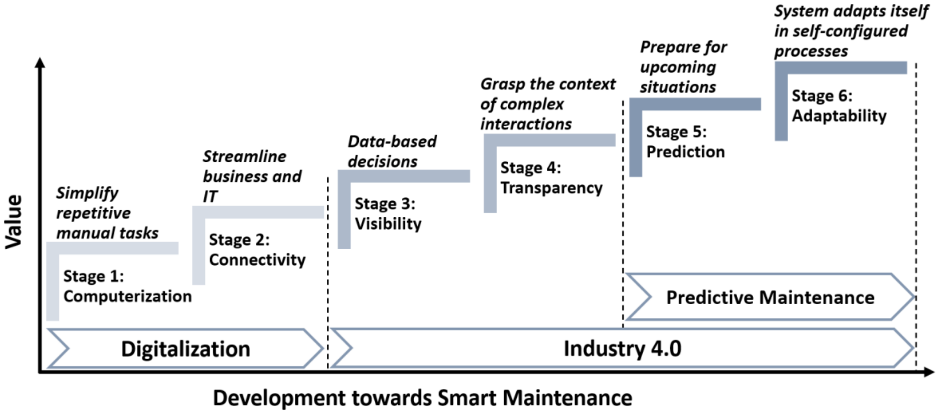


Figure 2.3: Positioning central stages, and their objectives, within digitalization, Industry 4.0, and predictive maintenance in the development towards Smart Maintenance, adapted from [53, 55, 56].

2.1.1 Maintenance management

A definition of maintenance management is [1]: "*All activities of the management that determine the maintenance requirements, objectives, strategies and responsibilities, and implementation of them by such means as maintenance planning, maintenance control, and the improvement of maintenance activities and economics.*" There are many models, definitions, work processes, and different perspectives on maintenance management. In Norway, the standard NORSOK Z-008:2017 Risk based maintenance and consequence classification [57] is used by several big companies in the process industry to help guide their activities within maintenance and maintenance management. Here, a maintenance management model is described, which is inspired by the maintenance baseline study performed by The Norwegian Petroleum Directorate [58]. The standard describes important steps within each of the elements in the model, e.g., how the process of performing consequence classification creates a foundation for the element named "Maintenance programme" and, further, how this can support the element "Planning". Figure 2.4 presents this maintenance management model [57, 58].

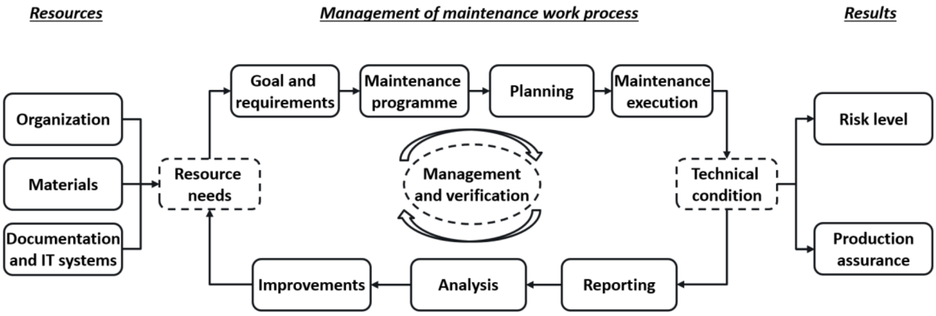


Figure 2.4: Maintenance management model, adapted from [57, 58].

Outside of Norway, a more established standard is the IEC 60300-3-14:2004 Dependability management part 3-14: Application guide - Maintenance and maintenance support [38], which presents activities within maintenance management and the connection to other central maintenance processes. Figure 2.5 shows this linkage between maintenance management and other important maintenance processes [38].

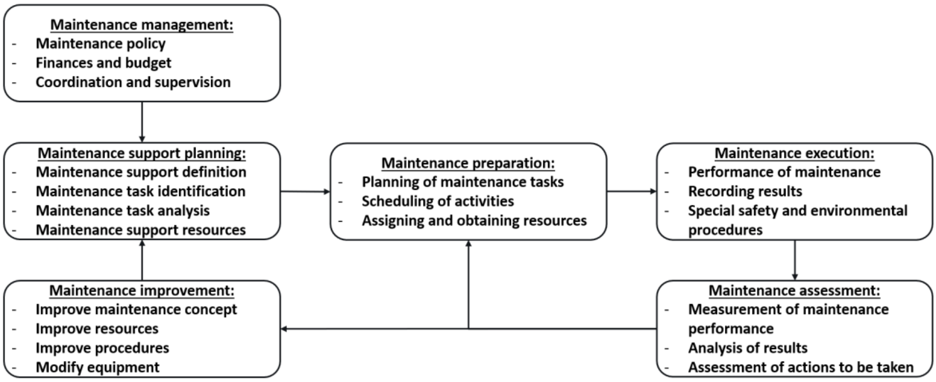


Figure 2.5: Maintenance management linked to essential maintenance processes [38].

The standard EN 17007:2017 Maintenance process and associated indicators [59] presents an overview of the overall maintenance process. Additionally, to help in identifying other maintenance processes, the standard has classified three main process families [59]: First, “management process” includes determining the objectives and policy to be implemented to achieve them, beneficial use of company funds and allocation of resources. This ensures coherence with the other two process families; it includes measuring and monitoring the process system and using the results to improve performance. Second, “realization process” concerns those who directly contribute to achieving expected results and is designed to ensure that customer needs are satisfied; it encompasses all activities related to the realization cycle of the product or service. Third, “support processes” ensure functioning of the other processes and provides them with necessary resources, including activities within human resources, financial resources, material resources and their maintenance, and information processing. Figure 2.6 presents this overall maintenance process with the management process at the top of the figure, realization process in the center, and support processes at the bottom of the figure [59].

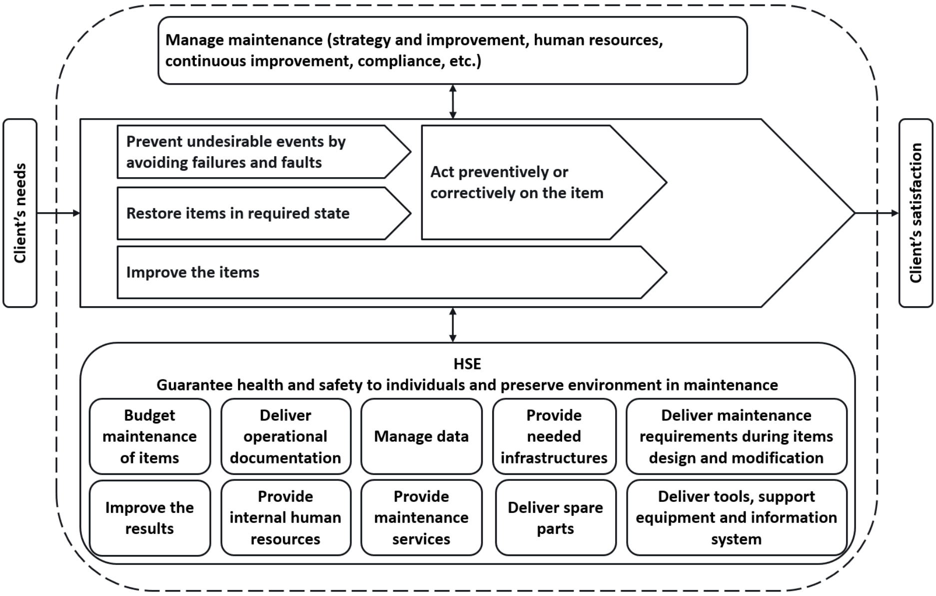


Figure 2.6: Overall maintenance process, adapted from [59].

One common characteristic for the models, processes, and definition of maintenance management presented above is the inclusion of continuous improvement. Within continuous improvement, a well-known concept is the Plan-Do-Check-Act (PDCA) cycle. Continuous improvement and the PDCA cycle are further described in Chapter 2.2.2.

Moreover, succeeding with maintenance management is a comprehensive and challenging task [20, 21]. Maintenance departments must coordinate a wide variety of actions and activities. As an example, Figure 2.7 presents an overview of activities necessary for a maintenance department to handle and coordinate, while focusing on minimum total cost and being effective, safe, and legal [21].

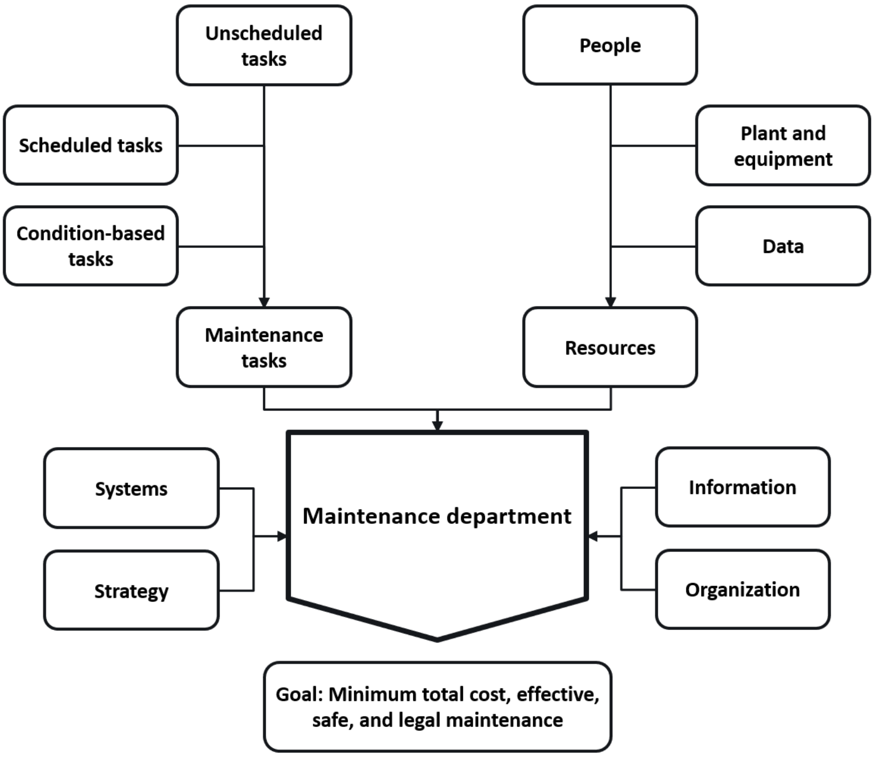


Figure 2.7: Overview of important elements a maintenance department should manage, adapted from [21].

In addition, the complexity of performing maintenance increases significantly when there is a continuous production process being maintained [21]. Figure 2.8 illustrates three phases for a maintenance engineering task, taking plant availability into account.

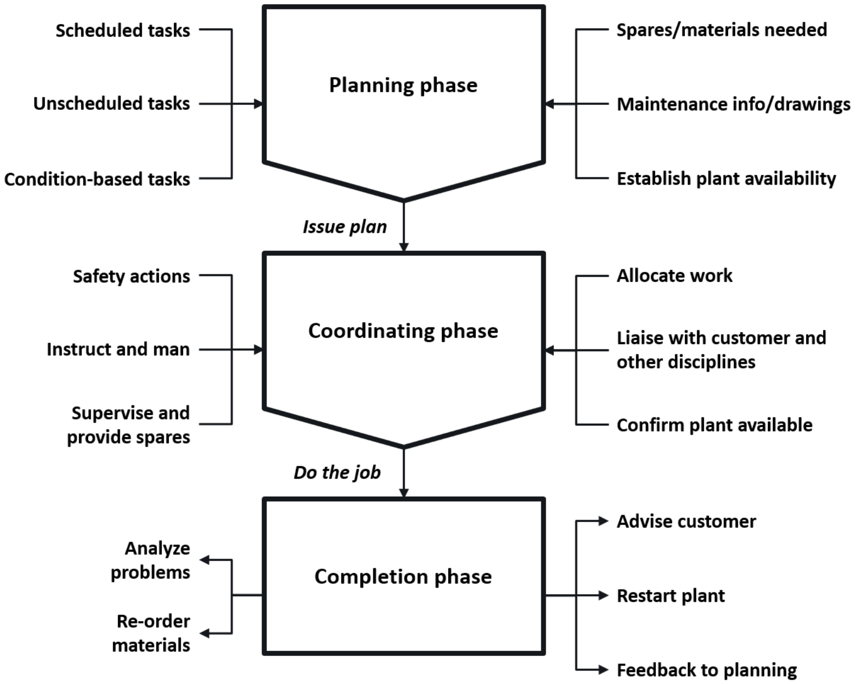


Figure 2.8: Three main phases of a maintenance engineering task, adapted from [21].

Combined, Figure 2.7 and Figure 2.8 underpin the need for handling maintenance in a logical fashion. In large companies, several hundred maintenance tasks can occur each day. The challenges involved in avoiding chaos, transferring information, coordinating and controlling maintenance tasks have resulted in increased use of computer-based planning systems, known as computerized maintenance management system (CMMS) or enterprise asset management (EAM), to help organizations stay in control. Moreover, for a maintenance department to perform valuable maintenance analysis, handle the workload in an effective manner, and ensure smooth operation, utilizing these systems capabilities is essential [60].

In general, the field of maintenance management has increased its scope, supported by the impact of IT, and will need to be further integrated with operation management in the future [60]. Studies also show that the traditional practice of making maintenance and production decisions independently can increase cost and that it is beneficial to make these decisions in an integrated fashion for strengthening preventive activities, quality improvements, and manufacturing capabilities [60-62]. The expanding scope of maintenance is also seen in recent standards, e.g., the standard EN 16646:2014 Maintenance - Maintenance within physical asset management [44], further describes the connection between maintenance and operation. Figure 2.9 presents the relationship between the maintenance process and the operation process with an overview of inputs from the processes “operate assets” and “maintain assets” [44].

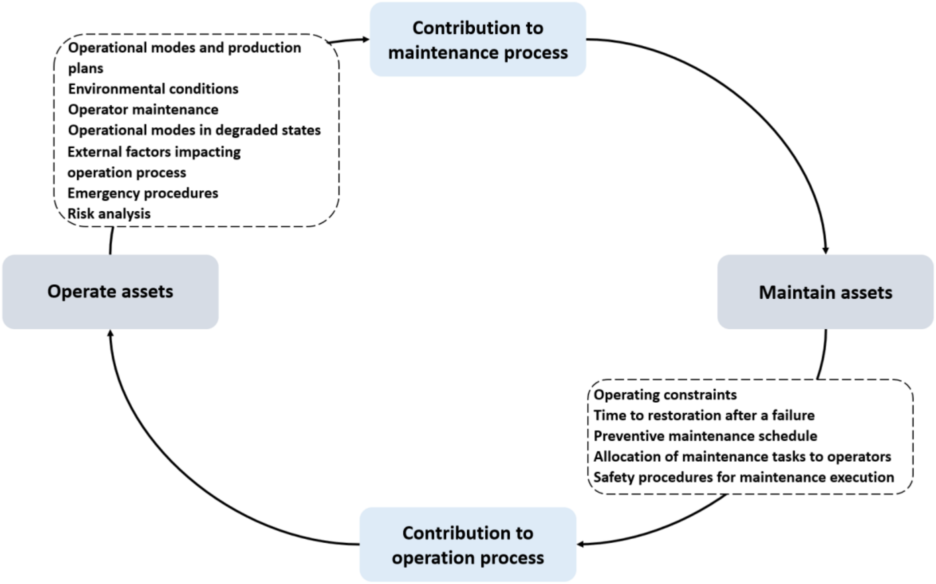


Figure 2.9: Relationship between the maintenance process and operation process, adapted from [44].

The Operate assets process provides the following information and input to the maintenance process [44]:

- **Operational modes and production plans** – which are established for the plant over a given period. These involve operating profiles for each asset, specifying the number of units of use, e.g., hours, starts/stops, that can cause degradation. This information determines the required periods during which invasive preventive maintenance actions shall not be done. Further, this information shall be used in maintenance plans to calculate and schedule intervals for maintenance activities.

- **Environmental conditions** – these conditions depend on where and when the assets are being operated and can have an impact on the failure mechanisms of the assets.
- **Operator maintenance** – involving operators in monitoring and maintenance is important for the maintenance process, as operators can perform first line maintenance on routine maintenance actions effectively and detect degradations and failures.
- **Operational modes in degraded states** – shall be known in order to assess the criticality of the failures. The possibility of running at non-nominal operating conditions can reduce the consequences of a failure. Acceptable thresholds, such as vibration levels, and acceptable times to repair without needing shutdown are important information for the maintenance process.
- **External factors impacting operation process** – these may be strikes, social conflicts, change or lack of raw materials, and changes in organizational patterns.
- **Emergency procedures** – can require particular conditions for asset performance and maintenance tasks to test these procedures shall be done regularly.
- **Risk analysis** – performed by the operation team provides valuable information which should be used in the maintenance process to identify failure modes of the assets and their criticality.

On the other hand, the Maintain assets process provides information and input to the operation process [44]:

- **Operating constraints** – given on items to avoid or to reduce the acceleration of failure mechanisms. In addition to constraints due to physical quantities, such as acceleration, velocity, or temperature gradients, specified by the manufacturer, maintenance personnel can add constraints based on observations of degradation levels higher than expected.
- **Time to restoration after a failure** – which includes time for fault detection, logistic support, repair and restart of the asset, shall be known by operators.

Time for preventive maintenance impacting availability or the operating mode shall also be known. These times are evaluated by the operators to manage operations during down states or degraded states.

- **Preventive maintenance schedule** – is communicated and discussed with the operating team. The dates for carrying out maintenance tasks should be fixed considering the expected operating mode.
- **Allocate maintenance tasks to operators** – who are better positioned to detect symptoms of failure modes. These maintenance tasks may be monitoring or inspections and are identified through the maintenance plans, and operators are requested to perform them.
- **Safety procedures for maintenance execution** – when a maintenance action causes a safety risk, a demand is sent by maintenance personnel with safety procedures needed to be performed by operating staff.

The standard IEC 62264-1:2013 Enterprise-control system integration also supports the importance of maintenance within production, and highlights the role of maintenance information, preventive maintenance information, and predictive maintenance information in the context of production capability information, as shown in Figure 2.10 [63].

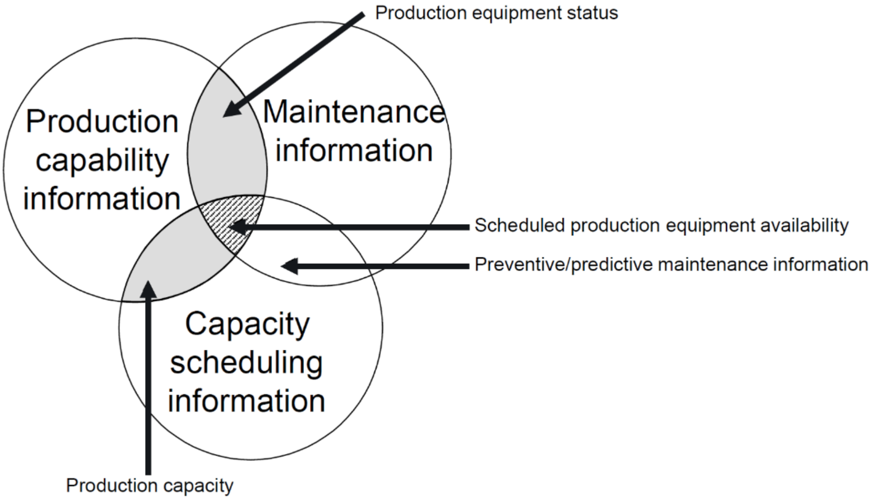


Figure 2.10: Maintenance information within production capability information, from [63].

2.1.2 Predictive maintenance

The work on PdM has contributed to changing the traditional view on maintenance, from being a costly unwanted necessity to seeing maintenance as a competitive advantage. For industrial maintenance, PdM is widely discussed both by practitioners and academics. The two main objectives for industrial maintenance are to deliver a high availability of production equipment and low maintenance costs [64]. PdM is expected to have a significant impact on these objectives, but PdM is also showing its relevance to a wide range of fields, e.g., PdM for home appliances is presented in [65].

An overview of PdM system architectures, purposes and approaches is given in [66]. PdM aims to maximize the life of equipment and reduce both planned and unplanned downtime, and, as a result, minimize maintenance costs. This is possible by analyzing data collected from components and equipment, then using those analyses to predict when a part will fail, enabling performance of maintenance actions at the right time. In terms of Industry 4.0, PdM is claimed to be central for asset utilization, services and after-sales [55]. For asset utilization, PdM is expected to decrease total machine downtime by 30% to 50%, and extend operation lifetime by 20% to 40% [55]. PdM combined with remote maintenance for services and after-sales is assumed to reduce maintenance cost by 10% to 40% [55]. Thus, the expected outcomes are significant, but several studies show that PdM seems to fall short of its possibilities to deliver what it promises [23, 67]. In fact, the added value of stand-alone PdM machine projects is often lower than asserted, as companies have extensive experience with wear and tear on their machines. Thus, there is a need for an overall concept for using digitization in an advantageous and holistic manner [23]. This is also supported by a Sino-German working group on PdM for Industry 4.0 [6, 68], where they conclude that the increasing flexibility and heterogeneity of future manufacturing systems requires a systematic approach for PdM with a modular architecture. In more detail, the architecture should enable easy adding or enhancing of functional components for sensing, condition status assessment, diagnosis, and prediction [6, 68]. In addition to these functional components, there should be a flexible deployment of findings to different resources – e.g., data from a sensor can both be visualized in a dashboard at the equipment and used in a cloud center for conducting analyses with other contextual data [6, 68]. Figure 2.11 shows the overall structure for PdM, which is considered to be settled in [68], and further elaborated in [6].

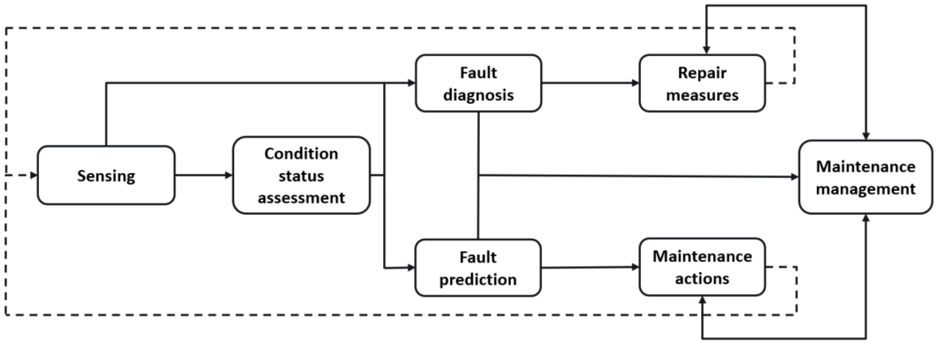


Figure 2.11: Structure for predictive maintenance, adapted from [68].

The PdM structure presented in [68] consists of seven interconnected elements. First, “Sensing” focuses on sensor modality and strategy for sensor placement. The selection of sensor technology and sensor placement are essential tasks for creating the most representative picture of asset condition, i.e., asset health. Further, sensing techniques can be categorized into direct sensing (measuring actual quantities directly indicating asset condition, e.g., toolmaker’s microscope) and indirect sensing (measuring symptoms caused by degradation or a defect, e.g., change in vibration or temperature). Indirect sensing methods are often cheaper, less complex, and enable continuous measurement without interrupting operation [6]. Second, “Condition status assessment” is about assessing the collected data to determine asset health state, which creates a foundation for determining the current status on asset condition, i.e., an asset health indicator. The indicator can be visualized in the form of a traffic light, providing a fast and simple overview. Asset condition status on a whole system, or comprehensive equipment, can be given by aggregating the condition status of its functional components [6]. Third, “Fault diagnosis” (which can be divided into fault detection, fault location, fault isolation, and fault recovery) and “Fault prediction” (predicting the fault and RUL of an asset or a system) are both challenging tasks and consist of several possible methods based on analytical models, qualitative empirical knowledge, and data-driven methods. These are coherent elements which provide a basis for the optimum “Repair measures”, element four, and time for executing the “Maintenance actions”, element five [6]. The last element, “Maintenance management” is where the information from the other elements is used for decision-making in terms of developing an economical maintenance schedule, cost-effective maintenance strategy, and resource allocation (people, spare parts, tools, and time). Further, a linkage between maintenance management and operations management should also be present, as data from operations can improve PdM capabilities, but PdM can also support rapid and data-driven decision-making across operations [6].

Prediction of RUL, which is defined as [69]: *“RUL is the useful life left on an asset at a particular time of operation”*, serves as one major challenge within predictive maintenance. Uncertainty in data creates difficulties for RUL predictions. Challenges that must be overcome include missing data/outliers/noisy data, but also different sampling times and data lengths, e.g., huge amounts of data collected at different life cycles of a central asset, meaning data have different lengths for different batches at time-varying operational conditions [69, 70]. In addition to RUL, anomaly detection has received increased attention and delivered promising results, as focusing on an early warning of potential harmful events and failures has proven to provide value by reducing latencies from an event until a maintenance action takes effect [71, 72]. Figure 2.12 illustrates latencies which can be reduced with anomaly detection [53].

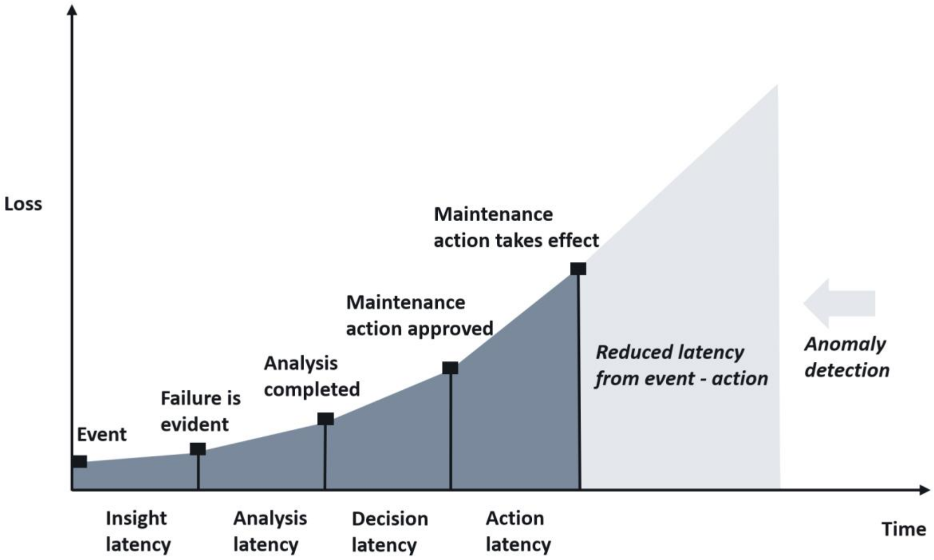


Figure 2.12: Anomaly detection reducing latencies between an event and action, adapted from [53].

Table 2.1 presents examples of measurements and parameters used for diagnostics in condition monitoring from the standard ISO 13379-1:2012 Condition monitoring and diagnostics of machines – Data interpretation and diagnostics techniques, which is also relevant for anomaly detection [73].

Table 2.1: Examples of measurements and parameters relevant for anomaly detection [73].

Performance	***Mechanical***	***Electrical***	***Oil analysis, product quality and others***
• **Power consumption** • **Efficiency** • **Temperature** • **Pressure** • **IR thermography** • **Flow**	• **Thermal expansion** • **Position** • **Fluid level** • **Temperature** • **Vibration displacement** • **IR thermography** • **Vibration velocity** • **Vibration acceleration** • **Audible noise** • **Ultrasonic waves**	• **Current** • **Voltage** • **Resistance** • **Inductance** • **IR thermography** • **Capacitance** • **Magnetic field** • **Insulation resistance** • **Partial discharge**	• **Oil analysis** • **Ferrography wear debris analysis** • **Product dimensions** • **Product physical properties** • **Product chemical properties** - **color** - **visual aspect** - **smell** - **other non-destructive testing**

2.2 Value chain

The value chain concept was first introduced by Michael E. Porter in 1985, and can be defined as [2]: *"A value chain is a set of activities that a firm operating in a specific industry performs in order to deliver a valuable product or service for the market."* The value chain concept was originally aimed at identifying value activities, as these are the building blocks of competitive advantage, and focusing on these activities can be used to define improvement needs or opportunities for companies [2]. Porter also introduced two other concepts linked to the value chain concept, namely, "five forces" and "generic strategy." The five forces concept allows a firm to assess both the attractiveness of its industry and its competitive position within that industry, with the five forces being the threat of new entrants to the industry, the threat of substitute products, the power of buyers or customers, the power of suppliers, and, finally, the degree and nature of rivalry among companies in the industry [74]. The generic strategy concept is based on an analysis of the five forces, and can provide a generic competitive strategy for an organization with differentiation or cost leadership, capable of delivering superior performance through an appropriate configuration and coordination of its value chain activities [74]. Together, these three concepts can be regarded as the major analytical frameworks of the competitive positioning paradigm and are central elements within business strategy courses [74].

Each value chain activity consists of two components, namely, a physical and an information processing component. The former includes the physical tasks required to fulfill the activity, and the latter consists of the steps required to capture, manipulate, and channel data necessary to perform the activity [2, 36]. The value chain includes all those activities that contribute to the final value of an organization's product [74], and Porter identified two types of activities called primary and support activities. First, the primary activities are inbound logistics, operations, outbound logistics, marketing and sales, and, finally, service. These are defined as activities within the main value creation process for a traditional and general manufacturer, and directly contribute to the production of the good or services and its provision to the customer [74]. Second, the support activities are firm infrastructure, human resource management, technology development, and procurement. The role of these activities is to create a foundation for enabling and improving the function of primary activities, and they do not directly add value themselves [2, 74]. Margin is the difference between total value and the collective cost of performing the value activities, and can be measured in several ways [2]. Figure 2.13 shows the value chain concept, as introduced in [2].

