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A self-assessment model for intelligent predictive maintenance analytics: An update of the Analyses Module in the Maintenance Baseline Study

By

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Abstract

Today's industrial era is rapidly changing due to digitization of information and automation of work processes. Digitalization is disrupting several industries and the vision of fully autonomous production facilities, also known as Industry 4.0, is becoming more and more likely every day. In all manufacturing and production facilities maintenance is a core activity to secure reliability, availability, and safety. This is a wildly accepted truth in asset heavy industries and digitalization projects in multiple industries have been started to take advantage of available technologies. For the oil and gas (O&G) industry, digitalization has focused on making assets smart through sensing technology and digital control systems.

On the Norwegian Continental Shelf offshore oil and gas platforms are well equipped with condition monitoring equipment that collect performance- and health data continuously. The problem arises when analyzing aggregated data as decision support for maintenance planning. Trending and subjective opinions are still the most used methodologies even though artificial intelligence (AI) and Big Data analytics could improve this task significantly. AI has the potential to screen huge quantities of data and discover patterns, correlations and calculate statistical possibilities which would improve fault detectability, fault recognition (i.e. diagnostics) and remaining useful life and degradation rate (i.e. prognostics) accuracy. To implement predictive AI analytics there are a set of predetermined requirements that need to be included in the maintenance work process. However, the state-of-practice self-assessment methodology (i.e. Maintenance Baseline Study) does not include state-of-the-art technologies such as AI and ML analytic tools, nor maintenance strategies as predictive maintenance.

Thus, the purpose of this thesis is to develop a new self-assessment model where readiness to implement AI analytics is the governing theme. With the Analyses Module in the Maintenance Baseline Study as a benchmark, the goal was to develop an easy to use, accessible and up-to-date self-assessment model that allows companies to assess their readiness to implement AI analytics tools related to a predictive maintenance strategy. The updated self-assessment model was developed after a thorough literature review of operation- and maintenance theory and Industry 4.0 enabling technologies. This theoretical background formed the basis of the new model, and further developments helped achieve the following improvements:

1. An online self-assessment platform provides accessibility from any device connected to the internet.

2. Multiple-choice reduces complexity, assessment time and provides all responses in a quantitative format which simplifies group / industry analysis if desirable.
3. The models focuses on predictive maintenance and AI technologies are visionary, i.e. the insight received by conducting the self-assessment is essential information for building a system for predictive analysis.

An important part of model development was review and feedback gathering from operation- and maintenance professionals. Through an iterative process of review, feedback and updates, the model was highly influenced by industrial expertise. This was an important measure to secure its validation, and to verify its value.

To summarize, an updated version of the Analysis Module in the Maintenance Baseline Study has been developed to include state-of-the-art technology with the mean to assess a company's readiness to implement AI technology. The new model offers an intuitive layout, is user friendly, accessibility and emphasizes a predictive maintenance strategy with the use of AI in predictive analysis. Furthermore, several recommendations for future research have been highlighted as a measure to progress industrial excellence.

Acknowledgment

This thesis is submitted as a mandatory part of a MSc degree in Industrial Economics at the University of Stavanger (UiS). The thesis was prepared and completed during the spring semester of 2020 as a final measure to fulfill all requirements.

I would like to express my deepest gratitude to Professor Jan Frick, and Professor Idriss El-Thalji, for valuable guidance and support during this project. It has been a turbulent semester due to COVID-19 and a cancelled exchange program, however, throughout this semester have both professors showed a patient, flexibility, and problem solving attituded which has been vital for this submission.

I would also like to thank all industry experts who took their time to assist me during model development. Thanks to Megha Singh Tveit for proof-reading my thesis, and finally, thanks to Tonje Bølge Tveit for your patient, support and encouraging words when I needed it most.

Alexander Carlsen

Bergen, 14.07.2020

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Abbreviations and Definitions

Throughout this thesis abbreviations and terms are used to bring meaningful contributions. Table 1 is an overview of abbreviations and their meaning, while Table 2 is an overview of terms and their definition, which are important to understand their meaning in given context.

Table 1 - Abbreviations [made by writer]

Abbreviations	Word / Phrase
AI	Artificial Intelligent
CM	Condition Monitoring
CMMS	Computerized Maintenance Management System
CPS	Cyber Physical Systems
FMEA	Failure Mode and Effect Analysis
FMECA	Failure Mode, Effect and Criticality Analysis
FMSA	Failure Modes Symptom Analysis
IoT	Internet of Things
ICT	Information and Communication Technology
MBS	Maintenance Baseline Study
ML	Machine Learning
NCS	Norwegian Continental Shelf
O&G	Oil and Gas
O&M	Operation and Maintenance
PLC	Product Life Cycle
RUL	Remaining Useful Life
SCADA	Supervisory Control And Data Acquisition
WEF	World Economic Forum

Table 2 - Definitions [made by writer]

Term	Definition	Ref.
Condition Monitoring	*"Acquisition and processing of information and data that indicate the state of a machine over time"* Note 1: The machine state deteriorates if faults or failures occur.	[1]
Diagnostics	*"Examination of symptoms and syndromes to determine the nature of the faults or failures"*	[1]
Prognostics	*"Analysis of the symptoms of faults to predict future condition and residual life within design parameters"*	[1]
Fault	*"Condition of a machine that occurs when one of its components por assemblies degrades or exhibits abnormal behavior, which my lead to the failure of the machine"*	[1]
Failure	*"termination of the ability of an item to perform a required function"*	[1]
Symptom	*"Perception, made by means of human observation and measurements (descriptor), which may indicate the presence of one or more faults"*	[1]
Descriptor	*"Data item derived from raw or processed parameters or external observations"*	[1]
Parameter	*"Variable representing some significant measurable system characteristics"*	[1]
Data	*"Sampled measurement of a physical quantity"*	[2]
Maintainable item	*"item that constitute a part or an assembly of parts that is normally the lowest level in the equipment hierarchy during maintenance"*	[3]
Reliability	*"Ability of an item to perform a required function under given conditions for a given time interval"*	[3]
Availability	*"Ability to be in a state to perform as required"*	[3]
Failure Mode	*"Manner in which failures occurs"*	[3]
Down Time	*"Time interval during which an item is in down state"*	[3]

Down State	*"<of an item> state of being unable to perform as required, due to internal fault, or preventive maintenance"*	[3]
Up Time	*"Time interval during in which an item is in up state"*	[3]
Up State	*"<of an item> state of being able to perform as required"*	[3]
Zero Philosophy	*"Accidents don't simply occur but have a root cause. Accidents can thus be prevented with a target of zero injuries and accident. This is possible through risk management, obviation and learning throughout the entire organization"*	[4]
Risk	*"Risk is uncertainty about and severity of the consequences of an activity with respect to something that human's value"*	[5]

1. Introduction

1.1. Background

In the age of digitalization industries need to transform and take advantage of available technology to survive in an increasingly competitive environment. Digitization of information, communication and data have disrupted multiple industries with lean organizations by enabling new business models, changing the value-chain, and establishing new markets. [6] Automation of work processes due to labor cost, productivity and convenience are now possible with the use of algorithms where computers interpret, make decisions, and execute simple and repetitive tasks based on digitized information (data). [7]

However, this is just the beginning. With the exponential development in technology soon there will be systems where physical assets and cyber systems are integrated at all levels. This will allow the integration of computation into physical processes which will compute, communicate, control physical processes, provide feedback loops, and optimize processes based on how the process is affected by computation and vice versa. But this is just one function of the value chain in Industry 4.0. The Industry 4.0 vison is the connection between people, physical objects, and systems to create a natural flow of information to optimize value added activities through the entire value chain across companies. With use of available real time information and self-organizing systems, optimization parameters can be adapted from business to business and industry to industry. [8] With the industrial evolution, drawing the lines from the first industrial revolution and to this day, it is difficult to imagine a world without Industry 4.0. Today's sensing technology, Internet of Things (IoT) and Cloud Computing (CC) lay the very foundation of an industry where physical objects, computers, organizational processes and market demand is merged into one system that is self-controlling, self-adjusting and self-improving.

In 2017 the World Economic Forum (WEF) published a report on digital transformation in the oil and gas (O&G) industry. The report focused on four themes where digital transformation would have a central role for the digitalized industry. The four themes were – Digital Asset Life Cycle Management, Circular Collaborative Ecosystem, Beyond the Barrel and Energizing New Energies. A subcategory of Digital Asset Life Cycle Management that was highlighted was Predictive Maintenance due to technologies such as automation, and advanced analytics and modeling. The WEF estimates that the value-at-stake of Predictive Maintenance between 2016-2025 would be 160 USD billions distributed on industry profits, costumers, society, and environmental benefits worldwide. [9]

If we look at the Norwegian Continental Shelf (NCS), the Confederation of Norwegian Enterprise (NHO) states in their yearly report, Business Perspective Message 2018, that the Norwegian O&G industry has signaled significant investment into digitalization, automation and robotization in the coming years. As a high-cost nation such investment will be crucial to secure a competitive industry in a global market. [10] Adding operational expenses to this equation the potential impact becomes much clearer. Forecasts made by the Norwegian Ministry of Petroleum and Energy and Norwegian Petroleum Directorate estimates total operational expenses over the next five years (2020-2025) of 308 NOK billions. Of the main subcategories maintenance (excl. wells) is the second largest cost with a forecast of 80 NOK billions. This is roughly 26% of all operational expenses on the NCS. [11]

Another important aspect of maintenance is safety. Maintenance ensures that equipment functions as intended, and a lack of or inadequate maintenance could lead to unexpected shutdowns and dangerous situations with potentially catastrophic consequences. In the Norwegian Petroleum Safety Authorities (Ptil) Report from 2018, on risk levels in the Norwegian petroleum industry, an increasing lag on maintenance activities was highlighted. This applied to both critical and non-critical HSE related maintenance. It is worth mentioning that the overall risk levels are declining and this shows a positive trend. However, it also shows that maintenance related activities are increasing and that the industry is struggling to keep up. [12] [13]

With these implications the offshore O&G industry could gain several benefits by implementing an operation- and maintenance system with an Industry 4.0 vison. With their complex system and vulnerable location, moving from a preventive to a predictive maintenance approach has the potential to extend the lifetime of assets, reduce risk by early detection of faults and optimize planning- and operation execution, all in a cost-effective matter.

1.2. Problem presentation

The evolution of digitalization in the petroleum industry has been accompanied by an increased curiosity on how these technologies can improve their operations. For companies with activity on the NCS, with its extreme operational environment, challenging accessibility and high investment cost, production up state is an important performance index. Additionally, the widely adopted "zero philosophy" to minimize risk of accidents which can inflict damage on humans and the environment, the provision of safe and reliable production facilities is the main operational objective.

The O&G industry has started to implement various solutions with the Industry 4.0 vison to increase operational stability and safety. The focus has largely been on production operations, however, at the core of production reliability is maintenance. Duque and El-Thalji (2018) advocate the importance of maintenance as a core supportive function in operations and production capabilities and emphasize a need to lift digitalization of maintenance on the agenda. Thus maintenance must be addressed along with system digitalization to improve overall performance. [14]

As condition monitoring equipment is already installed in large scale on O&G offshore platforms it is possible to utilize this information to improve maintenance activities. According to a study on data analytics used to improve offshore asset operations and maintenance on the United Kingdom Continental Shelf (which is comparable with NCS), O&G installations had adequate monitoring equipment installed, and 60% reported good to excellent transmission and storage capabilities. The problem seems to be lack of knowledge or awareness of digital technology to gain insight from this data. [15]

Furthermore, a study performed by PWC in 2017 on PdM 4.0 (e.g. next generation predictive maintenance) maturity levels revealed that roughly 63% of survey participants used only basic knowledge such as visual inspection, inspector expertise and instrument readouts as decision support. Twenty-two percent used pre-established alarm rules and/or critical values based on condition monitoring (CM), while only 11% were at the highest level where CM alarms activates a prediction analysis where live data together with big data are analyzed using sophisticated analytics. The survey was conducted in collaboration with companies in different industries, including energy and mining, construction, manufacturing, chemical and more. [16] It is easy to see parallels within the O&G industry based on the collection of data through inspection and CM, but also the lack of utilization of available information.

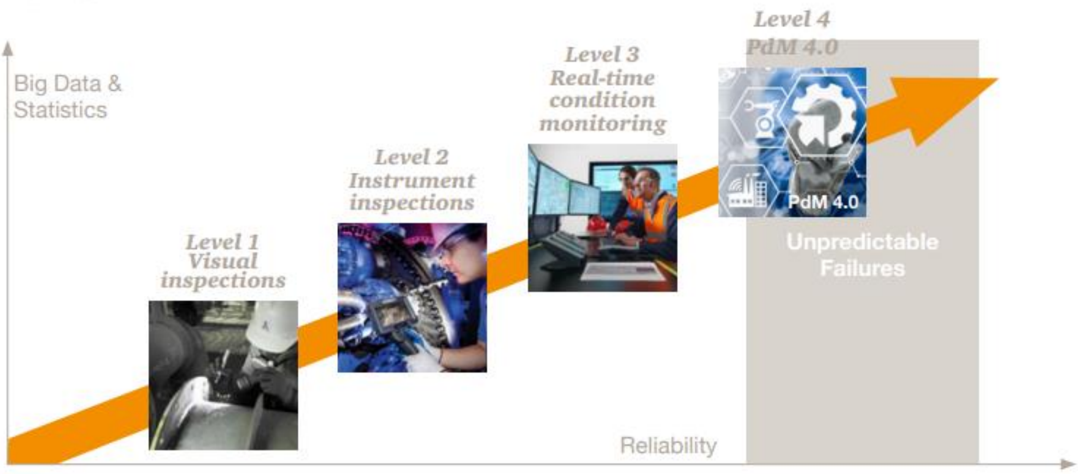

Figure 1 - PdM maturity levels as defined by PWC [16]

These similarities point in the same direction and address one of the main challenges with the current situation: to efficiently analyse available data (i.e. live data, historical data, and external data) to create reliable and objective decision support for managers.

The offshore O&G industry has the potential to build trustworthy AI models to predict future events based on all available data. However, this is a laborious and time demanding process that requires guidance. To extract meaningful information from such huge volumes of data, companies need to understand and review at least three aspects of the analytics process:

1. The physical asset – is there a good understanding of system functionality and failure modes, failure symptoms and the relation between failure symptoms and maintainable items?
2. Condition Monitoring – is condition monitoring equipment systematically assessed and reviewed together with asset functionality to select an appropriate system?
3. Analyses – which methodologies and tools are used when analysing condition monitoring data to determine diagnosis and prognosis? Is multi variable analysis used during the analysis? Is enterprise data considered when planning maintenance activities?

By understanding state-of-the-art O&M strategies and through thorough review of state-of-the-art technology, manual tasks and subjective decisions can be changed through AI analytics and automation. However, to achieve this companies need an understanding and overview of their readiness to implement AI technology to plan applicable measures. This can be done through a self-assessment method like the Maintenance Baseline Study.

1.3. Objective

The Maintenance Baseline Study (MBS) is a self-assessment method developed by the Norwegian Petroleum Directorate (NPD) to improve a company's Maintenance Management System. The NPDs objective was twofold: 1 – "*to contribute to a general improvement of the quality of the operator's system for managing safety-related maintenance*", and 2 – "*provide better predictability for the operators in terms of the NPD's expectations and requirements in this area*". Furthermore, the study is intended to work as a tool for continuous improvement and it is highlighted how the guidelines will be updated ad how "best practice" and technical development within the field will be shared amongst stakeholders. [17]

The MBS is yet to be updated in accordance with the technological development and there is a gap between available technology and assessments methods. Especially in data analytics has there been a major development in Big Data analytics with artificial intelligence (AI) which should be considered a technical development that could improve a maintenance management system. The O&G industry is well known for information gathering (e.g. PLC docs., condition monitoring data, reports, test data, etc.), however simple analysis and subjective opinions are the ruling analyses when planning for maintenance today. Consequently, the main objective of this thesis is to update the Analyses Module in the MBS to include AI technology. This requires a new self-assessment model, and to realize this objective several intermediate goals are set:

- Introduce the Analyses Module in the MBS and its purpose
- Study operations- and maintenance (O&M) management, its evolution, and state-of-the-art strategies
- Explain the vision of Industry 4.0 and enabling technologies
- Determine goals and constraints for updating the self-assessment model
- Determine requirements for the new self-assessment model
- Extract key stakeholders' requirements to ensure their needs are met
- Derive questions, which will ensure stakeholders needs are met and at the same time assess a company's readiness to implement AI technology as an assistant analysis tool.