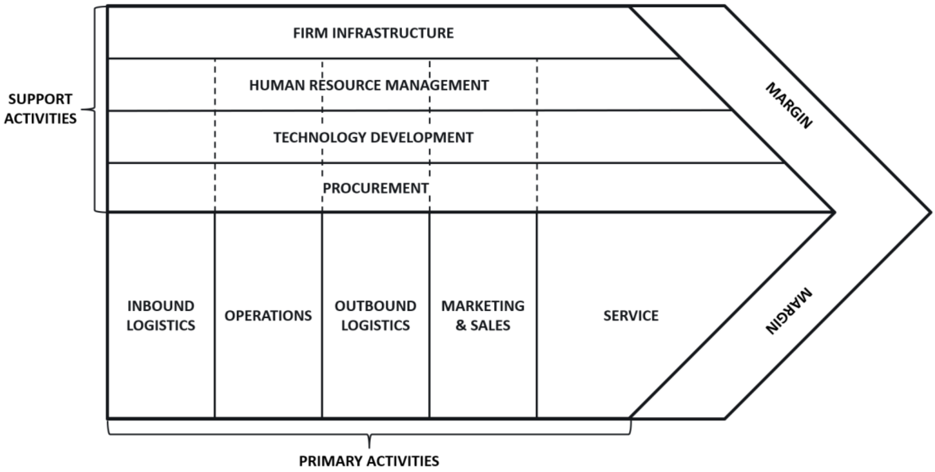


Figure 2.13: The generic value chain, redrawn from [2].

A description of the five generic primary activities is given as follows [2]:

- **Inbound logistics –** *Activities associated with receiving, storing, and disseminating inputs to the product, such as material handling, warehousing, inventory control, vehicle scheduling, and returns to suppliers.*
- **Operations –** *Activities associated with transforming inputs into the final product form, such as machining, packaging, assembly, equipment maintenance, testing, printing, and facility operations.*
- **Outbound logistics –** *Activities associated with collecting, storing, and physically distributing the product to buyers, such as finished goods warehousing, material handling, delivery vehicle operation, order processing, and scheduling.*
- **Marketing and sales –** *Activities associated with providing a means by which buyers can purchase the product and inducing them to do so, such as*

advertising, promotion, sales force, quoting, channel selection, channel relations, and pricing.

- **Service** - *Activities associated with providing service to enhance or maintain the value of the product, such as installation, repair, training, parts supply, and product adjustment.*

On the other hand, the four generic support activities are described as follows [2]:

- **Firm infrastructure –** *consists of a number of activities including general management, planning, finance, accounting, legal, government affairs, and quality management.*
- **Human resource management –** *consists of activities involved in the recruiting, hiring, training, development, and compensation of all types of personnel.*
- **Technology development –** *every value activity embodies technology, be it know-how, procedures, or technology embodied in process equipment. Technology development consist of a range of activities that can be broadly grouped into efforts to improve the product and process.*
- **Procurement –** *refers to the function of purchasing inputs used in the firm's value chain, not to the purchased inputs themselves. Purchased inputs include raw materials, supplies, and other consumable items as well as assets such as machinery, laboratory equipment, office equipment, and buildings.*

As a result of the introduction of the value chain concept, the term value chain management (VCM) has also been introduced. VCM targets the improvement of overall performance of the entire value chain through an analysis of each link and process in a systematic manner to see how speed, certainty and cost-effectiveness can be enhanced [30]. A definition of VCM is provided by [15]: "*Value chain management is a coordinating management process in which all of the activities (and their suppliers) involved in delivering customer value satisfaction are integrated such that customer satisfaction is maximised and the objectives of the stakeholders involved (the suppliers of activities, processes, facilitating services, etc.) are optimised such that no preferable solution may be found.*"

With the introduction of Industry 4.0 and new technology, many industries have reshaped their value chain and focused on higher information content in both products and processes [2, 9]. Moreover, three key features are seen as essential to success in implementing Industry 4.0. These features are prerequisites expected to be the reality in future production networks and are defined as three types of value chain integration. Combined, they focus on how new technology can be utilized to improve the overall value chain, with expected benefits being higher sales thanks to a larger market, increased customization, improved resource efficiency and productivity, and reduction of internal operating costs. The three types of integration are [75-77]:

- Vertical integration of hierarchical subsystems to create flexible and reconfigurable manufacturing systems.
- Horizontal integration as a basis for developing inter-company value chains and networks.
- Digital end-to-end engineering across the entire value chain of both the product and the associated manufacturing system.

For vertical integration, the importance of integrating the various information subsystems at different levels in the company is underpinned by [76]. This is also discussed in [77], where it is claimed to be essential with: *"vertical integration of actuator and sensor signals across different levels right up to the enterprise resource planning (ERP) level to enable a flexible and reconfigurable manufacturing system."* Figure 2.14 shows elements of a vertical value chain [78, 79].

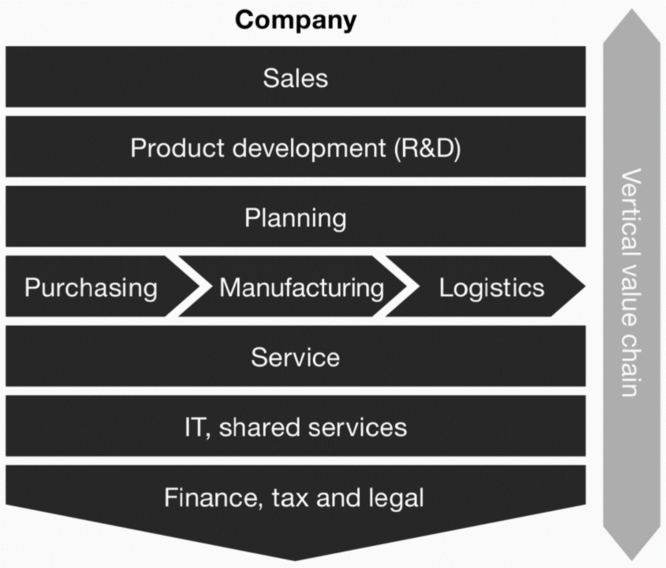


Figure 2.14: Elements of a vertical value chain in a company, adapted from [78, 79].

Further, horizontal integration should focus on inter-corporation collaboration where information and material can flow fluently, enabling new value networks and business models [76, 77]. Figure 2.15 shows an example of a horizontal value chain layout [78, 79].

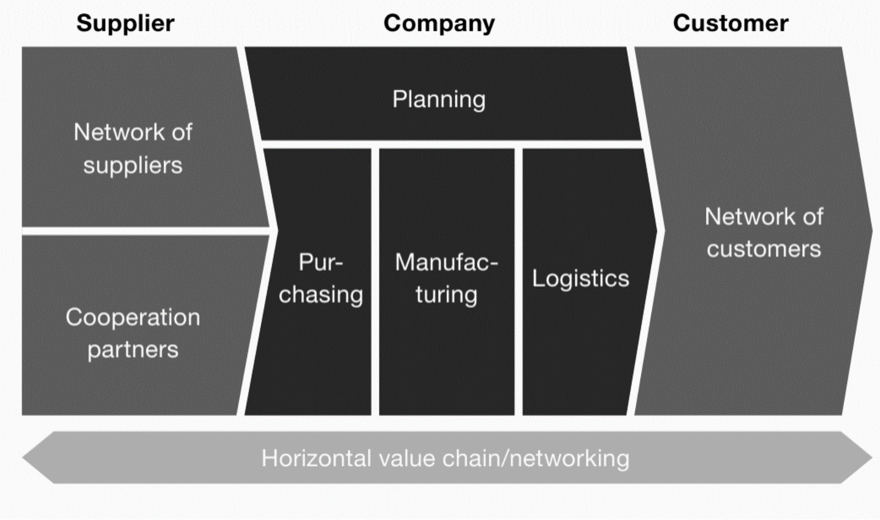


Figure 2.15: Example of a horizontal value chain layout, adapted from [78, 79].

The end-to-end integration across the entire value chain will include cross-linking of stakeholders, products and equipment, from raw material acquisition to end of life [76]. The development towards a more digitalized and integrated value chain is further described in Chapter 2.3.2.

2.2.1 Value chain performance and indicators

There seems to be a lack of a clear and unified definition of value chain performance (VCP). However, the term value is defined in the standard EN 1325:2014 Value Management as follows [80]: *"measure which expresses how well an organization, project, or product satisfies stakeholders' needs in relation to the resources consumed."* Moreover, a definition of performance management is provided by [81]: *"Performance management is a continuous process of identifying, measuring, and developing the performance of individuals and teams and aligning performance with strategic goals of the organization."* Within the definition of performance management, performance measurement is also covered, which is about measuring the performance itself. To support gathering and utilization of performance information, an effective performance management system is required for aiding improved decision-making [82, 83]. Performance management refers to several activities initiated by organizations to improve performance of individuals and units, with the overall goal of improving organizational effectiveness. These activities may be the setting of corporate, departmental, team, and individual targets, and the use of appraisal systems, bonus strategies, training schemes and individual career plans [82]. In [84], they claim that performance management is a dynamic and iterative process which aims to maintain or alter patterns in organizational activities. Along with their employees, managers use performance management to define goals, measure and review results and honor achievements or plan necessary actions, to improve performance, with the overall goal of enhancing the organization's success. Further on, the same authors present three elements to describe the process of performance management [84]:

- **Performance planning and implementation -** This step is about making decisions on metrics, targets, measurement intervals and review periods.

Procedures regarding data collection, metric calculation and how results will be presented and discussed are also areas of focus in this step.

- **Performance measurement -** Measurements of performance, within the given metrics, at predetermined intervals.
- **Performance evaluation, corrective action and continuous improvement -** In order to provide correct feedback, the performance must be evaluated and compared to its associated targets. Action plans must be compiled when deliverables are insufficient. Additionally, good results need to be recognized and celebrated.

Based on the above-mentioned, VCP can be seen as a measure of competitiveness in the utilization of available resources and stakeholders' satisfaction. Figure 2.16 shows the process for using key performance indicators (KPIs) and benchmarking for improving business performance, as presented in the standard ISO 14224:2016 Petroleum, petrochemical and natural gas industries – Collection and exchange of reliability and maintenance data for equipment [85].

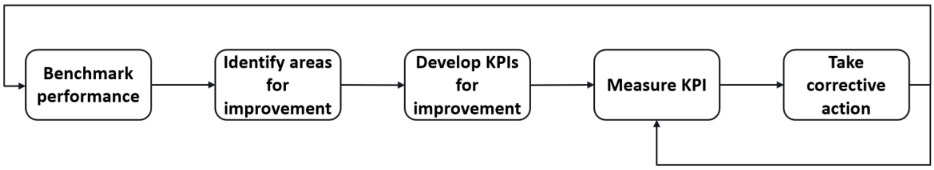


Figure 2.16: Benchmarking and KPIs for improving business performance [85].

To quickly assess measurements, suitable indicators are often used. A number of standardized indicators acknowledged as KPIs are used by organizations to provide benchmarking, evaluate current performance, and visualize the road to improved performance. KPIs are defined as [86]: *"A metric measuring how well the organization or an individual performs an operational, tactical or strategic activity that is critical for the current and future success of the organization."* Hence, organizations should select and link KPIs to their defined main objectives, to work towards the overall strategy and vision. The use of KPIs has become more important for the success of manufacturers, and many are seeking guidance to improve on performance management and to utilize benchmarking in their industry as a benefit [87]. The importance of establishing indicators that describe the past, the present and the future status of the value chain is also underpinned by [25]. Figure 2.17 shows steps of improvement in the maintenance process based on KPIs, as presented in the standard EN 15341:2019 Maintenance – Maintenance Key Performance Indicators [88], linked to the concept of PDCA.

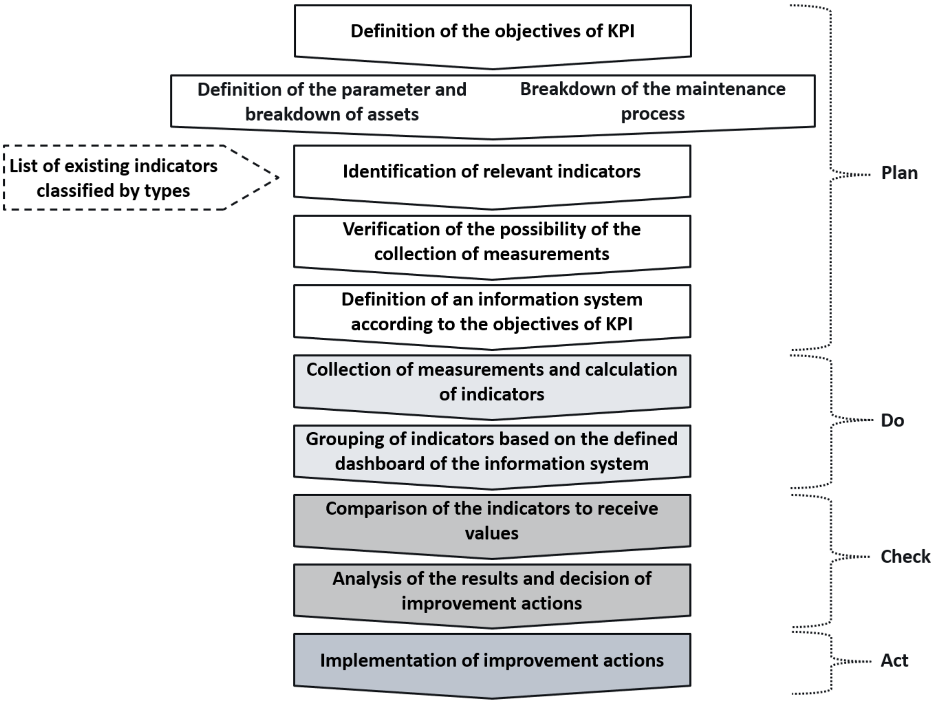


Figure 2.17: Improvement steps for the maintenance process based on KPIs linked to PDCA, adapted from [88].

Indicators are critical for supporting and managing production improvements [89]. Overall equipment effectiveness (OEE) is one example of a well-known and accepted indicator in this context, and has been adopted by several managers and directors desiring to improve their production systems [90]. The OEE indicator provides a quantitative metric based on availability, performance and quality, in order to measure the performance effectiveness, and reliability [91], of individual equipment or entire processes [92]. Possessing an OEE of 85% is acknowledged as a World Class Maintenance (WCM) level [93]. WCM is a collection of best maintenance practices implemented by various organizations with the overall goal of transforming themselves into a world class manufacturer [94]. Within the concept of WCM, a set of WCM indicators is proposed by [94]:

- Preventive maintenance (PM) to corrective maintenance ratio.
- Annual maintenance cost as a percent of replacement asset value.
- Maintenance schedule compliance.
- Equipment availability.
- Percent of PM or predictive maintenance hours to total hours.
- Store service level.
- Reactive hours as a percent of total hours.

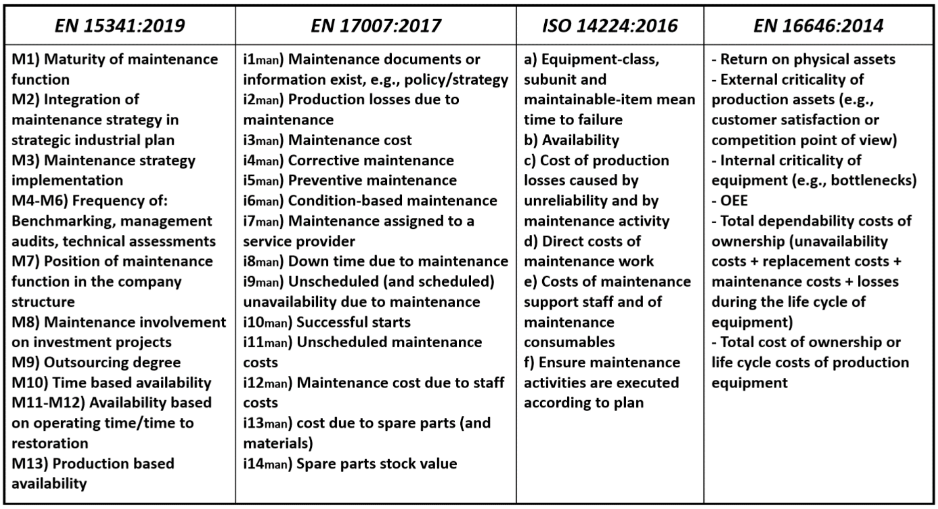
Currently, these indicators, along with more established indicators such as failure rate, mean time to failure/repair, downtime, OEE, and maintenance cost, are mainly the indicators used by maintenance managers [94]. Further, key figures of industrial maintenance are classified in a hierarchical manner and presented as follows in [64]:

1) **External business-oriented objective variables** – Business-oriented key figures such as return on investments and OEE.
2) **Internal objective variables for maintenance** – Metrics for the effectiveness of maintenance operations, e.g., availability of machinery, and the sum of lost production and maintenance costs.
3) **Exogenous variables (external conditions)** – Indicators helping management to interpret variables and to evaluate the state of affairs, e.g., utilization rate of production equipment, amount of production equipment, and integration level of production.
4) **Intermediate internal objective variables (follow-up variables)** – Performance indicators providing information about development needs that may act as intermediate objective variables towards reaching the main objective, e.g., mean time to repair is an intermediate objective for the main objective of minimizing lost production.

5) **Action variables of maintenance function** – Tools that maintenance managers can use to help achieve the objectives, such as outsourcing and operator maintenance.
6) **Internal explanatory variables** – Give additional information, e.g., about cost and organization structure, cost level and capital intensity of the maintenance function.

In the years to come, with the development of Industry 4.0 and maintenance, there will also be a need for developing indicators responding to these advancements, e.g., the profit loss indicator (PLI) [14, 95]. Table 2.2 presents examples of relevant KPIs for maintenance management from EN 15341:2019 and EN 17007:2017 [59, 88], overall reliability and maintenance effectiveness from ISO 14224:2016 [85], and maintenance function and processes from EN16646:2014 [44].

Table 2.2: Examples of KPIs (from left to right) within maintenance management [59, 88], overall reliability and maintenance effectiveness [85], and maintenance function and processes [44].



EN 15341:2019	*EN 17007:2017*	*ISO 14224:2016*	*EN 16646:2014*
M1) Maturity of maintenance function **M2) Integration of maintenance strategy in strategic industrial plan** **M3) Maintenance strategy implementation** **M4-M6) Frequency of: Benchmarking, management audits, technical assessments** **M7) Position of maintenance function in the company structure** **M8) Maintenance involvement on investment projects** **M9) Outsourcing degree** **M10) Time based availability** **M11-M12) Availability based on operating time/time to restoration** **M13) Production based availability**	**$i1_{man}$) Maintenance documents or information exist, e.g., policy/strategy** **$i2_{man}$) Production losses due to maintenance** **$i3_{man}$) Maintenance cost** **$i4_{man}$) Corrective maintenance** **$i5_{man}$) Preventive maintenance** **$i6_{man}$) Condition-based maintenance** **$i7_{man}$) Maintenance assigned to a service provider** **$i8_{man}$) Down time due to maintenance** **$i9_{man}$) Unscheduled (and scheduled) unavailability due to maintenance** **$i10_{man}$) Successful starts** **$i11_{man}$) Unscheduled maintenance costs** **$i12_{man}$) Maintenance cost due to staff costs** **$i13_{man}$) cost due to spare parts (and materials)** **$i14_{man}$) Spare parts stock value**	**a) Equipment-class, subunit and maintainable-item mean time to failure** **b) Availability** **c) Cost of production losses caused by unreliability and by maintenance activity** **d) Direct costs of maintenance work** **e) Costs of maintenance support staff and of maintenance consumables** **f) Ensure maintenance activities are executed according to plan**	**- Return on physical assets** **- External criticality of production assets (e.g., customer satisfaction or competition point of view)** **- Internal criticality of equipment (e.g., bottlenecks)** **- OEE** **- Total dependability costs of ownership (unavailability costs + replacement costs + maintenance costs + losses during the life cycle of equipment)** **- Total cost of ownership or life cycle costs of production equipment**

2.2.2 Continuous improvement in the value chain

Several companies from fields such as aerospace, consumer products, industrial products, and metals processing have tried to imitate the Japanese multinational automotive manufacturer Toyota and implement elements of TPS into their own business system [96]. TPS (known as the precursor of Lean thinking, which was the term John Krafcik coined in 1988 [97], also referred to as Lean manufacturing) was invented by Sakichi Toyoda, the founder of Toyota Industries, his son Kiichiro Toyoda and the production engineer Taiichi Ohno. TPS is seen as the source of Toyota's outstanding performance as a manufacturer and enabler for continuous improvement [96]. TPS can also be seen up against the value chain aspect, as a well-functioning and well-implemented business system can be an essential enabler for succeeding with continuous improvement throughout the value chain.

Industrialists and researchers worldwide have investigated Japan's management philosophy, especially TPS, which has received much attention for its competitive success. With the book *The Key to Japan's Competitive Success* from 1986, the term Kaizen was introduced. Translated from Japanese, Kaizen means "continuous improvement" and the Japanese word can generally be defined as [98]: "*the process of continuous improvement in any area of life, personal, science, home, or work.*" In terms of business, Kaizen can be defined as [98]: "*the process of gradual and incremental improvement in a pursuit of perfection of business activities.*" Kaizen is known as *"the Japanese way"* and the philosophy behind the model is that *"not a single day should go by without some kind of improvement being made somewhere in the organization"* [98]. Kaizen serves as a cornerstone in TPS.

There are several ways of classifying improvement, but breakthrough and continuous improvement are often used [99]. The former is also known as innovation-based improvement and is about performing radical changes in how the operation works. Such changes could be to implement a new and more efficient machine in a plant or change other types of essential assets within an organization. Generally, breakthrough improvements provide an immediate effect on operational procedures and performance. However, these changes are usually connected to high costs and significant investments. In addition, it is often necessary to shut down the current ongoing workings of the operation and to make changes in the product/service or process technology [99]. The latter is defined by Bhuiyan and Baghel as follows [100]: "*A culture of sustained improvement targeting the elimination of waste in all systems and processes of an organization. It involves everyone working together to make improvements without necessarily making huge capital investments.*" Moreover, continuous improvement is about performing many small incremental improvement steps to enhance the level of performance. An example of this could be to change the way a product is mounted on a machine to reduce changeover time. Traditionally, these changes are not automatically going to result in new improvement steps, but this is what the continuous improvement philosophy is targeting: to ensure the organization is continually hunting for ways to improve, and, most importantly, perform necessary activities to address these possibilities for improvement [99]. A central part of continuous improvement is to repeatedly question the relevant activity or process. This cyclical questioning is often referred to as the concept of improvement cycles. The PDCA cycle, also known as the Deming cycle, and the Define-Measure-Analyze-Improve-Control (DMAIC) cycle are the two that are mostly used. The PDCA cycle consist of four steps [99, 101]:

- **Plan** – This step is about investigating a present problem or method. Collection and analyses of data within the problem area are used to compile a plan for making improvement measures.
- **Do** - Here, the plan compiled in the first step is put into action. It is often necessary to involve several micro PDCA cycles to handle upcoming problems which occur during implementation.
- **Check** – The implemented measures are evaluated in this step.
- **Act** – This stage of the cycle aims to decide whether the implementation has been successful or not. If successful, the actions are standardized and used to improve other areas. If not successful, valuable lessons are learned and utilized when starting the PDCA cycle again.

Figure 2.18 shows the concept of the PDCA cycle exemplified with value chain activities [99, 101].

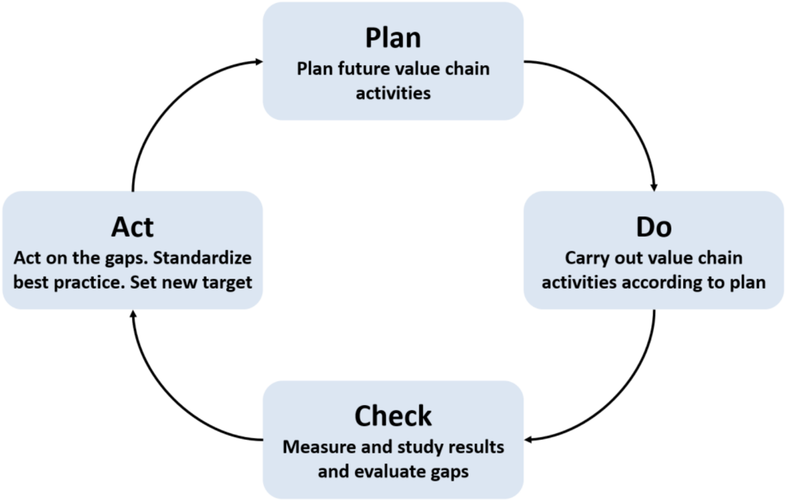


Figure 2.18: The PDCA cycle linked to value chain activities, inspired by [99, 101].

Succeeding with continuous improvement in an organization requires great efforts and depends highly on the inclusion of its employees. The following statement from the book *Toyota Culture - The Heart And Soul Of The Toyota Way*, underpins the importance of including employees in TPS [102]: "*The key to success is to have a production system that highlights problems and a human system that produces people who are able and willing to identify and solve them.*"

Value stream mapping is a popular Lean tool and mapping a process from raw materials to finished goods to discover non-value-adding activities is seen as an effective way to reduce waste and improve processes. Lean tools focus on the product value stream but pay little to no attention to one of the most critical value streams within an organization, namely, the people value stream. At Toyota, the product value stream and the people value stream are intertwined into a system. Contrary to Lean, TPS focuses more on employees and how to involve them in problem solving. An essential part of Toyota's culture is just that, involving employees in problem solving. It is the continual focus on discovering new problems and involving employees to solve them which connects the two value streams [102]. As a process industry example in this regard, the evolution and success of Elkem ASA are often traced back to the strategic initiative in the 1990s that involved the development of EBS, which focuses a lot on continuous improvement and empowering Elkem employees through TPS principles. This focus serves as a central element in Elkem, and can be seen in the EBS concept of the double integrated value chain, as shown in Figure 2.19 [103].

Figure 2.19: The double integrated value chain in Elkem, as presented in [103].

The idea of the double integrated value chain is that world-class quality products require world-class performers, and is summarized in [103] as follows:

- *Only people can identify and solve problems.*
- *Continuous improvement and problem solving are the best way to develop people.*
- *More problem solvers mean more problems solved.*
- *Competent people implement strategies.*
- *Learning organization – skilled and motivated workers.*

Moving towards a more digital value chain and new ways of working, a prerequisite for staying competitive and succeeding with continuous improvement in a digital environment is to enable new digital competence in the workforce and ensure the necessary digital tools are well-implemented [104, 105].

2.3 Digitalization

There are several definitions and meanings regarding the term digitalization and its role within industry, especially Industry 4.0. In recent years, both industrialists and researchers have increased their use of the terms digitization, digitalization, and digital transformation. However, there seems to be a lack of unified definition and common understanding of these terms. Some use them interchangeably, while others state there is a major difference [106]. In general, and as a result of new embedded usage of digital technology, companies succeeding in this area can potentially optimize resource utilization, reduce costs, increase employee satisfaction and improve work efficiency [3]. To give some clarifications on how this PhD project view is on the mentioned three concepts, the following definitions are provided:

- **Digitization [106]:** *"The conversion from an analog format into a digital format."*
- **Digitalization [3]:** *"The exploitation of digital opportunities."*
- **Digital transformation [106]:** *"Creating new business opportunities through the use of digital data and technology."*

Figure 2.20 provides an overview of the relationship between digitization, digitalization, and digital transformation [106].

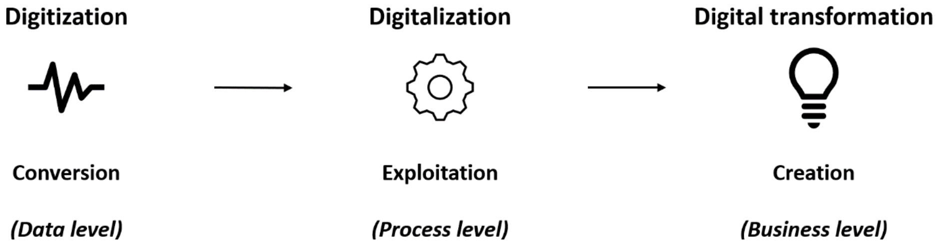


Figure 2.20: Digitization, digitalization, and digital transformation, adapted from [3, 106].

The promised benefits and opportunities connected to the above-mentioned terms are significant in a wide range of fields, and the importance of succeeding on the digital journey is acknowledged not only by big companies, but also by nations and unions that are putting this on their agenda. Examples include the European Union 7.5 billion EUR "Digital Europe Programme" [107] and the China initiative "Made in China 2025", also called "China Manufacturing 2025", which focuses on accelerating development of intelligent manufacturing equipment and products, and advanced manufacturing process intelligence [68, 108]. The USA has "Advanced Manufacturing" as its strategic plan, aiming to develop and transition new manufacturing technologies, educate, train, and connect the manufacturing workforce, and expand the capabilities of the domestic manufacturing supply chain [109]. Common to these initiatives is the acceptance of the significant changes digitalization will have for society and industry, and the importance of adopting new technology for utilizing the imminent changes as opportunities to gain competitiveness. There is also a widely accepted understanding on the importance of managing data in the years to come, e.g., in White Paper no. 22 (2020-2021) *"Data as a resource – Data-driven economy and innovation"* the Norwegian Government has presented four national principles for sharing and using data, translated as follows [110]:

1. *Data shall be open when they can and shielded when required.*
2. *Data should be available, retrievable, usable, and compatible with other data.*
3. *Data shall be shared and used in a way that provides value for the business community, the public sector and society.*
4. *Data shall be shared and used so that fundamental rights and freedoms are respected, and Norwegian societal values are preserved.*

In [110], they also present five main technological drivers, namely, *Cloud services, Sensor technology and Internet of Things (IoT), Big Data, Artificial Intelligence (AI), and High Performance Computing*. These technologies are also seen as central elements in Industry 4.0, and [111] have defined these, in addition to *Analytics*, as base technologies for Industry 4.0.