An updated Analyses Module can contribute towards improving the overall quality of the MBS and close the gap between the current self-assessment model and technological feasibility to improve analysis predictability. The updated self-assessment model will assist companies to map their present work processes which can be used to develop an implementation strategy to realize the use of AI.

1.4. Project limitations

As this project is a master's thesis with a predetermined timeframe, the project has some limitations. The planned timeframe stretched from 15th February to 15th July 2020. In this period everything from planning, literature review, strategy and development was to be executed.

The global situation concerning COVID-19 resulted in a forced cancellation of the author's exchange program, forced upon a change to thesis objective. These special circumstances also reduced available time and industry involvement. To enhance the Analyses Model and secure its validity, input from domain experts is required to achieve a viable result. Sourcing industry feedback will be prioritized, but time will tell to what extent this has been possible.

Given these constrains, thesis limitation is listed below:

1. There is no company involved providing information for the case study, so several assumptions had to made. These are stated in each section where applicable.
2. The thesis will not go into technical details of condition monitoring equipment and software.
3. The thesis will not go into details about diagnostic and prognostic algorithms, or recommendation of available models.
4. Life cycle cost analyses will not be performed for implementation of AI/ML analytics.
5. The project will focus on readiness to implement AI/ML analytics on operating assets, i.e. the operations- and maintenance life cycle phase.

1.5. Project plan

Table 3 - Project and activity plan

	ACTIVITY	PLAN START (week)	PLAN DURATION (weeks)	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
1	Problem understanding and description	13	1																	
2	Thesis framework development	13	2																	
3	Literature review	14	5																	
4	Data collection and analysis	17	4																	
5	Model development	19	6																	
6	Model demonstration and discussion	24	2																	
7	Industrial review; verification iterations and finalizing model	25	3																	
8	Conclusion and finalizing thesis deliverables	27	2																	
9	Submission deadline	29	1																	

1.6. The structure of the thesis

The thesis structure is based on a recommended guide developed by UiS and a discussion with supervisors. The thesis includes six sections, where section one introduces the thesis objective with an overall description of background, problem statement and limitations. Section two is a review of relevant theory and outlines the foundation for further development. Section three is an explanation on the methodology used and section four is a detailed process of model development. Section five is where the model is discussed and validated, and section six is the conclusion.

1. Introduction, problem statement and thesis objective.
2. Theory
    a. Introduction to the Maintenance Baseline Study with a focus on the Analyses Module.
    b. Introduction to the evolution of O&M management.
    c. Introduction to Industry 4.0, the fundamental idea and enabling technologies.
3. Methodology
4. Self-assessment Model Development
    a. Derive Mission Requirements
    b. Stakeholders Analysis and Requirements
    c. System Requirement, i.e. Self-assessment Platform
    d. Questionnaire Requirements
5. Validation, discussion, and recommended research
6. Conclusion

2. Theoretical Background

To provide a theoretical foundation for understanding the topic and its application, this chapter will start with an introduction to the Maintenance Baseline Study (MBS) and its intention. Further, a systematic review of operation- and maintenance systems and the era of Industry 4.0 will be presented. An historical review of the evolution in maintenance will be illustrated with the objective of providing the reader with a theoretical basis for imagining the future of operation- and maintenance systems in compliance with the Industry 4.0 vision.

2.1. The Analyses Module in Maintenance Baseline Study

From both a safety and economic perspective, maintenance of offshore O&G gas platforms plays a vital role. The combination of location, dynamic equipment, degradation, high pressures, and potential hydrocarbon leakage creates a complex system with many potential hazards that can lead to production stop, or at worst, loss of life. To optimize operators' maintenance management systems the Norwegian Petroleum Directorate released the self-assessment model in 1998. The objective was to develop a systematic and comprehensive method to allow companies to gain a documented basis for further improvement of safety related maintenance. Even if the study was built on the foundation of technical condition of machinery to secure safe operations, it also allows individual modification to include matters such as economics- and production regularities. [17] The generic process using the self-assessment model can simply be described in five steps, depicted in Figure 2.

Figure 2 - Generic use of the self-assessment method [18]

As part of the model development the maintenance management loop was introduced with same structures as a quality system. Their goal was to prioritize continued improvement, continued identification of problems, standardization of good solutions, define maintenance functions and design work processes as quality loops containing all phases in a problem-solving process. This includes allocation of resources such as personnel / departments, materials and supporting documents so that desired results are achieved in the form of technical condition, risk levels and regularity. (ibid)

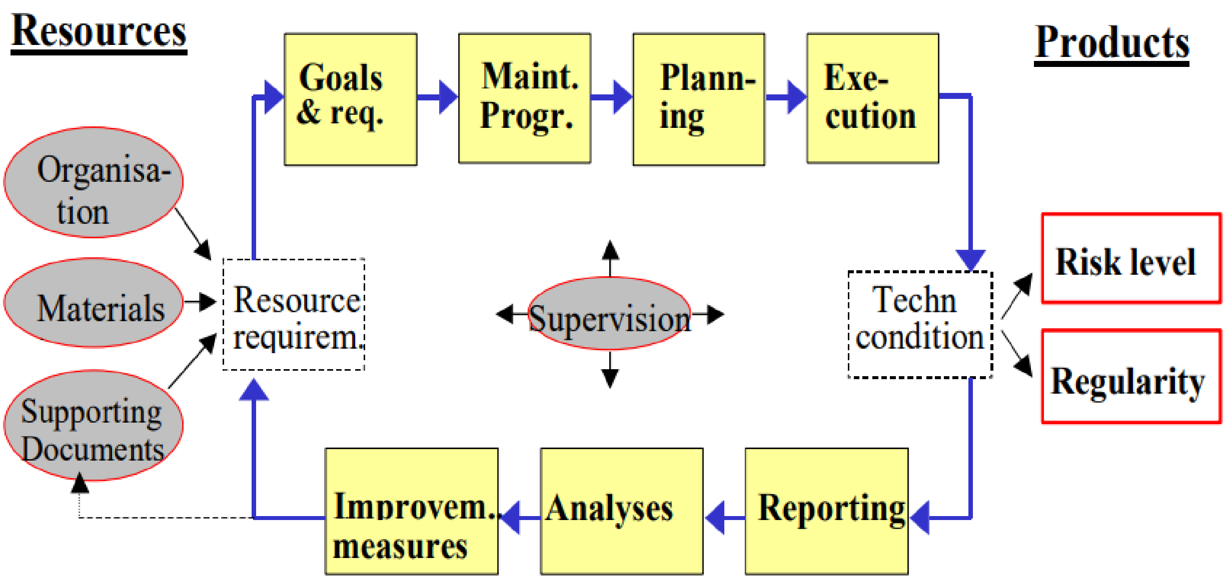

Figure 3 - Maintenance Management Loop [17]

In the maintenance management loop the analyses module aims to answer what, why and which parts of a system fail based on events and empirical data. Analysis of undesired events during maintenance activities, equipment failures, and causal connection are examples of analyses that should be performed to map, initiate, and supervise measures so that underside events are not repeated. To achieve this the MBS divides the analyses phase into four segments: (ibid)

1. *Requirements related to analyses* with a focus on control parameters that trigger an analysis and analysis routines.
2. *Causal analyses* focusing on methods and analysis tools to perform analyses.
3. *Event/accidents* focusing on how an event/failure should be analyzed.
4. *Responsibility and resource* focusing on available resources such as expertise, time, methods, and tools to conduct an analysis of desired quality.

In this perspective intelligent analytics can have a major impact on the volume of information being analyzed, resulting in early deviation detection, faster failure root cause conclusion, better technical understanding, higher statistical accuracy and better understanding of failure correlation of maintainable items (components) in a system. With available condition monitoring technology, cloud technology, computational power, and AI, it is now possible to increase the utilization of these technologies.

At the core of state-of-the-art maintenance strategies (i.e. Predictive Maintenance (PdM)) are sensors that can monitor the overall health of assets so that empirical diagnosis- and prognosis analysis can be performed to optimize maintenance activities. Processes, machines, and components are given "intelligence" through sensors and perception data can then be stored, cleaned, and analyzed returning a failure prognosis and remaining useful life (RUL). This will provide operators with "worry free" uptime and reduce maintenance activity on their assets. This "predict and prevent" approach has the advantages of reducing life cycles costs, improved sustainability and increased operational efficiency while decreasing risk. [14]

2.2. The evolution of maintenance

Maintenance as a business function has many definitions, but common to them all is the involvement of some activity to prevent or restore a system to an acceptable operational condition. NS-EN 13306 (2017) defines maintenance as the *"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"*. [19] However, this is a modern way of think in terms of operation and maintenance activity. From a historical perspective maintenance has evolved from a "necessary evil" to "cooperative partnership" where it today is a part of a strategic plan to achieve corporate objectives according to Pintelon and Parodi-Herz (2008). Figure 4 is an illustration of this evolution and the way of thinking maintenance. [20]

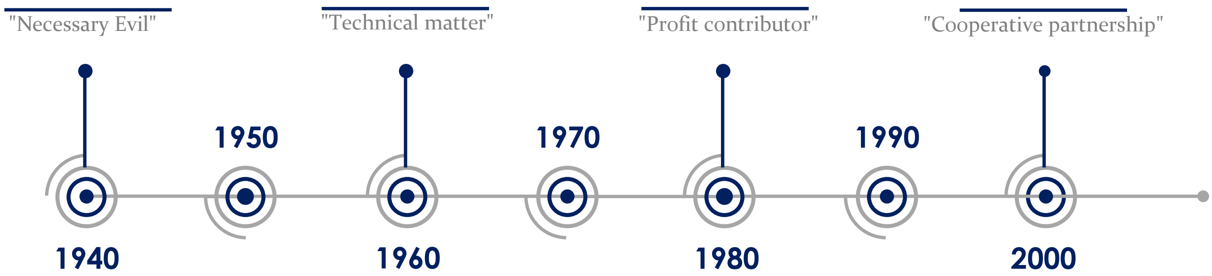

Figure 4 - The maintenance function in a time perspective [20]

As a "necessary evil", maintenance was based on a corrective strategy. Machines would run-to-failure and repairs were only conducted when needed, without any questions regarding optimization. When seen as a "technical matter", maintenance optimization was included and got more attention in organizations. The transition into "profit contributor" is the period where maintenance became it's own business function and part of a strategy. Technical- and management responsibility was combined to cope with the increasing dynamic business environment. Nowadays "cooperative partnership" is the ruling view, especially in asset heavy industries. Maintenance has become an important part of the strategy and specialized organization on operations- and maintenance activities has emerged. This has established cross-organizational partnerships and provided the opportunity for outsourcing of maintenance function. (ibid)

2.2.1. Maintenance actions, policies, and concepts

According to Pintelon and Parodi-Herz (2008) are there two main actions[1] within maintenance activity, precautionary and corrective. This is maintenance in its very basic format, where precautionary actions are explained with four different policies[2], preventive, predictive, proactive, and passive. The two main actions, together with policies, can be explained as follows: [20]

1. Corrective maintenance: "run-to-failure" where maintenance is carried out after a fault is detected to restore the machine/product into working condition.
2. Precautionary maintenance: maintenance actions performed with the mean to reduce the probability of a failure to occur.
    i. Preventive - maintenance actions performed according to predetermined time intervals.
    ii. Predictive - maintenance actions performed based on inspection- or condition monitoring data.
    iii. Proactive - design out or take measures at an early stage to avoid issues later in the machine/product life cycle.
    iv. Passive – maintenance action performed when an opportunity arises.

Figure 5 is a graphic presentation of these main categories with given policies and concepts[3] to plan, control and improve over time. Depending on application, complexity, objective, etc., the various concepts have their pros and cons. To choose a concept is not an easy task and is not solely based on technical considerations, but also industry, risk involvement and techno-economic perspectives. Corrective maintenance is still applicable in cases where cost is equal or lower than preventive actions, or where random failure / fault on machinery makes it difficult to reduce failure probability. In high-risk industries (e.g. aviation and petroleum) where reliability is the focus area, safety and ecological integrity are the ruling decision parameters. Here, precautionary measures will be at the core of asset life cycle maintenance planning. Along with increasingly custom-made machines, equipment and facilities, in-house developed concepts have emerged. Companies now "pick and choose" ideas to create

[1] Maintenance Actions is the *"basic maintenance intervention, elementary task carried out by a technician"*. [20]
[2] Maintenance Policy is the *"rule or set of rules describing the triggering mechanism for different maintenance actions"*. [20]
[3] Maintenance Concepts is defined as the *"set of maintenance policies and actions of various types and the general decision structure in which these are planned and supported"*. [20]

customized maintenance concepts to ensure strategy alignment and compliance to industry regulations. [20]

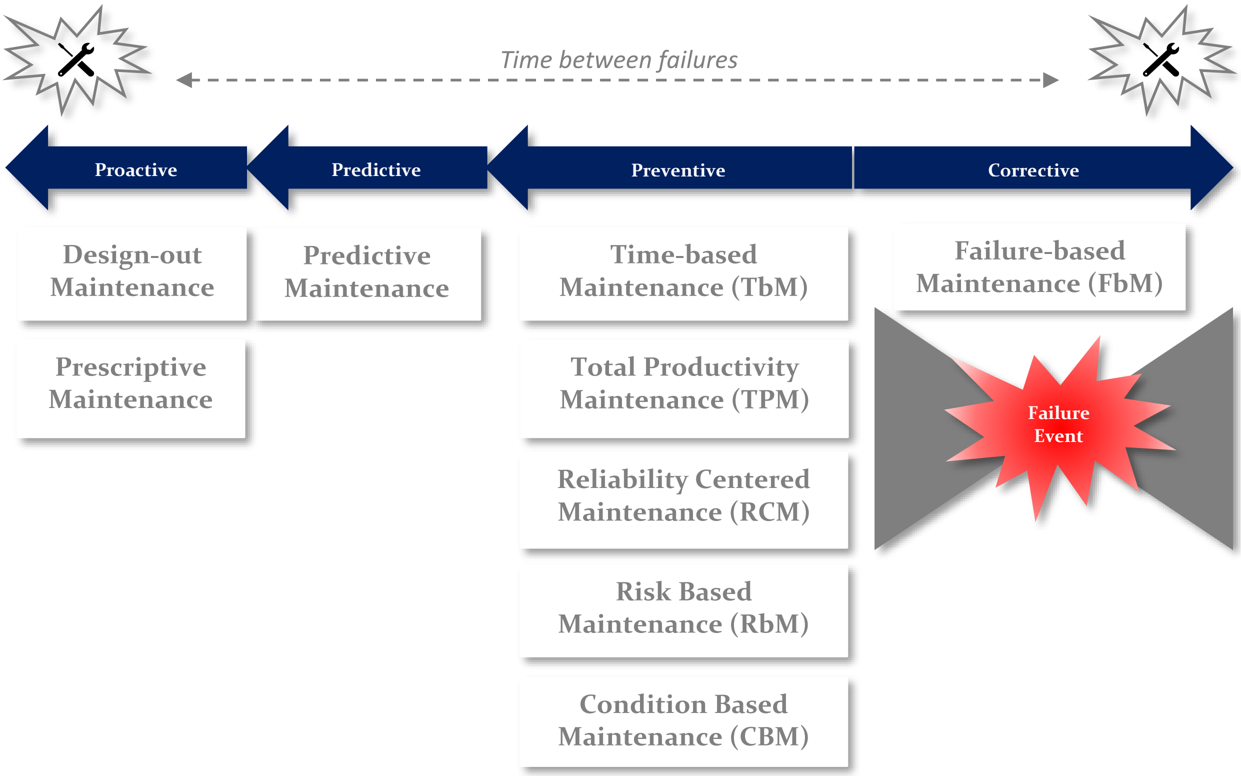

Figure 5 – Maintenance categories, policies, and concepts overview [21]

2.2.2. Corrective Maintenance

Maintenance concept is the strategy decided by an organization to manage, conduct, and control maintenance activity to achieve the overall business target. In some cases, Failure-based Maintenance (i.e. corrective maintenance), is a reasonable solution. There is no maintenance related cost before a failure occurs. This reactive approach is particularly useful where repair cost is cheaper than alternative preventive solutions, or where faults occur randomly and without good fault prediction models. [20] An example of this can be equipment where a functional defect has been categorized as non-critical and where it has been found less costly to run-to-failure than applying preventive maintenance measures.