2.3.1 Industry 4.0

There are several definitions of Industrie 4.0/Industry 4.0, supplementing the one presented in Chapter 1.1. A more detailed definition of Industry 4.0, first presented in [112] and later used in [76], goes as follows: *"Industry 4.0 is a collective term for technologies and concepts of value chain organization. Within the modular structured smart factories of Industry 4.0, cyber-physical systems (CPS) monitors physical processes, creates a virtual copy of the physical world and makes decentralized decisions. Over the internet of things (IoT), CPS communicates and cooperates with* *each other and humans in real-time. Via the internet of services (IoS), both internal and cross-organizational services are offered and utilized by participants of the value chain."* Industrie 4.0 was first introduced at the Hannover Messe in 2011, a German industrial fair, as an illustration of the new trend towards the networking of traditional industries [108], and it is now seen as the Fourth Industrial Revolution. Industrie 4.0 was included in the German "High-Tech Strategy 2020 Action Plan" and is defined as a necessity for German companies aiming to be world class in the years to come. Figure 2.21 presents the evolution from the First Industrial Revolution to the Fourth Industrial Revolution with their main characteristics and timeline [113-116].

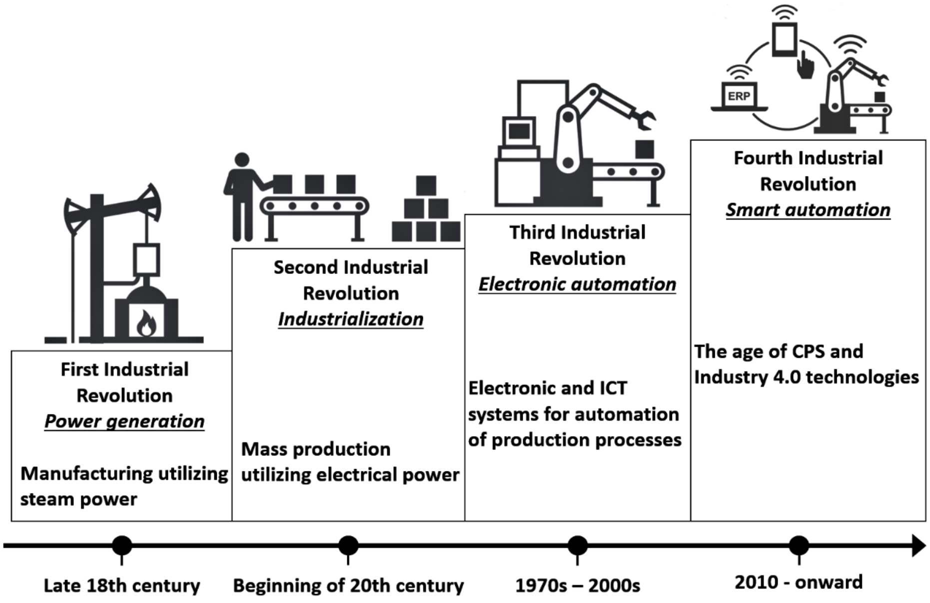


Figure 2.21: The evolution from the First Industrial Revolution to the Fourth Industrial Revolution, adapted from [113-116].

The First Industrial Revolution began at the end of the eighteenth century and marked the beginning of the transition from an economy based on agriculture and handcraft to industry. It was initiated by mechanical manufacturing systems utilizing water and steam power, and the inventions of the power loom, steam engine, and machine tools were central contributors [113]. The Second Industrial Revolution focused on implementing electricity into production processes and producing in high volumes, enabled by assembly lines and interchangeable parts which reduced manufacturing cost and increased output [113, 114]. The introduction of automation and microelectronic technology to manufacturing is known as the start of the Third Industrial Revolution. Advancements within ICT resulted in widespread adoption of computer numerical control machines and industrial robots, which both significantly contributed to automating previously manually performed activities [113, 114]. Finally, the Fourth Industrial Revolution represents the age of CPS and utilization of Industry 4.0 technologies [113, 114, 117]. Despite a lack of clarity in the terms and how to define Industry 4.0, it emerges clearly that a technology push and a company pull are fueling Industry 4.0 as a hot topic. The former push represents the availability, affordability, and increased awareness of possibilities with new technologies such as IIoT, AR, 3D printing, AI, wireless sensors, and big data analytics. The latter pull describes companies, especially those located in high-cost countries, never-ending quest to improve resource and asset utilization in a market increasingly driven by more demanding customers, while at the same time pursuing possibilities for competitive advantages [56, 105, 113, 114, 117]. As an example, in [32] they investigated the role and impact of Industry 4.0 and IoT on the business strategy of the value chain in Hungarian companies.

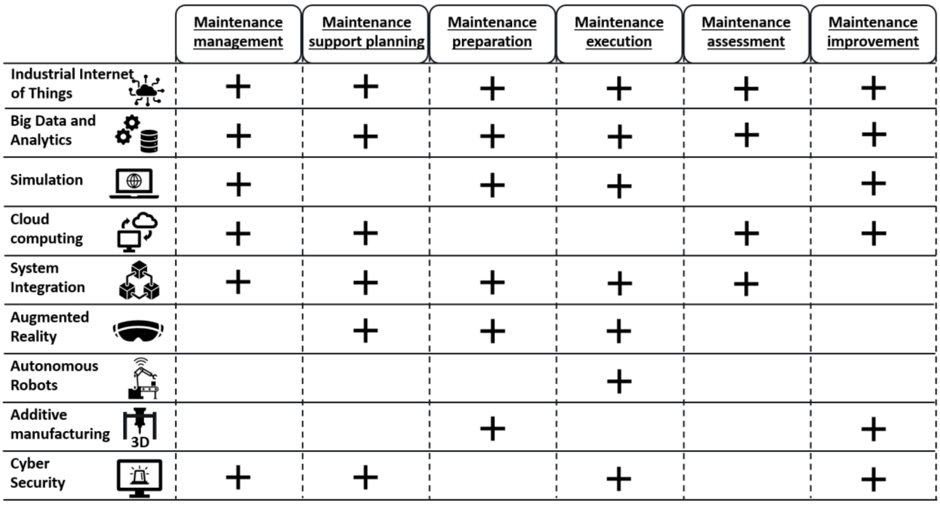
Industry 4.0 technologies are developing at a rapid pace. Among researchers, there seems to be an agreement on nine main technological pillars of Industry 4.0, which are presented in [37]:

- **Industrial Internet of Things (IIoT)** – Extends the concept of IoT to an industrial field with connected devices. The IIoT enables interconnections of physical objects through sensors using standard internet protocols. This is also seen as the basic technology of CPS, building a bridge between the physical and digital world by transferring data without human-to-human or human-to-computer interaction.
- **Big Data and Analytics** – Provides support for real-time decision-making, powerful computation capacity, and high bandwidth of data transmission. The basis is data collected through the CPS and customer-management system. Big

Data consists of four parts, known as the 4 V’s: Volume of data, Variety of data, Velocity of generation of new data and analysis, Value of data.

- **Simulation** – Refers to digital tools supporting the design of smart manufacturing systems and validation of engineering design choices. These tools can also be used to predict the behavior of real manufacturing systems, supporting operational and maintenance decisions.
- **Cloud computing** – Allows sharing of processing resources and other devices on demand, meaning users and companies can process data through a shared pool of configurable computing resources such as networks, servers, storage solutions, applications, and services. Cloud technology also enables sharing of information between systems, e.g., from a production line to the entire plant, and offsite analysis.
- **Horizontal and vertical system integration** – Represents the connection between all actors in a highly dynamic manufacturing system. System integration is central in enabling the three key value chain integrations for Industry 4.0, as discussed in Chapter 2.2.
- **Augmented Reality (AR)** – Extends the concept of Virtual Reality (VR) by superimposing digital data onto reality. This serves as a human-machine interaction technology and can provide operators with real-time information, such as maintenance data and technical drawings or instructions, through smart devices as wearable AR or head mounted devices.
- **Autonomous Robots** – Capable of interacting with other robots and systems, can help operators (autonomous robots serving as cobots) to perform their tasks.
- **Additive manufacturing** – Refers to converting a digital design to a physical object, e.g., a 3D computer-aided design drawing physically constructed with a 3D printer.
- **Cybersecurity** – Concerns technology providing protection of information and CPS from cyberattacks. Cybersecurity is essential for stable operation of systems and reliable manufacturing in an Industry 4.0 environment.

Figure 2.22 presents a possible positioning of these technologies in the context of maintenance management and its main processes as given in IEC 60300-3-14:2004 Dependability management part 3-14, and discussed in Chapter 2.1.1 [37, 38].



	Maintenance management	Maintenance support planning	Maintenance preparation	Maintenance execution	Maintenance assessment	Maintenance improvement
Industrial Internet of Things	+	+	+	+	+	+
Big Data and Analytics	+	+	+	+	+	+
Simulation	+		+	+		+
Cloud computing	+	+			+	+
System Integration	+	+	+	+	+	
Augmented Reality		+	+	+		
Autonomous Robots				+		
Additive manufacturing			+			+
Cyber Security	+	+		+		+

Figure 2.22: Possible positioning of Industry 4.0 technologies in the context of maintenance management and its main processes, adapted from [37, 38].

It emerges clearly that Industry 4.0 technologies have the capability of radically changing the way industrialists operate and conduct maintenance [37]. As shown in Figure 2.22, IIoT as well as Big Data and Analytics are highly relevant to the field of maintenance. The former is especially concerning the use of sensors, including off-the-shelf sensors, custom sensors, and virtual sensors, for collecting complex information, e.g., regarding machine status, for enabling advanced maintenance activities [118, 119]. The latter is expected to bring several advantages such as achieving near zero downtime, ensuring PdM, improving maintenance planning and decision-making [37]. In [120], they have discussed the future of maintenance and presented perspectives and several interesting provocative questions within maintenance, such as; *"Is it cybernetic or is it human?"*, *"Real-time communication in maintenance?"*, *"Explicit modeling or data-driven pragmatics?"*, *"How to apply Virtual Reality and Augmented Reality?"*, *"Service robotics for maintenance?"*. These are examples of questions providing input to how implementation of new technologies will change maintenance practices and strategies going forward.

Another central element in Industry 4.0 is CPS, as presented in the Industry 4.0 definition introducing this chapter. This is supported by [121], where CPS and IIoT are believed to have a major role in the emerging Industry 4.0. Both IoT and CPS emphasize the interaction between the cyber and physical world, but CPS is referred in [122] as: *"the system that can efficiently integrate both cyber and physical components through the integration of the modern computing and communication technologies, aiming to changing the method of interaction among the human, cyber and physical worlds. CPS emphasizes the interactions between cyber and physical components and has a goal of making the monitoring and control of physical components secure, efficient, and intelligent by leveraging cyber components."* The term "Cyber" means using modern sensing, computing, and communications technologies to effectively monitor and control physical components. "Physical" represents the physical components in the real world, and "System" reflects the complexity and diversity [122]. A set of capabilities of a CPS is presented in [123]:

- *Enhancement of physical entities with Cyber capabilities;*
- *Networked at multiple and extreme scale;*
- *Dynamic behavior (plug and unplug during operation);*
- *High degrees of automation, the control loops are typically closed;*
- *High degree of autonomy and collaboration to achieve a higher goal; and*
- *Tight integration between devices, processes, machines, humans and other software applications.*

Moreover, the objective of CPS is presented as follows in [122]: *"to measure the state information of physical devices and ensure the secure, efficient, and intelligent operation on physical devices. In CPS, the sensor/actuator layer, communication layer, and application (control) layer are present. The sensor/actuator layer is used to collect real-time data and execute commands, communication layer is used to deliver data to upper layer and commands to lower layer, and application (control) layer is used to analyze data and make decisions."* Based on these three layers, CPS can be seen as a vertical architecture. On the other hand, IoT can be seen as a horizontal architecture, emphasizing a networking infrastructure to integrate communication layers of CPS applications for achieving interconnection. The main objective of IoT is presented in [122] as follows: *"The main objective of IoT is to interconnect various networks so that the data collection, resource sharing, analysis, and management can be carried out across heterogeneous networks. By doing so, reliable, efficient, and secure services can be provided."* The vertical architecture perspective of CPS is supported by [46], where a 5C architecture for CPS is presented, as shown in Figure 2.23. This 5C architecture is further elaborated in an Industry 4.0 environment in [121] and can also be seen in the context of the five-level functional hierarchy, addressing the interface between plant production scheduling and operation management and plant floor coordination, presented in the standard IEC 62264-1:2013 Enterprise-control system integration [63].

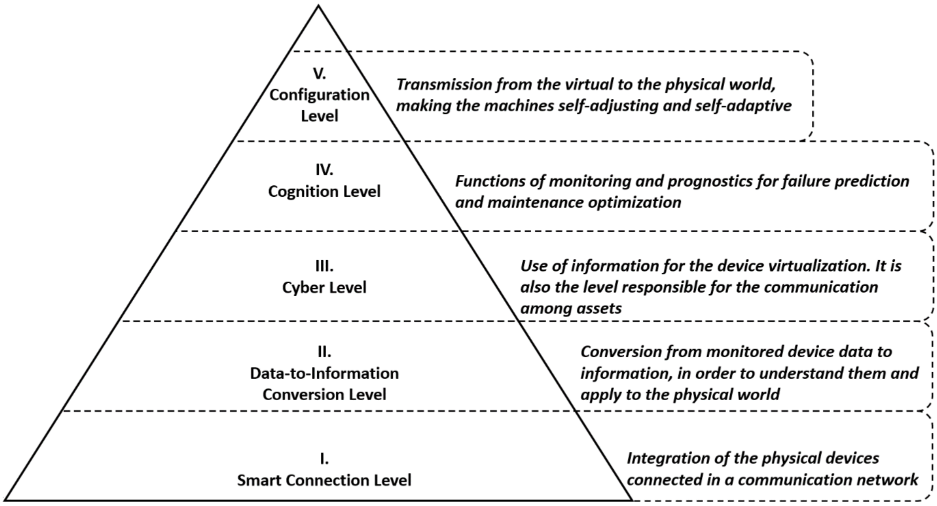


Figure 2.23: 5C architecture for CPS with description of each level, adapted from [46, 121].

The 5C architecture is discussed in [124], and claimed to be focused more on vertical value chain integration and less on horizontal integration. As a response, an 8C architecture is proposed, adding 3C facets to the established 5C architecture. The 3C facets are expected to increase both vertical and horizontal value chain integration, and are presented as follows [124]:

- **Coalition** – Focuses on the value chain integration and production chain integration among different parties involved in the production process. Alliance partners co-schedule production lines to yield specific products in a more flexible and timely manner.
- **Customer** – Represents the customer’s role in the design and production process, and after-sales service of the product. This can be seen as part of the shift from mass production to mass customization.
- **Content** – Describes all production information, such as raw materials, parameters on production process/environment/shipment, and especially after-sales service details such as maintenance and parts replacement. This provides feedback to the manufacturing process, production design, customer service, and prediction of product market trends.

For the field of maintenance, CPS shows promising results for enabling predictive and proactive maintenance, e.g., the MANTIS project focusing on a platform for proactive maintenance of industrial machines [120, 125], and the CPS-Plant project including an asset management strategy and maintenance perspective for Norwegian industries [126]. Summarized, Industry 4.0 technologies and CPS are seen as central in enabling the three key value chain integrations for Industry 4.0 [121], as discussed in Chapter 2.2.

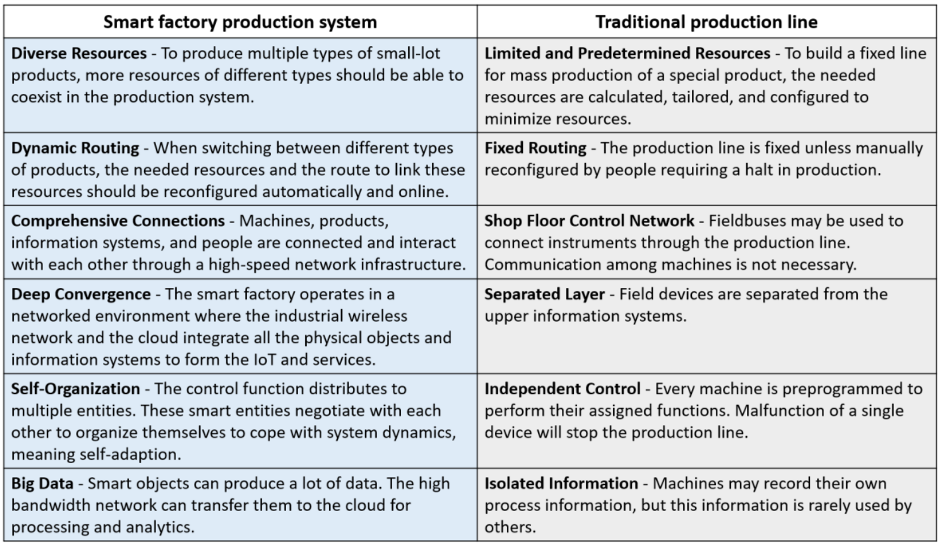
2.3.2 Digitalized and integrated value chain

The age of CPS and Industry 4.0 technologies is radically changing the requirements for companies aiming to lead the way in their industry. Advancements in technology, tools, machines, and capabilities of smart products are examples of areas making it necessary to adapt and rethink the way of working [9, 24]. Being best in class requires a seamlessly integrated value chain that leverages these opportunities, put together with a workforce possessing a digital and continuous mindset of improvement.

The accessibility of data and sensors has increased significantly, and the importance of competence on utilizing the generated data for gaining competitive advantages is underpinned by practitioners and academics [22]. However, a common challenge for industrialists is connected to managing big data and the capability to extract and utilize relevant data from multiple data sources [23, 127]. For data and sensors to provide value, analyses and competence within data contextualization are crucial for enabling data-driven decision-making [77]. Contextual data focuses on unlocking organizational and technological data silos, and aims to integrate and make data from a range of sources available such as real-time streams of sensor data from equipment and process, historic behavioral data from historians, and information from third parties on external factors [128]. The journey towards information governance for smart manufacturing is discussed in [129], where three pillars of information governance are presented:

- **Data quality and information reliability** – Data quality can be evaluated in terms of accuracy, completeness, consistency, and validity. Good principles of data governance reduce opportunities for errors in the first place and provide a basis for testing to find those introduced.
- **Semantic context for data analysis and decision-making** – Providing metadata, data that provides information about other data, to capture the context and meaning of the data. E.g., in smart manufacturing, data from equipment and sensors at different points in time need to be combined with data from other sources to provide context.
- **System context to enable integration, validation, and verification** – All data is created within a system context and its use outside of that context must be carefully controlled to avoid inappropriate use. E.g., performance data does not necessarily generalize beyond the specific machine on which it was generated, such as to the type of machine.

A survey [128] with 160 decision makers in IT and operations roles in global industrial companies showed that over 80% of the firms recognized the importance of industrial data in driving their business decisions and innovation. On the other hand, 83% experienced challenges in utilizing the data for delivering insights across their organization. A key finding from the survey was that data contextualization will be crucial for succeeding with this challenge [128]. This is also supported by [77], where deep convergence and comprehensive connections are presented as two of six technical features for smart factory production systems. Further, these six features are presented and compared to a traditional production line in [77], as shown in Figure 2.24.



Smart factory production system	Traditional production line
Diverse Resources - To produce multiple types of small-lot products, more resources of different types should be able to coexist in the production system.	**Limited and Predetermined Resources** - To build a fixed line for mass production of a special product, the needed resources are calculated, tailored, and configured to minimize resources.
Dynamic Routing - When switching between different types of products, the needed resources and the route to link these resources should be reconfigured automatically and online.	**Fixed Routing** - The production line is fixed unless manually reconfigured by people requiring a halt in production.
Comprehensive Connections - Machines, products, information systems, and people are connected and interact with each other through a high-speed network infrastructure.	**Shop Floor Control Network** - Fieldbuses may be used to connect instruments through the production line. Communication among machines is not necessary.
Deep Convergence - The smart factory operates in a networked environment where the industrial wireless network and the cloud integrate all the physical objects and information systems to form the IoT and services.	**Separated Layer** - Field devices are separated from the upper information systems.
Self-Organization - The control function distributes to multiple entities. These smart entities negotiate with each other to organize themselves to cope with system dynamics, meaning self-adaption.	**Independent Control** - Every machine is preprogrammed to perform their assigned functions. Malfunction of a single device will stop the production line.
Big Data - Smart objects can produce a lot of data. The high bandwidth network can transfer them to the cloud for processing and analytics.	**Isolated Information** - Machines may record their own process information, but this information is rarely used by others.

Figure 2.24: Technological features of a smart factory production system compared to a traditional production line, adapted from [77].

The smart factory is under the umbrella of smart manufacturing, which is the United States equivalent of Industrie 4.0 in Germany [130], and is defined as follows in [131]: *"Smart factory is an intelligent production system which utilizes the integration of manufacturing and services. It integrates communication process, computing process, and control process to meet the industrial demands."* In [132], they define the smart factory as: *"A manufacturing cyber-physical system that integrates physical objects such as machines, conveyers, and products with information systems such as manufacturing execution system and enterprise resource planning to implement flexible and agile production."* In terms of Industry 4.0, the smart factory is claimed to be enabling vertical integration, which in turn supports horizontal integration through value networks, and end-to-end digital integration of engineering [77, 132]. The role of the smart factory in Industry 4.0 is also investigated in [130], where they state that: *"The fourth industrial revolution is characterized by the introduction of the Internet of things (IoT) and Internet of services concepts into manufacturing, which enables smart factories with vertically and horizontally integrated production systems."* Although the term smart factory lacks a unified definition, and there are different viewpoints on the matter, the smart factory can be seen as a plant level conceptualization for the three types of value chain integration for Industry 4.0 presented in Chapter 2.2.

To close the gap between a smart factory and traditional production line, and realize the potential of Industry 4.0 outlined above, significant work has been done in several nations and unions to provide guidance and direction for companies and researchers. A frequently emphasized factor is the importance of standardization and usage of standards, as this provides common ground for companies, service providers and a unified understanding between practitioners and academics. According to [133, 134], the top four countries by share of global manufacturing output (2019 numbers with output measured on a value-added basis in current US dollars) are listed as follows:

1. China – 28.7%
2. United States – 16.8%
3. Japan – 7.5%
4. Germany – 5.3%

The following pages will present each nation’s main reference architecture relevant for the transition to a more digitalized and integrated value chain. In Germany, the Reference Architecture Model Industrie 4.0 (RAMI 4.0) is well established. RAMI 4.0 was first developed as part of their initiatives on Industrie 4.0, serving as a uniform conceptual and methodological structure forming a basis for ensuring that experts in various disciplines master the complexity and speak the same language while showing standardization status and gaps. RAMI 4.0 is now published in IEC PAS 63088:2017 Smart manufacturing – Reference architecture model industry 4.0 (RAMI 4.0) [135], and seems to be becoming established in Europe. The following description of RAMI 4.0 is given in [5]: *”RAMI 4.0 serves as an orientation framework for the stakeholders and classification of applications in the industrial sector. RAMI 4.0 introduces all elements and IT components in a layer and life cycle model and divides complex processes into manageable packages - including data protection and IT security. The reference architecture can be regarded as a model pattern, i.e. an ideal-typical model for the class of architectures to be modelled. Industrie 4.0 does not specify “the” architecture per se with RAMI 4.0, but only the framework with minimum requirements.*

This includes the definition of terms and a methodology with rules for describing the physical world for the purpose of mirroring (reflection) into the information world." Thus, RAMI 4.0 focuses on value chains in the manufacturing industry and can be seen as a holistic representation of main aspects within the comprehensive realm of Industry 4.0, through a three-dimensional model consisting of three main axes [5, 121, 136]. Figure 2.25 shows the RAMI 4.0 model, as presented in [135].

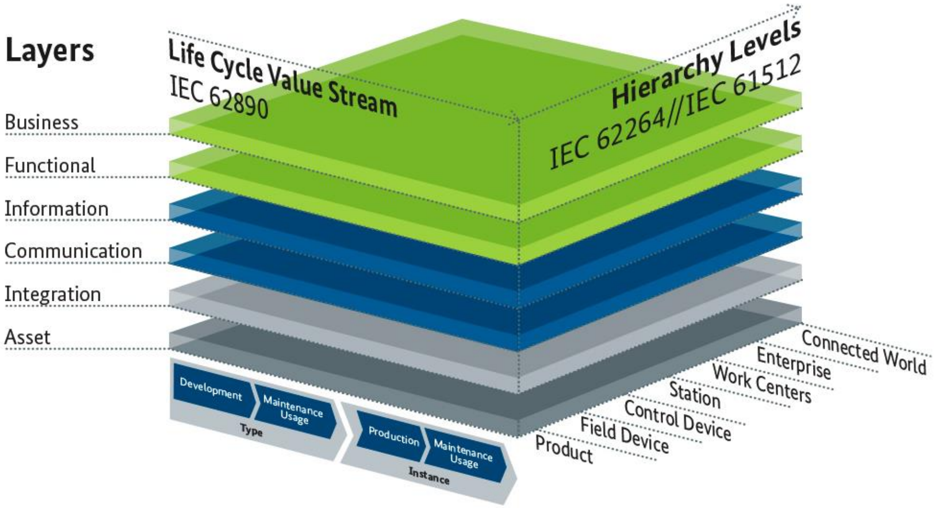


Figure 2.25: The German RAMI 4.0 model, as presented in [135].

The three main axes are described as follows in [135]:

- **The architecture axis "Layers"** – Describes the architecture in terms of properties and system structures with their functions and function-specific data in the form of the following six layers (including examples of basic business idea questions):
  - *Business layer* – Is the commercial view, e.g., mapping business models and processes, monetary conditions, and ensuring integrity of functions in the value-added chain. What is the customer willing to pay for?

  - *Functional layer* – Describes (logical) functions of an asset (technical functionality) and its role within the Industry 4.0 system. What should the product do?
  - *Information layer* – Concerns the data that is used, generated or modified by the technical functionality of the asset. What data does the product have to provide?
  - *Communication layer* – Describes Industry 4.0-compliant access to information and functions of a connected asset by other assets. Hence, describing which data is used, where it is used and when it is distributed. How to access the data?
  - *Integration layer* – Represents the transition from the physical world to the information world. An event in the real world generates an event in the integration layer. This is where the properties and process-related functions that make the asset usable for its intended purpose are stored, e.g., a human-machine interface. Which parts of the product are digitally available in the network?
  - *Asset layer* – The assets, including humans, that exist in the physical world. The material reality which is virtually represented in the layers above it. How to integrate the product with the process to move it in the real world?
- **The "Life Cycle Value Stream" axis** – Describes an asset at a particular point in time during its lifetime. The asset is characterized by its state at a particular time at a particular location.
- **The "Hierarchy Levels" axis** – Is based on the reference architecture model for a factory along the lines of IEC 62264-1 Enterprise-control system integration and IEC 61512-1 Batch control. The terms "Enterprise", "Work centers", "Station", and "Control device" are from the two mentioned standards. "Connected world" (the relationship between an asset or combinations of assets), "Field device" (e.g., sensors and actuators), and "Product" (refers to the product being integrated to the Industry 4.0 network, meaning smart product capabilities such as feedback to design and operation and maintenance) are modified and supplemented to reflect the prerequisites for enabling Industry 4.0.

China has presented the China Intelligent Manufacturing System Architecture (IMSA) as part of the strategic initiative China Manufacturing 2025, also known as Made in China 2025. The IMSA model is aligned with RAMI 4.0, as Germany and China initiated a sub-working group on Intelligent Manufacturing/Industrie 4.0 of the Sino-German Standardisation Cooperation Commission in 2015 [137]. As a result of this, the IMSA model emphasizes several of the same topics and viewpoints as RAMI 4.0. Figure 2.26 shows the IMSA model, as presented in [137].

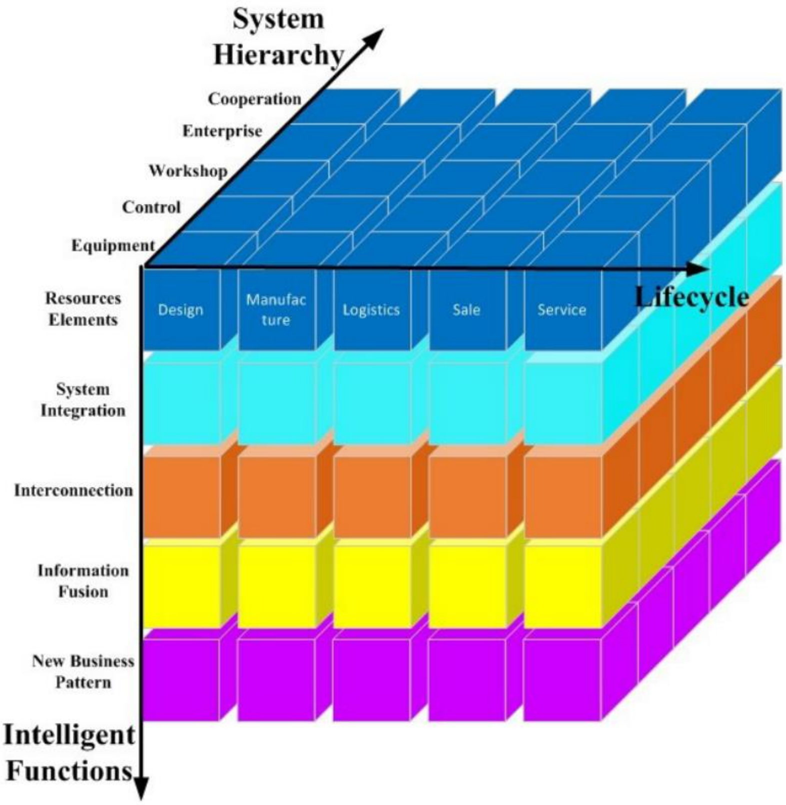


Figure 2.26: The China IMSA model, as presented in [137].

The IMSA model consists of three main dimensions. First, “Lifecycle” refers to the connected value creation activities from initial product prototype research and development to product recycling and remanufacturing. The lifecycle-activities are divided into design, manufacturing, logistics, sales, and service (including recycling), with capability for iterative optimization involving characteristics such as sustainable development in all activities [137]. The lifecycle reflects end-to-end value chain integration and can be compared to the Life Cycle Value Stream in RAMI 4.0 [137, 138]. Second, the System Hierarchy dimension represents the hierarchy division of the organizational structure related to the enterprise's manufacturing activities. These are described as follows [137, 138]:

- **Equipment** – The hierarchy for how the enterprise utilizes sensors, instruments and meters, machines and devices to realize, perceive and control the physical process.
- **Control** – Is about how the enterprise achieves information processing and monitors and controls the physical process, e.g., including programmable logic controllers (PLC) and supervisory control and data acquisition (SCADA) systems.
- **Workshop** – Represents the production management of the workshop or factory, including the manufacturing execution system (MES).
- **Enterprise** – Concerns structuring effective enterprise management and operation management, including enterprise resource planning (ERP), supply chain management (SCM), and customer relationship management (CRM).
- **Cooperation** – Focuses on interconnection and sharing of internal and external information to enable coordinated research and development, precise logistics and intelligent service realized by different enterprises.

The first four levels of the System Hierarchy dimension reflect vertical value chain integration, while the cooperation level can be seen as horizontal value chain integration [138]. Finally, the Intelligent Functions dimension includes five layers and represents the introduction of ICT to manufacturing activities and enabling intelligent functions. Capabilities such as self-sensing, self-learning, self-decision, self-execution, and self-adaptation are examples of the intelligent functions, and they are described for each layer as follows [137, 138]:

- **Resources Elements** – Refers to resources and tools used in the manufacturing process to achieve the digital process. Seven kinds of resource element are strategy and organization, employee, equipment, energy, raw materials, knowledge and market.
- **System Integration** – Focuses on integrating manufacturing resources. This can realize the integration of intelligent equipment in the intelligent production unit, intelligent production line, digital workshop, intelligent factory, and intelligent manufacturing system from small to large scale. Vertical integration within the enterprise refers to integration of intelligent equipment, instrument and meter, automatic control system, MES and ERP system. Horizontal integration refers to information integration of product design, manufacturing, logistics, and after-sales service for the whole product life cycle. End-to-end integration between enterprises refers to the capacity for managing the supply of materials and spare parts automatically through the integration of information system.
- **Interconnection** – Represents the connection of machines, equipment and control systems between enterprises through wired, wireless and other communication technology.
- **Information Fusion** – Is about realizing collaborative information sharing through system integration and with new technology such as cloud computing and big data. Seven functions related to information fusion are the data fusion platform, data cleaning and data quality improvement, data safety, workshop-level data fusion, factory-level data fusion, enterprise-level data fusion and integration of virtual reality and the physical world.
- **New Business Pattern** – Refers to performing value chain integration between enterprises to create new industry conformations by the enterprise. Five important new business patterns are personal customization, networked collaborative, intelligent marketing, remote operation of equipment and products, and industrial cloud and big data service. Remote operation includes online monitoring, fault forecast and diagnosis, and health status assessment.

Summarized, in terms of value chain integration, the key of IMSA is presented as [137]: *"to achieve vertical integration through the enterprise equipment hierarchy, control* *hierarchy, workshop hierarchy, factory hierarchy, cooperation hierarchy at different hierarchies, the horizontal integration across resources, interconnection and interworking, information fusion, system integration and new business pattern at different hierarchies, as well as the end-to-end integration of covering design, manufacture, logistics, sales and service."*

In Japan, the Industrial Value Chain Reference Architecture Next (IVRA Next) was published in 2018 by the Industrial Value Chain Initiative (IVI), a forum to promote and define smart manufacturing with over 260 companies involved, such as Toyota, Sony, and Siemens [139]. Additionally, Japan has a cooperation with Germany on Industrie 4.0, IIoT, and the Japanese initiatives Connected Industries and Society 5.0 [140]. The latter is defined as [141]: *"A human-centered society that balances economic advancement with the resolution of social problems by a system that highly integrates cyberspace and physical space."* Society 5.0 represents the new society following the four earlier types of societies: the hunting society, the agrarian society, the industrial society, and the information society. It looks beyond Industry 4.0 by transferring the radical technological advancements and progress of ICT into building a super-smart society [142], including responsible economic development and solving of sustainability issues [141]. The IVRA Next includes aspects of Society 5.0 but emphasizes smart manufacturing, where the IVRA Next is defined as the structure that can realize smart manufacturing [139]. Figure 2.27 shows the smart manufacturing unit (SMU) of the IVRA Next, as presented in [139].

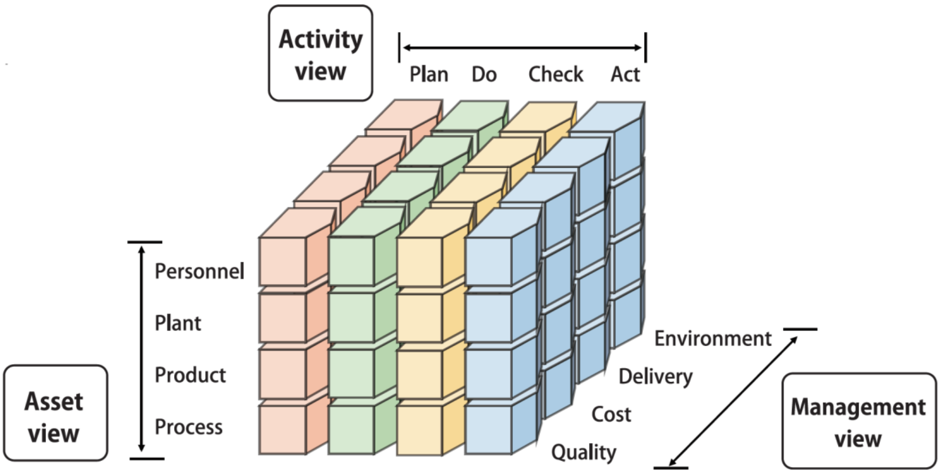


Figure 2.27: The Japan IVRA Next SMU, as presented in [139].

The SMU is divided into three main views. First, the Asset view shows valuable assets to the manufacturing organization, which executes activities proactively and on-demand. Personnel assets are defined as the personnel working at production sites, and they perform operations to produce a product in the physical world. Plant assets refer to equipment, machines and devices used for manufacturing, including tools, jigs, and subsidiary materials. Product assets are products created as an outcome of manufacturing and materials used during production. Materials that become a part of a product, such as components and assemblies, are also seen as product assets. Process assets describe manufacturing sites' valuable knowledge of operation, such as production processes, methods, and know-how. This knowledge about processes is seen as an asset for manufacturing [139]. Second, the Management view concerns control of assets and activities in terms of quality, cost, delivery, and environment, which can be managed independently but examined together to determine whether the SMU is optimized. Quality measures how the characteristic of a product or service meets the needs of the customers. Quality improvements include product quality, quality of plants or equipment, and the value of methods and personnel. Cost is the sum of financial resources and goods spent, directly and indirectly, for an SMU to provide a product or service, including materials, services invested for operating equipment, energy consumption, and financial resources and goods indirectly spent to maintain and manage plants. Delivery accuracy indicates whether the time required to deliver the product or service meets the needs of the SMU's customers. Environment is an index measuring the degree to which an SMU's activities harmonize with the environment without unnecessarily stressing the natural world, including maintaining a good relationship with the environment and neighboring regions, managing emissions, material flows, and optimizing energy consumption [139]. Third, the Activity view covers the activities performed by SMUs at manufacturing sites in the real world, which can be seen as a dynamic cycle continuously improving targeted issues proactively. Value created in the SMU is from the outcome of human and machine activity. All types of activities are composed of the cycle of four key activity classes, namely, “Plan”, “Do”, “Check”, and “Act”. This refers to the PDCA cycle, which is discussed in Chapter 2.2.2. Moreover, “Plan” is the activity of making a list of action items to be executed within a given time, which can include the goal of behaviors for completing a given mission or achieving the objectives of an SMU. “Do” refers to actions performed to achieve a certain goal by executing defined activities at the actual site in the physical world. These actions can create new assets or change the state of existing assets. “Check” comprises activities to evaluate whether the goal set in the Plan activities has been accomplished. These include analytically measuring changes in the physical world based on the executed planned actions and investigating causes if some goals have not been accomplished. “Act” refers to Kaizen, as presented in Chapter 2.2.2, and improving the function of an SMU by defining the ideal situation and tasks for fixing any problems in achieving the target. This includes changing the structure or system of the SMU itself to fill any gaps. An SMU with human intervention changes its mechanism autonomously [139]. Summarized, the Japan IVI have defined three required elements for all companies and factories attempting to achieve smart manufacturing [139]:

- **Value chain by connected factories** – Each manufacturing site has the means required for connecting to the digital world and suppliers, increasing value to the customer. Manufacturers synchronize with the needs of their customers and markets, and provide value in a timely manner.

- **Autonomous systems on loosely defined standard** – The parts of individual companies that contribute to their competitiveness are kept closed, but common areas are boldly opened. To find common ground on areas to connect between companies, loosely defined standards that recognize individual company differences are adopted. Strict standards are avoided, and characteristics of individual companies are maintained.
- **Ecosystem on data-driven platforms** – In addition to physical locations, physical goods, and realities that form the analog aspects of manufacturing, the ratio of cyber and digital worlds will increase. Platforms allowing various activities to be connected in the digital world must be mutually linked as a decentralized ecosystem (system of systems), and should grow while also involving stakeholders with diverse values.

The ecosystem element is also seen on the other side of the Pacific Ocean, where the National Institute of Standards and Technology (NIST), a non-regulatory agency of the United States Department of Commerce, has presented a Smart Manufacturing Ecosystem. The NIST Smart Manufacturing Ecosystem was first presented in 2015 in [143], and further elaborated in 2016 [144]. Figure 2.28 shows the NIST Smart Manufacturing Ecosystem, as presented in [129].

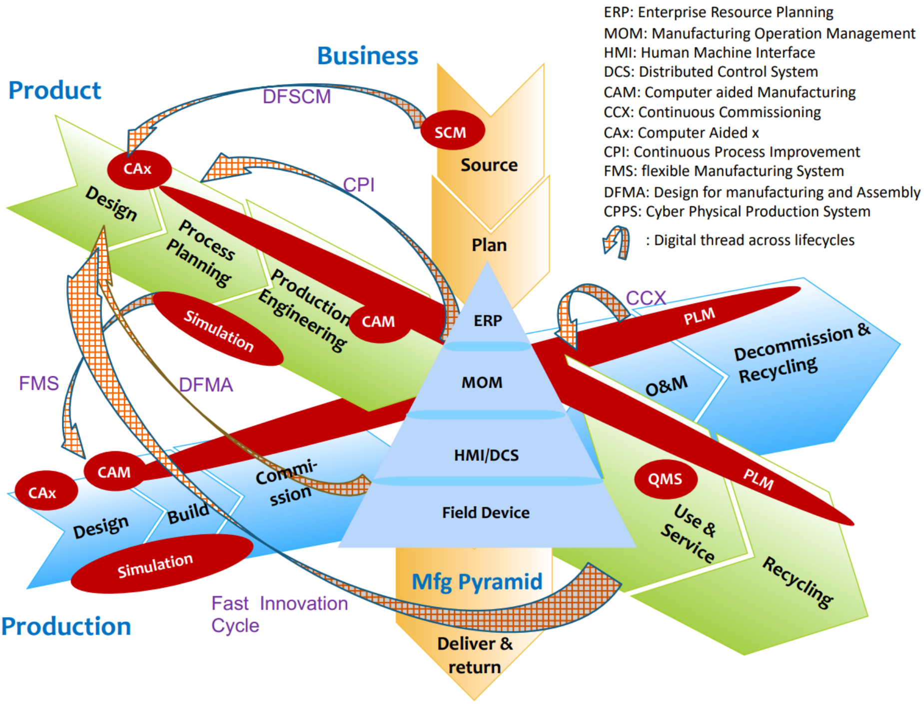


Figure 2.28: The NIST Smart Manufacturing Ecosystem, as presented in [129].

Many companies have invested in off-the-shelf MES and ERP systems to help utilize their data and to manage complexity and data in specific functional areas. However, with the transition to digitalization of manufacturing, value can be increased by using data more cross functionally and integrating system providers. Moreover, the need for more open information management is summarized in four motivating factors [129]:

- Sharing data across system boundaries within an organization.
- Interacting with multiple partners in a supply chain.
- Archiving the digital version of the product.
- Qualifying production processes.

The NIST Smart Manufacturing Ecosystem serves as a standard landscape and ecosystem that identifies standards, such as those from ISO, IEC, American Society for Testing and Materials (ASTM), and American Society of Mechanical Engineers (ASME), which companies can consider in their process of integrating elements of a smart manufacturing system. Thus, it provides a conceptual overview emphasizing manufacturing applications and provides a manufacturing planning perspective [129, 143, 144]. As shown in Figure 2.28, the three dimensions production, product, and business are included and positioned in their own life cycles. The production life cycle refers to the collection of machines, equipment, and auxiliary systems organized to create goods and services from various resources. The main life-cycle phases for a production system are Design, Build, Commission, Operation and Maintenance (O&M), and Decommission & Recycling. E.g., for the O&M phase the NIST Smart Manufacturing Ecosystem has listed standards that define data processing, communication and presentation standards for condition monitoring and diagnostics of machines such as the ISO 13374 family [129, 143, 144]. The product life cycle represents the information flows and controls beginning at the early product design stage and continuing through the end-of-life of the product. It consists of the phases Design, Process Planning, Production Engineering, Manufacturing, Use & Service, and Recycling [129, 143, 144]. The business life cycle consists of the Source – Plan – Make – Deliver & Return cycle for managing the manufacturing supply chain, and information exchange between stakeholders. To enhance supply chain efficiency and manufacturing agility, standards are essential as they ensure smoothness for interactions between manufacturers, suppliers, customers, partners, and, sometimes, competitors, including manufacturing specific modeling standards and corresponding message protocols [129, 143, 144].

Combined, the production, product, and business life cycles are integrated in the Manufacturing Pyramid (Mfg Pyramid). This is the core of the Smart Manufacturing Ecosystem, and several standards are critical for supporting integration from machine to plant to enterprise systems. Integration is vital for manufacturers to [143]: 1) access field and plant data for making quick decisions and optimizing production throughput and quality, 2) provide accurate measures for energy and material use, and 3) improve shop floor safety and to enhance manufacturing sustainability. The standard ISA95, which has been included in IEC 62264-1:2013 Enterprise-control system integration, positions the standards in their relevant hierarchy in the Mfg Pyramid. For a smart operation, autonomous and intelligent machine behaviors, including self-awareness, reasoning and planning, and self-correction are important, but information resulting from these behaviors must flow up and down the Mfg Pyramid. Summarized, smart manufacturing enables integration across the three dimensions by using cloud-based service and data integration capabilities. Some examples are shown by the digital thread across life cycles in Figure 2.28, and are described as follows [129]:

- *Production data can be used for continuous product design improvement (CPI), e.g., features requiring an extraordinary amount of energy or time in fabrication should be modified to improve efficiency, reduce cost, and reduce the environmental impact.*
- *Continuous Commissioning (CCX) engages ongoing monitoring, diagnosis, prognosis of production equipment and can be used to develop more sophisticated maintenance strategies and improve production system performance.*

It emerges clearly that the presented reference architectures from China, United States, Japan, and Germany are aligned when it comes to the need for standards and ensuring common ground for practitioners and academics, when moving towards a more digitalized and integrated value chain. This is also underpinned by the various collaboration initiatives between the nations, and in other organizations such as the Industry IoT Consortium [145] with their Industrial Internet Reference Architecture (IIRA) [121], and the Open Connectivity Foundation [146], the most influential IoT standard organization [147], which has provided input to the ISO/IEC 30118-1:2021 Information technology – Open Connectivity Foundation (OCF) Specification [148] (including the other seventeen parts of ISO/IEC 30118). The conclusion in the report from NIST [144] is that standards are a fundamental component of the evolution to smart manufacturing, but existing manufacturing standards are insufficient to fully enable smart manufacturing. They also stress that standards development organizations, national manufacturing initiatives, and industrial consortiums are identifying requirements for new smart manufacturing standards [144]. The technical report ISO/IEC TR 30166:2020 Internet of things (IoT) – Industrial IoT can be seen as a response to this development [149].

Several studies have investigated the above-mentioned reference architectures in an Industry 4.0 environment, e.g., [121] performed a literature review on RAMI 4.0, the 5C architecture, and the IIRA for IIoT applications in Industry 4.0, and concluded that future works should explore a clearer and unified standardization solution capable of ensuring interoperability among different industrial systems. Further, future work should also include trending technologies such as wireless sensor networks, 5G, Blockchain, and Future Internet in Industry 4.0 reference architectures design [121]. Another study [150] presented the state of the art and future trends for Industry 4.0 reference architecture including RAMI 4.0, IIRA, and IVRA Next, and concluded that reference architectures could become the backbone for the full realization of the fourth industrial revolution if their maturity and sustainability are increased, but currently [150]: *"the existing reference architectures are not completely suitable yet to support Industry 4.0 processes, mainly due to their high level of abstraction and/or missing of detailed documentation, together with a lack of completely automated support, which makes it difficult to instantiate them to real-world Industry 4.0 projects."* Thus, there is an agreement on the need for further investigating the mentioned reference architectures from both a practitioner and an academic perspective.

To an increasing extent, the transition to a more digitalized and integrated value chain calls for close cooperation between the partners along the value chain. For the field of maintenance, the need for close cooperation among different service providers also applies, because maintenance types such as preventive and corrective maintenance are increasingly being replaced by predictive ones in forthcoming Industry 4.0 environments. A prerequisite for succeeding in this field is providing sufficient scope for machine manufacturers, operators, and industry service providers, to enable evaluation of maintenance-related data in the context of predictive maintenance [5, 13]. Figure 2.29 shows the interactions for maintenance in an Industry 4.0 environment, which is also discussed in [5, 13].

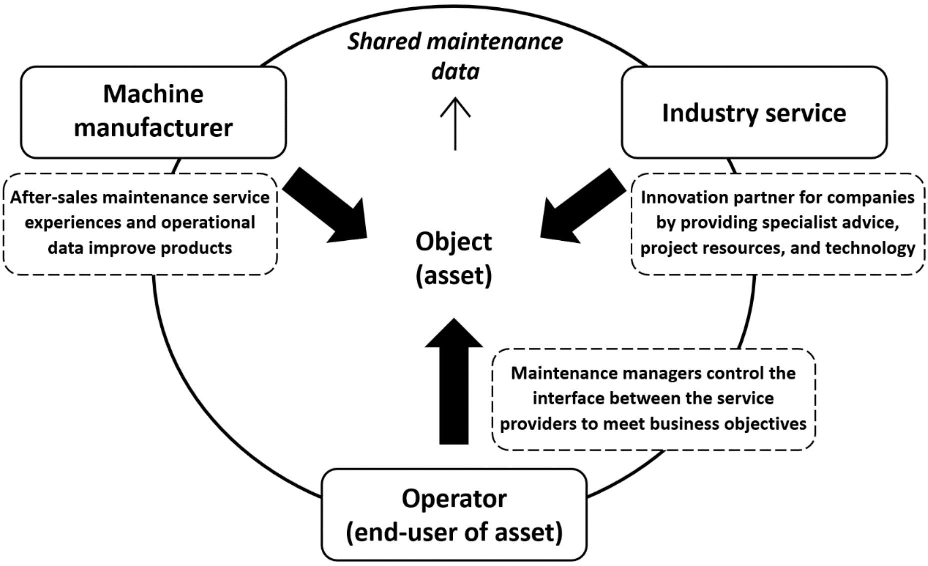


Figure 2.29: Maintenance interactions in an Industry 4.0 environment, adapted from [5, 13].

3. Methodology

A commonly used definition of research is presented as follows [151]: *"Research is a scholarly, scientific, and systematic investigation to establish facts or principles, or to collect information on a subject to be presented in a detailed and accurate manner"*. Moreover, having a sound research methodology is important, as it will enable others to scrutinize and evaluate the research. This chapter presents the research methodology and research design chosen for this PhD project. First, the scientific method and different research methods are presented. Second, a description of the research design applied in this PhD project is given. Finally, reflections on research quality, limitations, and ethical aspects are provided.

3.1 Research methods

This PhD project follows the main concepts of the scientific method, shown in Figure 3.1. The first phase starts with the idea from the researcher, which is inspired from prior theoretical knowledge and observations from the researchers' field. This idea is then defined and formulated into a problem/hypothesis. In the second phase, the experiment is designed with a suitable research methodology. The third phase is where the designed experiment is conducted, and the problem/hypothesis is tested. This includes collection, processing, and analysis of data. The result of the testing decides the next step for the researcher, as a rejected hypothesis means returning to the first phase and making modifications, while a successfully proven hypothesis is the way to the last phase. This is where theory is refined, to clarify the conclusion, highlight research contributions and make suggestions for further work [151].

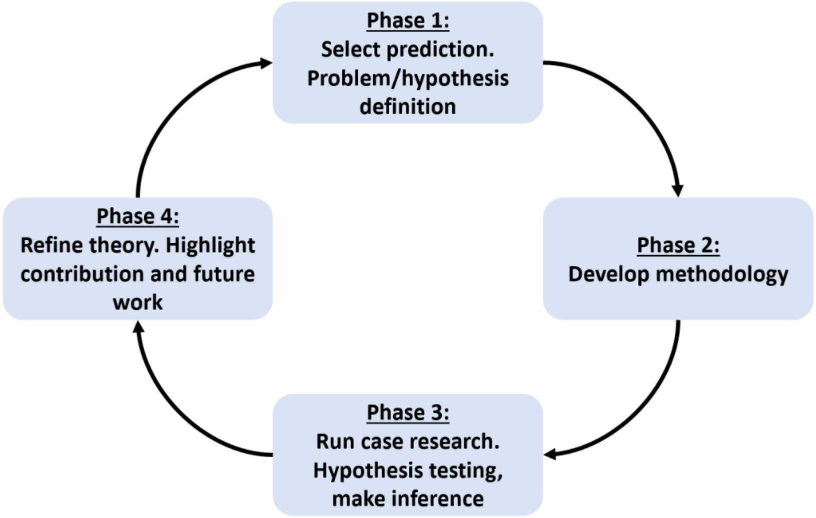
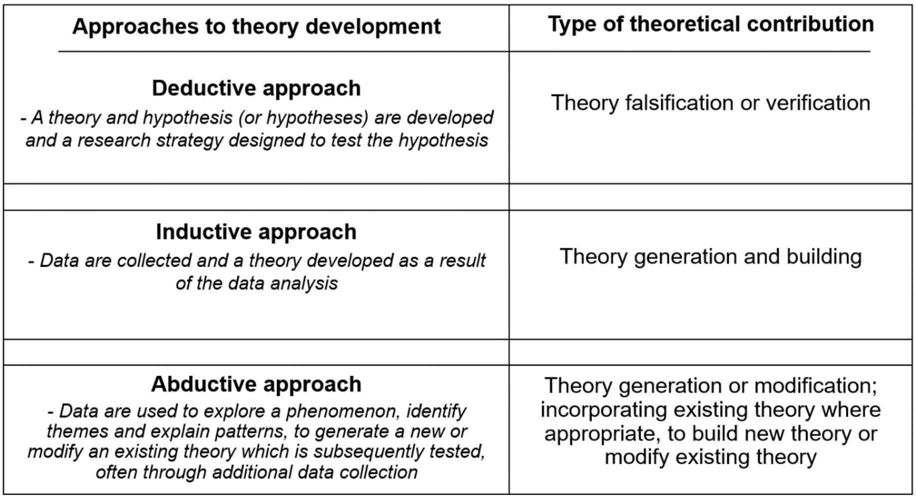


Figure 3.1: Research phases based on the scientific method, inspired by [151].

There are many ways of conducting research, and it is common to distinguish between two research strategies, namely, qualitative research and quantitative research [152]. Qualitative research can be defined as [152]: *"Research approach that examines concepts in terms of their meaning and interpretation in specific contexts of inquiry."* On the other hand, quantitative research can be defined as follows [152]: *"Research approach that examines concepts in terms of amount, intensity, or frequency."* These two research strategies both have their pros and cons, and it is common to use a mix of the strategies in research projects [152]. Further, the research approach can be divided into deduction and induction. The deduction approach entails theories that predict one or more outcomes, which are tested through experiments, i.e., rationalism. On the other hand, the induction approach involves making observations that lead to the generation of new theory and conclusions, i.e., empiricism [152]. In [153], they also present abduction, also called retroduction, as an approach. Here, instead of moving from theory to data (deduction) or data to theory (induction), the abductive approach combines the two and goes back and forth. Different combinations of the approaches can be used within the same piece of research and this is often advantageous, as no approach is better than the others, but some may be more suitable in different areas. The selection should thus be based on research emphasis, research philosophy, and the nature of the research topic [153]. An overview of the approaches is given in Table 3.1 [153].

Table 3.1: Approaches to theory development, adapted from [153].



Approaches to theory development	Type of theoretical contribution
Deductive approach *- A theory and hypothesis (or hypotheses) are developed and a research strategy designed to test the hypothesis*	Theory falsification or verification
Inductive approach *- Data are collected and a theory developed as a result of the data analysis*	Theory generation and building
Abductive approach *- Data are used to explore a phenomenon, identify themes and explain patterns, to generate a new or modify an existing theory which is subsequently tested, often through additional data collection*	Theory generation or modification; incorporating existing theory where appropriate, to build new theory or modify existing theory

Another common way of positioning the type of research is case study or case research. This type is often recommended when the planned research is of an exploratory nature, and when investigating contemporary events while being unable to manipulate behavioral events [154]. A definition of a case study is presented in [154]: *"The essence of a case study, the central tendency among all types of case study, is that it tries to illuminate a decision or set of decisions: why they were taken, how they were implemented, and with what result."* This definition introduces different types of case studies, which are also discussed in [152], where they present the following three main types of case research:

- Case research as theory generation – the main driving force is induction. Generating theory using empirical analysis.
- Case research as theory testing – the main driving force is theoretical deduction but is not exclusively limited to it. Propositions are derived from theory.
- Case research as theory elaboration – Similar to theory testing but strives to elaborate instead of testing the logic.

Defining and positioning a research project in terms of the research method and type of research can sometimes be challenging. The variety of definitions, classifications and methodologies within this realm is comprehensive, and deciding to lock on an absolute research method can also hinder the research. In general, all research projects start with a research basis, a knowledge interest, and research questions which together lead to research results. As a guidance tool within this matter, a case research decision tree, focusing on the type of theory emphasis, is shown in Figure 3.2 [152].

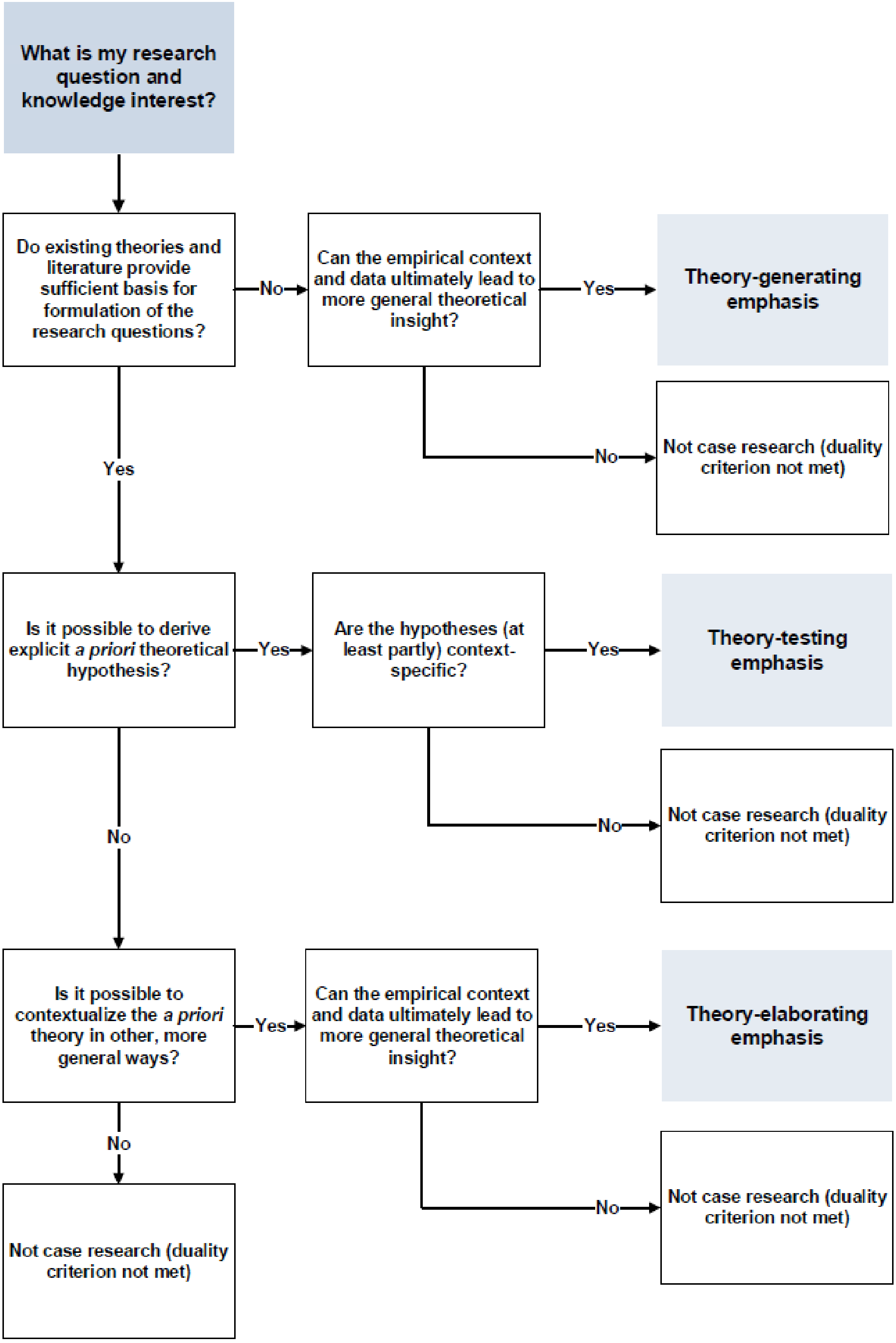


Figure 3.2: Case research decision tree, adapted from [152].