However, the picture is more nuanced than this and in today's "specialized industry" complex machinery and systems often require more extensive maintenance strategies. Thus, it is crucial to perform appraisals of maintenance needs before selecting a strategy. Corrective maintenance is considered as the most expensive maintain management strategy due expenses associated with spare part inventory, shipment cost, labor cost (e.g. overtime), production down time, and reduced equipment availability. According to Mobley (2002) the average cost and repair time of a run-to-failure event is about three times higher than it would have been in a schedule preventive program. [22]

2.2.3. Preventive Maintenance

Pintelon and Parodi-Herz's (2008) argue that there are only two maintenance categories, corrective and precautionary. [20] Looking closer to the precautionary category it involves the three sub-categories of preventive, predictive and proactive which have their respective framework and basic idea of strategy. For preventive programs the core is time-driven scheduling. This can be calendar-based or usage-based maintenance routines of periodic inspection, adjustments, lubrication and fixing small issues to prevent larger problems. Actions are carried out based on pre-determined time intervals of operations on the assumption that equipment will degrade within a specific timeframe. Maintenance schedule is based on mean-time-to-failure (MTTF), which is calculated based on equipment statistics. [22]

The MTTF, also known as the bathtub curve, indicates that equipment has a high probability of failure in the first weeks after installation, before stabilizing at a low failure probability level. This initial high failure probability is related to installation and start up issues. After these challenges are sorted and the equipment runs within operational limits the failure probability is reduced and stable before increasing sharply with elapsed time. Machinery and its component will degrade over time and the degradation rate will accelerate when physical wear has appeared. (ibid)

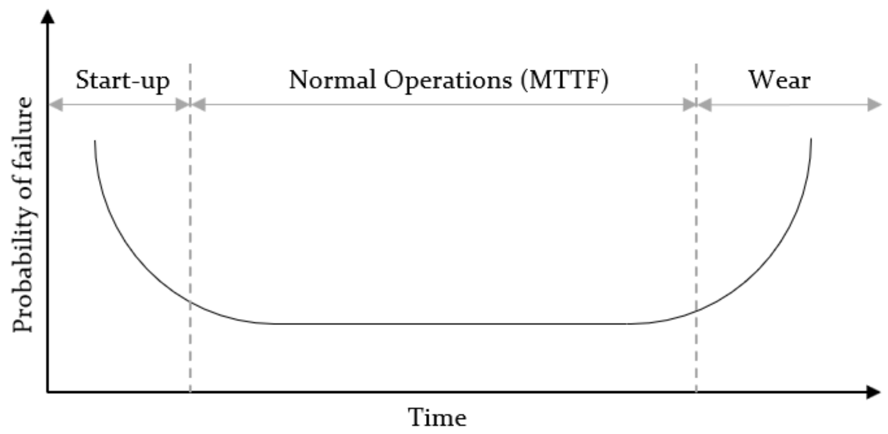

Figure 6 - Illustration of bathtub curve [made by writer]

However, this maintenance approach has limitations. Equipment, e.g. a compressor, is often performing a specific job within a lager system. If the compressor's mean-time-between-failure

(MTBF) is 12 months, that compressil will be removed from service and rebuilt after 11 months. Depending on variables affecting the operations (i.e. system variables) the MTBF will vary from system to system. Furthermore, all equipment within the same system is unlikely to have the same MTBF and the equipment with the shortest MTBF will then dictate system shut down. Consequently, scheduled maintenance could result in unnecessary shutdown, or could have longer/shorter time intervals. Essentially one must choose between two evils: either waste resources on unnecessary repairs or run-to-failures which will have an even higher cost. (ibid)

2.2.4. Predictive Maintenance

According to Mobley (2002), predictive maintenance (PdM) has many definitions, which solely center around equipment monitoring with the means to detect incipient problems. Furthermore, he explains how this interpretation is inadequate as it only addresses monitoring and detection. [22] Condition monitoring is defined as *"acquisition and processing of information and data that indicate the state of a machine over time"* [3], while PdM is much more than just monitoring. Condition monitoring has without a doubt been an important enabler for PdM, but data need to be analyzed to determine the health status of equipment and predicted time parameters such as RUL to bring value. [23] Instead of relying on average-life statistics, other indicators such as mechanical condition, operational environment, system efficiency, etc. is used to calculate the actual MTTF leading to a condition-driven maintenance strategy. This approach can provide early detection of potential failures to optimize asset availability by improving productivity, quality, and the overall effectiveness by scheduling maintenance activities on an as-needs basis. [22]

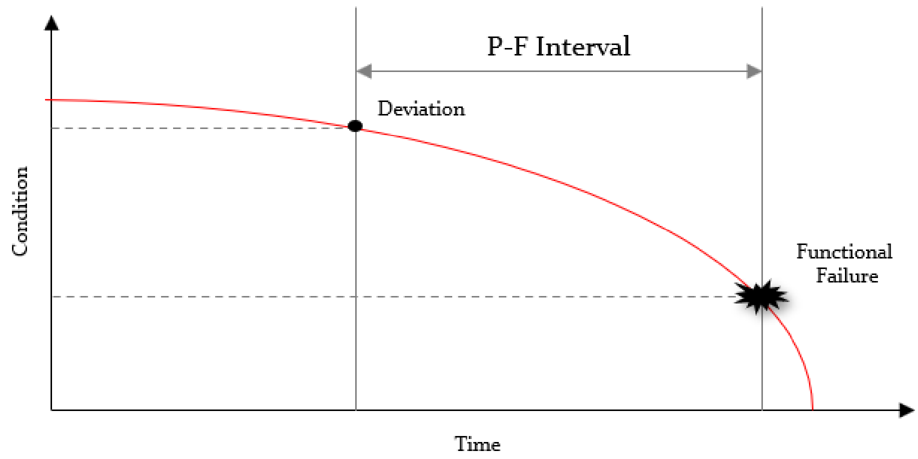

Figure 7 - P-F Interval [made by writer]

PdM utilizes the advantage of asset knowledge to predict future failure by determining diagnostics based on asset condition and providing prognostics to optimize a plan for production shut down and maintenance activities. Knowledge gathering should start at the asset design phase and continue throughout the entire life cycle. [16] [24] Asset knowledge should be available from PLC documentation (BOM, FMECA, FMSA, RAMS, RCM and performance and health parameter) or through asset expertise (visual inspection), live data (condition monitoring), historical data (e.g. maintenance reports) and external data. [24] For the utilization of this knowledge we need to understand how it should be exploited. If we put ISOs condition monitoring and diagnostics design cycle as a basis, it is obvious how preliminary studies to obtain accurate and detailed asset information are a necessity to build a system based on condition monitoring equipment to collect health data that can be analyzed for diagnostics and prognostics by an AI / ML algorithm. [25]

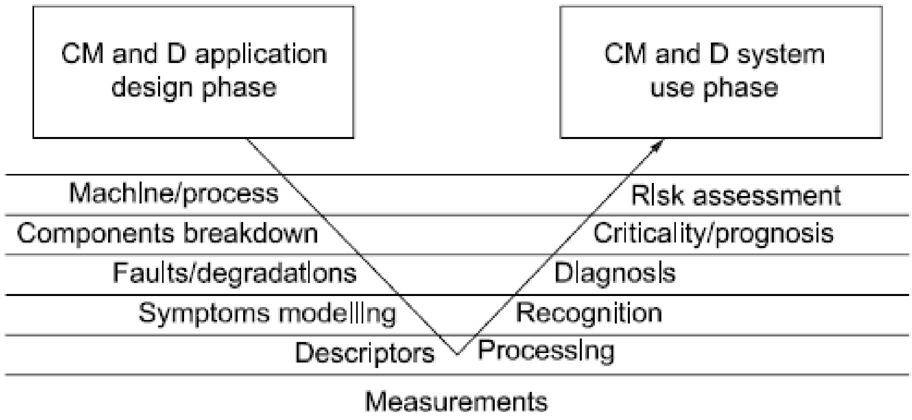

Figure 8 - Condition Monitoring and Diagnostics (CM and D) Cycle [25]

The norm of data-based predictions is mostly based on simple forecasting methods as trending and asset expertise. [26] The result is a weak, subjective decision of what went wrong, why it happened and when maintenance activity should be performed. Furthermore, only very little of available knowledge is considered during the analysis process. Humans simply do not have the patience, time or required expertise to analyze and incorporate all available knowledge into a prescriptive maintenance plan. Figure 9 is an illustration of the coherence between knowledge complexity and the need for automated processes and software analytics to achieve good predictions of future events and optimization of maintenance activities.

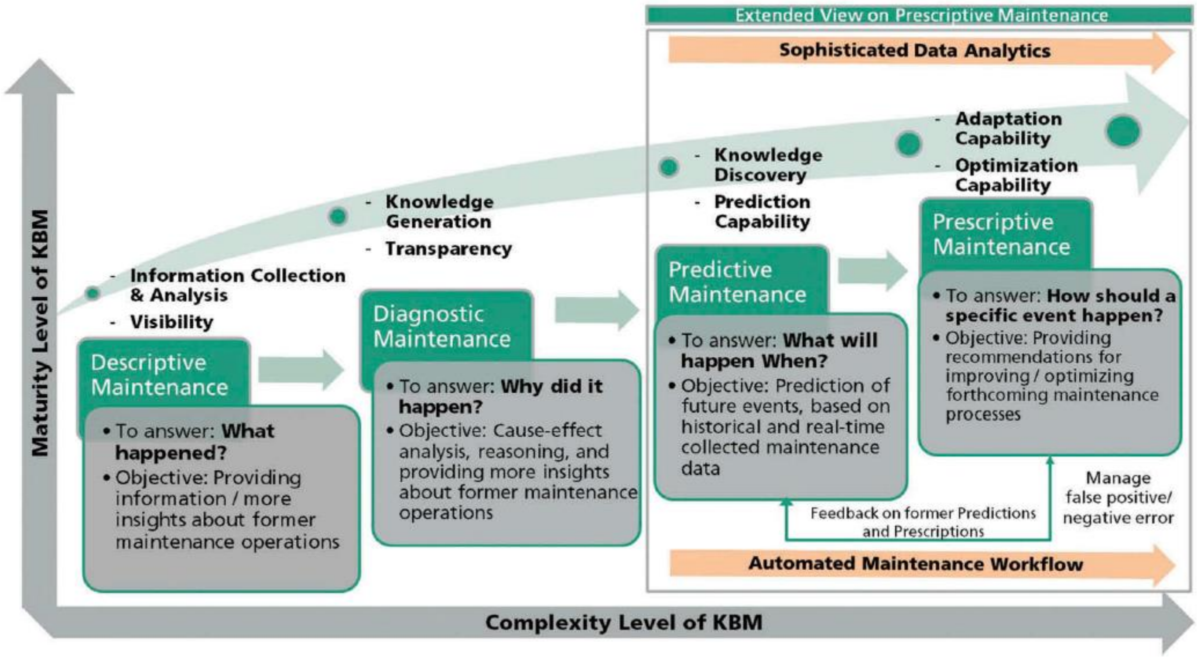

Figure 9 - Knowledge Based Maintenance [24]

To what extent available knowledge is used in the analysis process depends on the organization and it's PdM maturity level. PdM 4.0, as coined by PWC, is the highest level of maturity and corresponds largely with the highest level of Knowledge Based Maintenance (KBM) maturity, prescriptive maintenance, as shown in Figure 9. Both maintenance strategies emphasize the goal to bring forth the most effective proactive measures with the help of advanced analytics, which screen all relevant information to maximize availability and reliability. [24] [16] Moreover, PdM also includes the integration of work processes, organization, and technology to maximize the value of maintenance activities. To achieve this domain experts, monitoring technology (i.e. condition monitoring), information technology infrastructure, data storage and data analytics software needs to viewed together with the relevant asset. [22] Thus, the PdM framework consists of four dimensions:

1. Organization - all organizational changes need to start from the top in an organization. This means that it needs to be a defined strategy that management support and that necessary resources are allocated.
2. Asset - defined work processes to describe equipment functionality, criticality, relevant objects, and technical feasibility to implement CM.
3. Work process - defined work processes of selection appropriate CM equipment and data analysis methods/software.

4. Technology - get an overview of current information and communication infrastructure (ICT) and assess how sensor data, storage and analysis can be performed or highlight feasible changes to achieve strategy target.

This complete integration of equipment, operations and resource management has been discussed in many research papers and business surveys under different names. Terminology such as Predictive Maintenance 4.0 [16], Intelligent Maintenance [27], E-Maintenance [28], Knowledge Based Maintenance [24] and Maintenance 4.0 [14], have all be used to describe more or less the same process. The common thread linking each strategy to Industry 4.0 is the sophisticated data technology that is used to enhance and automate processes related to operation- and maintenance management.

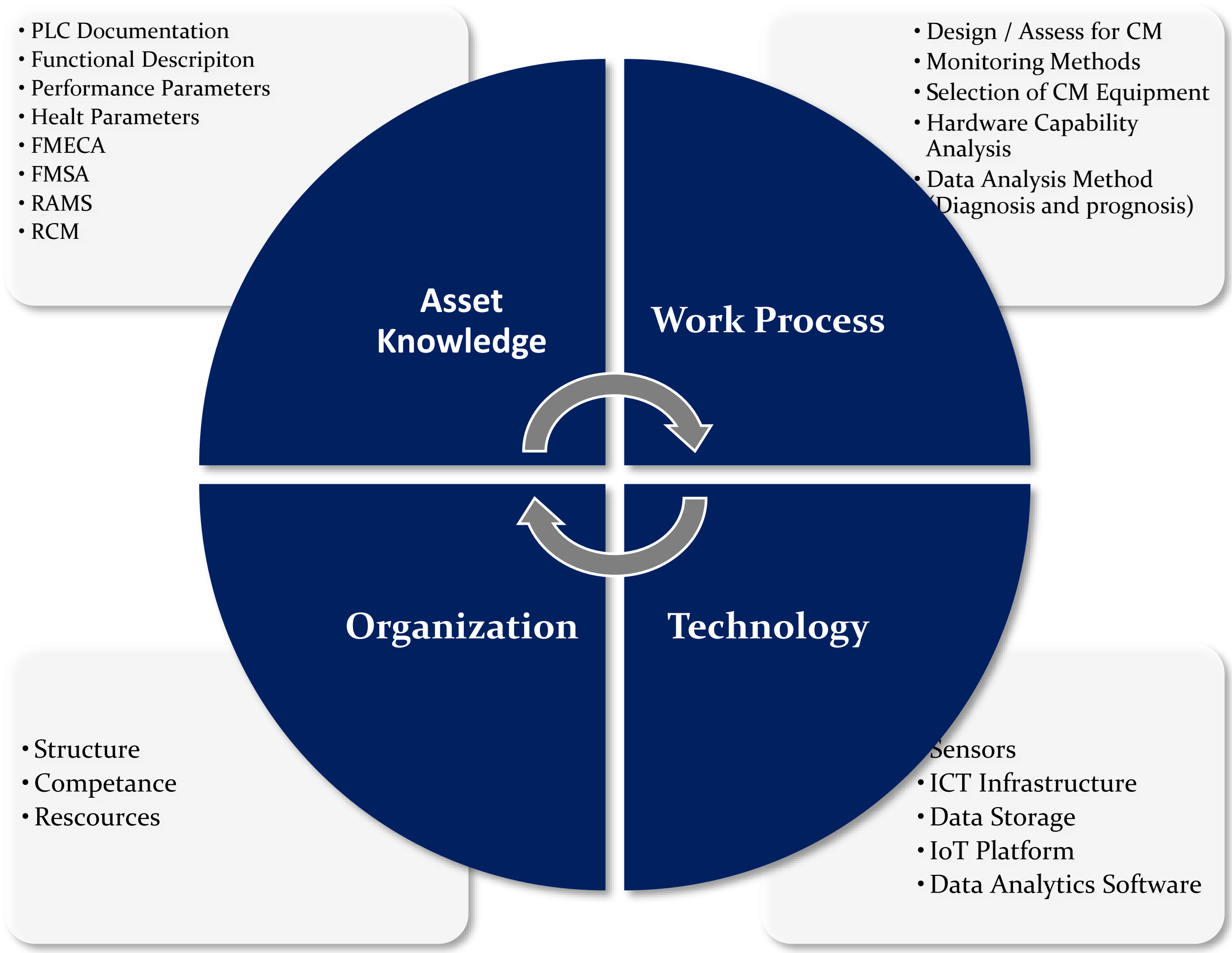

Figure 10 - PdM Framwork [made by writer]

2.3. Industry 4.0

As part of the High-Tech Strategy 2020 Action Plan launched in 2011, the term Industry 4.0 first appeared. This initiative was put forward by the German government to secure German manufacturing industry competitiveness by focusing on technological innovations for the future. [29] Nowadays the term has become widely used where technology and computers are implemented as replacements- or supportive business functions.

Industry 4.0 is a reference to the fourth industrial revolution. To get a deeper understanding of it's meaning we need to look at the history behind the concept. In the late 18th century the first industrial revolution became a reality when mechanical equipment power by water and steam was introduced to the manufacturing industry. This revolutionized the production of goods. The second industrial revolution started at the beginning of the 20th century. Electrification and mass production through moving assembly lines and dedicated workstations accelerated production speeds significantly. From the 1970s electronics and information technology (IT) were introduced which improved the productivity rate due to a higher level of automatization by utilizing computations and calculations. This is known as the third industrial revolution. The fourth industrial revolution is the optimization of the third industrial revolution. Industrialization is now characterized by the integration and interaction of computation capabilities, physical assets, organizational processes, and people in Cyber-Physical Systems (CPS).

In the "*Final report of the Industrie 4.0 working group*" Kagrmann, Wahlster and Helbig (2013) write: "*Industrie 4.0 will deliver greater flexibility and robustness together with the highest quality standards in engineering, planning, manufacturing, operational and logistics processes. It will lead to the emergence of dynamic, real-time optimised, self-organising value chains that can be optimised based on a variety of criteria such as cost, availability and resource consumption."* Such changes are now possible through integration of the virtual world (computers) and the physical world (machines, components, etc.). The recent decades of technology development has made this possible and allows for a much higher degree of control, flexibility, and adaptability than before. Thus, the fourth industrial revolution involves a significant technological change with endless possibilities, elevating industrial processes to the next level. [29]

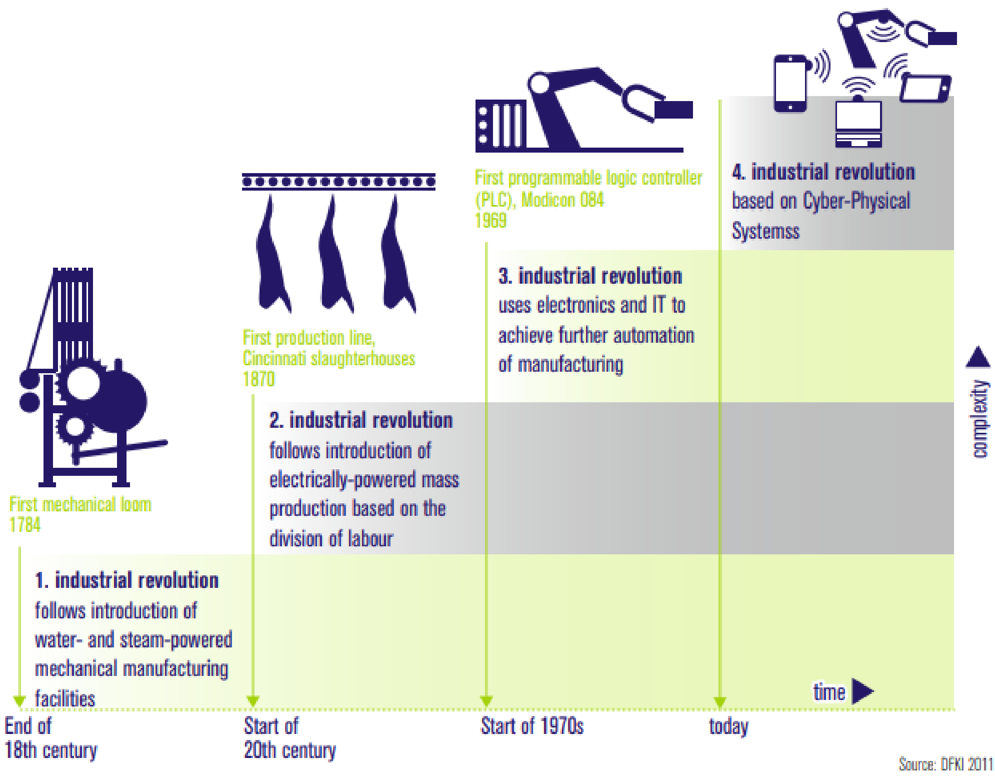

Figure 11 - The four stages of the Industrial Revolution [29]

Erol, Schumacher and Sihn (2016) state that the Industry 4.0 vision propagates on a fundamental paradigm shift in production industries. By implementing emerging technologies within information and communication, IoT and embedded system (ES) smart factories will be integrated into inter-connecting networks of multiple companies. This will allow complete control and real-time information sharing in the entire value-chain, which brings positive effects on business- and engineering processes. In such networks quick and agile response to changes in market demands is possible while focusing on value-adding activities. [30] The information and communication in these end-to-end digitized ecosystems, creates digital "horizontal value-chain" of the normal vertical value-chain. This connection between resourses, processes, information, and communication through the entire value-chain is a realization of real-time manageability. [31]

Cyber Physical Systems (CPS) is a necessity to those who want to achieve interconnection between objects and systems. Lee, Bagheri and Kao (2015) define CPS as *"transformative technologies for managing interconnected systems between its physical assets and computational capabilities."* Furthermore they explain that CPS in general can be split into two attributes: [32]

1. Connectivity to ensure real-time data acquisition from the physical world and information feedback from cyber space.
2. Intelligent data management, analytic tools and computational capabilities to archive desired process outcome.

In other words, CPS monitor, collect, store, and analyze data retrieved from sensors and returns instruction for both physical and digital processes.

2.3.1. Industry 4.0 Technologies

Industry 4.0 has now been introduced with key concepts such as smart factory, CPS and IoT. To enable these concepts several technologies are applicable and have been discussed in various industry outlooks, but with certain inconsistency. Whereas the Boston Consulting Group talk about nine transformative technologies [33], PWC highlight eleven contributing innovations [31], while Deloitte put forward fourteen potential disruptive technologies in the manufacturing industry. [34] Common to them all is that they can be explained by two different collective terms; IoT and Artificial Intelligence (AI). In general, IoT generates data and provides monitoring, while AI uses data to give insight, optimization, and prediction.

2.3.2. IoT devices and Big Data

Internet of Things is a reference to the ad hoc networks of connected devices. The various devices, e.g., sensors, actuators, controllers, RFID tags, smartphones, backend servers, etc., are connected to the internet via unique Internet Protocol (IP) which allows information sharing and communication between devices in a network. [35] These unique networks of devices enable the possibility to cross-function interaction and collaborate to reach a common goal. [36]

According to the Cisco Annual Internet Report (2020) devices connected to IP networks will consist of 29,3 billion devices in 2023, where 14,7 billion are machine to machine (M2M) connections. M2M connection (without smartphones) is projected to be the fastest growing category between 2018-2023. [37] The data generated by these devices increases day by day and the more complex the networks, the higher the data production is generated. To bring forth valuable insight from Big Data special methods and technologies are needed due to the vast number of sources, data volume, and complexity of the data. This also lays the foundation for the most used definition of Big Data, the 5 V's: [38]

1. Volume - is related to the enormous size of available data to be stored and process which can be used to create value. The volume is exponentially growing and has no bounds.
2. Velocity - is related to volume and when data volume is exponentially growing, this velocity creates bigger and bigger bases.
3. Variety - is the different forms of available data, which includes structured data, semi-structured data, and unstructured data.
4. Veracity – is related to accuracy, authenticity, and accountability of the data. Is the data meaningful and reliable? Huge volumes can be problematic for verification and inaccurate data may lead to wrong decisions.
5. Value - is the goal with big data analysis. To extract hidden information from datasets and uncover meaningful insights that can add value to processes, organizations, etc.

Initially this definition, or conceptual explanation, was defined by Volume, Velocity and Variety, and Veracity and Value was added later. [39] [40] However, there are many V's described in the realm of big data (three to seven V's) but the most widely accepted V's are mentioned above. Other V's described in the literature are Variability, Visualization [41], Virtual, Volatility and Validity. [38]

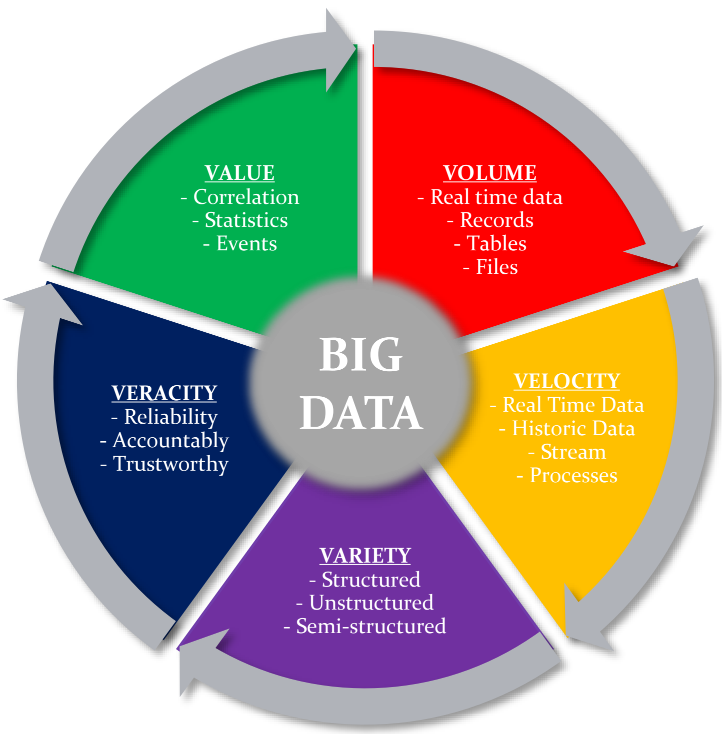

Figure 12 - The 5 V's of Big Data [made by writer]

Data are typically categorized as structured, semi-structured or unstructured which is determined by the source and format. Table 4 is an overview of the various categories, data sources and characteristics. Depending on data format, different analysis tools, methods, and algorithms are used to process datasets.

Table 4 - Overview of Big Data categories [42]

Data Format	Data Source	Characteristics
Structured	➢ Excel files ➢ SQL databases ➢ ERP systems	Exciting data in tables where row and columns are discrete so data can be access separately or jointly together with other databases.
Semi-structured	➢ Sensors ➢ XML[4] ➢ JSON[5]	Semi-structured data is a form of structured data that do not have the formal structure of rows and columns. However, the data contains marks and tags that is self-descriptive structure which reduces its complexity.
Unstructured	➢ Text ➢ Image ➢ Video ➢ Audio	Unstructured data does not have predefined models and is not organized in a predefined matter. This "fuzziness" makes it difficult to analyze and requires specific technologies and tools to extract relevant information.
Meta	➢ Data about data	This is not a separate data format but provides additional information about specific datasets, e.g. time and date stamps, location, origin, and size. In big data mate data is important when analyzing huge datasets.

[4] XML is a markup language to describe, store and transport data between information systems. The format organizes information hierarchically where marks and tags provide its contents (text, numbers, tables, etc.). [67]
[5] JSON is a formation language to transport textual documents for data interchange. [66]

2.3.3. IoT Architecture

To fully exploit the potential of IoT devices and the generated data, a unique scheme of data flow is necessary. Systems architecture is a well described strategy in the literature to implement IoT technologies in a structured way. IoT architecture is a process description divided into layers to provide a logical path from data origin to application with means to create value. Lee, Bagheri and Kao (2015) suggest the 5C CSP architecture (Connection, Conversion, Cyber, Cognition and Configuration) as a framework for deploying data in a structured manner. [32] However, according to Trappey et al. (2016), there is as many as nine layers described in the literature (five to nine). After their evaluation they purpose a four-layer architecture of perception, transmission, computation, and application. They argue that these four layers are best suited in industrial application. [43]

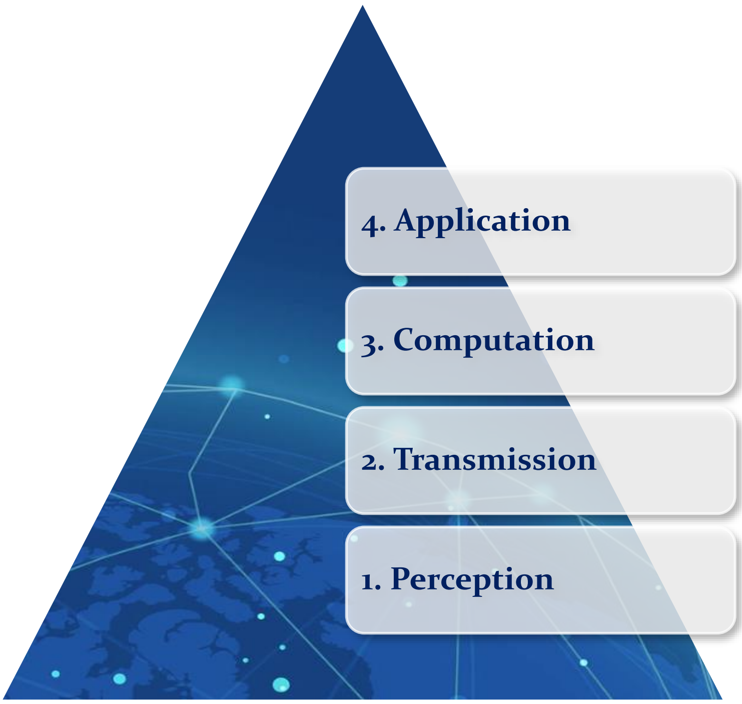

Figure 13 - IoT Architecture [43]

1. The perception layer is where sensors, actuators, controls, and RFID tags (IoT devices) give an object "intelligence" by perceiving its health, location, response, etc. Perception is the foundation to provide micro intelligence to the application layer. From an industrial perspective, sensors send signals to detect changes in quantities, qualities, and events. Typical sensors are temperature, pressure, flowmeters, vibrations, acceleration, motion, humidity, gas detection and location. The goal of the outputs is to enable an objective measure of an asset's health and performance.

2. The transmission layer is where sensor output is transformed into meaningful information for further evaluation. E.g. data acquisition where analog signals from sensors are transformed into digital signals which are readable and possible to analyze. The connection between IoT devices signal transmission can be wired or wireless.
3. The Computation layer is where digital information is received, stored, cleaned, and analyzed as decision support to the Application layer.
4. The application layer is where processed information from lower layers provides insight which allows more accurate decision making to optimize value.

The computational layer is where all available information is collected and analyzed, and includes hardware, software, algorithms, cloud platforms and encryptions. [43] It is a complex and important stage in the architecture where input-signal from IoT-devices is essentially transformed into meaningful information for better decision-making.

2.3.4. Artificial Intelligence

The enormous amount of data generated by IoT devices makes it difficult to store, process and analyze though traditional database technologies. Big Data is multi-source, heterogeneous and real-time which becomes available throughout a product’s life cycle and creates "lakes" of information of various format, structure, and quality.

Data in such a "vacuum" is worthless, but the potential value of evidence-based decision making from "hidden" information must not be underestimated. [44] To process and analyze such complex and exponentially increasing datasets Artificial Intelligence (AI) is needed. According to Umbel, approximately 44 zettabytes of data will exist in 2020 and humans have limited expertise, patience, and time to processes all the relevant data. [45]. With the enormous volume of available information, computers outperform humans' abilities to process and analyze Big Data, and AI is the tool that makes this possible.