3.2 Research design

For this PhD project, the main research design is presented in Figure 3.3. The research design is inspired by the scientific method described in Chapter 3.1. Step 1 in the figure is to perform a literature review, and, additionally, through the CPS-Plant project and other industrial projects, meet the industry to understand industrial challenges and possibilities. The author's work experience from the process industry will also support Step 1. Combined, this forms the research basis and knowledge interest. The development of theoretical assumptions to Step 2 is not a straightforward logic path, but also consists of creative intuition by the author. Further, Step 2 will consist of concepts, frameworks, and tools relevant to the problem and research questions presented in Chapter 1.3. Step 3 is to perform conceptual testing and industrial testing. The testing will mainly be driven by deduction, based on derivation from the theoretical assumptions in Step 2. In the last step, Step 4, the theory and conclusion are refined towards new knowledge, and a scientific contribution within the scope of this PhD, as described in Chapter 1.4, is given.

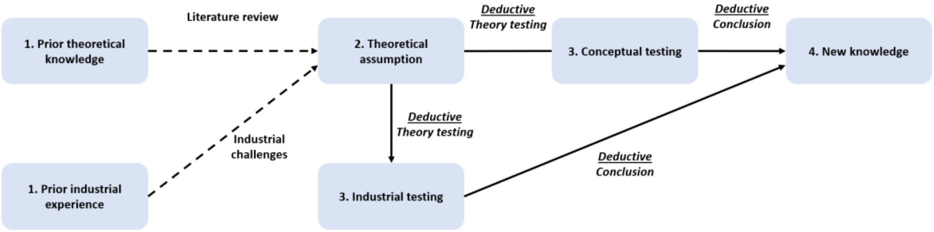


Figure 3.3: Research design for this PhD project.

In terms of the case research decision tree presented in Figure 3.2, theory-testing and theory-elaborating emphasis will be the focus for this PhD. Moreover, there will be some variations in research methodology in the different articles included in this PhD. In general, the research is based on a qualitative approach, but not exclusively limited to it, and utilizes the collective forces, sharing of insights, and interaction between academia and industry throughout the CPS-Plant project, focusing on doing collaborative problem solving while having a research interest in mind. Finally, and of high relevance for research projects conducted during the Covid-19 pandemic, in terms of defining a research method it is also claimed that [155]: *“researchers cannot definitively state the unit of analysis at the outset of the research; it must come into focus as the research progresses.”*

3.3 Evaluation of research quality

Being a PhD candidate is in many ways like an expedition in unknown land. There is a high degree of uncertainty in what to expect, a wide range of challenges that are necessary to overcome, and a test of patience and persistence, but a great sense of accomplishment and character-building learning outcomes when the finish line gets closer. With this metaphor in mind, the time as a PhD candidate has provided a lot of knowledge on the process of conducting research through PhD courses, discussions with supervisors and colleagues, feedback on articles, and reading books and reports, to mention some examples. The research design shown in Figure 3.3 has guided the research for this PhD, but as time went on, there was sometimes a need to take a step back and readjust. The research process itself thus involved several iterative loops. As the finish line approaches, looking back on the path and evaluating how things could be done differently and better is a natural part of the journey. This PhD is no exception to this, and reflections on research quality are provided below.

Research quality lacks a unified definition, and the available scientific literature on the topic is scarce [156]. As a contribution within this realm, a concept hierarchy of research quality has been developed by [156], as shown in Figure 3.4.

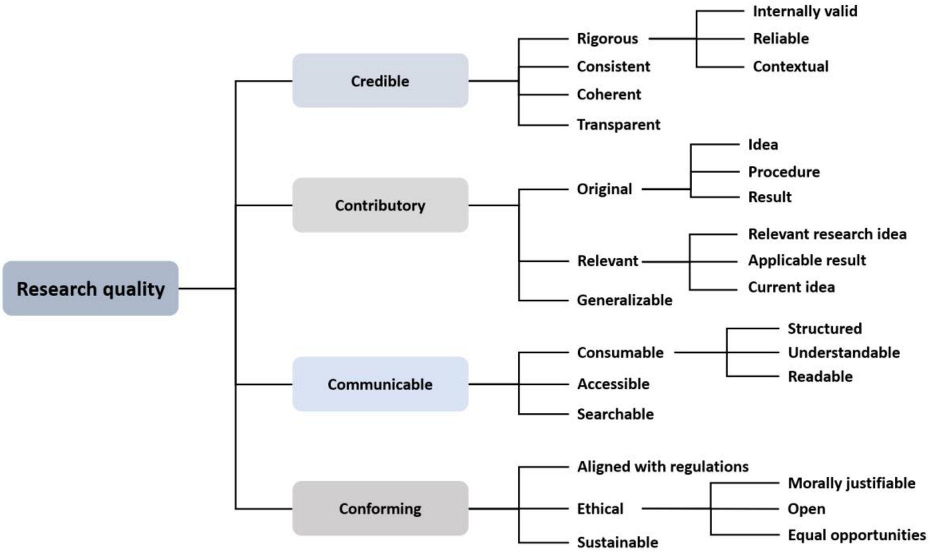


Figure 3.4: Research quality, adapted from [156].

The description of research quality includes four main elements, namely, *Credible*, *Contributory*, *Communicable*, and *Conforming*, which are further connected to other concepts for a more detailed evaluation of research quality [156]. First, *Credible* is defined as [156]: "*Research that is coherent, consistent, rigorous and transparent*." As an example, research in a university is often very transparent and open, while research in an industrial company may be more closed, meaning the importance of this particular concept may differ based on the researcher's perspective. Second, *Contributory* is defined as [156]: "*Research that is original, relevant and generalizable*." Here, the focus is on the importance of originality in the research, relevancy for the target group, and that the new knowledge is practically or theoretically useful. Third, *Communicable* is defined as [156]: "*Research that is consumable, accessible and searchable.*" This means that the research needs to be understandable, easily accessible, and well-structured for the target group. Finally, *Conforming* is defined as [156]: "*Research that is regulatory aligned, ethical and sustainable*." Hence, a high degree of research quality also depends on alignment with relevant regulations, ethical standards, and sustainable development aspects.

The research questions and problem addressed in this PhD project have been developed under the framework of the research project CPS-Plant, and industrial partners in the consortium and supervisors have both inspired and supported their development. To the best of our knowledge, the research questions and problem, as well as the results, are in line with the four main elements of research quality presented above. In terms of credible, the PhD has followed the scientific method and a research design which is in relation to the context and questions at hand, providing a link between existing and new knowledge. Transparency of the research and sharing of results has also been a focus area throughout this PhD, and publishing articles, participation in conferences, and seminars with the CPS-Plant project has provided valuable input. When it comes to being contributory, the research is original as it is positioned in an area between maintenance and the value chain, where previous research has mainly focused on one of these two fields. By adding digitalization and integration between these fields, the research is relevant to industrialists and researchers investigating Industry 4.0, and the knowledge is also generalizable to contexts other than the CPS-Plant project. For the communicable part, the research has focused on being structured and understandable, and results have been made available by publishing articles in searchable forums. Moving over to conforming, the research is under the umbrella of the CPS-Plant project, meaning that reporting of the research conducted is a requirement and includes alignment with Norwegian regulations. The CPS-Plant project also embrace sustainability, as this is part of the strategy for the industrial partners in the consortium. Ethical aspects are of high importance when conducting research, and these are discussed further in Chapter 3.4.

3.4 Ethical aspects of the research

The research in this PhD has been conducted in accordance with the NTNU code of ethics [157], and requirements for ethical standards in research given by The Research Council of Norway [158], as this PhD has been within the framework of CPS-Plant. Supervisors and expertise available in this framework have provided valuable guidance and helped in assuring the scientific quality of the research conducted in this PhD.

Ethical aspects are of great importance when conducting research. For this PhD project, the following ethical aspects have been considered: environmental aspects, ethical issues on digitalization in the industry, potential conflict of interest.

One of the overall goals of this PhD has been to investigate how industrialists can increase their performance. This can lead to more production, which can result in increased use of energy and raw materials, meaning an increased potential for contributing to global warming. On the other hand, the performance improvements this PhD focuses on are mainly connected to the fields of the value chain and maintenance. Improvements in these areas can support sustainability and the environment [159], and especially the field of PdM has been linked to these matters, as presented in [160]: *"A new sustainable world is envisioned on the foundation of new technology, new strategies and solutions, and new business models, and this vision holds particularly true for the manufacturing sector. Predictive maintenance can be considered to illustrate the primary discipline to be used for this goal."* Further, the NTNU code of ethics says the following about environmental aspects [157]: *"Employees must be aware of how their behaviour and decisions might affect the external environment and sustainable development, in terms of research, education, operations or administration."* It is not expected that this PhD project will have a negative effect on the environment, but environmental awareness has been maintained in the work with this PhD.

The PhD project focuses on digitalization and new ways of working. The debate on whether digitalization, with robots, AI, and increased automation, is putting jobs at risk is something to be aware of. At the same time, industrialists need to follow the technological development to stay competitive in their field and produce in a more sustainable manner.

The author confirms that he has no conflict of interest related to this PhD project.

4. Main Results and Discussions

This chapter will discuss the main results of this PhD project. The first part discusses the contribution to science and revisits the research questions, presenting results on possible underlying factors explaining the findings for each research question. The next part presents implications for practitioners. General recommendations regarding maintenance and how the transition to a more digitalized value chain should be approached are also included. Table 4.1 provides an overview of the research problem and research questions related to the articles, with main results, included in this PhD thesis.

Table 4.1: Research problem and research questions related to the articles included in this PhD thesis.

Research problem: How to integrate the fields of maintenance and value chain, in order to increase industrialists' level of performance?		
RQ 1: **What is the connection between maintenance and the value chain?**	**RQ 2:** **How can the development of technology, maintenance and maintenance management improve industrialists' value chain and level of performance?**	**RQ 3:** **How to implement an integrated maintenance and value chain approach in an industrial setting?**
Article number	**Main results**	**Related RQ**
Article 1	An overview of sensor management and trends within maintenance is presented. A novel concept for sensor management, its linkage to maintenance and improvement of operational availability is given.	**RQ 2**

Article 2	New knowledge on how maintenance programs can benefit from including a value chain perspective. A concept for balanced maintenance programs in asset-intensive industrial plants is also presented.	**RQ 1, RQ 2, RQ 3**
Article 3	A concept for an indicator measuring the level of performance of planned maintenance stops, and a discussion on how this indicator will support continuous improvement. The article also discusses the industrial development and need for new indicators within maintenance management and performance management.	**RQ 2**
Article 4	The article evaluates maintenance and value chain management in a new perspective, focusing on how maintenance indicators can be used to enhance value chain performance. An overview of the development of standards within maintenance and development of, and need for, new maintenance indicators is also provided.	**RQ 1, RQ 2**
Article 5	An overview of trends within World Class Maintenance and a discussion on the role of maintenance management in the value chain is given. Positioning the Profit Loss Indicator in the context of World Class Maintenance and a proposed structure for its effect on a company value chain is also presented.	**RQ 1, RQ 2, RQ 3**

Article 6	The article investigates the role of operators, maintenance personnel and other relevant job categories in an Industry 4.0 environment. The article also presents a framework for qualification criteria for Operator 4.0 and identifies relevant Industry 4.0 technologies.	**RQ 3**
Article 7	A discussion on how maintenance and value chain data can be used to improve value chain performance through prediction is given. The article also presents a case of a company that has chosen to apply a predictive maintenance platform, the implications and determinants of this decision.	**RQ 2, RQ 3**

4.1 Contribution to science

4.1.1 The connection between maintenance and the value chain

The first research question aimed at investigating the connection between the field of maintenance and the value chain:

RQ 1: *What is the connection between maintenance and the value chain?*

To answer this research question, investigation of existing literature, conceptual development, experiences from process industry and CPS-Plant formed the foundation used to address RQ 1. Articles 2, 4, and 5 present results related to RQ 1. Based on this, main findings related to RQ 1 can be summarized as follows:

Main findings RQ 1: *The connection between maintenance and the value chain seems to have changed along with increased industrial digitalization and the introduction of Industry 4.0 technologies. Initially, maintenance was seen as a hindrance in the value chain and equipment maintenance was an unwanted necessity, making firefighting the primary way of conducting maintenance. Currently, maintenance has evolved to a field* *serving as a toolbox for enabling Industry 4.0, supporting sustainable production, and encouraging value chain integrations, by aiding the connection between the physical and digital world and complementary integrating machines, systems, and humans in a value-adding fashion.*

Articles 2, 4, and 5 go further into discussing the underlying factors that may explain these findings. The literature agrees on the previous view of maintenance being an unwanted and costly necessity, resulting in a reactive way for practitioners to conduct maintenance. This view can be connected to a lack of technological readiness, supported by low availability and high cost of technology required for enabling more sophisticated maintenance strategies. Consequently, the connection between maintenance and the value chain has been rudimentary, not seeing maintenance as an opportunity for adding value to the value chain. For many companies, the lack of contextual and predictive capabilities results in a silo mentality isolating fields such as production and maintenance, resulting in suboptimal value chain performance. Several studies have investigated the lack of integration and connection, and its associated performance reductions, between production and maintenance in different perspectives, e.g., integrated maintenance planning in [95]. With the introduction of Industry 4.0, significant performance increasements have been expected for industrialists. This calls for increased integration between several fields and new connections throughout the companies’ value chain. Maintenance can be seen as an essential enabler for reaping the promised benefits of Industry 4.0 and for ensuring availability in complex Industry 4.0 systems. Additionally, maintenance can act as a driver for innovation through acquiring knowledge by analyzing large volumes of data from machines, systems, and products, causing the opportunity for a new value-adding connection between maintenance and the value chain.

It is interesting to see how national initiatives by leading manufacturing nations, within the transition to a more digitalized and integrated value chain, connect maintenance to their reference architectures. E.g., the German perspective is quite clear on how the maintenance function will need to interact with other service providers in an Industry 4.0 environment, where it serves as a connection hub between machine manufacturer, industry service, and operator, and allows sharing of maintenance data [5, 13]. This underpins both the imminent changes in how industrialists will conduct maintenance going forward and the role and connection that maintenance has in the value chain for these industrial stakeholders. Another example is the United States NIST Smart Manufacturing Ecosystem, which sees continuous commissioning as engaging ongoing monitoring, diagnosis, and prognosis of production equipment, allowing development of more sophisticated maintenance strategies, and improving production system performance [129]. The need for and importance of standards is shared between all the national initiatives presented, and this can be seen as a fundamental element in providing quality for the interaction between stakeholders, and the connection between maintenance and the value chain. An overview of advancements for maintenance standards is given in Article 4.

Article 2 discusses the connections between maintenance and the value chain and presents the internal and external value chain effects of six maintenance program objectives experienced in the process industry, as shown in Figure 4.1.

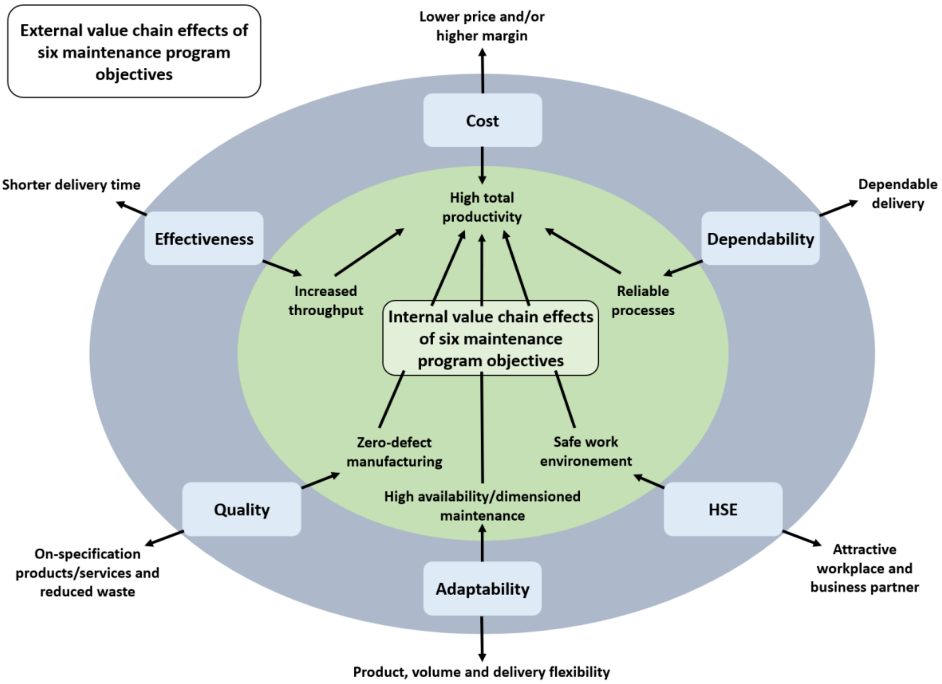


Figure 4.1: Internal and external value chain effects of maintenance program objectives.

The six objectives underpin the relationship between maintenance and the value chain. In terms of Smart Maintenance, adaptability is one desirable objective of a maintenance program and facilitates a dimensioned maintenance and high availability, benefiting the customer through increased flexibility in product, volume, and delivery. The objective of cost focuses on having a cost-efficient maintenance program and is affected by the other objectives. Thus, improving in the other objectives will improve value chain productivity, enabling lower product prices for customers and/or higher margins for the company. Next, a maintenance program should enable dependability. This will provide reliable processes, which the customer will experience as dependable deliveries. Further, a maintenance program is an important element in ensuring compliance with health, safety and environment (HSE) regulations. Internally, a focus on HSE will support a safe work environment, while the external image of the company will be corroborated as an attractive workplace and business partner. Quality in maintenance execution supports zero-defect manufacturing internally, and on-specification products and services for the customer. Finally, effectiveness in maintenance execution increases availability, which internally means increased throughput, and shorter delivery time is an external value chain effect. Figure 4.1 can be seen as a contribution to the functional connections between maintenance management and manufacturing operations management presented in the standard IEC 62264-1:2013 [63]. Article 4 goes further into the six objectives and discusses advancements in the maintenance function and how maintenance will play an even more important role in the value chain for future years. The maintenance function is described as a combination of several disciplines and resources, such as knowledge, methodologies, technologies, processes, and competences to create and develop an appropriate mix of actions to maintain the required level of functionalities of physical assets and achieve the assigned company objectives. This shows the importance of maintenance and underpins its role in moving towards more complex Industry 4.0 systems, supporting [39, 52]. Article 5 also presents trends in manufacturing and world class maintenance, discussing how the role of maintenance has changed. Another result presented in Article 5 is that maintenance has direct effects on the total operating cost of manufacturing and production plants, meaning that measuring maintenance performance is a way to find potentials in increasing value chain performance. For measuring maintenance performance, a set of maintenance indicators are structured in a focus diagram in Article 5, as shown in Figure 4.2, where output represents the effect on the value chain. Summarized, this highlights connections between maintenance and the value chain, which can be seen as input to the element “Goals and requirements” in the maintenance management model in the standard NORSOK Z-008:2017 Risk based maintenance and consequence classification [57].

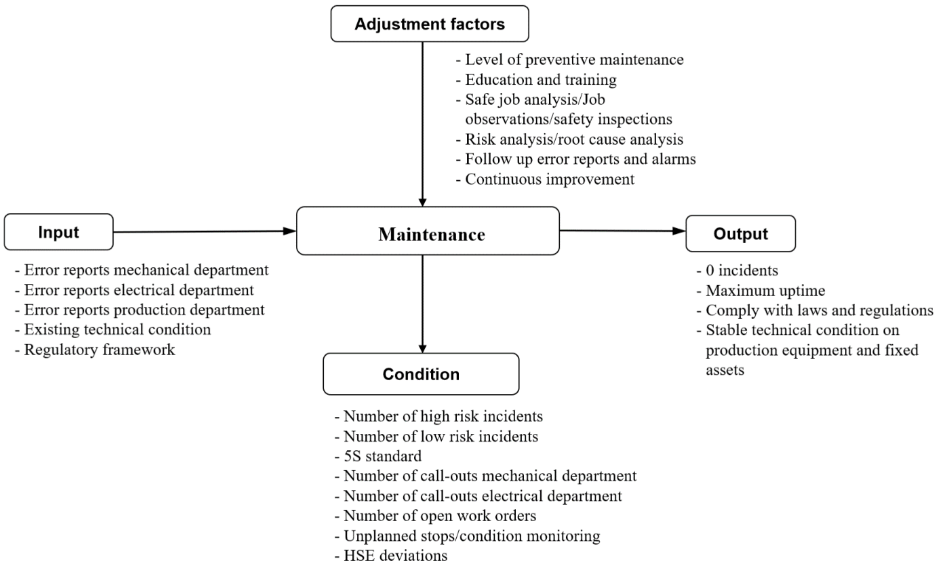


Figure 4.2: Focus diagram of maintenance with indicators.

4.1.2 Technology and maintenance improving value chain performance

The second research question targeted investigating how the development of technology, maintenance and maintenance management could improve industrialists’ value chain and performance:

RQ 2: *How can the development of technology, maintenance and maintenance management improve industrialists’ value chain and level of performance?*

To address this research question, investigation of existing literature, conceptual development, experiences from process industry and CPS-Plant, and a case study formed the foundation used to address RQ 2. Articles 1, 2, 3, 4, 5, and 7 present results related to RQ 2. Based on the discussions and results from this, main findings related to RQ 2 can be summarized as follows:

Main findings RQ 2: *The rapid development in technology has expanded the role of maintenance and maintenance management in industrialists' value chain. Industry 4.0 technologies such as IIoT, big data and analytics, and system integration provide numerous opportunities to improve existing maintenance practices and maintenance management. Predictive and contextual capabilities for monitoring, analyzing, and detecting trends and anomalies, and consequently predicting critical and unexpected events, can be used to develop more sophisticated maintenance strategies and improve value chain performance.*

From the literature point of view, the role of maintenance and maintenance management is starting to be positioned within Industry 4.0 technologies and succeeding in combining these fields is acknowledged to provide performance improvements in several areas, e.g., within sustainability [5, 6, 49, 160]. Another example is the study by [37], positioning Industry 4.0 technologies in the maintenance process, as presented in the standard EN 17007:2017 Maintenance process and associated indicators [59], and presenting how succeeding in maintenance is becoming a prerequisite for succeeding with Industry 4.0. From an industrial point of view, interest and willingness to adapt new technology and ways of working have been established for many, but the path from deciding on a digital initiative to seeing value added is still challenging for the majority.

Article 7 discusses how maintenance management and operations management must be integrated to balance decisions involving strategic investments, production plan, quality control and risk management, with the overall goal of improving value chain performance. Further, for decision-making, the article also shows how contextualized data is a prerequisite, as data from operations can improve PdM capabilities, but maintenance data can also support decisions across operations, e.g., by indicating utilization of machine capacity and whether the required function is available when desired. The findings in Article 7 regarding contextualization are in line with the three pillars of information governance for smart manufacturing presented in [129]. The article also shows the journey for a company deciding on investing in sensor technology and to seeing return on investment. As another contribution on utilizing new technology within maintenance, Article 1 presents a concept for sensor management, which can be positioned under the umbrella of IIoT, as shown in Figure 4.3.

Figure 4.3: Novel concept for sensor management within maintenance.

Article 1 discusses sensor management and its applicability to maintenance. It also provides the following definition of sensor management: *“Sensor management aims to optimize a configuration of sensors, with the goal of improving operational availability for a given system”*. The concept can be seen in light of the three elements “Maintenance execution”, “Technical condition”, and “Reporting” in the maintenance management model in NORSOK Z-008:2017 [57], and the element “Maintenance execution” presented in IEC 60300-3-14:2004 Dependability management part 3-14: Application guide - Maintenance and maintenance support [38]. How the concept can increase operational availability is also presented, where the technical condition of a given equipment/system is evaluated based on data collected by off-the-shelf wireless sensors. Use of cloud storage makes the technical condition, historical data, and trends (along with notifications) directly available on smartphones/tablets/web apps. Adjustable control limits with an alarm function, which notifies maintenance personnel immediately when deviations occur, result in reduced time for initiating maintenance execution. The effect of the performed action can then be evaluated directly, by comparing historical data with the continuous stream of new measurements from the sensors. Summarized, the concept focuses on simplicity and ease of implementation, and does not include advanced prediction analytics or decision support, but instead strives to maximize the value of the maintenance personnel's experience and knowledge.

Article 2 presents a concept linked to the element "Maintenance programme" in the maintenance management model in NORSOK Z-008:2017 [57]. It shows how traditional maintenance programs can benefit from including machine learning to create a balanced maintenance program. The concept provides decision support for how the maintenance program should be adjusted, based on the parameters "machine anomalies", i.e., anomaly detection, and "machine load". Combining these parameters will enable adaptability in the maintenance program, meaning a more flexible, dimensioned, and predictive maintenance is possible. Figure 4.4 shows the concept for a balanced maintenance program, as presented in Article 2.

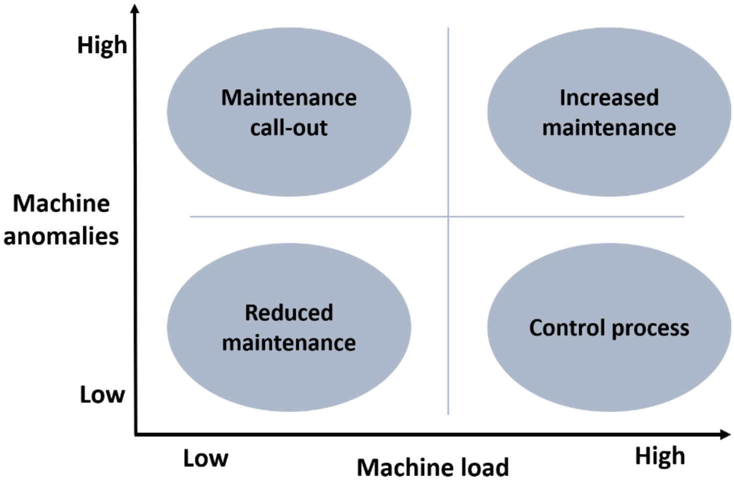


Figure 4.4: Concept for a balanced maintenance program.

The four different actions can be linked to Figure 4.1, and evaluation of different measures may be seen in the context of how they will internally and externally affect the value chain. For example, if the machine load is high and the suggested action is to control the process, an evaluation of dependability must be done, considering the high machine load against the risk of reduced process reliability, and a dependable delivery. This gives a more holistic view to how maintenance affects the value chain, and underpins the importance of integrated maintenance planning, as discussed in [95].

Moreover, Articles 3, 4, and 5 investigate new and existing indicators and their position in maintenance and the value chain, and how industrial development introduces a need for new KPIs, which confirms that indicators for measuring industrialists' performance are more important than ever. Article 3 provides an overview of indicators within maintenance management and performance management and presents a concept for the overall stop effectiveness (OSE) indicator, which measures the performance of planned maintenance stops. This can be seen as a contribution regarding continuous improvement in the value chain. Article 4 discusses the approach for developing KPIs within predictive maintenance related to the six maturity stages for the development towards Smart Maintenance, as shown in Figure 2.3, and is a contribution in terms of how industrialists can enable new areas of performance improvements with the use of new technology such as sensors, ERP and MES systems. Finally, Article 5 discusses how, for a company aiming to lead the way in its market, the maintenance function must be at a WCM level. The article also investigates how the onset of digitalization and the breakthrough technologies introduced with Industry 4.0 leads to expectations of more advanced analytics for WCM. As a contribution in this regard, PLI has shown promising results in measuring several parameters, such as time losses in production in monetary terms. Together with other maintenance indicators, PLI can provide an indication of the value chain performance, highlighting opportunities for improvement. As presented in Article 5, Figure 4.5 shows a proposed structure (DuPont) of PLI and how it can be related to the company level and its effect on the value chain, e.g., how lack of life extensions, i.e., suboptimal maintenance, in assets requires investments in new equipment, ultimately leading to loss in asset and reduced value chain performance.