As a general term AI includes all intelligent systems and associated technologies that provide computers with the ability to learn, reason and predict. It is considered a special field combining data science, logic, mathematics, psychology, and neuroscience. AI can be divided into two types: 1 - rule based models, and 2 - data driven models. Rule based models are task driven, meaning that they are programmed to solve specific problems through a rule-based system. These intelligent systems are made of algorithms where each algorithm is a precise and complete description of a specific process which instructs computers what do next with specific rules (e.g. "if", "then", "and", "or", "not", etc.). In data driven models, known as

Machine Learning (ML), the models are programmed to learn from inputs and generate new algorithms and new rules to improve the output. [46] The logic of these systems makes them very flexible and allows multiple algorithms to connect. Such systems can screen complex datasets for irregularities, specific values, patterns, correlation, or statistics and extract meaningful information. The most advanced model of AI is known as Deep Learning and is an imitation of neural networks inspired by the human brain. [47]

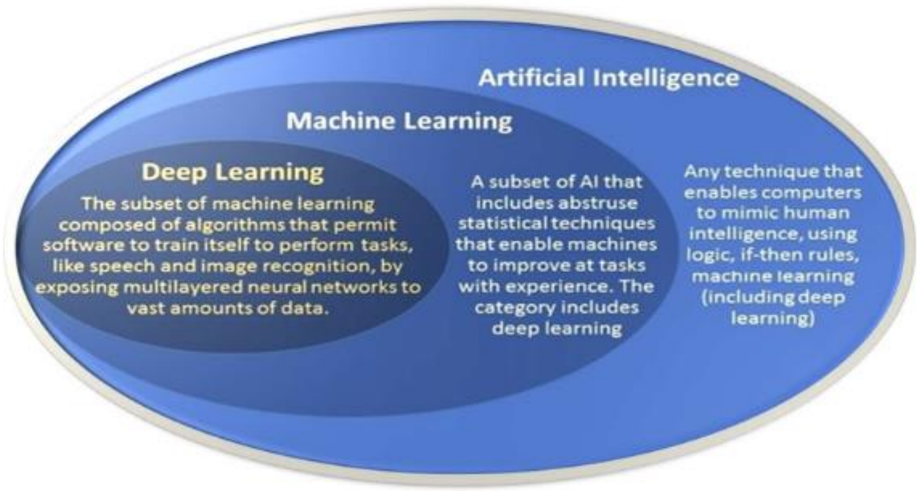

Figure 14 - Relationship between AI, ML and DL [48]

West (2018) states that AI refers to *" machines that respond to stimulation consistent with traditional responses from humans, given the human capacity for contemplation, judgment, and intention"*. In other words, the intelligence in AI is artificial, programmed by humans to perform human activity with the ability to sense, reason, plan, interact, perform, and learn. Furthermore West (2018) describes three essential qualities of AI systems: [49]

1. Intentionality - AI systems are designed by humans with an intention to make a decision based on historical data, real-time data or both. Unlike systems with predetermined responses, AI combines information from different sources, instantly analyzes the data and acts based on insight from the data.
2. Intelligence - AI systems often have incorporated Machine Learning (ML) and data analytics, which enable intelligent decision-making. ML screens data for underlying patterns, trends and correlations and learns to recognize unique features, which can then be used to solve practical problems.

3. Adaptability (automation) - AI's ability to learn and adapt is the incorporation of experience, history, and real-time data to adjust according changes in conditions, circumstances, or environment. By integrating external information machines can learn from other machines' experiences, and through real-time sensing, this knowledge can be used to adjust accordingly.

An important aspect of AI is how a system can learn and then self-improve and ML is where statistics are used to train an algorithm instead of programming an algorithm. Essentially this means that algorithms generate new algorithms. By giving an algorithm an instruction to learn, and not step-by-step instructions to solve, new rules are made based on data inference from "training sets". [50] By feeding the algorithm with labeled data (i.e. "training set") and then testing the algorithm by examining a "test set", one can verify if the algorithm has learned to recognize trends, patterns, correlations, etc. in order to suggest a solution and not just memorized information. [51] Mitchell's (1997) definition of ML captures the essence of this explanation in a simple, intuitive matter. He defines ML as *"a computer program is said to learn from experience E with respect to some class of task T and performance measure P, if its performance at task in T, as measured by P, improves with experience E*". [52] Several definitions exist and have been reviewed [53] [54], however, Mitchell's definition is precise and widely used in the literature.

ML algorithms are typically grouped into three main categories: 1 - supervised learning, 2 - unsupervised learning, and 3 - reinforced learning. [55] [56] In addition, there is semi-supervised learning. This technique uses a combination of supervised and unsupervised learning techniques to train models. [57] Unsupervised learning is still a challenge to achieve, but according to Ruder (2018) researchers have made a lot of progress in this area by combining supervised and unsupervised learning. [58] Table 5 is an overview the different ML categories and supplementary information.

Table 5 - Machine Learning categories, applications and characteristics [55] [56] [57] [58] [59] [60]

Category	Technique	Applications	Characteristics
Supervised learning	Task/Rule driven	➢ Classification ➢ Regression	The algorithm creates an unknown function knowing that inputs predict the output. By feeding the algorithm with example-label pairs (training sets with correct target value), the algorithm can predict an output and be given feedback if the answer was right or wrong. Over time the algorithm approximations will improve.
Unsupervised learning	Data driven	➢ Clustering ➢ Dimensionality Reduction ➢ Finding Association Rules ➢ Anomaly Detection	With unlabeled data without input/output relations, the algorithm is feed with "training sets" to understand different data properties, patterns, trends, etc. The algorithm can then categorize, organized, and structure the data for further analysis.
Semi-Supervised learning	Task/Rule and data driven	➢ Semi-classification ➢ Semi-Regression ➢ Semi-Clustering ➢ Nonlinear Dimensionality Reduction	As the name implies, semi-supervised learning uses both labeled and unlabeled data. Small data sets with labels are used to train the model to produced proxy labels on unlabeled data, which in tuned are used as targets for further learning. Essentially the model is given a set of constraints to modify or reprioritize the unlabeled data based on labeled data.
Reinforced learning	Learn from mistakes	➢ Game Theory ➢ Simulation ➢ Automation ➢ Resource Management	In cases with several solutions to desired target the algorithm will be reinforced by getting positive feedback with "good behavior" (i.e. improvement of performance) and negative feedback with "bad behavior". In problems without specification on how to solve a problem, these types of algorithms are well suited.

3. Methodology

In the previous section operation- and maintenance management theory has been presented along with the vison of Industry 4.0 and its enabling technologies. The review has outlined the essence of operation- and maintenance management, which is the optimization of production whilst minimizing the risk of unplanned shutdowns. The explanation of Industry 4.0 shows how far certain technologies have come by allowing much improved insights in huge datasets.

3.1. Qualitative Method

The methodology used in this thesis is a qualitative research method where data, mainly in text format, is collected and analyzed. Qualitative data is typically descriptions of observations, research (e.g. papers, focus group methodology, etc.) and unstructured interviews. Furthermore a content analysis is performed on selected information to detect common characteristics, patterns, and concept equality. The goal is to get in-depth knowledge of a subject to formulate hypotheses, theories or formulate generalities theories. [61]

3.2. Data collection and Arguments

The information gathering process was divided into two search groups: operation- and maintenance management and Industry 4.0 and enabling technologies. Information was collected mainly from course curriculum at the University of Stavanger, Oria and Google Scholar, but Google's search engine was also used when it was necessary to gain a broader understanding on a subject. The information stretches from unstructured interviews / discussions, academic literature, research papers, journals, presentations, and internet databases.

1. The first step was to understand how and on what foundation organizations assess their ability to perform data analysis. MBS was selected as the benchmark, focusing on the Analyses Module, as this self-assessment methodology is widely used in the offshore O&G industry today.
2. Step two was to provide a theoretical understanding of operations- and maintenance (O&M) theory and highlight its development over the last 60-80 years. This is important to understand O&M's increasing business impact and how technological development has improved business objectives. The literature used to describe this development comes from course curriculum in OFF510 Operations and Maintenance Management, and OFF540 Condition Monitoring and Management at the University of Stavanger.

3. Step three was to understand the vision of Industry 4.0 and its enabling technology. The idea was to create an understanding of the potential within Industry 4.0 so that available technologies could be matched with O&M theory to improve business objectives. The search for information started with the "*Final report of the Industrie 4.0 working group industry*" [29] and industry outlooks from the Boston Consulting Group [33], PWC [31] and Deloitte [34] [31]which introduced Industry 4.0 as a term, enabling technologies and digital enterprises. These papers led to further knowledge seeking within IoT devices and architecture, Big Data and AI to understand its basics and how their capabilities could be used to fill the gap between current PdM analytic methods and AI driven analytics.
4. The fourth stage was model development following the structure pictured in Figure 16 with the help of an adaptive method for system design proposed by D.M. Buede (2016) [62]. System requirements are derived based on stakeholders needs, functionality and thesis objective. These are then viewed in the context of theory in section 2 Theoretical Background to formulate applicable questions to develop an updated version of the Analyses Module in MBS.
5. The fifth stage was to get feedback from industry experts as validation. This was performed in three interactions so the model could be updated according inputs and needs. The feedback was a combination of mail correspondence, discussions, and unstructured interviews.

Steps 4 and 5 were performed in iterations following the steps in Figure 15. As a measure to ensure a systematic process, the new self-assessment model was evaluated after each update to discover any areas of improvement.

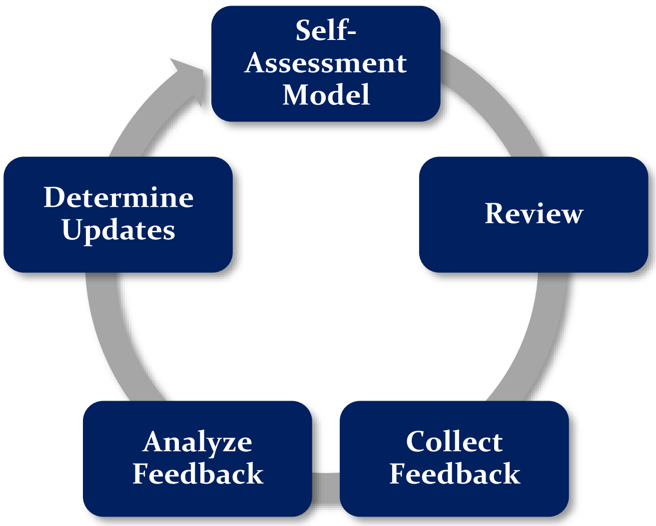

Figure 15 - Research iteration process [made by writer]

3.3. Development

In terms of development methodology the thesis was divided into three phases. The initial phase (steps 1-3) was conducted to create a complete understanding of the Analyses Module in the MBS, O&M management, and Industry 4.0. To gain knowledge and understand the core of relevant domain(s) is essential when developing a tool that is applicable to assessing a company's readiness to implement AI analytics.

The second phase (step 4), Model Development, was performed using the Creative Research Systems five-stage framework depicted in Figure 16. [63] First one needs to determine a goal and what they want to learn. With Objective as a basis, a system-of-system (SOS) chart was used to place these objectives in an industrial context to reduce complexity and determine scope boundaries. Secondly, when the scope constraints were complete, a stakeholder analysis was performed. Looking at the operations- and maintenance life cycle phase, stakeholders were identified, and their key objective was highlighted. Furthermore, key stakeholders were analyzed to illuminate their needs, requirements, and criterions for fulfilled needs. The next task was to find a suitable platform where the self-assessment could be performed. Functional requirements were derived through a model breakdown structure from user(s) and developer perspectives. The goal was to determine a set of achievable criterions, which would secure user(s) and developer requirements related to overall objective, effectiveness, availability, cost, etc. Multiple concepts were discussed and reviewed. Using derived criterions, potential concepts were evaluated and ranked (worse, equal, better) against the current solution (i.e. MBS) using a scoring matrix method. To verify outcome, this task was repeated, but this time each criterion was given a weighting depending on its impact. When stakeholders' requirements and functional requirements were in place, the fourth task was to determine what to ask. The questionnaire was structured to follow a generic IoT architecture, and questions were derived by combining predictive maintenance (i.e. PdM framework) and ISOs condition monitoring and diagnostics design cycle. This combination provided a logical structure of how asset knowledge should be utilized to develop an automated diagnostic- and prognostics system. In addition, questions related to Industry 4.0 and enabling technology were introduced to explore if relevant technologies and mindsets were already present.

The third phase was validation (step 5) where industry experts were addressed to provide feedback on the new self-assessment model. Companies in the vertical- and horizontal O&G value chain were contacted to get a broad feedback perspective. The iterative process of industry review and model updates was performed to verify the updated self-assessment model.

4. Model Development

To deliver on the thesis objective an updated version of the Analyses Module in MBS shall be developed with focus on PdM strategy where intelligent analytics (i.e. AI and ML algorithms) are used as supporting technology. By carefully constructing a self-assessment model based on the PdM framework and state-of-the-art technology, the questionnaire findings can highlight internal strengths and weaknesses, and external opportunities and threats within a company. Such a self-assessment model exists in different formats to assist manufacturing companies planning their digital transition, but not specifically for intelligent analytics related to maintenance activities. By helping the assessor(s) to map the status quo, this information can be used to develop a strategy so that the merging of O&M management and Industry 4.0 can start.

Questionnaires are a great method for information gathering and by getting feedback from relevant stakeholders the information can be analyzed and serve as a foundation for decision-making. However, to collect reliable information it is important to design the questionnaire properly and avoid misinterpretations leading to unreliable results. Creative Research Systems five-stage design process is a systematic approach where important tasks in each stage are discussed in order to develop a successful questionnaire. Stages 1-4 should start by answering one simple question as a starting point to successfully construct a survey that will assist in meeting research goals. The last stage is to validate the questionnaire before release so that any misinterpretations and pitfalls can be avoided. The five stages are depicted in Figure 16. [63]

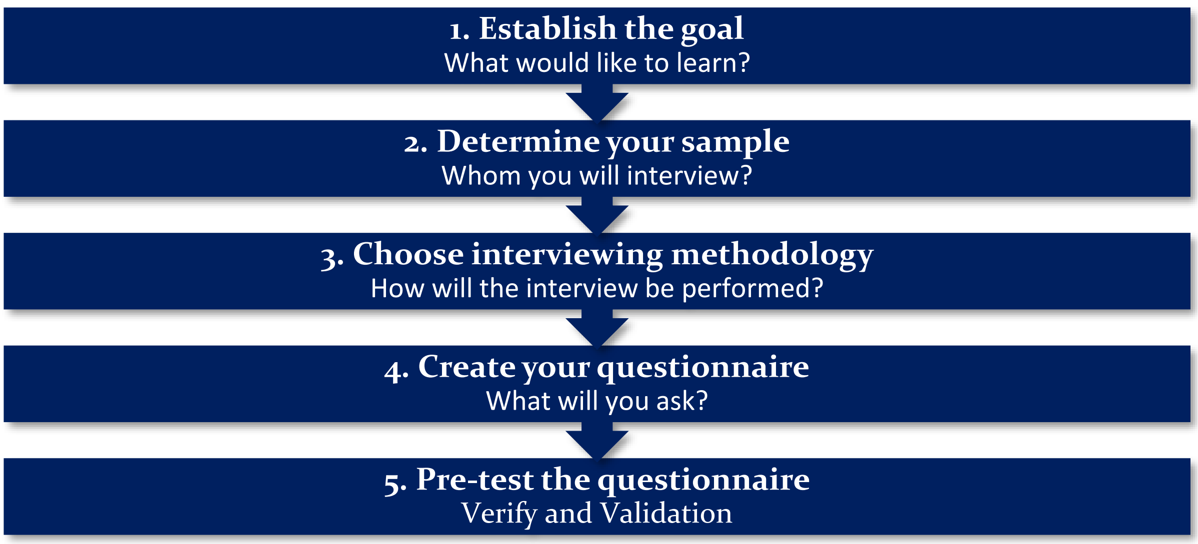

Figure 16 - Five-stage questionnaire design process [made by writer]

To perform each stage in the above process, the requirements need to be established. Requirements are the cornerstones and foundation for all system engineering processes and are essential for understanding the system context, its stakeholders and how to meet their needs. To fully exploit a simple idea for improvement and derive a solution, the requirements need to be viewed and assessed hierarchically starting with the mission requirement (goal), followed by stakeholder requirements (whom to interview), system requirements (how to perform the interview), component requirements and configuration item requirements. Component- and configuration items are not applicable in this project. Instead, questionnaire requirements, based on stakeholder needs and theory review, will be the lowest "hierarchy level" in this development process. These different aspects and requirements can then be evaluated, sorted, and prioritized to design a new solution that will meet all stakeholders' needs. The following attributes provide a decision-rich design basis to ensure that the development process is not over-constrained, but at the same time focuses on helping stakeholders to serve their purpose. [62]

Figure 17 - Modified system requirements hierarchies [63]

4.1. Mission Requirements

To establish a goal, you need to know what you want to learn. The goal of the questionnaire needs to be clear and will determine who you should ask and what to ask them. [63]

What would like to learn?

Mission requirements are related to the objectives of system stakeholders and are defined and constrained in a context called system-of-system (SOS). SOS helps to separate passive and active stakeholders to one system within the SOS by creating boundaries and reducing complexity. The outcome is a manageable scope for further development. Furthermore, SOS highlights the primary objective and how each meta-system will influence each other's system requirements. [62]

For example, offshore O&G production is essentially the extraction of raw material for energy production which is distributed to consumers. To achieve a steady supply of raw materials (e.g. oil and gas) maintenance is an important function of offshore production. However, maintenance and its stakeholders (active) have no interaction with the distribution organizations and their stakeholders (passive). With that said, both are important contributors within in the same SOS due to their necessity in the energy supply chain.

Figure 18 is the illustration and breakdown of the SOS chart and how the MBS Analyses Module can be understood as part of a more extensive system from energy distribution to maintenance activities. This chart also represents the scope boundaries of this thesis.

4.1.1. The Goal

With reference to section 1.2 Problem presentation, 1.3 Objective and the SOS breakdown, the goal for this thesis is to develop an easy to use, accessible and up-to-date self-assessment model to allow companies to assess their readiness to implement intelligent analytics tools (i.e. AI / ML algorithms) related to PdM so asset availability and reliability can be improved while reducing operational risk.

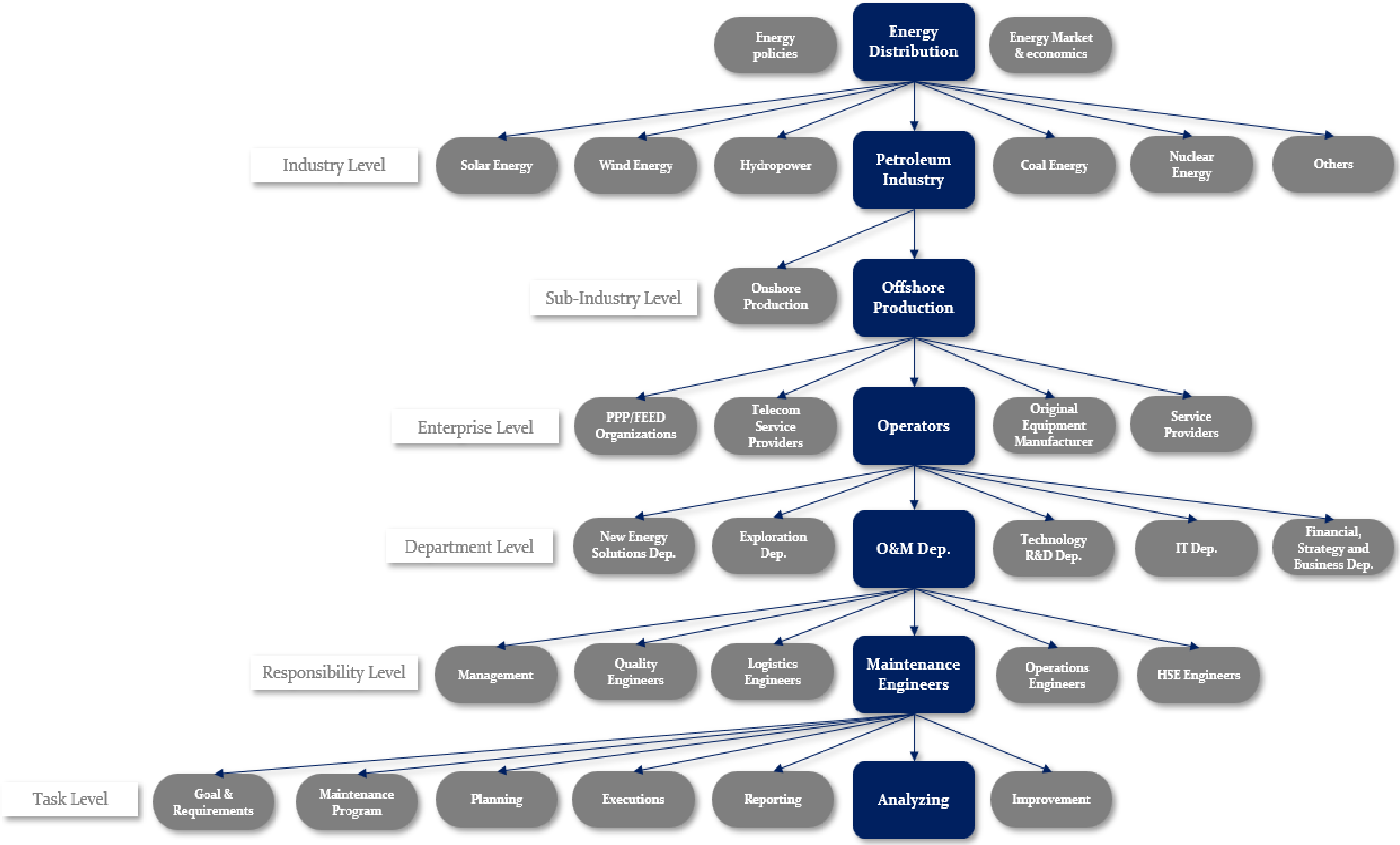

Figure 18 - System-of-System chart [made by writer]

4.2. Stakeholder Requirements

To reach a goal the relevant population, i.e. target group, needs to be determined. The population should be selected based on the goals and stakeholders you believe will help in reaching your goal. [63]

Whom you will interview?

When assessing key stakeholders in a system it is important to look at the entire life cycle process of the system or product. Each phase in the life cycle will have multiple stakeholders where some are limited to one phase, while others are involved in multiple phases. The PLC process can in general be divided into seven phases:

1. Research and Development (R&D)
2. Manufacturing
3. Procurement and Supply
4. Installation
5. Operation and Maintenance
6. Updates
7. Disposal

Figure 19 - Stakeholders in Operation and Maintenance life cycle phase [made by writer]

This stakeholder analysis is limited to phase 5. Operation and Maintenance focusing on Management, Operations Engineers, Maintenance Engineers, and HES Engineers which are the natural key stakeholders that should be addressed for a self-assessment model in this context.

Table 6 lists key stakeholders needs, requirements and criteria to fulfill their needs. If we view these needs in conjunction with section 2.2.4 Predictive Maintenance and the potential within AI and ML analytics as discussed in 2.3.4 Artificial Intelligence, available technology has the potential to meet several of these needs by improving decision foundation to the criterions.

1. Early detection of potential failures (diagnosis)
2. Better predictability of RUL (prognosis)

3. Better understanding of maintainable items (components), dependability and failure correlation (work order and planning)
4. More reliable production
5. Increased HSEQ

Table 6 - Needs, Requirements and Criteria of O&M key stakeholders [made by writer]

Stakeholder	Needs	Requirements	Criteria
O&M Management	Stable production while ensuring HSEQ and that all involving party's follow establish procedures and best practice guidelines.	➢ Regulations ➢ Stable, reliable, and predictable work process.	➢ HSEQ ➢ Cost Efficient ➢ Measurable
Operations Engineers	Close collaboration with Maintenance Engineers. Information about asset function, limitations, and operations parameters to secure safe and reliable operations in compliance with governmental, industrial, and internal regulations.	➢ Procedures ➢ Best Practices Guidelines ➢ Continuous Improvements	➢ Communication ➢ Reliability ➢ Predictability
Maintenance Engineers	Close collaboration with Operations Engineers. Information about asset function, failure modes, symptoms, effects, and criticality to secure safe and reliable operations in compliance with governmental, industrial, and internal regulations.	➢ Asset Condition ➢ PLC documentation ➢ FMECA ➢ FMSA ➢ Analyses Tools	➢ Communication ➢ Detailed Information ➢ Reliable Analytics ➢ Dependencies between maintainable items (i.e. components)
HES Engineers	Close collaboration with Operations- and Maintenance Engineers to ensure the health and safety of personnel and minimize environmental damage.	➢ Risk mitigation	➢ Communication ➢ Risk mitigation ➢ Task prioritization

4.3. System Requirements

There are several methods to perform an interview, e.g. personal, telephone, mail, on-line, etc, and they all have both advantages and disadvantages. Choosing the right interview methodology needs to be considered together with the target group and how to reach them. [63]

How will the interview be performed?

In this section, possible platforms for the self-assessment model were assessed and reviewed based on derived functionality requirements. There are several platforms and programs available to build a survey with desired features and each platform needs to be evaluated based upon functional requirements and fit for purpose. Three different platforms have been selected for further evaluation and in this section the best alternative is found.

4.3.1. Functional Requirements

When developing a self-assessment model there is a need to find a platform where the assessment shall be conducted and delivered according to user expectations. User requirements and developers' limitations need to be considered to build a functional self-assessment model which takes these constraints into account. In this evaluation, users and developers are the only stakeholders and a requirements analysis is performed on this basis. The goal is to find the best fit between user demands and the self-assessment method when developing a new interface.

The MBS is not particular user-friendly, and the Analyses Module is outdated in terms of involving "state-of-the-art" tools to improve analysis quality. There are few questions, they are general and do not cover the PdM framework sufficiently enough to assess PdM readiness or areas for improvement to implement AI / ML analytics. Thus, the questions shall be formulated more clearly and relate to the PdM framework. The amount of questions shall be considered to avoid duplications and unnecessary work. Furthermore, answer alternatives shall be formulated to improve usability and assessment time. Figure 20 illustrates the functional breakdown structure based on user- and developer functionality requirements and criterions.

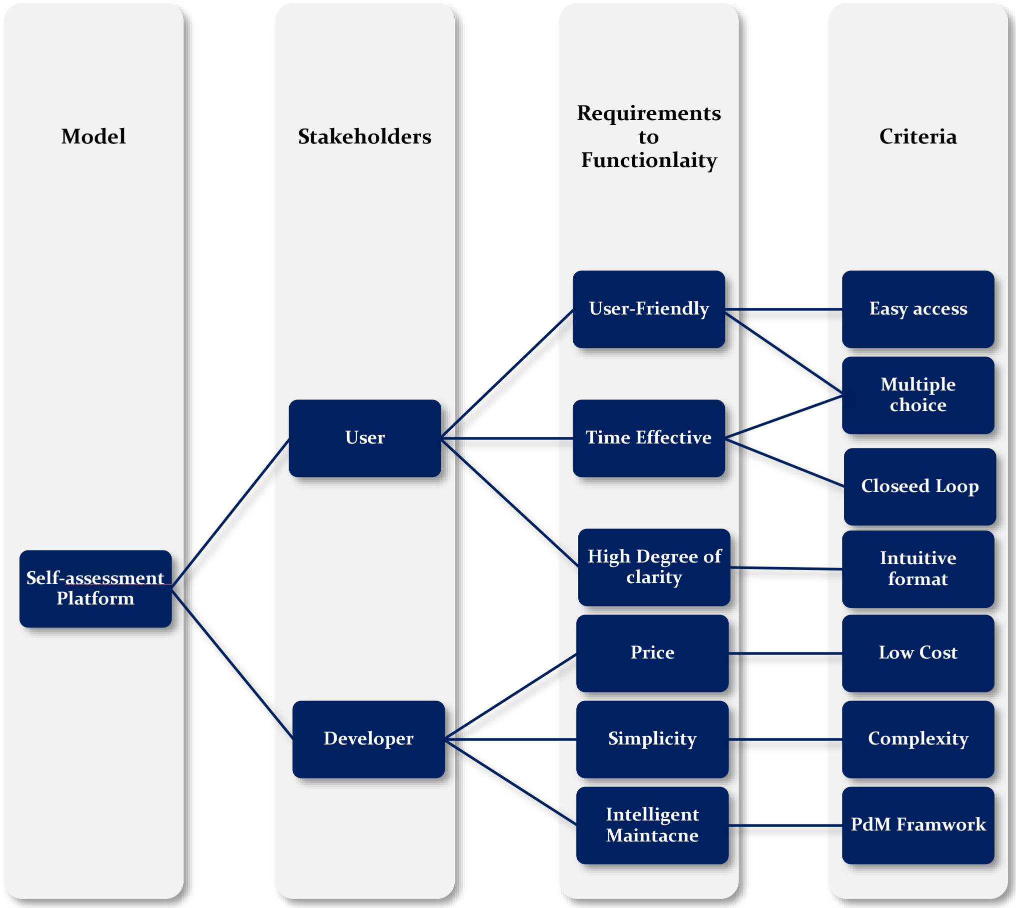

Figure 20 - Functional requirements breakdown structure and criteria [made by writer]

4.3.2. Conceptual Platforms

Three generated platforms for further evaluation was selected:

1. Software-based survey - A software-based tool for surveys gives high flexibility and is offered in an entire range of simple desktop applications to complex systems for development. It is possible to create attractive surveys resulting in intuitive and visual questionnaires that are easy to use. Several analysis functions are possible to program to autogenerate reports, statistics, etc.
2. Online Survey - An online survey is an accessible survey available on a webpage where data are collected through questions. Web-based surveys are very easy to program and to create an inviting appearance and intuitive layouts. The programming is flexible, and surveys can be made using any device (e.g. PC, mobile phone, etc.) connected to the internet. Several analysis functions are possible and performed based on answers. Additionally, these online survey services are often free.

3. Computer program - A self-assessment computer program is possible to develop and can provide high flexibility, detailed formats, and complex analytics. This type of survey can create the most optimal solution in terms of functionality, but they are expensive and have reduced accessibility.

With the use of derived requirements in section 4.1 Mission Requirements and focusing on platform criteria from Figure 20 a Pugh Matrix is used to apply criteria to each conceptual solution for evaluation. A Pugh Matrix is a criteria-based decision support tool where each criterion is given a score to determine which of several potential solutions should be selected. Each criterion in each possible solution is then compared with the baseline (MBS), resulting in three potential different scores: (-) refers to "worse than baseline", (0) refers to "about the same" and (+) refers to "better than baseline". The net score for each potential solution is summed and the solution with the highest score is the best option. [64]

Table 7 is an overview of the matrix where conceptual platforms are tested with derived criteria. Here the online alternative achieved the highest score, meaning that this is the best alternative.

Table 7 - Pugh matrix for conceptual decision making [made by writer]

	MBS	Conceptual Platforms		
Criteria	**Baseline**	**Software**	**Online**	**Computer**
• Easy Access	0	-	+	0
• Multiple Choice	0	+	+	+
• Closed Loop	0	+	+	+
• Intuitive format	0	+	+	+
• Cost	0	+	+	-
• Complexity	0	0	0	-
• PdM Framework	0	+	+	+
-		-1	0	-2
0		1	1	1
+		5	6	4
Total Score	0	4	6	2

(-) refers to "Worse than Baseline"
(0) refers to "About the same"
(+) refers to "Better than Baseline"

The development of the criteria list is an important first stage when using a Pugh Matrix as decision tool. To enhance, or verify the result, it is possible to rank each criterion by assigning a weight of their importance. The more important, the higher score. Depending on the number of criterions and their significance to project deliverables, the weighting can result in a different result without criterion ranking. The first stage of weighting is to determine a scale. The second stage is to give each criterion a weight and lastly each score in a potential solution is multiplied by the criterion weight. (ibid)

As a weighting scale (Table 8), it was decided to use Low, Medium, and High with weight values of 1, 2 and 3, respectively. Ranking of criteria was determined based on their impact on model development, and importance of thesis objective. Table 9 shows the weighted Pugh Matrix and once again the online-based alternative got the highest score.

Table 8 - Weight scale [made by writer]

Importance	Weight
• Low	1
• Medium	2
• High	3

Table 9 - Weighted Pugh matrix for conceptual decision making [made by writer]

	MBS		Conceptual Platforms		
Criteria	**Baseline**	**Weight**	**Software**	**Online**	**Computer**
• Easy Access	0	3	-3	+3	0
• Multiple Choice	0	2	+2	+2	+2
• Closed Loop	0	2	+2	+2	+2
• Intuitive format	0	2	+2	+2	+2
• Cost	0	3	+3	+3	-3
• Complexity	0	3	0	0	-3
• PdM Framework	0	3	+3	+3	+3
-			-3	0	-6
0			3	3	3
+			12	15	9
Total Score	0		9	15	3

(-) refers to "Worse than Baseline"
(0) refers to "About the same"
(+) refers to "Better than Baseline"

4.3.3. Platform Selection

Online survey tools are popular due to their accessibility, scalability, and ease of data collection. This is also the reason why there are so many different suppliers of online survey platforms. However, most suppliers have feature restrictions in their free version and will therefore not be considered. [65] After the initial screening three options stood out:

1. SoGoSurvey
2. Google Forms
3. Typeform

Of these tools it was decided to select Google's solution "Google Forms". This is the solution that offers the most in terms of adaptability, flexibility, and features. "Google Forms" have no limitations on size, questions, polls, etc. and they store all answers and data automatically in a Google Spreadsheet. In addition, the questionnaire is accessible and possible to perform on any device (e.g. PC, mobile phone, iPad, etc.) connected to the internet.