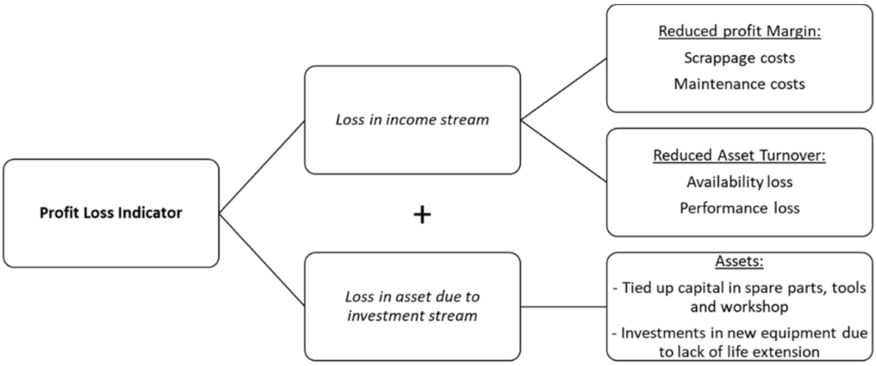


Figure 4.5: Proposed structure of PLI related to the value chain.

4.1.3 Integrated maintenance and value chain approach

The third research question aimed at exploring the implementation perspective of an integrated maintenance and value chain approach:

RQ 3: *How to implement an integrated maintenance and value chain approach in an industrial setting?*

Investigation of existing literature, conceptual development, experiences from process industry and CPS-Plant, and a case study formed the foundation used to address RQ 3. Articles 2, 5, 6, and 7 present results related to RQ 3. As a result of this, the main findings related to RQ 3 can be summarized as follows:

Main findings RQ 3: *An advantageous selection and implementation of maintenance types enables a robust maintenance function. Introducing Industry 4.0 technologies to the maintenance function allows for vertical and horizontal integration in the value chain. Combined, these actions support continuous improvement of the value chain's performance, new business opportunities, and an adaptable approach to the industrial setting in question.*

For industrialists to meet the potentials presented in this thesis, such as bridging the gap between a smart factory and a traditional production line, realizing the opportunities of Industry 4.0, and moving towards a more digitalized and integrated value chain, comprehensive changes and new implementation processes are required. This extensiveness is underpinned by the complex reference architectures created by several nations and unions to provide guidance and direction for their companies and researchers involved in the industrial evolution. The presented reference architectures from China, the United States, Japan, and Germany are aligned when it comes to the need for standards and ensuring common ground for practitioners and academics, defining this as a key element going forward. This is also underpinned by the several collaboration initiatives between the nations and the creation of other organizations such as the Industry IoT Consortium and the Open Connectivity Foundation. However, as concluded in [144], standards are a fundamental component of the evolution to smart manufacturing, but existing manufacturing standards are insufficient to fully enable and implement smart manufacturing. Thus, there is a need to further develop standards following the technological development. The reference architectures mentioned are also investigated in the literature, and there seems to be an agreement that reference architectures can become the backbone for the full realization of Industry 4.0 if their maturity and sustainability are increased, but currently they are not completely suitable to support implementation of Industry 4.0 technologies, mainly due to their high level of abstraction and/or lack of detailed documentation [121, 150]. Hence, they can provide a vision for practitioners and academics to gather on, but more specific entry-level solutions for building up digital capabilities are required for a successful implementation. As a contribution in this regard, Article 7 targets this gap for the field of maintenance and the value chain, exploring how a PdM platform can be implemented and improve value chain performance. Figure 4.6 shows the generalized approach for implementing a PdM platform, as presented in Article 7.

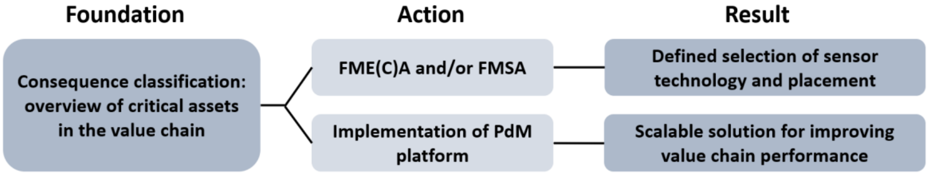


Figure 4.6: Generalized approach for implementing a PdM platform.

The first step is to ensure a foundation by performing consequence classification, according to the standard NORSOK Z-008:2017 Risk based maintenance and consequence classification [57], as an initial step for determining what assets are to be prioritized to the PdM platform and creating an overview of critical assets in the value chain. This step also supports understanding the process and agreeing on the required function for the critical assets. Next, determining the data collection and selection of sensor type and placement is based on a thorough analysis such as failure mode effects (and criticality) analysis (FME(C)A) and/or failure mode and symptoms analysis (FMSA), as presented in the standards ISO 17359:2018 [161], ISO 13379-1:2012 [73], and ISO 13381-1:2015 [162]. Additionally, the sensor management guidelines presented in Article 1 can be used to support this step. Further, the implementation of the PdM platform follows the structure presented in Chapter 2.1.2. Article 7 can also be seen as a contribution to bridging the gap between the generic overall PdM structures presented in [6, 68] and implementation of a PdM solution in an industrial setting. The importance and value of performing established maintenance methods, such as consequence classification and FME(C)A and FMSA, in the initial phase of digital initiatives is emphasized. Moreover, the PdM platform presents examples of technologies to be used and relevant integrations with other systems, providing a possible solution for implementing the two initial levels in the 5C architecture discussed in Chapter 2.3.1. Suggestions for standards and methods relevant to implementation and use of the PdM platform are given to aid users. Figure 4.7 shows the implemented PdM platform, as presented in Article 7.

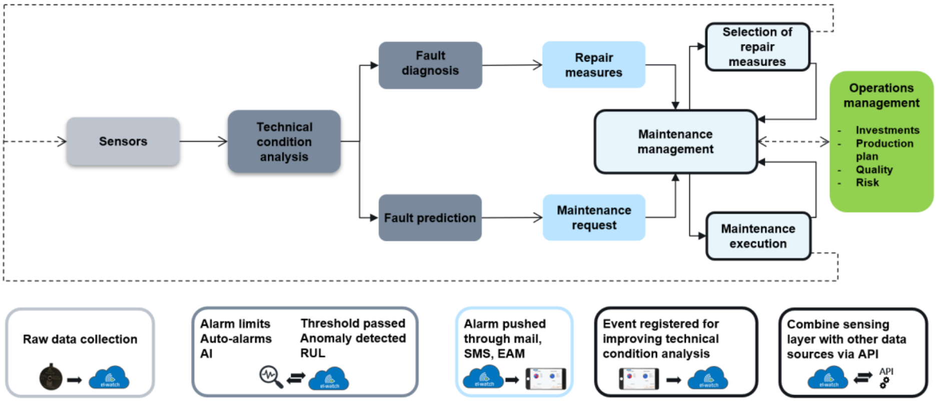


Figure 4.7: PdM platform.

The PdM platform is divided into five parts supporting the overall structure. After the raw data have been collected, the data arrive in the IIoT cloud and are processed, labeled, stored, and, if desirable, pushed to other clouds through an application programming interface (API). Here, technical condition analysis combines the sensor data with historical data and previous experience to set alarm limits qualitatively and manually. The sensor data and alarm limit thresholds are monitored by computer algorithms, which immediately act if limits are breached or anomalies are detected, and provide the maintenance request. For fault diagnosis, the FME(C)A and/or FMSA together with a root cause analysis can form a qualitative approach to pinpoint possible repair measures. Further, the triggered alarms, maintenance request and repair measures are presented to the user. Depending on the degree of importance, this may be in the form of an alarm pushed by email, text message, or dashboard with further integration, through API, to e.g., an EAM system. The next step concerns a cost-benefit selection of repair measures, planning and scheduling of maintenance execution. The PdM platform also underpins the need for maintenance management and operations management to be integrated, for balancing decisions involving strategic investments, production plan, quality control and risk management with the overall goal of improving value chain performance. This is in line with [77], where the importance of deep convergence and comprehensive connections is underpinned for a smart factory production system. Further, data can be integrated through an API between e.g., the EAM system and MES, supporting horizontal integration of value chain data, which can be seen as an exemplification of the Mfg Pyramid in the NIST Smart Manufacturing Ecosystem presented in Chapter 2.3.2. Finally, and as a link to continuous improvement and PDCA, executed maintenance actions are registered and serve as input for improving technical condition analysis and raw data collection, increasing understanding of the asset behavior and its implications for value chain performance. This also supports the feedback loop from maintenance execution to maintenance improvements emphasized for maintenance management in Figure 2.4 and Figure 2.5.

A key element in any implementation process is to ensure that the workforce affected by the imminent changes is motivated, supported, and provided with the necessary training and tools to meet the new workday. In this regard, Article 6 provides a contribution on how this will affect and set new requirements for maintenance personnel and operators, collectively named Operator 4.0, in a cyber-physical production plant, ultimately supporting implementation of Industry 4.0 technologies. This can be seen in the context of [5], where the importance of considering how actions of human actors are taken into account in a PdM system is highlighted. For the operators in Article 7, the sensor data provided a better understanding of the technical condition, and how maintenance actions and changes in machine load could affect this. Moving from decisions based on guesswork to real-time data enabled the operators to perform their job more efficiently. The degree of ownership also increased, as their actions could be seen as changes in the data and connected to the mentioned improvements. For the maintenance management team, the successful application of the PdM platform provided motivation for scaling the solution and including other production equipment. It is also interesting to see the clear expectations regarding how the transition to a more digitalized and integrated value chain calls for close cooperation among different service providers within the field of maintenance, as presented in [5, 13]. A prerequisite for the success of these interactions is that machine manufacturers, operators, and industry service providers have implemented a high degree of digital capabilities to seamlessly utilize each other's expertise and strengths.

Most of the studies presented in this thesis regarding the implementation perspective are of a conceptual nature. In addition, the technological readiness level among most practitioners often lags behind the rapid development for Industry 4.0 technologies. Hence, to provide relevance for practitioners, the need for more empirically based studies in an industrial setting is emphasized. With this in mind, the concept for a balanced maintenance program and connections between maintenance and the value chain presented in Article 2 can be used as motivation for further investigation of the implementation perspective. As an element to measure the success of an implementation, relevant indicators should be investigated and applied. Article 5 contributes to this by presenting trends within WCM, indicators, and how this also applies to the value chain.

4.2 Implications for practitioners

In addition to the theoretical contributions to science, the findings presented in this PhD thesis should also provide practical relevance for practitioners interested in applying new technology to improve their value chain and how their maintenance function can support this.

The transition to a more digitalized and integrated value chain as well as trends related to Industry 4.0 are being closely followed by managers and industry leaders around the world. The largest manufacturing nations also have extensive projects to take advantage of the opportunities introduced with new technology, and research on how this can strengthen their companies' position in the global market is a key goal for national industrial strategies. However, achieving the promised benefits of digitalization and the vision of Industry 4.0 is not a straightforward task. This PhD thesis presents new knowledge and concepts relevant to practitioners starting the journey on digitalizing their value chain, with a focus on how this relates to the maintenance function.

The findings in this PhD thesis highlight the connections between maintenance and the value chain, and how advancements in technology have increased the importance of acknowledging this in a contextual manner. The insights on how maintenance has evolved and can aid the connection between the physical and digital world and integrate machines, systems, and humans in a value chain should be used by practitioners developing roadmaps for outlining the direction to successfully meet their long-term strategic goals. Article 1 and Article 2 present different examples of how maintenance and Industry 4.0 technologies can be integrated. These articles also provide valuable insights into how Industry 4.0 technologies enable opportunities for improving existing maintenance practices and expanding the role of maintenance management. The opportunities for monitoring, analyzing, and detecting trends and anomalies, as well as predicting critical and unexpected events, can support practitioners in developing more sophisticated maintenance strategies and improving value chain performance. However, it might be tempting for many to focus only on implementing new technology at the expense of attention to more basic maintenance, but Article 7 indicates that fundamental maintenance methods such as consequence classification and FME(C)A and FMSA can be used to advantage as a basis for implementing new technology and ways of working.

The need for thoroughly understanding the process in question, what the required function is, and the importance and value of building a foundation with basic maintenance practices, supplementing digitalization efforts, is a take-home message for practitioners.

In the shift towards a more digital value chain and introducing new ways of working, a prerequisite for staying competitive and succeeding with continuous improvement is to enable new digital competence in the workforce and ensure the necessary digital tools are well-implemented. Hence, maintenance personnel must be thoroughly prepared for the tasks involved in ensuring the functionality and integrity of Industry 4.0 systems. These tasks should form part of the training requirements for maintenance personnel, and it will be essential to create appropriate training modules to take full advantage of the potential with Industry 4.0 technologies. These challenges are discussed in Article 6, and managers can use the discussion on Operator 4.0, which includes the role of operators, maintenance personnel and other relevant job categories in an Industry 4.0 environment, and the framework for qualification criteria for Operator 4.0 and its relevant technologies for competency mapping and guidance for how this can be further improved in the organization.

The traditional view on the maintenance function in a value chain must develop in line with the introduction of Industry 4.0 technologies. Increased collaboration and interactions within the field of maintenance require that machine manufacturers, operators, and industry service providers possess digital capabilities for smooth communication and seek to comply with standards to ensure common ground. Practitioners should also contribute to the development of standards and define cooperation platforms emphasizing sharing data and knowledge. Article 4 shows the structure for the maintenance function and can be used for mapping standards and specifications relevant to a company. Combined, this will support utilizing expertise and strengths between the different actors involved in the maintenance function, supporting companies to achieve more sustainable processes and products, and to reduce waste.

In the years to come, increased availability of technology, such as sensors, will enable practitioners to measure what previously has been unmeasurable. This requires the development of indicators that respond to the new data and opportunities for improvement. Articles 3, 4, and 5 investigate new and existing indicators and their position in maintenance and the value chain, and how the industrial development introduces a need for new indicators. Practitioners should ensure that digitalization initiatives are not implemented at the expense of focus on established indicators and continuous improvement, but instead are used to measure the success of digital initiatives, discovering new areas of measurements, ultimately combined to improve value chain performance.

5. Conclusion

This chapter marks the end of this PhD thesis by first presenting a short summary of the results together with some concluding remarks. Next, the thesis is concluded with proposals for further research.

5.1 Concluding remarks

In this thesis, the field of maintenance, value chain, and industrial digitalization have been investigated. Previous research has mainly studied these areas individually. This thesis has provided a thorough presentation of the development in each area and how they can be combined to improve value chain performance. This has been done through different research approaches, such as literature review, conceptual development, case study, and participation in the Norwegian research project CPS-Plant.

The objectives of this PhD research are to provide a better understanding and knowledge of the connection between maintenance and the value chain, how can the development of technology, maintenance and maintenance management improve the value chain, and how to implement an integrated maintenance and value chain approach. The research problem is: *How to integrate the fields of maintenance and value chain, in order to increase industrialists' level of performance?* The research goals have been to contribute to filling a competence gap between the fields of maintenance and the value chain, and develop frameworks, tools, and methodology which builds on the new competence. Based on this, three research questions were defined and answered through seven articles, briefly outlined as follows:

RQ 1: *What is the connection between maintenance and the value chain?*

Concluding remarks:

- Article 2: Proposed internal and external value chain effects of six maintenance program objectives.
- Article 4: Evaluation of maintenance and value chain management in a new perspective.

- Article 5: New knowledge on the role of maintenance management in the value chain.

RQ 2: *How can the development of technology, maintenance and maintenance management improve industrialists' value chain and level of performance?*

Concluding remarks:

- Article 1: Proposed concept for sensor management, including its linkage to maintenance and improvement of operational availability.
- Article 2: Proposed concept for a balanced maintenance program with a value chain perspective.
- Article 3: Proposed concept for an indicator measuring the level of performance of planned maintenance stops, including new knowledge on how industrial development requires new indicators within maintenance management and performance management.
- Article 4: An overview on the development of the maintenance function and standards within maintenance. New knowledge on how maintenance indicators can be used to enhance value chain performance.
- Article 5: A discussion on how the maintenance function for top performing companies requires possessing a WCM level.
- Article 7: Proposed concept for a PdM platform and how it can improve value chain performance.

RQ 3: *How to implement an integrated maintenance and value chain approach in an industrial setting?*

Concluding remarks:

- Article 2: The concept for a balanced maintenance program and connections between maintenance and the value chain can be used as a framework for further investigating into the implementation perspective.
- Article 5: Overview of trends within manufacturing and WCM, and how indicators can be used to measure the success of an implementation in the value chain.

- Article 6: A framework for qualification criteria for Operator 4.0 and identification of relevant Industry 4.0 technologies, including new requirements for maintenance personnel and operators to support implementation of Industry 4.0, and how this relates to the value chain perspective.
- Article 7: A proposed generalized approach for implementing a PdM platform.

In addition to articles and theoretical contributions to science, the findings presented in this PhD thesis should also provide relevance for practitioners. This thesis provides new knowledge and concepts relevant to practitioners starting the journey towards digitalizing their value chain, with a focus on how this relates to the maintenance function. Findings suggest that digitalization initiatives should be supported by complementary maintenance practices to improve value chain performance. New technology should not be implemented at the expense of a thorough understanding of the process in question, and what the required function is. The main contributions of this thesis can be summarized as follows:

- New knowledge and concepts within digitalizing the value chain, with a focus on how this relates to the maintenance function.
- Provided increased understanding of the connections between maintenance and the value chain, and how advancements in technology have increased the importance of acknowledging this in a contextual manner.
- Presentation of valuable insights into how Industry 4.0 technologies enable opportunities for improving existing maintenance practices and expanding the role of maintenance management into the value chain.
- New knowledge on how fundamental maintenance methods can be used as a basis for implementing new technology and ways of working.
- Presentation of new and existing indicators and their position in maintenance and the value chain, and how the industrial development introduces a need for new indicators.
- A framework for qualification criteria for Operator 4.0 and identification of relevant Industry 4.0 technologies, and discussion on the role of operators,

maintenance personnel and other relevant job categories in an Industry 4.0 environment, and how this relates to the value chain perspective.

5.2 Further research

Based on the theory, articles, and contributions to science presented in this thesis, several remarks regarding further research are proposed:

- Article 1: Further development of the sensor management concept and discovery of ways in which it can adopt other technologies for condition assessment and diagnostics and prognostics.
- Article 2: Development of the balanced maintenance program concept, and further research on how a value chain perspective can support and improve the maintenance function in a company.
- Article 3: Defining the main and sub-elements of the proposed indicator and investigating how it can be tested and evaluated.
- Article 4: Further research to develop maintenance indicators utilizing product-usage data in the value chain, and how to perform implementation, testing, and evaluation.
- Article 5: Testing new approaches for calculating PLI in case studies as well as relating it to other maintenance indicators that affect the value chain.
- Article 6: Further work on the proposed framework of Operator 4.0 and elaboration of relevant Industry 4.0 technologies.
- Article 7: Further development of the PdM platform and how other Industry 4.0 technologies can be added. More detailed investigation of how the PdM platform can integrate maintenance management and operations management for enabling contextualized data-driven decision-making throughout the value chain.

Moreover, all the seven articles highlight the need for conducting case studies in different industries and companies for further testing and evaluation. Generally, involving industry to a greater extent is seen as a prerequisite for bridging the gap between contributions to science and implications for practitioners, and should be prioritized in further research.

Further research should continue to investigate how new technology affects the value chain and how the field of maintenance can utilize the possibilities introduced by emerging digital technologies for improving value chain performance. The rapid development and availability of technology, and the possible change in the perception of industrial digitalization, underpin the value of follow-up studies to investigate the holistic understanding of maintenance and the value chain. Further research should also investigate the three following proposed directions regarding the implementation perspective, first, by continuing studies regarding Operator 4.0 and how the role of operators and maintenance personnel will be impacted by increased use of Industry 4.0 technologies. Second, the reference architectures presented in this thesis should provide guidance for practitioners and academics, but research is needed to determine how these can be implemented in practice and provide value. Hence, more studies of entry-level solutions and standards reflecting the development can aid their maturity and technological readiness level. Third, more research should be conducted on value chain integrations and technology enabling new opportunities for companies’ maintenance function and how the field of maintenance can best be applied to contribute to sustainability. As research in this realm advances, an imperative step should be to establish an implementation framework for how the industry can better handle emissions, enable more sustainable manufacturing, improve products and services to be in line with a circular economy, and reduce waste by enhanced engineering and utilization of new technology, ultimately supporting the Sustainable Development Goals.

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Part II – Articles

Article 1

Initiating Industrie 4.0 by implementing sensor management – improving operational availability

Article 2

Balanced maintenance program with a value chain perspective

Article 3

Indicator for measuring performance of planned maintenance stops – an enabler for continuous improvement

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Article 4

Enhancing value chain performance with maintenance indicators – an overview of advancements

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Enhancing value chain performance with maintenance indicators – an overview of advancements

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Abstract - With the imminence fourth industrial revolution and the nonstop increase in global competition, industrialists faces new challenges such as how to stay sustainable for future years, continuously improve value chain performance (VCP), and keep up with the technological development. This development applies equally to the field of maintenance, which also is developing rapidly. The maintenance function has traditionally been regarded as a costly necessary evil. Currently, with the possibilities predictive maintenance and smart maintenance introduces, maintenance is now regarded by many as an opportunity for gaining a competitive advantage. The concept of value chain management (VCM) is becoming prevalent among industrialists. However, the development of literature within the field is lacking, especially on how maintenance can be included into VCM and utilized to enhance VCP. Thus, the aim of this paper is to evaluate maintenance and VCM in a new perspective, focusing on how maintenance indicators can be used to enhance VCP. The paper will also present an overview on the development of standards within maintenance and development of, and need for, new maintenance indicators.

Keywords – Value chain performance, value chain management, maintenance management, performance management, maintenance indicators

1. INTRODUCTION

The fourth industrial revolution has introduced enabling technologies such as wireless sensor networks, Big Data, Digital Twin, Internet of Things, and cloud computing into the manufacturing environment. This revolution was originally called “Industrie 4.0”, and was a part of the “High-Tech Strategy 2020 Action Plan” of the German government. Industrie 4.0 presented a Cyber-Physical System (CPS) which integrated production facilities, warehousing systems, logistics and, and social requirements to establish global value creation networks. Following, similar strategies were soon presented by USA with “Industrial Internet”, and China with “Internet +” (Wang, Wan et al., 2016).

Industrie 4.0, by many called Industry 4.0, is recognized as a “make it or break it” situation for industrialists, and succeeding with implementing Industrie 4.0 is acknowledged as a significant competitive advantage (Brenna Snidermann, 2016, René Waslo, 2017). In order to successfully implement Industrie 4.0, the German report “Recommendations for implementing the strategic initiative Industrie 4.0” lists the following three key features as essential (Kagermann, Helbig et al., 2013):

- *Development of inter-company value chains and networks through horizontal integration*
- *Development, implementation and vertical integration of flexible and reconfigurable manufacturing systems within businesses*
- *Digital end-to-end engineering across the entire value chain of both the product and the associated manufacturing system*

The three key features focuses on how new technology can be utilized to improve the value chain, and presents two accompanying potential benefits. First, one potential benefit will be higher sales thanks to a larger market and higher customer satisfaction. Second, reduction of internal operating costs through digital end-to-end integration of the value chain is also an expected benefit (Kagermann, Helbig et al., 2013). A definition of value chain is presented by (Walters and Lancaster, 2000): “*The value chain is a tool to disaggregate a business into strategically relevant activities. This enables identification of the source of competitive advantage by performing these activities more cheaply or better than its competitors. Its value chain is part of a larger stream of activities carried out by other members of the channel-suppliers, distributors and customers*”.

Further on, value chain management (VCM) targets the improvement of overall performance of the entire value chain through an analysis of each link and process in a systematic manner to see how speed, certainty and cost-effectiveness can be enhanced (McGuffog, 1997). The following definition of VCM is provided by (Walters and Lancaster, 2000): “*Value chain management is a coordinating management process in which all of the activities (and their suppliers) involved in delivering customer value satisfaction are integrated such that customer satisfaction is maximised and the objectives of the stakeholders involved (the suppliers of activities, processes, facilitating services, etc.) are optimised such that no preferable solution may be found.*”

Another area expected to provide a significant potential benefit and to improve industrialists level of performance is the field of maintenance. Along with predictive maintenance and smart maintenance, the maintenance function has evolved from the perception of being a hindrance for throughput and scheduling, to an opportunity for gaining a competitive edge by predicting and being one-step ahead of failures (Fordal, Rødseth et al., 2019). The maintenance cost can represent 10% to 25% of the costs of goods produced in some industries, and underpins the potential. For future years, with more automation and new technologies, maintenance will increasingly be more important for improving availability, product quality, fulfillment of safety requirements, and plant cost-effectiveness (Han and Yang, 2006). Maintenance is defined in the standard EN 13306:2017 Therminology as (Standard, 2017): “*combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function.*”

The potential benefits within maintenance are strengthened by the introduction of smart, connected products, which have the built-in capability of transferring product-usage data back to the manufacturer. According to (Porter and Heppelmann, 2015), this new capability and having accessibility to data will reshape and alter every activity in the value chain. Further on, performing analytics on this data can contribute in identifying patterns and areas of improvement, which can help organizations to sense and react to supply risk, predict delivery, asset utilization, improve maintenance and products, productivity, and sales forecast (Arunachalam, Kumar et al., 2018). Fig. 1 shows how the new digital value chain regard maintenance as value-added, and focuses on utilizing data and connectivity for improving automation, predictive maintenance and services.

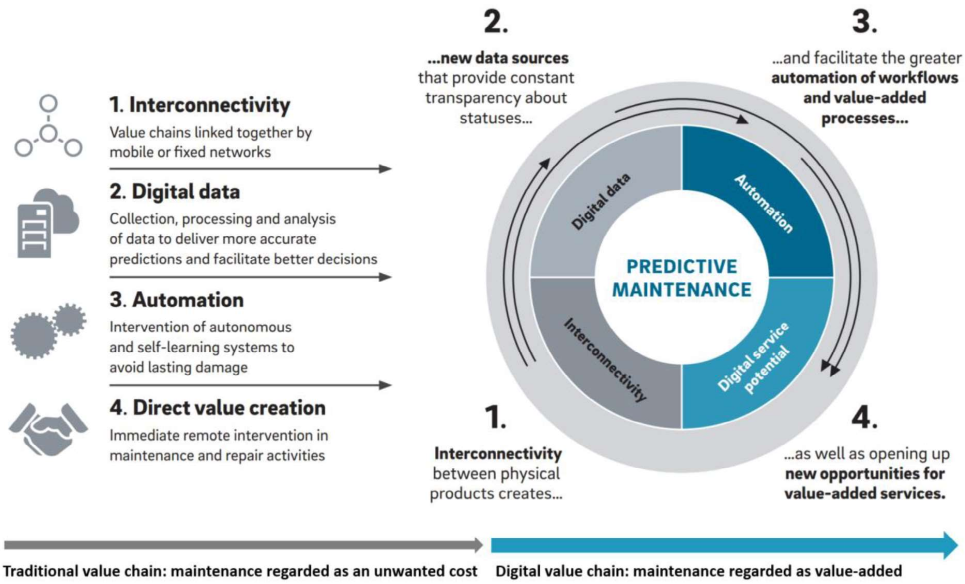

Fig. 1 Predictive maintenance in the digital value chain, adopted from (Berger, 2017)

It emerges clearly, that the development within maintenance and value chain competence can provide great benefits if implemented and utilized correctly, and not only for improving industrialists performance, but also in terms of circular economy towards more sustainable economic growth by the 3R principles of reduce, reuse, and recycle (Ranta, Aarikka-Stenroos et al., 2018). However, the development of literature within VCM is claimed by (Al-Mudimigh, Zairi et al., 2004) to be lacking, and the maintenance function is not included in value chain frameworks proposed by (Porter, 1985, Walters and Lancaster, 2000, Bowman and Ambrosini, 2010). On the other hand, findings by (Sutarmin and Jatmiko, 2016), shows that the original generic value chain framework presented by (Porter, 1985) differs from the value chain framework of their case company, which includes maintenance. Thus, there is a need to further evaluate maintenance and VCM in a new perspective, which is the aim of this paper - along with discussing how maintenance indicators can be used to enhance VCP. The paper will also present an overview on the development of standards within maintenance and development of, and need for, new maintenance indicators.

The structure of this article is as follows: Section 2 presents an overview within VCP and maintenance indicators. Section 3 discusses the advancements within standards and the maintenance function, and, lastly, Section 4 gives concluding remarks.

2. VALUE CHAIN PERFORMANCE AND MAINTENANCE INDICATORS

2.1 Value chain performance

There seem to be lack of a clear definition of the term value chain performance in the literature. However, the term value is defined in the standard EN 1325:2014 Value Management as follows (Standard, 2014): *“measure which expresses how well an organization, project, or product satisfies stakeholders´ needs in relation to the resources consumed.”* Further on, a definition of performance management is provided by (Aguinis, 2013): *“Performance management is a continuous process of identifying, measuring, and developing the performance of individuals and teams and aligning performance with strategic goals of the organization.”* Within the definition of performance management, performance measurement is also covered, which is about measuring the performance itself. In order to quickly assess measurements, indicators are used. Moreover, a number of standardized indicators acknowledged as Key Performance Indicators (KPIs) are used by organizations to provide benchmarking, evaluate current performance, and visualize the road to improved performance. KPIs are defined as (Kerzner, 2011): *"A metric measuring how well the organization or an individual performs an operational, tactical or strategic activity that is critical for the current and future success of the organization."* Hence, organizations should select and link KPIs to their defined main objectives, in order to work towards the overall strategy and vision. Based on the above-mentioned, the authors propose the following meaning of value chain performance: Value chain performance is a measure of competitiveness on utilization of available resources and stakeholders' satisfaction.

With this meaning of value chain performance and the development within maintenance and the industry, it emerges clearly, that product-usage data will be an important resource to utilize for maximizing value chain performance. The feedback of data will especially be of value for the maintenance function, where predictive maintenance and smart maintenance have proven to give competitive advantages (DIN and DKE, 2018). In order to support that utilization of maintenance data receive focus in the value chain, maintenance indicators targeting this matter should be developed and implemented. This suggestion is underpinned by the concept of "what you measure is what you get" - meaning the selection of indicators and measurement system strongly affects the organizations strategical choices and employee behavior (Kaplan and Norton, 1992).