4.4. Questionnaire Requirements

A questionnaire should be short, simple and to the point, meaning that the questions are relevant to your goal and provide you with necessary information. [63]

What will you ask?

To fully exploit the opportunities condition monitoring and AI could provide in PdM, several steps need to be considered through the entire PLC. This is reflected in the questionnaire as information from R&D could significantly impact the feasibility of selecting and installing condition monitoring equipment which will eventually impact the possibility of introducing AI / ML algorithms to analyze aggregated data.

The questionnaire is constructed with the idea to evaluate the assessor(s) company's current procedures on asset knowledge, selection of condition monitoring equipment, data processing, and existing information and communication (ICT) infrastructure. This will allow the assessor(s) to discover internal strengths and weaknesses, and external opportunities and challenges that are necessary for building a condition monitoring system and associated AI / ML algorithm. An implementation strategy can then be prepared to secure optimal equipment for all assets and automatic data processing.

The focus in this thesis is the operation phase, meaning that asset R&D, manufacturing, procurement, and installation are performed. This leads to several assumptions which will apply to both the asset and the company. All assumptions are listed below, and additional assumptions are mentioned at the beginning of each section, where necessary.

Assumption(s):

1. The assessor(s) company has mechanical assets such as turbines, compressors, pumps, motors, gearboxes, etc. where CM equipment is installed or possible to install.
2. The assessor(s) company has a goal, or desire, to implement PdM.
3. The assessor(s) company sees maintenance as a core supportive operational function.
4. The assessor(s) company sees the potential within AI and ML to analyze data.
5. The assessor(s) company has a long-term strategy in the vision of Industry 4.0.

4.4.1. Model Building Blocks and Use Case Diagram

Questions are derived in the context of the PdM framework, CM and diagnostics design cycle and IoT Architecture described in 2.2.4 Predictive Maintenance and in 2.3.3 IoT Architecture, respectively. The goal is to evaluate state-of-the-art practices and the derived questions which follow the natural structure of the IoT reference architecture demonstrated in Figure 13. Additionally, the questionnaire is developed based on the PdM framework (i.e. work process, asset knowledge and technology) and IOS's CM and diagnostics design cycle to highlight the necessity of preparatory studies, their goal, and how these findings are realized. Figure 21 depicts the connection between the strategy (i.e. PdM), design models (i.e. ISO) and IoT reference architecture.

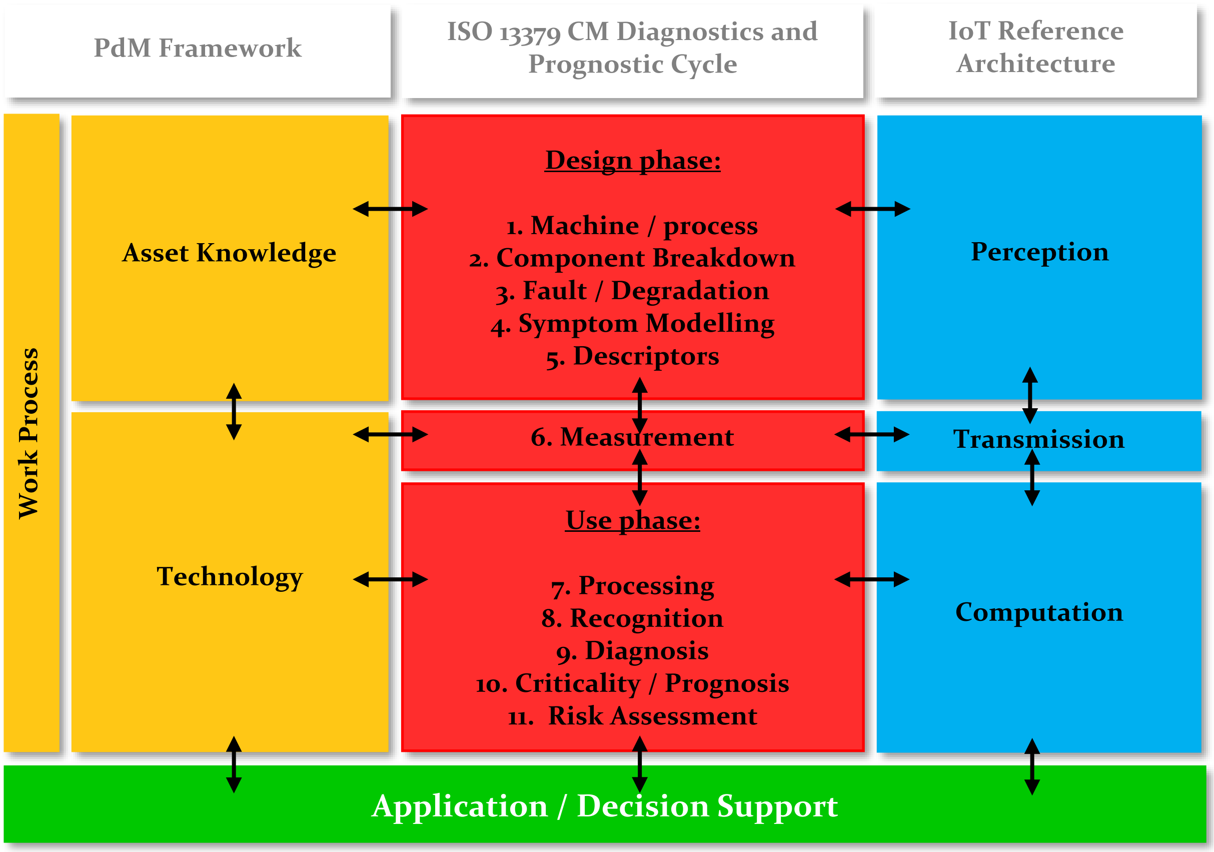

Figure 21 - PdM framework, IOS's CM and diagnostics design cycle and IoT architecture [made by writer]

In addition, Figure 22 describes a potential use-case scenario of how an AI / ML analytics system could operate from data origin (asset) to visualization of decision support. When one or several descriptions are defined as evaluation parameters, appropriate sensors are selected to measure these parameters. The signals from sensors are then transformed from analog to digital. The digital signal is stored in a historical database before further processing. From the historical database the data are sent to three different phases:

1. Risk involved with the asset is sent for integration with the visualization of analysis conclusion.
2. Live data is sent for screening to look for patterns, correlations, or other statistical findings of interest. These findings are then sent back to the database as labeled data to the AI/ML algorithm.
3. Historical labeled data are sent for data integration where live data are compared with historical data.

After data integration the diagnostic and prognostic analysis is performed before the results are presented in a self-evident matter. The results from the analysis will also be sent back to the database as labeled data to improve AI / ML algorithms.

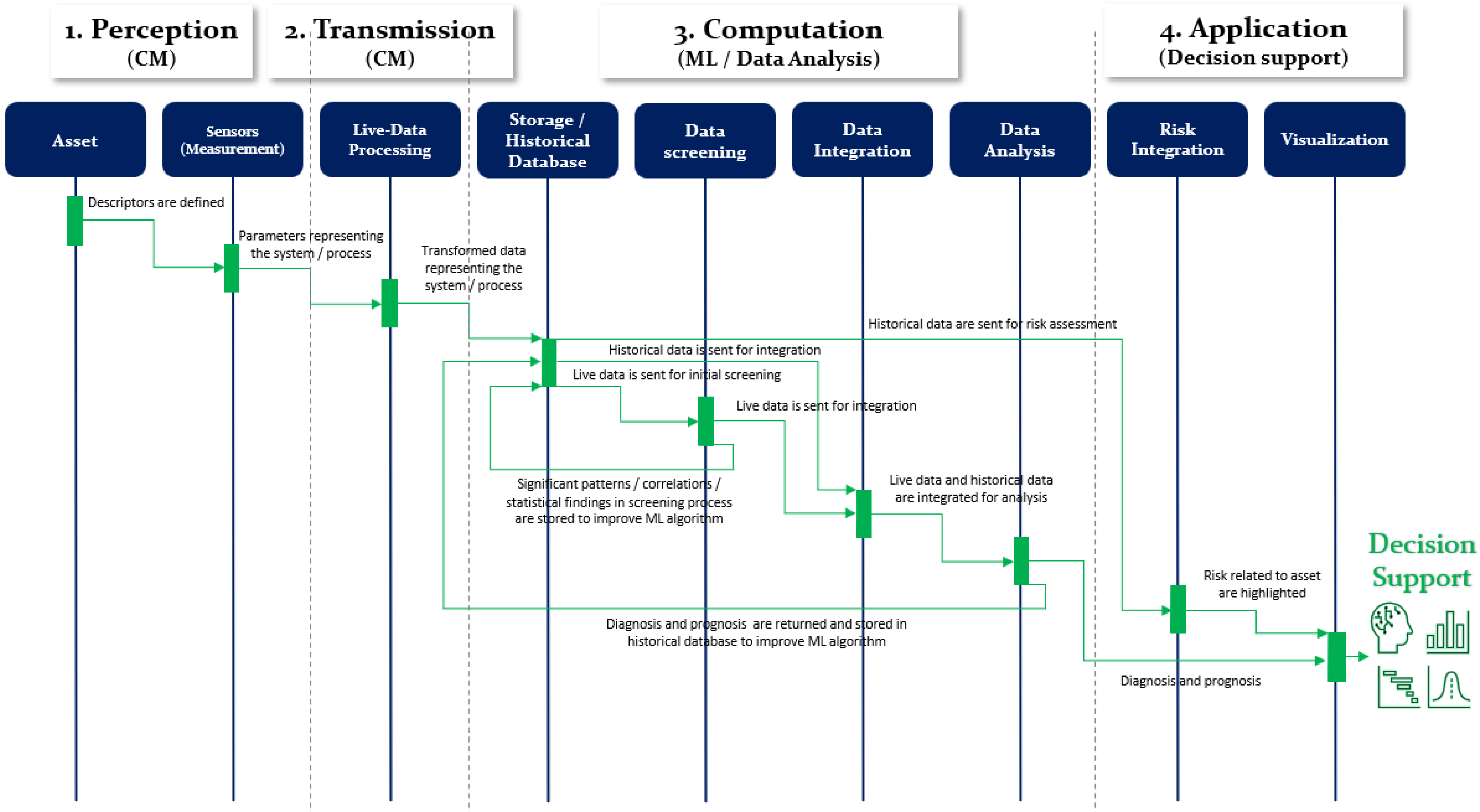

Figure 22 - Potential use case diagram for an AI/ML processes [made by writer]

4.4.2. IoT Layer 1 - Perception

The perception layer in the IoT architecture is where physical objects are given "intelligence" through IoT devices. To achieve this, it is vital to understand system functionality, its components, failures modes and potential symptoms of failures modes. With this information appropriate IoT devices can be incorporated to maximize perception accuracy.

4.4.2.1. The Necessary Foundation

Assumption(s): Assets are tagged and classified in a functional hierarchy and system criticality.

Asset knowledge, criticality and potential failures are fundamental information for planning maintenance activities. This suggests that Asset Knowledge (Figure 10) as discussed in 2.2.4 Predictive Maintenance is available and is based on asset functionality. Information about asset criticality, failure modes, symptoms and root causes should be accessible in addition to associated documentation, as the PdM framework requires.

To perform data driven analytics, one needs to assess how technology can monitor and detect potential errors / deviation. FMCA, FMSA and RCM analysis are important foundations for selecting appropriate condition monitoring equipment. Questions 1-4 relate to systems functional descriptions, failure modes, symptoms and root causes that could help select appropriate condition monitoring strategy and equipment.

Table 10 - Question 1-4: The necessary Foundation [made by writer]

No.	Question	Answer alternative
1	To what extent are assets evaluated for condition monitoring / PdM?	All: >80% All critical: >60% Some critical: >40% Few: >20% None: <20%
2	To what extent are failure modes and their causes as component faults analyzed?	All: >80% All critical: >60% Some critical: >40% Few: >20% None: <20%
3	To what extent are fault symptoms registered in the management system and analyzed? Note: Example of fault symptoms could be excessive vibration, reduced /increased pressure, reduced/increased flow, reduced/increased temperature, reduced/increased speed, etc.	All: >80% All critical: >60% Some critical: >40% Few: >20% None: <20%
4	To what extent are descriptors defined by operation variables to evaluate (recognized) fault symptoms? Note: Example of operation variables could be vibration, pressure, flow, temperature, speed og acoustics.	All: >80% All critical: >60% Some critical: >40% Few: >20% None: <20%

4.4.2.2. Selecting Appropriate CM Equipment

Assumption(s): Detailed description of systems functionality is present for further evaluation.

Correct condition monitoring equipment needs to be selected based on system variables and the measurement technique which is best suited to detect/ cover failure modes. Questions 5-7 relate to selection of appropriate condition monitoring equipment.

Table 11 - Question 5-7: Selection Appropriate CM Equipment [made by writer]

No.	Question	Answer alternative	
5	To what extent is condition monitoring equipment installed / selected based on failure mode and detectability? Note: tools as coverage index	Always: Often: Sometimes: Rarely: Never:	>80% >60% >40% >20% <20%
6	To what extent are multiple condition monitoring techniques considered when selecting condition monitoring equipment? Note: Data in this perspective could be vibration, temperature, acoustics, pressures, etc.	Always: Often: Sometimes: Rarely: Never:	>80% >60% >40% >20% <20%
7	To what extent are sensors installed to monitor the performance and health of company assets? (e.g. pressure, temperature, vibration, flow, etc.)	All: All critical: Some critical: Few: None:	>80% >60% >40% >20% <20%

4.4.3. IoT Layer 2 - Transmission

The transmission layer is where analogue sensor signals are transformed to digital signals, which are readable, intuitive, and possible to analyze. In most sensors and data acquisition system this signal conversion process is considered a matter of course. Thus, it was decided not to derive questions only for this layer, as the selection of condition monitoring equipment and measurement technique is a much more important task.

4.4.4. IoT Layer 3 - Computation

The computation layer is where digital information is received, stored, cleaned, and analyzed. This demands a structured data flow with multiple steps and processes to create historical databases and datasets that can be analyzed by AL / ML algorithms. As discussed on page 21 in section 2.3 Industry 4.0, information and communication technology (ICT) are fundamental to achieving interaction between computers and physical assets. Consequently, there is a need for intelligent data management and the right ITC platform is vital for this.

4.4.4.1. Data Storage

To accomplish the intention of the computation layer all acquired condition monitoring data should be routed and stored on a common platform enabling immediate access to real-time and historical data. Questions 8-11 relate to the current ICT platform and infrastructure and to ascertain if data are stored in a structured manner that facilitates advanced Ai/ML analytics.

Table 12 - Question 8-11: Data Storage and ICT Infrastructure [made by writer]

No.	Question	Answer alternative
8	Which information and communication platform/software (ICT) is used by your company? Specify program / software: - ERP System: - CMMS program: - SACA systems: - Other:	NA
9	Is condition monitoring data automatically stored? If yes: Where is the data stored? - ERP System: - CMMS: - SCADA System: - Local database: - External database: - Other:	Yes/No
10	Is condition monitoring data classified and stored accordingly? If yes: What classification requirements are used to organize the data? • Asset Tag no.: • Data format (e.g. vibration, temperature, pressure, etc.): • Time: • Date: • Other:	Yes/No
11	Are reports (maintenance, inspection, repairs, etc.) stored on the same platform and with the same classification requirements? • If no: Specify platform or location, and classification rules for storage.	Yes/No

4.4.4.2. Data Evaluation

Databases with historical information of asset failures (maintenance reports, inspection reports, repairs, etc.) could have a lot of value if used correctly. The problem with this data is human interaction and a lack of standards / procedures when specifying performed tasks and asset condition. The result is huge variation in data quality.

We know from section 2.3.2 IoT devices and Big Data and Table 4 - Overview of Big Data categories that the analysis of unstructured data as text, images, video and audio haven't gotten as far as structured data. Unstructured data is equivalent to unlabeled data as discussed in 2.3.4 Artificial Intelligence and requires more humane interaction to improve the ability of AI / ML algorithms to understand data properties, discover patterns and recognize trends.