2.2 Maintenance indicators – a need for development

Fig. 2 illustrates the maturity development model towards smart maintenance (Rødseth, Schjølberg et al., 2017, Schuh, Anderi et al., 2017). To develop KPIs for predictive maintenance, several stages in this approach must be performed.

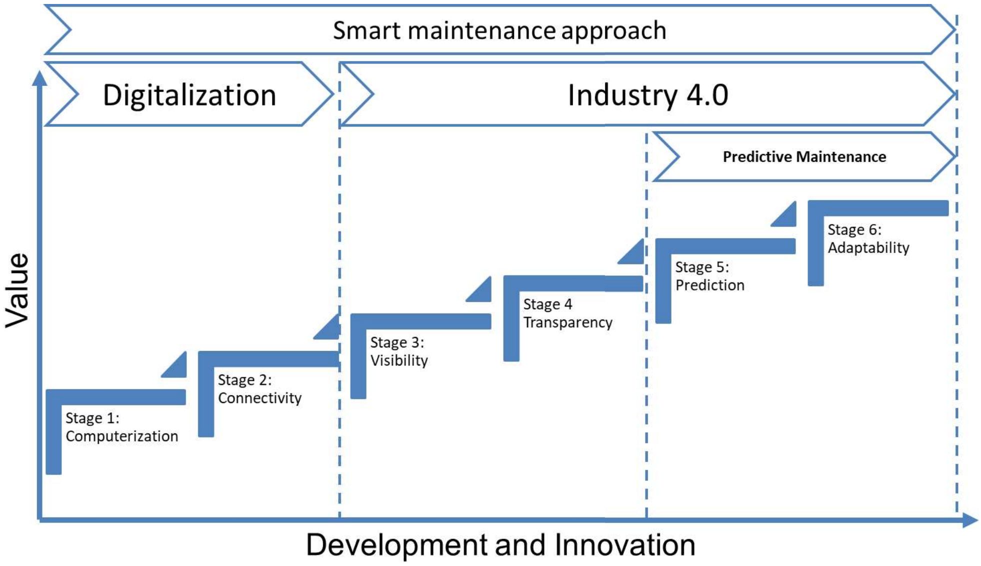

Fig. 2 Maturity model towards smart maintenance (Rødseth, Schjølberg et al., 2017, Schuh, Anderi et al., 2017)

The starting point towards smart maintenance is digitalization in terms of computerization and connectivity in **stage 1** and **stage 2**. First, computerization will require sensors connected to the PLC-systems that can further perform the necessary computation in e.g. data-ware house. In this stage, a “standard” KPI is possible to be calculated. An example of such a KPI could be preventive maintenance costs/total maintenance costs. Second, the next stage in digitalization is to ensure connectivity to enable remote access in terms of e.g. remote maintenance.

When the digitalization phase has been completed the Industry 4.0 phase can start. The visibility capability for the company is developed at **stage 3** and will result in an up-to-date digital model of the plant. This model is referred to as the digital shadow of the company. A main function for the digital shadow is to allow all data to be integrated. Instead of only collecting data for specific analysis, it is more interesting to integrate all relevant data with different sources of sensors and data sources such as ERP and MES systems. Regarding the KPIs, it is in this stage possible to rapidly present real-time KPIs and dashboards for example to adjust the production planning when future possible problems occurs.

At **stage 4**, the company understands the reasons why something is happening, and use company insight to create knowledge with root cause analysis (RCA). This knowledge can be used in carrying out condition monitoring of machinery, and will also be an important requirement for predictive maintenance. In this step, the indicator referred to as profit loss indicator (PLI) is introduced, which has proven its importance in understanding the tradeoff between speed losses and material utilization in a saw mill (Rødseth, Skarlo et al., 2015). PLI has also a foundation from the maintenance philosophy total productive maintenance (TPM), where the aim of TPM is to (Japan Institute of Plant, 2017): *“…forming a corporate culture which can pursue the maximum possible efficiency of the overall production system”*. To ensure this pursue for maximum possible efficiency, the elimination of the 16 big losses in the company is pivotal. The calculation of PLI is therefore related to all of the 16 big losses.

At **Stage 5** and **Stage 6,** the predictive maintenance capability will be developed including two important functions:

- Prediction of future degradation and future failures. For KPIs, this can be an early warning indicator (EWI) (Rødseth and Andersen, 2013).
- Adaptability, where the company can receive a “digital advice” of changing the future operation. For these advices, the KPIs must be presented with different uncertainty measures.

3. OVERVIEW OF ADVANCEMENTS

As mentioned in the introduction, the maintenance function will play an even more important role in the value chain for future years. The maintenance function is a combination of several disciplines and resources, such as knowledge, methodologies, technologies, processes and competences to create and develop an appropriate mix of actions to maintain the required level of functionalities of physical assets and achieve the assigned company objectives. Moreover, the maintenance function is operating in various industrial plants, facilities, infrastructures, different frameworks and contexts with different size, structure, objectives, specific constraints and influencing factors. Fig. 3 illustrates the Maintenance Function and the core framework as defined by CEN TC 319 Maintenance.

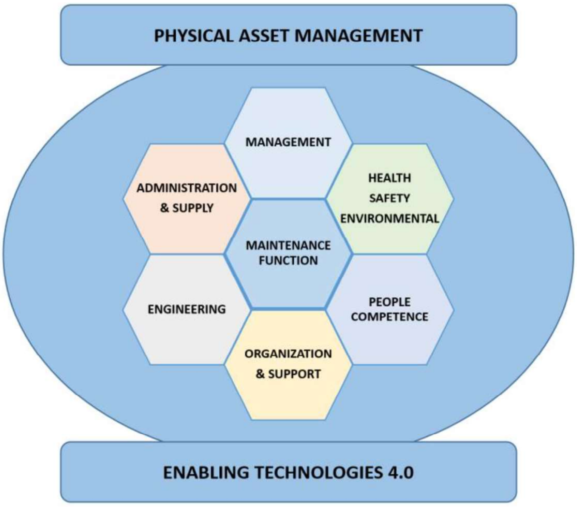

Fig. 3 The structure of the Maintenance function and core framework, CEN TC 319

The importance of standards within maintenance is underpinned in (DIN and DKE, 2018), where they claim that standards and specifications are essential tools in the transition process maintenance is facing. Thus, the maintenance function must ensure that its own strategy, organization and management adapt to this transition. Standards and specifications can support this matter, as they contribute in regulating the cooperation between the various actors involved in maintenance, and provide a common understanding of terminology and the maintenance process. Fig. 4 presents an overview of advancements within maintenance standards in CEN TC 319 Maintenance.

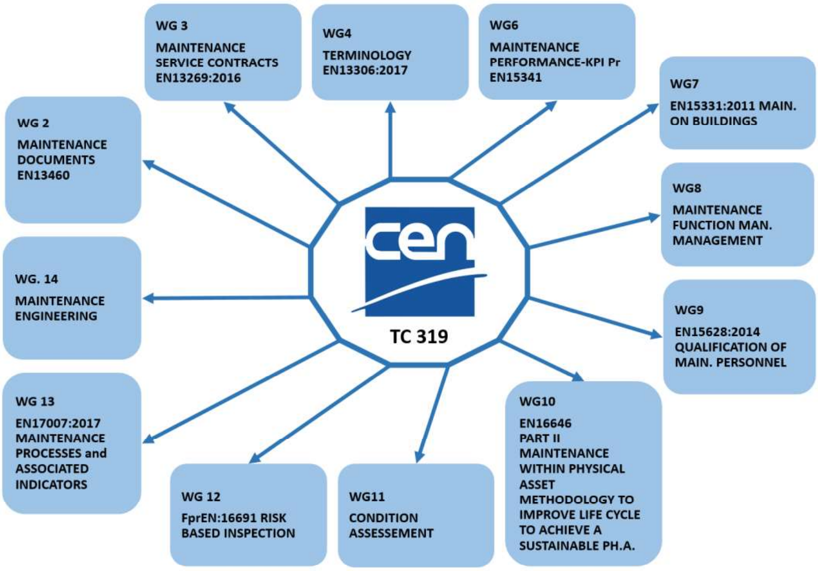

Fig. 4 CEN TC 319 Maintenance activities working groups

5. CONCLUDING REMARKS

This article has provided an evaluation of maintenance and VCM in a new perspective. Traditionally, maintenance has been regarded as an unwanted cost and is not included in several value chain frameworks. Currently, smart maintenance and predictive maintenance can be seen as enablers for Industrie 4.0 and has proven to provide competitive advantages, as these maintenance methodologies are responsible for ensuring that CPS are kept efficient and that equipment provides the required function at any time. Further, both smart maintenance and predictive maintenance are dependent on big amounts of data to perform meaningful analytics. Thus, in terms of enhancing value chain performance, the article fills what seem to be a gap in the literature, by focusing and highlighting the need for developing and implementing maintenance indicators for measuring the utilization of product-usage data in the value chain.

An overview of advancements within maintenance standards is given. Standards and specifications are essential tools in the transition process maintenance is facing, as they contribute in regulating the cooperation between various actors involved in maintenance, and provides a common understanding of terminology and the maintenance process. Development of the maintenance function is also described.

Summarized, further research is needed to develop maintenance indicators, which can measure the utilization of product-usage data in the value chain. Research on how these indicators can be implemented, tested and evaluated is also proposed. Case studies on the importance of maintenance and maintenance indicators in modern value chains are also suggested for further work.

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Authors' Biography

Passport size photo 	**Jon Martin Fordal** PhD Candidate Jon Martin Fordal is currently working on a PhD with the title “Digitalization of the value chain – improving value chain performance with prediction.” Examples of research areas include maintenance management, digitalization, sensor management, predictive maintenance, performance management. Prior to the PhD, he worked as a maintenance engineer in Elkem ASA. His main supervisor is Dr. Per Schjølberg.
	**Harald Rødseth** Postdoctoral Fellow Harald Rødseth is currently working at Department of Mechanical and Industrial Engineering at Norwegian University of Science and Technology (NTNU). In particular, he is an active research member in the project CPS Plant that includes the academic partners NTNU and SINTEF, as well as the industrial partners Hydro Aluminum, Hycast and Benteler. Furthermore, he is specializing his research within the topics Smart maintenance and Predictive maintenance. His education as a PhD is within maintenance management and reliability engineering with focus on indicators and integrated planning.

	**Per Schjølberg** Dr. Per Schjølberg is an Associate Professor and the former Head of the Production and Quality Engineering Department at the Norwegian University of Science and Technology, NTNU, Trondheim. He sits in the board of several organizations.
	**Franco Santini** Franco Santini has been a maintenance/asset manager in several Italian manufacturing companies. He has also been a consultant for leading companies. Main topics are maintenance management, maintenance function, maintenance indicators, future maintenance, and facility management. Furthermore, he has been president in the European Federation of National Maintenance Societies (EFNMS) for three years. Currently, he is a chairman for CEN TC319 Maintenance, and he is a convenor for the following committees: CEN TC319 Maintenance Indicators, and TC319 Maintenance function. Today, he is a treasurer in EFNMS. He is often used as a lecturer within maintenance, both in Italy and globally.

Article 5

The journey towards world class maintenance with profit loss indicator

Article 6

Operator 4.0 – emerging job categories in manufacturing

Article 7

Application of sensor data based predictive maintenance and artificial neural networks to enable Industry 4.0

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Application of sensor data based predictive maintenance and artificial neural networks to enable Industry 4.0

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Abstract Possessing an efficient production line relies heavily on the availability of the production equipment. Thus, to ensure that the required function for critical equipment is in compliance, and unplanned downtime is minimized, succeeding with the field of maintenance is essential for industrialists. With the emergence of advanced manufacturing processes, incorporating predictive maintenance capabilities is seen as a necessity. Another field of interest is how modern value chains can support the maintenance function in a company. Accessibility to data from processes, equipment and products have increased significantly with the introduction of sensors and Industry 4.0 technologies. However, how to gather and utilize these data for enabling improved decision making within maintenance and value chain is still a challenge. Thus, the aim of this paper is to investigate on how maintenance and value chain data can collectively be used to improve value chain performance through prediction. The research approach includes both theoretical testing and industrial testing. The paper presents a novel concept for a predictive maintenance platform, and an artificial neural network (ANN) model with sensor data input. Further, a case of a company that has chosen to apply the platform, with the implications and determinants of this decision, is also provided. Results show that the platform can be used as an entry-level solution to enable Industry 4.0 and sensor data based predictive maintenance.

Keywords Predictive maintenance (PdM) platform · Industry 4.0 · Value chain performance · Anomaly detection · Artificial neural networks (ANN)

1 Introduction

Industry 4.0, predictive maintenance (PdM), and advanced manufacturing are examples on terms which have been prominent on industrialist's agenda for the last years. Additionally, national and union initiatives, e.g., the European Union 7.5 billion EUR "Digital Europe Programme" [1], targeting the mentioned terms is witnessed worldwide, underpinning the importance of succeeding with the digital transformation. Industry 4.0, or Industrie 4.0, was first introduced at the Hannover Messe in 2011, a German industrial fair, as an illustration for the new trend towards the networking of traditional industries [2], and is now seen as the fourth industrial revolution. Further, Industry 4.0 was included in the German "High-Tech Strategy 2020 Action Plan". China initiated "Made in China 2025", also called "China Manufacturing 2025", which focused on accelerating development of intelligent manufacturing equipment and products, and advanced manufacturing process intelligence [2, 3]. Moreover, USA has "Advanced Manufacturing" as their strategic plan, aiming to develop and transit new manufacturing technologies, educate, train, and connect the manufacturing workforce, and, lastly, expand the capabilities of the domestic manufacturing supply chain [4].

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To successfully implement Industry 4.0, three key features are seen as essential. These are prerequisites expected to be the reality in future production networks and are defined as three types of value chain integration. Combined, they focus on how new technology can be utilized to improve the overall value chain, with expected benefits being higher sales thanks to a larger market, increased customization, improved resource efficiency and productivity, and reduction of internal operating costs. The three types of integration are as follows [5–7].

(i) Horizontal integration as a basis for developing intercompany value chains and networks;
(ii) Vertical integration of hierarchical subsystems to create flexible and reconfigurable manufacturing systems;
(iii) Digital end-to-end engineering across the entire value chain of both the product and the associated manufacturing system.

The accessibility to data has increased significantly with the introduction of Industry 4.0 technologies, e.g., Internet of Things and Big Data, and the importance of competence on utilizing this data for gaining competitive advantages is underpinned by practitioners and theorists [8]. Examples of data-demanding technologies are cloud computing, artificial intelligence (AI) and PdM. Together with new smart technology, cloud computing is contributing to radically changing the manufacturing industry and reshaping enterprises worldwide. Cloud computing aims to offer on-demand computing services and, for industrialists, access to business-critical data and analytics will be essential for moving the focus from hindsight to foresight. Further on, cloud computing can form intelligent factory networks who support and enhance the level of collaboration throughout the value chain [9]. AI is a technology under rapid development, and with a wide application area. For example, AI is seen as central for data-driven methods within Industry 4.0, and in the field of maintenance, a model for deep digital maintenance with an AI module providing predictions of remaining useful life (RUL) is proposed [10]. AI applications for failure diagnosis, failure prognosis and lifetime estimation of wind turbines are also showing promising results [11, 12]. Another field delivering valuable opportunities is artificial neural network (ANN), which is an encouraging method for fault detection, diagnosis, prognosis, prediction, and classification. ANN models emulate a biological neural network, i.e., the central nervous systems of animals, particularly the brain [13, 14]. These models can deal with complex problems without sophisticated and specialized knowledge, provide an effective classification technique, and deal with nonlinear systems and low operational response time after the learning phase [15]. ANN models have been applied to a wide range of fields [12–17], but it is still of interest to explore ANN models into PdM and especially with sensor data as the main input.

For PdM, which aims to predict when an equipment failure might occur [14], there has been conducted numerous studies and the promised cost savings with successful implementation of PdM have been significant [10]. More development of PdM is expected, but currently, PdM seems to fall short of its possibilities in order to deliver what it promises [18, 19]. In general, a common challenge for industrialists to realize the promised advantages with PdM, is connected to manage big data and the capability to extract and utilize relevant data from multiple data sources [18, 20]. The founding bricks in accessing data and connecting the physical and digital world are sensors, and, as a result, they are one of the most critical factors for succeeding with Industry 4.0 and PdM [14, 19, 21]. However, for sensors and data to provide value, analyses and competence within data contextualization are crucial for enabling data-driven decision making [7]. Contextual data focus on unlocking organizational and technological data silos, and aim to integrate and make data from a range of sources available such as real-time streams of sensor data from equipment and process, historic behavioral data from historians, and information from the third parties on external factors [22]. In Ref. [22], they conducted a survey with 160 decision makers in IT and operation roles in global industrial companies, which showed that over 80% of the firms recognized the importance of industrial data in driving their business decisions and innovation. On the other hand, 83% experienced challenges with utilizing the data for delivering insights across their organization. A key finding from the survey, was that data contextualization will be crucial for succeeding with this challenge [22]. This is also supported by Ref. [7], where deep convergence and comprehensive connections are presented as two out of six technical features for smart factory production systems.

As shown in Refs. [23, 24], there exists numerous suppliers who provide sensors, data analytical services and other digital solutions. Additionally, in Ref. [25] they conducted a review on industrial wireless networks within Industry 4.0, showing the large number of applications. However, succeeding with contextualizing and utilizing data for enabling data-driven decision making within maintenance and value chain remains a challenge for many [7, 24], and design of successful applications is still lacking [25, 26]. To provide an Industry 4.0 vision for practitioners and academics to gather on, reference architectures such as the German reference architectural model Industrie 4.0 (RAMI 4.0) [27] and the China intelligent manufacturing system architecture (IMSA) [28] can be used. These reference architectures can become the backbone for full realization of Industry 4.0 if their maturity and sustainability are increased, but currently they are not completely suitable to support implementation of Industry 4.0 technologies, mainly due to their high level of abstraction and/or lack of detailed documentation [29, 30]. The need for more entry-level solutions for building up digital capabilities is required for successful implementation. Thus, a gap has been witnessed between the literature point of view, and the lack of empirical implementation experiences in practice. Based on this, the overall research question for this paper is: "How to develop an entry-level solution to enable Industry 4.0 and sensor data based predictive maintenance?". This paper investigates on how maintenance and value chain data can collectively be used to improve value chain performance through prediction, and presents a novel concept for a PdM platform and an ANN model using sensor data as input. A case study on a company that has chosen to apply the PdM platform and the ANN model, with the implications and determinants of this decision, is also given. Research outcomes are expected to provide concrete suggestions regarding how such a PdM platform and ANN model can be constructed, implemented, and give examples of benefits. Solution for scaling and application to other companies and processes is also discussed.

The structure of this article is as follows. Section 2 discusses how Industry 4.0 is changing the view on maintenance and value chain, and presents the novel concept for a PdM platform. Section 3 provides the case study and ANN model, and Section 4 discusses the case study findings. Lastly, Section 5 concludes the paper.

2 Literature background

A definition of Industry 4.0 is presented in Ref. [6] as: "Industry 4.0 is a collective term for technologies and concepts of value chain organization. Within the modular structured smart factories of Industry 4.0, cyber-physical system (CPS) monitor physical processes, create a virtual copy of the physical world and make decentralized decisions. Over the internet of things (IoT), CPS communicates and cooperates with each other and humans in real-time. Via the internet of services (IoS), both internal and cross-organizational services are offered and utilized by participants of the value chain." Industry 4.0 has been on everyone's tongue during the last years, and industrialists have been expecting substantial gains in productivity, significantly higher levels of automation, and drastic improvements in resource efficiency by putting Industry 4.0 on their agenda [31]. However, reaping the promised Industry 4.0 benefits is challenging [31]. The following two sections present how developments within the field of maintenance and value chain can contribute in overcoming this challenge.

2.1 Predictive maintenance

The introduction of Industry 4.0, new technology and demands within the industry, also requires a significant increase in the level of maintenance [8], and, as a result, PdM has been highlighted. The work on PdM has contributed in changing the traditional view on maintenance, from being a costly unwanted necessity into seeing maintenance as a competitive advantage. The two main objectives for industrial maintenance are to deliver a high availability of production equipment and low maintenance costs [32], and PdM is expected to have a significant impact on these objectives with the introduction of Industry 4 technologies. PdM is also showing its importance to lean manufacturing and total productive maintenance (TPM). Lean manufacturing seeks to improve on productivity, quality, focus on the elimination of waste and to be customer oriented, and share similar goals as Industry 4.0 [33, 34]. TPM also includes the goal of elimination of waste, reduces costs and downtime through an improved maintenance function [35]. For both lean manufacturing and TPM, PdM can provide several ways of performance improvements, e.g., through better predictions reducing unnecessary maintenance, such as early replacement of components (identifying RUL) or increased production downtime due to equipment failures. PdM can also improve maintenance plans and procedures [36]. An overview of PdM system architectures, purposes and approaches is given in Ref. [37], and a definition of PdM is provided by EN 13306:2017 [38]: "Condition-based maintenance carried out following a forecast derived from repeated analysis or known characteristics and evaluation of the significant parameters of the degradation of the item." The standard EN 13306:2017 [38] classifies PdM under the umbrella of preventive maintenance and condition-based maintenance (CBM), but PdM goes beyond CBM by adding a forecast to the maintenance being carried out.

PdM aims to maximize the life of equipment and reduce both planned and unplanned downtime, and, as a result, minimize maintenance costs. This is possible by analyzing data collected from components and equipment and using those analyzes to predict when a part will fail, enabling to perform maintenance actions at the right time. In terms of Industry 4.0, PdM is claimed to be central for asset utilization, services and after-sales [10]. For asset utilization, PdM is expected to decrease total machine downtime from 30% to 50%, and extend operation lifetime from 20% to 40% [10]. PdM combined with remote maintenance for services and aftersales, is assumed to reduce maintenance cost from 10%

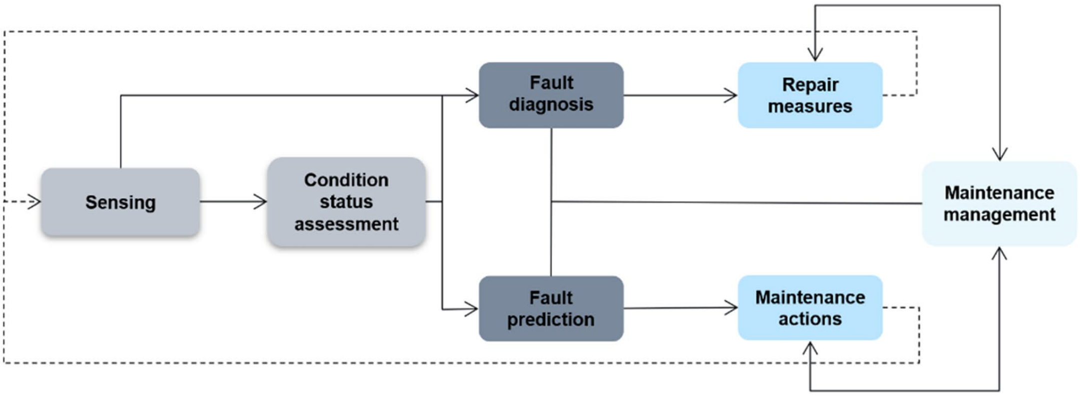


Fig. 1 PdM structure with its main elements, redrawn from Ref. [3]

to 40% [10]. Thus, the expected outcomes are significant, but several studies show that PdM seems to fall short of its possibilities in order to deliver what it promises [18, 39]. In fact, the added value of stand-alone PdM machine projects is often lower than asserted, as companies have extensive experience with wear and tear on their machines. Thus, there is a need for an overall concept for using digitization in an advantageous and holistic manner [18]. This is also supported by a Sino-German working group on PdM for Industry 4.0 [3, 40], where they conclude that the increasing flexibility and heterogeneity of future manufacturing systems, requires a systematic approach for PdM with a modular architecture. In more detail, the architecture shall enable easy adding or enhancing functional components for sensing, condition status assessment, diagnosis, and prediction [3, 40]. In addition to these functional components, it should be a flexible deployment of findings to different resources, e.g., data from a sensor can be visualized both in a dashboard at the equipment and used in a cloud center for conducting analyses with other contextual data [3, 40]. Figure 1 shows the overall structure for PdM, which is considered to be settled in Ref. [3], and further elaborated in Ref. [40].

The PdM structure presented in Ref. [3], consists of seven interconnected elements. First, “Sensing” focuses on sensor modality and strategy for sensor placement. The selection of sensor technology and sensor placement are essential tasks for creating the most representative picture of asset condition, i.e., asset health. Further, sensing techniques can be categorized into direct sensing (measuring actual quantities directly indicating asset condition, e.g., toolmaker’s microscope) and indirect sensing (measuring symptoms caused by degradation or a defect, e.g., change in vibration or temperature). Indirect sensing methods are often cheaper, less complex, and enable continuous measurement without interrupting operation [40]. Second, “Condition status assessment” is about assessing the collected data to determine asset health state, which creates a foundation for determining the current status on asset condition, i.e., an asset health indicator. The indicator can be visualized in the form of a traffic light, providing a fast and simple overview. Asset condition status on a whole system, or comprehensive equipment, can be given by aggregating the condition status of its functional components [40]. Third, “Fault diagnosis” (which can be divided into fault detection, fault location, fault isolation, and fault recovery) and “Fault prediction” (predicting the fault and RUL of an asset or a system) are both challenging tasks and consist of several possible methods based on analytical models, qualitative empirical knowledge, and data-driven methods. The premise of RUL prediction is the definition and identification of failure modes, and RUL of a manufacturing system can be defined as [41]: “The duration of the stable production of high-quality products.” Here, ANN can be seen as an artificial intelligence technique for RUL prediction [42]. Together, “Fault diagnosis” and “Fault prediction” are coherent elements which provide a basis for the optimum “Repair measures”, element four, and time for executing the “Maintenance actions”, element five [40]. The last element, “Maintenance management” is where the information from the other elements are used for decision making in terms of developing an economical maintenance schedule, cost-effective maintenance strategy, and resource allocation (people, spare parts, tools, and time). Further, a linkage between maintenance management and operation management should also be present, as data from operations can improve PdM capabilities, but PdM can also support rapid and data-driven decision making across operations [40].

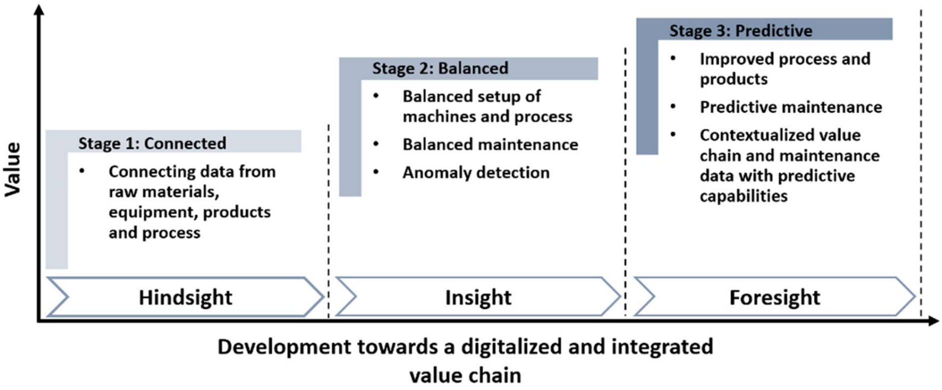


Fig. 2 Three conceptual stages towards a digitalized and integrated value chain

2.2 Digitalized and integrated value chain

The value chain concept was first introduced by Michael E. Porter in 1985, and the term was defined as [43]: “A value chain is a set of activities that a firm operating in a specific industry performs in order to deliver a valuable product or service for the market.” The value chain concept was originally aiming at identifying value activities, as these are the building blocks of competitive advantage, and focusing on these activities can be used to define improvement needs or opportunities for companies [43]. Each value activity consists of two components, namely, a physical and an information processing component. The former includes the physical tasks required to fulfill the activity, and the latter are steps required to capture, manipulate, and channel data necessary to perform the activity [43, 44]. Porter identified two types of activities, namely, primary and support activities. First, the primary activities are inbound logistics, operations, outbound logistics, marketing and sales, and, lastly, service. These are defined as activities within the main value creation process for a traditional and general manufacturer. Second, the support activities are procurement, technology development, human resource management, and firm infrastructure. The role for these activities is to create a foundation for enabling and improving the function of primary activities [43], meaning that support activities also need to pursue technological advancements.

With the introduction of Industry 4.0 and new technology, many industries have reshaped their value chain, and focused on higher information content in both products and processes [43, 45]. For vertical integration, the importance of integrating the various information subsystems at different levels in the company is underpinned [6]. This is also discussed in Ref. [7], where it is claimed to be essential with: “vertical integration of actuator and sensor signals across different levels right up to the enterprise resource planning (ERP) level to enable a flexible and reconfigurable manufacturing system.” Further, horizontal integration should focus on inter-corporation collaboration where information and material can flow fluently, enabling new value networks and business models [6, 7]. The end-to-end integration across the entire value chain will include cross-linking of stakeholders, products and equipment, from raw material acquisition to end of life [6].

Summarized, with the advancements in technology, increased level of competition, more demanding customers focus on sustainable production, the need for development goes for both the field of maintenance and value chain, and, additionally, the integration between the two fields. In Fig. 2, three conceptual stages with coherent elements seen as important in succeeding when moving to a digitalized and integrated value chain are proposed.

The proposed three conceptual stages are also defined into hindsight, insight, and foresight, describing the way of working. Stage 1 “Connected”, targets to create a data foundation from raw materials, equipment, products and process, as conceptualized in Ref. [46]. At this stage, the way of working is focused on hindsight. Hence, a reactive approach is presented and the ability of understanding the whys, hows and potential improvements are only obvious after an event has occurred. Stage 1 creates the foundation for data-driven decision making in stage 2, “Balanced”. Here, data are utilized to provide insight, and an accurate and deep understanding of the current situation. Thus, setup of machines and process can be balanced based on need and variance is managed to keep processes lean and stable. For example, in Ref. [47], the concept of a balanced maintenance program is presented, with anomaly detection and machine load as critical factors for deciding maintenance actions. Lastly, stage

3 "Predictive", aims at predicting future maintenance need, setup and design of both value chain process and final products. Possessing contextualized value chain and maintenance data with predictive capabilities, enables decision making and working in a foresight manner. For example, Ref. [48] presents a method for combining knowledge-driven and data-driven anomaly detection, fault recognition and root cause analysis (RCA) for PdM.

The proposed three conceptual stages can also be seen up against the six stages in the development towards smart maintenance presented in Ref. [10], which evaluate the degree of succession of maturity stages within Industry 4.0.

2.3 Predictive maintenance platform

In terms of platforms within digitalization and Industry 4.0, there is a lack of unified use of terminology and definitions. Some examples on use of terminology are sensor platform [49, 50], industrial internet of things (IIoT) platform [51], Industry 4.0 system/platform [52], PdM platform [53–55], smart manufacturing system [56], and digital platform [57]. The research institute Mercator Institute for China Studies published a report on the development within digital platforms in China. Here, they claim that for China, digital platforms are a crucial tool to realize its goal of becoming an industrial superpower by 2025, and present that [57]: "digital platforms in the manufacturing sector are considered crucial to upgrade industry, improve productivity, optimize resource allocation and increase employment". Further, the same report also presents a working definition of a digital industrial platform [57]: "a digital industrial platform, often also referred to as an industrial internet of things (IIoT) platform, is essential for linking machines and devices in a smart, connected factory with applications (typically on a cloud). The platform collects, stores, processes and delivers data and is the basis for monitoring manufacturing processes, for predictive and automated maintenance, digital integration of value chains or customization of design and production." This working definition underpins the importance of PdM and digital integration of value chains for succeeding with Industry 4.0, which also is highlighted in German reports [5, 39, 40, 58]. However, and another similarity for China and Germany, it is challenging for industrialists to reap the promised benefits connected to PdM. This is also seen in small and medium-sized enterprises (SMEs) in China, where the phrase "not daring to use it, not being able to use it, can't be bothered to use it" has been used to describe SMEs general view on implementing data-based solutions like PdM [57]. For SMEs in Europe and USA, a similar situation is claimed to be present and the importance of developing special approaches to introduce and apply Industry 4.0 technologies is highlighted [59, 60]. As a contribution in this regard, the authors have developed and proposed a novel concept for a PdM platform, presented in Fig. 3.

There is no unified way for how a digital platform or PdM platform should be designed. Although, as an inspiration, according to Refs. [59, 61], an IoT architecture includes four main layers.

(i) Sensing layer—is integrated with available hardware objects to sense the statuses of things, e.g., a sensor connected to a machine;
(ii) Network layer—is the infrastructure for sharing and exchanging data and enables wireless or wired connection between the things;
(iii) Service layer—is to create and manage services required by users or applications;
(iv) Interface layer—is the interaction methods with users or applications.

2.4 Novel concept for a predictive maintenance platform

Advances in platforms for Industry 4.0 have made good progress for generic models. For example, the German RAMI 4.0 has presented the main layers for a holistic approach to Industry 4.0, and serves as an orientation framework for the stakeholders and classification of applications in the industrial sector [27]. On the other hand, more in-depth detailed concepts, and industrial implementation experiences are needed to provide successful and scalable solutions for Industry 4.0 and PdM. One of the research objectives for this paper is to provide concrete suggestions regarding how a PdM platform can be constructed, implemented, and give examples of benefits. This includes discussing solutions for scaling and usability. The purpose of the PdM platform is to serve as an entry-level solution to enable Industry 4.0 and sensor data based PdM. Figure 3 presents a novel concept for a PdM platform, which includes elements from the PdM structure presented in Refs. [3, 40], and a value chain perspective.

The first step in the PdM platform is determining the raw data collection. Selection of sensor type and placement is based on a thorough analysis, e.g., failure mode effects (and criticality) analysis (FME(C)A) or failure mode and symptoms analysis (FMSA), as presented in the standard ISO 17359:2018 [62]. Additionally, to support this selection process, sensor management guidelines, as proposed in Ref. [46], can be used. Performing consequence classification, as described in the standard NORSOK Z-008 [63], as an initial step for determining what assets to be prioritized to the PdM platform is also suggested. For ensuring ease of implementation and bringing costs down, the sensors are battery powered, wireless, and measure physical data, e.g., vibration, temperature, pressure, flow or level, which is digitized at sensor level and locally transported to an IIoT gateway

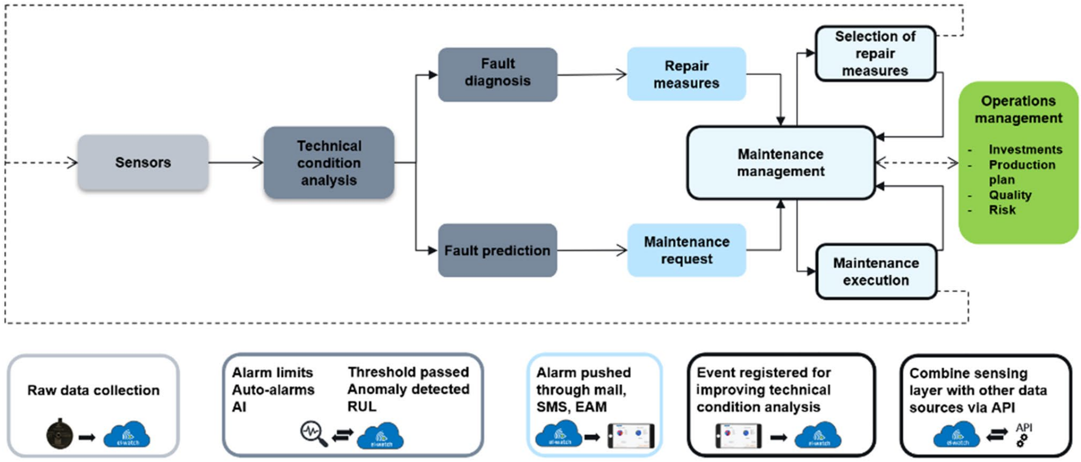


Fig. 3 Novel concept for a PdM platform

by short range radio connection (ISM 868/915 MHz or 2.4 GHz). The IIoT gateway utilizes 4G/5G cellular connection, ethernet connection or a combination to deliver the sensor data (using MQTT) to the IIoT cloud for further processing. The IIoT gateway can also act as an edge device and relay messages directly back to other local devices, reducing use of bandwidth.

In the second step, the raw data have arrived to the IIoT cloud and are processed, labeled, stored, and, if desirable, pushed to other clouds through API. Here, technical condition analysis combines the sensor data, historical data, and previous experience to qualitatively and manually set alarm limits. The sensor data and alarm limit thresholds are monitored by computer algorithms, which immediately act if limits are breached or anomalies detected. Thus, anomaly detection, which is further described in the standard ISO 13379-1:2012 [64], is the initial form of prediction and provides the maintenance request. More advanced algorithms and modules based on AI, such as ANN models, and generating suggestions for auto-alarms and calculations of RUL, can be added when more experience is gained, and contextualized data are available. Further, for fault diagnosis, the FME(C)A and/or FMSA can together with an RCA form a qualitative approach to pinpoint possible repair measures. A quantitative approach to fault diagnosis with ANN models and other data-driven methods can also be added on a later stage.

Step three is where the triggered alarms, maintenance request and repair measures are presented to the user. This can be in the form of an alarm pushed by, depending on degree of importance, electronic mail, text message, or dashboard with further integration, through an application programming interface (API), to e.g., an enterprise asset management (EAM) system.

Lastly, step four concerns a cost-benefit selection of repair measures, planning and scheduling maintenance execution. Maintenance management and operation management must be integrated to balance decisions involving strategic investments, production plan, quality control and risk management, with the overall goal of improving value chain performance. For this matter, the functional connections between maintenance management and manufacturing operations management presented in the standard IEC 62264-1:2013 [65] can be used as guidelines. For decision-making, contextualized data are prerequisites, as data from operations can improve PdM capabilities, but maintenance data can also support decisions across operations, e.g., by indicating utilization of machine capacity and if the required function is available when desired. Here, sensor data can be integrated through API between, e.g., the EAM system and manufacturing execution system (MES). Registration of the executed maintenance action finalizes this step and serves as input for improving the technical condition analysis, raw data collection, and enhancing anomaly detection and ANN models understanding of asset behavior.

3 Case study

To discuss the technological development within maintenance and value chain, and contribute with empirical implementation experiences within these fields, a case from Talgø MøreTre AS is studied. This company has chosen to apply

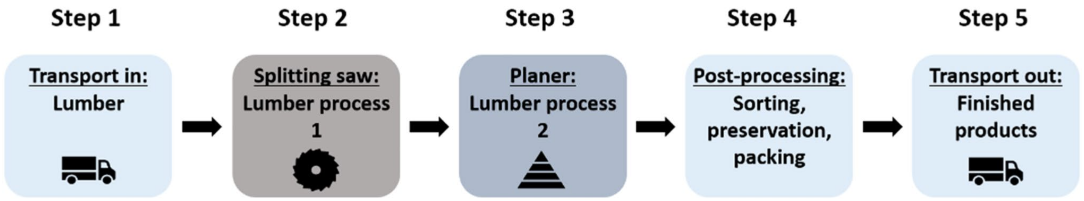


Fig. 4 Simplified overview of the main steps in the value chain at Talgø MøreTre AS

a PdM platform to their production process. The case study is designed to investigate potential verification of the theoretical concept for the PdM platform, by generating an in-depth, multi-faceted understanding of the PdM platform in an industrial setting. It is also investigated how an ANN model can utilize the obtained sensor data, including confusion matrix, loss function, and accuracy rate developed with the software TensorFlow. The case study was proceeded with the following steps.

(i) Provide an overview of the main steps in the value chain for the case company and select the most critical asset to be evaluated;
(ii) Determine raw data collection and define sensor technology and placement through an FMSA for the critical asset;
(iii) Implementation of the PdM platform and development of an ANN model using sensor data as main input;
(iv) Evaluation of case study findings and usability of the results for decision support.

The next three sections describe the case study and company, present the development of the ANN model and case study findings.

3.1 Case study description

Talgø MøreTre AS is an SME located in Surnadal municipality in Norway and is a lumber producer which has established itself as a significant player in the Norwegian lumber market. Their products are mainly within terraces and cladding, as well as finished elements, and lumber is delivered for approximately 58.9 million USD annually (2019) to Norwegian building material stores and other construction industries.

Since 2014 Talgø MøreTre AS, with its 70 employees, has increased their production capacity from 20 000 m^3 to 80 000 m^3 of lumber running through their value chain. Simultaneously with this increasement, a continuous challenge of ensuring stable technical condition of the production equipment occurred. The technical condition of a splitting saw was highlighted as a major concern by the operators, as it was the bottle neck in their value chain. Figure 4 presents a simplified overview of the main steps in the value chain at Talgø MøreTre AS.

The first step in the value chain is transportation of lumber into the production facility at Talgø MøreTre AS. Second, the lumber is fed through the splitting saw for dimensioning, which is the initial lumber process, i.e., lumber process 1. Third, the lumber is run through a planer, for surface and thickness adjustments, i.e., lumber process 2. Fourth, post-processing includes sorting, preservation of the lumber with a variety of treatment solutions, and packing. Lastly, the finished products are transported out to the customers. With the mentioned overall increase in production capacity, the splitting saw needs to be operated over its design capacity. Additionally, the splitting saw is without external cooling, and, as a result, managing overheating of the saw blade and saw wheels has been a major challenge. High temperature increase on the saw blade results in loss of saw blade tension, which leads to lack of quality and rejected products. In addition to loss of saw blade tension, the 450 kg saw wheels can also be overheated when the splitting saw is under heavy load and the saw blades are worn. Other damages of the system are also a risk with continued temperature increasement. Replacing the saw blade and letting the saw wheels cool down result in approximately two hours of unplanned downtime. Figure 5 provides a picture of the splitting saw.

As the splitting saw was operated over its design capacity and no data measurements, e.g., temperature, was available directly from the machine, calculating the optimal operation speed could be categorized as guesswork performed, individually, by the 14 operators. Thus, to avoid high costs connected to unplanned downtime and maintenance repairs, the operating speed for the splitting saw was kept well down on the safe side. On the other hand, this strategy resulted in splitting saw becoming a major bottleneck, leading to challenges in meeting the increasing customer demand.

To overcome the challenges with the splitting saw, the management team at Talgø MøreTre AS discussed investing in a new splitting saw, a cost of approximately 400 000 USD. However, they decided to first investigate on using wireless sensors for condition monitoring (CM), as this potentially

Fig. 5 Splitting saw at Talgø MøreTre AS

could lead to insight into optimal operation speed. The selected solution was to implement a PdM platform, as presented in Fig. 3, with a wireless infrared (IR) temperature sensor, vibration sensor, and power usage sensor as a basis for the raw data collection. The IR sensor was placed on the chassis of the splitting saw for measurement of the saw blade surface temperature. The vibration sensor and power usage sensor were placed on the 55 kW electrical engine running the splitting saw. Table 1 shows the simplified FMSA for the critical subparts of the splitting saw.

Measurements from the sensors, every two minutes, are sent via radiofrequency 868 MHz to a gateway, and stored in the IIoT cloud. Further, the measurements are presented as a live temperature graph in a web-based dashboard available for the operators through tablets and mobile phones. After gaining operational experience, sensor data, and insight on the saw blade surface temperature from the IR sensor, an alarm limit was set when the surface temperature reached 48 °C. For the operators, this alarm limit provided an early warning, i.e., anomaly detection, to reduce operation speed, well in time to avoid overheating the splitting saw, and to start planning a maintenance action of changing the saw blade before failure and in line with the production plan.

Table 2 Input and outputs of ANN model

Model output	Input
Blade temperature (Sensor A)	Blade temperature (t–1, Sensor A) Current (t, Sensor B) Vibration acceleration RMS g (t, Sensor C) Sensor C temperature (t)

3.2 ANN model with sensor data input

To establish the normal behavior ANN model and make predictions on saw blade temperature and splitting saw operation, the variables that can affect this must be taken into consideration to build an accurate model. Accordingly, the sensor data providing input for the model are the IR sensor (Sensor A) measuring saw blade temperature, power usage (current measurement form Sensor B), vibration sensor with temperature measurement (Sensor C). Table 2 shows the parameters selected to establish the ANN model with its input and outputs.

The data collection and preprocess for the ANN model emphasize the connection between the operation of the saw blade and the saw blade surface temperature, which is the most critical part. The upper limit of temperature alarm 48 °C is further used in defining the data in use. The artificially constructed forward neural network is used to classify and recognize the state of the saw blade. Table 3 shows the raw datasets used for the ANN model [66].

Next, the temperature data, with total dataset being 8 360, were recorded in the csv file for the column with Â°C IR avg and the temperature was set to less than 48 °C to 0, and vice versa. Further, the program TensorFlow was used and LabelEncoder selected to code the data labeled,

Table 1 Simplified FMSA for the critical subparts of the splitting saw machine

Subpart	Function	Failure mode	Effect	Failure symptom	Recommended sensor for CM
Saw blade	Saw through wood	Loss of saw blade tension	Lack of quality and rejected products	Overheated and/or worn saw blade	IR sensor for measuring surface blade temperature
Saw wheel	Run saw blade	Overheating	Saw wheel malfunction and further damage	Overheating due to heavy load and/or worn saw blade	Vibration sensor and power usage sensor on the electrical engine

Table 3 Raw datasets [66]

Avg	High	Low	Â°C IR avg	Â°C IR high	Â°C IR low	Sample qty	rssi avg	rssi high	rssi low
0.274	0.891	0	24.2	28.6	22.7	30	69	−65.5	−106.0
0	0	−1	23.0	72.0	−1.0	38	−86	−79.5	−102.5
231	273	206	25.8	30.7	21.5	14	−78	−75.5	−82.5
0.002	0.007	0	24.2	25.5	22.8	31	−67	−65.5	−67.5
–1	−1	−1	−1.0	−1.0	−1.0	28	−84	−82.0	−94.0
206	207	205	21.3	21.5	21.1	15	−76	−76.0	−76.5
0.003	0.007	0	25.6	25.9	25.5	30	−66	−65.5	−67.5

and MinMaxScaler normalized the data. Figure 6 shows an example of normalized data, randomly selected 75% data as training set and 25% data (2 090 data) as testing set.

The model =Sequential() is used to build a forward ANN model and the structure of ANN model is shown in Fig. 7.

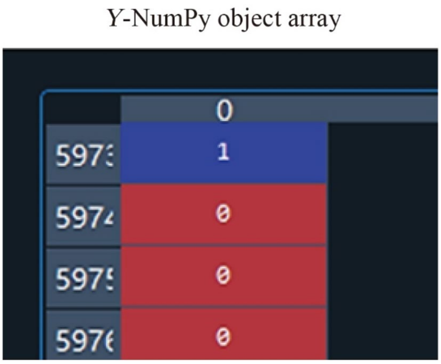


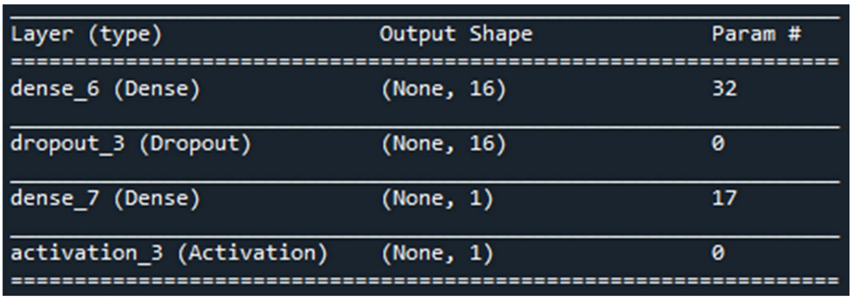
Fig. 6 Data normalization conducted through the software TensorFlow

Dropout technology is added to the network to prevent network over-fitting problems, and the activation function is set to sigmoid. Moreover, the cross entropy of the two classifications is used as the loss function, the Adam optimizer, with accuracy and confusion matrix are used in the model to evaluate the network classification. The 25% dataset is used as the validation set to get the loss function. The accuracy and confusion matrix results are shown in Figs. 8 and 9.

Through the results of the loss function and accuracy rate, it can be concluded that the classification accuracy rate of the ANN model is greater than 0.98, and the accuracy of the model recognition can also be seen intuitively in the confusion matrix, i.e., the accuracy of the saw blade state can be achieved through the presented ANN model.

3.3 Case study findings

After implementing the PdM platform, improvements in performance, safety, and maintenance costs occurred. In terms of performance, case results showed a 40% increase in capacity for the splitting saw. Along with this increasement, the production equipment next in the value chain, the planer, was now sufficiently fed. Thus, the splitting saw was no longer a bottleneck, and satisfactory performance in these



```
Layer (type)                 Output Shape              Param #
=================================================================
dense_6 (Dense)              (None, 16)                32
_________________________________________________________________
dropout_3 (Dropout)          (None, 16)                0
_________________________________________________________________
dense_7 (Dense)              (None, 1)                 17
_________________________________________________________________
activation_3 (Activation)    (None, 1)                 0
=================================================================
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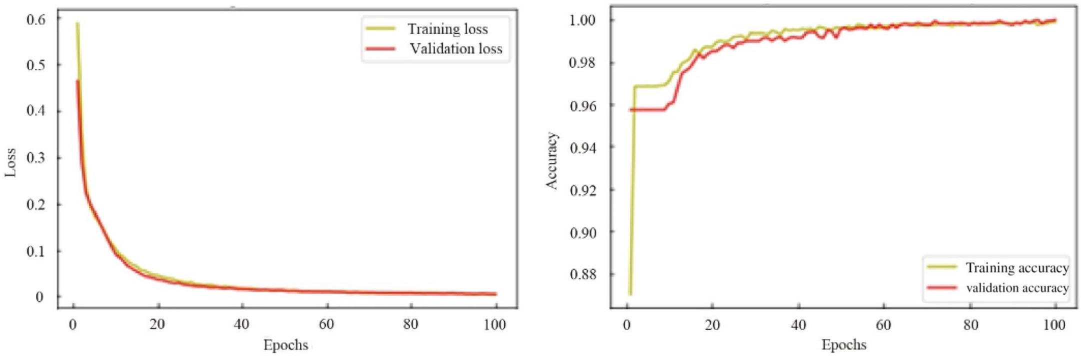
Fig. 7 Structure of ANN model developed with the software TensorFlow



(a) Training and validation loss **(b)** Training and validation accuracy

Fig. 8 Loss function and accuracy created through the software TensorFlow

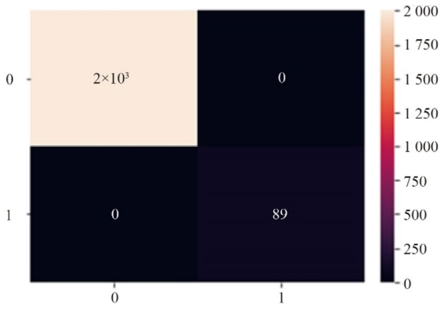


Fig. 9 Confusion matrix built in the software TensorFlow

two value chain steps could be achieved. Within safety, the reduction of saw blades failures improved the level of safety for the operators, as these failures could lead to metal fragments being ejected. For maintenance costs, moving from the strategy of run-to-failure on the saw blades, with a high degree of unplanned downtime, over to a more predictive strategy and enabling scheduling maintenance actions to planned stops, resulted in large maintenance cost savings and a high return on investment. The ANN model shows promising results for classification and recognizing the state of the saw blade, but more work is needed to develop predictive capabilities.

In addition to the mentioned improvements, a change in the way of working also developed. For the operators, the sensor data provided better understanding of technical condition of the splitting saw, and how maintenance actions and changes in machine load could affect this. Moreover, the degree of ownership also increased for the operators, as their actions could be seen as changes in the data and further connected to the mentioned improvements. For the maintenance management team, the successful application on the splitting saw provided motivation for scaling the solution to other production equipment. Thus, as a test, wireless sensors with combined vibration and temperature measurement was mounted inside the planer to gather data from the bearings connected to the spindle, as spindle failures were connected to high costs with unplanned downtime and maintenance repairs. The sensor data were intended to provide anomaly detection for the bearings, as RCA from previous spindle failures had shown that worn bearings often was the initiating event. After a test period, the data foundation was sufficient to enable anomaly detection and give an early warning for a maintenance action of changing the bearings.

4 Discussion of case study findings

The case study findings show that, prior to the implementation of the PdM platform, the view on Industry 4.0 technologies and PdM in Talgø MøreTre AS was quite similar as in most of the other SMEs in China, Europe, and USA. Hence, a general skepticism, which can be connected to lack of competence on new technology and its implementation, economic resources, and willingness to invest in new technology, and insufficient understanding for how such technologies can be utilized to improve value chain performance. As discussed in Ref. [6], this view is also present in other Norwegian SMEs, especially for companies with low level of production repetitiveness.

The novel concept for a PdM platform can be seen as a contribution to theory by bridging the gap between generic overall PdM structures, e.g., as described in Refs. [3, 40], and implementation of a PdM solution in an industrial setting. The PdM platform presents examples on technologies to be used, and relevant integrations to other systems. Suggestions on standards concerning methods, e.g., FME(C)A, FMSA, and anomaly detection, relevant for implementation and use of the PdM platform is given to aid the users. For Talgø MøreTre AS, a simplified FMSA was conducted to support sensor placement and selection of sensor technology, utilizing the extensive experience on the value chain and its bottleneck, the splitting saw. In terms of choosing method for fault prediction, anomaly detection was the natural choice for Talgø MøreTre AS, as an early warning on a well-known symptom for failure provided sufficient time for making adjustments and planning a maintenance action. In addition, the ANN model shows the opportunities of utilizing sensor data to a greater extent, and its position within PdM. The alternative of other quantitative approaches, e.g., RUL can be seen as a balance between cost and value. This trade-off can be linked to findings in Ref. [18], where it is claimed that the added value of stand-alone PdM machine projects is often lower than expected, as companies have extensive experience with wear and tear on their machines.

In the PdM platform, a value chain perspective is included to underpin the importance of focusing on the linkage and integration between maintenance and operation. Further, by bringing in this perspective and seeing the bigger picture, utilizing contextualized data and making decisions with the overall goal of improving value chain performance is highlighted. This is in line with Ref. [18], where the need for using digitization in an advantageous and holistic manner is presented, and the results in Ref. [22], showing that succeeding with data contextualization is crucial for delivering insights across the organization and for enabling data-driven decision making. For Talgø MøreTre AS, the three stages in Fig. 2 can be used to present their transition into possessing a more integrated and digitalized value chain. From initially being at “Stage 0”, to connecting sensors on the splitting saw and planer in Stage 1, into enabling anomaly detection in Stage 2, and predicting future maintenance need and planning this along with the production plan in Stage 3. For bigger companies with a more complex value chain, data from raw materials, environment, products, and process can be included in Stage 1 to provide a more comprehensive context for supporting data-driven decision making.

For operators at Talgø MøreTre AS, the implementation of the PdM platform resulted in increased ownership and understanding of how their actions affect the value chain. Moving from decisions based on guesswork over to data, enabled the operators to perform their job more efficiently. This can be seen up against Ref. [27], where the importance of considering how actions of human actors are taken into account in a PdM system is highlighted, and research on Operator 4.0, e.g., in Ref. [67], where it was investigated on how Industry 4.0 technologies would affect and set new requirements for operators working in an Industry 4.0 environment. The case study findings underpin the potential benefit of providing improved decision support for operators, as presented in Ref. [67], and can be seen as proof of concept on a sensor-based feedback system.

After implementation of the PdM platform, the maintenance management team at Talgø MøreTre AS quickly realized its potential and started looking for scaling opportunities. This is in line with Ref. [40], where the importance of a PdM structure being modular and scalable, and providing minimal configuration effort, is highlighted. Additionally, in terms of possibilities with Industry 4.0 technologies, the PdM platform provided an eye opener for Talgø MøreTre AS. As discussed in Ref. [6], this can be seen as an approach needed to initiate an Industry 4.0 journey. Further, the importance of a company or industry specific approach to reap the opportunities and benefits from Industry 4.0 is underpinned by Ref. [6]. As a contribution for this matter, a generalized approach for initiating a PdM platform is given in Fig. 10. Here, consequence classification creates a foundation and overview of critical assets to pursue a PdM strategy, performing FME(C)A and/or FMSA, along with PdM platform implementation, results in a defined selection of sensor technology and placement, and a scalable solution for enabling expansion and gaining improvements throughout the value chain.

5 Conclusions, limitations and further research

This paper has discussed the development, and need for integration, within the fields of maintenance and value chain along with the introduction of Industry 4.0. As a contribution for this matter, the paper presents a novel concept for a PdM platform and an ANN model, and a case study at Talgø MøreTre AS, a Norwegian SME, providing empirical implementation experience in an industrial setting. Case study shows that, with the implementation of the PdM platform, Talgø MøreTre AS moved from a firefighting maintenance strategy, into using contextualized data with predictive capabilities for enabling maintenance actions to be planned before failure and in line with the production plan. Sensor data available to the operators provided better understanding and competence on parameters affecting technical condition of the production equipment, and, as a result, increased the production capacity to a level that investments in new equipment could be postponed. This shows that the PdM platform can be used as an entry-level solution to enable Industry 4.0 and sensor data based PdM. The ANN model also shows promising results with high accuracy of determining the saw blade state. In terms of scaling and for companies with a more complex value chain, a generalized approach for initiating a PdM platform is given. This provides

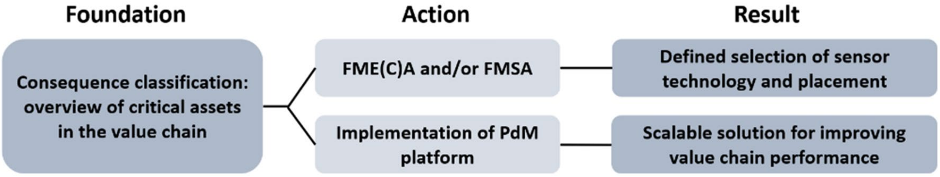


Fig. 10 Generalized approach for initiating a PdM platform

the necessary prerequisites for companies aiming to implement the PdM platform, by establishing an overview of critical assets in the value chain and conducting a FMSA to define selection of sensor technology and placement to be used in the PdM platform.

A limitation to the study and for evaluation of the PdM platform is the number of case companies included. Conducting a study in only one company limits the level of generalization of results, and if the approach is applicable to other companies or industries. Another limitation of the structure of the PdM platform is the lack of detail in terms of connectivity to other systems such as MES and EAM, which can be essential for companies requiring a high degree of contextual information for decision making. There is also a limitation that the ANN model and analysis methods used require a noteworthy amount of failure data before the results can provide decision support for end-users. Results are also highly dependent on correct selection and placement of sensors.

Further research should include case studies on the PdM platform and the ANN model in other companies and different industries to strengthen its maturity and sustainability. Further development of the PdM platform is proposed to include more ways to integrate historical data and systems such as MES and EAM. A more seamless integration with the ANN model should also be developed. Research is also needed on how other Industry 4.0 technologies can be added in a cost-beneficial way. Evaluating the generalized approach for initiating a PdM platform, and its role in a roadmap towards Industry 4.0, is also proposed for further work. More detailed investigation should be conducted on how the PdM platform further can integrate maintenance and operation for enabling contextualized data-driven decision making throughout the value chain in an Industry 4.0 environment.

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