However, such historical reports together with condition monitoring data have the potential to be valuable inputs as training sets to AI / ML algorithms. Questions 12-15 aim to highlight the importance of data cleaning and ascertain if the assessor(s) company has started the process.

Table 13 - Question 12-15: Data Evaluation [made by writer]

No.	Question	Answer alternative
12	Has the company established requirements related to data format and quality?	Yes/No
13	Has the company a work process to evaluate data quality?	Yes/No
14	Has the company a work process to evaluate data value?	Yes/No
15	Has the company started the data cleaning process of historical logs to meet established requirements to format and quality?	Yes/No

4.4.4.3. Analysis

When analyzing condition monitoring data, or events in general related to maintenance, the company needs to have a work process where an analysis is initiated based on requirements set by management. Furthermore, there should be a work procedure from initiation to report, where necessary resources are available to conduct an analysis of desired quality. [17] Questions 16-19 were derived to assist the assessor(s) evaluate their routines, and to understand if current procedure can be performed by computers.

Table 14 - Question 16-19: Data Analysis [made by writer]

No.	Question	Answer alternative
16	To what extent have specific requirements been established to initiate an analysis when operation parameters indicate nonconformance?	All: >80% All critical: >60% Some critical: >40% Few: >20% None: <20%
17	Is the analysis initiated automatically? • If yes: Elaborate how. • If no: Specify how an analysis is initiated and on what terms.	Yes/No
18	Has the company a defined toolbox of methods, analytic tools etc. to perform necessary analyses? • If yes: Please specify routines and analysis methods. • If no: Please elaborate routines or lack thereof.	Yes/No
19	Is a historical log of asset failures available and used in the analysis?	Yes/No

One of most significant changes from today's analysis norms and analysis performed in the vision of Industry 4.0 is the shift from single parameter analysis to multivariable analysis (i.e. Big Data). To improve accuracy in diagnostic- and prognostic analysis, heterogeneous data (e.g. vibration, temperature, pressure, etc.) is analyzed together. Furthermore, these analysis results are combined with enterprise data (e.g. spare parts inventory, available resource, future demand, etc.) to optimize maintenance planning and execution of maintenance activities. In section 2.3 Industry 4.0 the idea of real-time information sharing and incorporation of multiple decision variables through the entire value-chain was highlighted as one of the main value creating contributions of Industry 4.0. Questions 20-23 were derived to understand how data are utilized and if the assessor(s) company has started to implement multivariable analysis.

Table 15 - Question 20-23: Data Analysis in Industry 4.0 vison [made by writer]

No.	Question	Answer alternative
20	To what extent is performance- and condition monitoring data used to determine diagnosis and prognosis when an analysis is initiated?	Always: >80% Often: >60% Sometimes: >40% Rarely: >20% Never: <20%
21	To what extent is multivariable data used when determining diagnosis and prognosis? Note: Multivariable data analysis is when analysis is performed by combining different data inputs. Data inputs in this perspective could be vibration, temperature, acoustics, pressures, etc.	Always: >80% Often: >60% Sometimes: >40% Rarely: >20% Never: <20%
22	To what extent is enterprise data used to plan maintenance activities when a diagnosis and prognosis is determined? Note: Enterprise data are typically spar part availability, future production, planned shutdowns, available resources, etc.	Always: >80% Often: >60% Sometimes: >40% Rarely: >20% Never: <20%
23	To what extant are intelligent analytics (i.g. AI an ML algorithms) used to analyze data?	Always: >80% Often: >60% Sometimes: >40% Rarely: >20% Never: <20%

4.4.5. IoT Layer 4 - Application

From an Industry 4.0 perspective, the application layer is the utilization of information provided by lower layers as "steering instruction" to a machine. However, before reaching this stage of autonomy, perception, transmission, and computation need to be prioritized to gain reliable insight from aggregated data. To assess a company's ability to implement an autonomous production requires a whole different set of questions than only assessing maturity to implement AI / ML as analytic tool.

For this reason it was decided not to include this layer in the questionnaire. As the focus was on operation- and maintenance life cycle phase and AI / ML analytics, the final "need" was to display analysis outcome as the foundation for decision-makers.

4.4.6. Answering Format

The MBS is a comprehensive self-assessment method where questions answer alternatives are usually yes/no with follow-up questions for more in-depth descriptions. In the developed model, answer alternatives have been changed to a selective format as a measure to simplify the process. Where appropriate, scales have been assigned so the assessor(s) can mark the most suitable alternative. In questions where yes/no are the natural alternatives, additional information will be possible to add as the assessor(s) will asked to add a comment or to elaborate where additional information could be valuable. Figure 23 illustrates how this process is formatted on Google Forms.

Additionally, by changing the answer style from descriptive to selective, all responses will be stored in a quantitative format, which simplifies the analysis process later. Reply data can then be used in various applications to provide statistical insight from the industry and their transformation into a more digital business model.

21. Is the analysis initiated automatically? *

Mark only one oval.

- Yes
- No *Skip to question 23*

Automatically Initiated

22. Elaborate how and through which channels the analysis is initiated.

Not Automatically Initiated

23. Specify how an analysis is initiated and on what terms.

Figure 23 - Question 17 formatting details [made by writer]

5. Validation

Before releasing the questionnaire, it requires testing to avoid unanticipated problems related to wording, instructions, and accuracy. This is also a validation of the format and questions to ensure that correct information is collected so that the goal can be reached. [63]

Validate the questions.

To validate the updated Analyses Module, questions have been discussed, reviewed, and revised with industry experts. This has provided valuable feedback and has served as a verification tool to secure model validation. The correspondence has been though unstructured interviews, discussion, and mail. Documentation of this correspondence can be review in appendix B-E

Table 16 - Questionnaire revision history [made by writer]

Date	Version	Description	Participants
NA	0	First Draft.	AC
08.06.2020	1	Added questions on data evaluation / cleaning and the use of multivariable in analysis.	AC / Ex.1
12.06.2020	2a	Focus was more concentrated in operation phase. Number of questions was reduced by more the half. More standardization of language.	AC / Ex. 2
24.06.2020	2b	Few abbreviation changes and simplifying some sentences.	AC / Ex. 3
24.06.2020	3	Questions 1-5 were rewritten with minor changes. "CM" was changed to "condition monitoring" where applicable.	AC / Ex. 2

AC - Alexander Carlsen
Ex. 1 - Expert no. 1
Ex. 2 - Expert no. 2
Ex. 3 - Expert no. 3

5.1. Verification Process

Questions derived in section 4.4 Questionnaire Requirements and the questionnaire demonstrated in Appendix A - Complete self-assessment model including formatting is the final result based on 2 Theoretical Background and feedback from industry professionals. The current version is revision 3 and the verification process was performed through three iterations of review, updates and feedback from the industry. Each version was studied and commented by external experts and changed accordingly. The full revision history can be viewed in Table 16, where the main updates are highlighted in each version. Experts within the field of operations- and maintenance have been the verification sources making this possible. The complete revision- and validation process is explained in this section.

5.1.1. The First Draft

Revision 0 was develop based on the PdM framework discussed in 2.2.4 Predictive Maintenance and technology discussed in section 2.3 Industry 4.0. Revision 0 consisted of 42 questions, which involved all stages in the PdM framework, i.e. asset knowledge, organization, technology, and work process. The document was the first draft to the questionnaire and was understood as a "work-in-process".

To strengthen the validation, several industry professionals were contacted to ask for input. Field experts in both operating- and service companies were addressed to ask for their advice and provide feedback on the questionnaire. By targeting professionals at operating- and service companies, the idea was to obtain feedback from different perspectives within the industry. Two out of four responded to the request and fortunately one was working for an operator, while the other was working for a service company. Additionally, a PhD candidate at UiS, Expert no. 1, offered his services to review the questionnaire.

5.1.2. External Review no. 1

Revision 1 was sent to Expert no.1 for review. Feedback was received via mail and can be viewed (in Norwegian) in Appendix B - Mail correspondence with Expert no.1. Comments were generally positive, and, in his opinion, the survey layout was simple, clear and should be understandable for anyone within the industry. Regarding the questions, he addressed two "missing" subjects that are important when discussing data analysis in the vison of Industry 4.0. Below are both subjects addressed along with a summary of the feedback.

1. Data cleaning / data evaluation

Summary from feedback: "Comments Data evaluation and data cleaning could impact the accuracy of an AI/ML algorithm if the quality is good, but the evaluation and cleaning processes is time consuming and resources demanding. It the case of assessing a company's maturity to implement AI/ML analytics it would be interesting to know if the company has routines to *"qualify" new data and have started the process of historical data cleaning*." (Appendix B - Mail correspondence with Expert no.1.)

2. Multivariable Analysis

*Summary of feedback: "Multivariable analysis is one of the changes from traditional "Maintenance 3.0" and "Maintenance 4.0" is the use of multiple parameters (e.g. vibration, temperature, acoustics, pressure, etc.) to improve output accuracy. Next are these analyses results combined with enterprise data as spare part stock, production, available resources, etc. to plan the optimal time to conduct maintenance activities. It would be interesting to see how the assessor(s) company are performing data analysis today and if they are single- or multivariable analysis." (*Appendix B - Mail correspondence with Expert no.1)

Whereas data evaluation represents one of the challenges related to data quality and the potential value of historical databases, multivariable analysis represents the "next phase" and the possibility for improvement. Questions to cover these two subjects, as explained in 4.4.4.2 Data Evaluation and on page 54 in 4.4.4.3 Analysis were therefore added to the survey based on feedback and their significance for assessing a company's readiness to implement AI / ML analytics.

Revision 1 Updates:

- Four questions regarding data evaluation and data cleaning was added. (Questions 37-40)
- Question 27 was rewritten to apply multivariable analysis.
- Question 30 was added to apply enterprise data and to an extent this was included when planning for maintenance activities.
- Revision 1 of the survey consisted of 47 questions in total.

5.1.3. External Review no. 2

After receiving revision 1 of the questionnaire on 12th June Expert no. 2 (operator) was quick to review the document and had several comments, which would strengthen the questionnaires. In addition he provided several more general inputs for consideration. Expert no. 2 comments which were addressed immediately are listed below (Appendix C - MoM from Expert no. 2):

1. *"Concentrate about one phase of the product life cycle*
2. *"Reduced questionnaire to 20-25 Question. Max 40 min time to complete assessment."*

3. *"Question needs to be self-evident, i.e. all abbreviations must be explained."*
4. *"What is the meaning of intelligent analytics?"*

Multiple changes were performed as a response to the feedback from Expert no. 2 and to enhance the focus area, it was decided to concentrate on asset operation phase. This meant that questions regarding the organization (ref. PdM framework) could be removed. Additionally, revision 1 included a section on work processes in R&D project phase that was skipped. Furthermore, each remaining question was asked "must know" or "good to know". Consequently, the questionnaire was reduced to 22 questions in response to comments 1 and 2. In addition, multiple questions were revised and re-written to ensure that standardized abbreviations and definitions were used. Table 1 - Abbreviations [made by writer] and Table 2 - Definitions [made by writer] provide all the necessary information for the assessor(s). Lastly, "Intelligent analytics" was changed to "AI / ML algorithms " throughout the questionnaire to minimize the chance of misunderstandings and to connect the questionnaire with the theory provided in section 2.3.4 Artificial Intelligence.

Revision 2a Updates:

- Focused questionnaire to focus on operations phase.
- Total questions reduced from 47 to 22.
- Improved the consistency of wording and abbreviations used.
- "Intelligent Analytics" was changed to “AI/ML algorithms”.

Revision 1 of the questionnaire was also sent to Expert no. 3 on the 12th of June, but in the time between when Expert no. 3 received the questionnaire (revision no. 1) and our meeting on the 24th of June, the questionnaire had been revised based on feedback from Expert no. 2 (i.e. rev 2a). Thus, rev. 2a was explained and justified by the writer to Expert no. 3. After the presentation, Expert no. 3 provide some initial comments which are listed below (Appendix D - MoM from Expert no. 3):

1. *"Small target group when relating AI/ML to maintenance. The combination of data science, informatic and maintenance can make it problematic for "all" operations- or maintenance engineer to understand the context. Make sure that questions are as clear and intuitive as possible"*

To comply with this statement, questions were once again studied to remove any doubt related to writing, abbreviations, and sentences. Some minor changes were made.

Furthermore Expert no. 3 said he apricated the quantification / multiple-choice answer format as this would make it easier to analyze response data. He also mentioned the quantity of questions in revision 1, but as this had been addressed, he did not have anything more to add.

Revision 2b Updates:

- Minor changes to a few questions, such as changing abbreviations and simplifying sentences.

5.1.4. External Review no. 3

The third and last review iterations were conducted through mail, where the last revision 2b was sent to the involved parties for final review. Unfortunately, only one document with comments was returned. The feedback was generally positive, but some remarks were again addressed (Appendix E - Feedback external review no. 3):

1. *All abbreviations need to be explained.*
2. *Some general comment for improving question 1-5.*

The remarks concerning abbreviations were once again handled; "CM" was changed to "condition monitoring" to avoid the assessor(s) confusing this with "corrective maintenance". Additionally, questions 1-5 were rewritten to improve sentence structure and clarity in response to feedback.

Revision 3 Updates:

- "CM" changed to "condition monitoring" where applicable.
- Questions 1-5 rewritten.

5.2. Discussion and Remarks

The self-assessment model, as presented Appendix A - Complete self-assessment model including formatting is the result of multiple iterations of external review, feedback, and updates. This has led to a model that is largely influenced by industry experts and their opinion. In terms of accuracy to meet the thesis objective in 1.3 Objective and 4.1.1 The Goal , every party has been given the opportunity to influence the questions, questionnaire layout, and its platform. For this reason, the review iterations presented above could be understood as a validation process. Feedback from professionals has had a significant impact on the result to secure an industry-backed model. With that said, some remarks should be discussed further.

5.2.1. Industry Input

Industry inputs have had undeniable great value in the development process. Their open-minded attitude and willingness to share knowledge and insight has shed light on relevant areas and problems with the self-assessment model that needed improvement. Their varied background and employment has provided different perspectives on industry challenges and priorities, which in return has helped the writer to address issues from multiple angles when developing the questionnaire.

However, it is worth noticing that industry involvement has been at the minimum of what would be considered necessary to claim that the self-assessment model has been sufficiently validated. More review iterations with several industry experts should have been performed to enhance the model. The sum of numerous unfortunate incidents because of the COVID-19 outbreak made it challenging to get access to industry expertise. The Norwegian O&G industry was significantly affected by the repercussions of the virus, with the result that focus for operators and service companies was to sustain on-going operations. The industry has simply not had the available resources to assist the writer to an extent where validation could be considered successful.

5.2.2. Maintenance Baseline Study

The maintenance management loop was constructed as a benchmark for operation- and maintenance management systems, and the MBS is designed based on this management loop and its modules. From establishing goals and requirements, through planning, execution, reporting and analyses, the objective is to create a dynamic maintenance program under a continuous improvement philosophy. This requires that each module is given attention and assessed as a whole. Goals, criteria, and work processes determined in each module will be inputted to the next, and consequently give some boundaries and guidelines, which need to be considered.

Enhancing the Analyses Module alone could therefore be insufficient when it comes to assessing company readiness for PdM and the implementation of AI / ML analytics as assistant technology. If we look at all modules before analyses, each output will impact the entire loop. Regulations need to be accounted for and feasibility studies performed to secure compliance between technology capabilities and requirements. The maintenance program and maintenance planning need to be designed for applicable technology and a long-term strategy developed to improve the system accordingly. Execution and reporting need to be in a standardized format so that activities and data have a secure quality and value. Essentially, to improve the Analyses Module one need to look at the entire MBS and update according challenges related to PdM and AI / ML technology.

5.2.3. Reference Architecture

During the development of a new self-assessment model with focus on AI / ML technology it was necessary to assign an IoT reference architecture to serve as a "process map" from data origin to application. This provided a logical structure to the questions, and their context so important aspects in each layer could be addressed appropriately. Is was decided to use the four-layer architecture proposed by Trappey et al. (2016), however, this is a general concept and is not necessarily best suited for this thesis objective. [43] The Trappey et al. (2016) architecture was proposed after an investigation of multiple architectures with a range of five to nine layers. Due to time limitations, extensive analyses were not performed to investigate other architectures thoroughly, in terms of their layers and to match their capabilities with the thesis objective.

5.2.4. Answering format

The answer format was changed to simplify and reduce time used on the self-assessment questionnaire. However, feedback from the industry was varied, from positive to less positive. In light of these contradicting opinions, some choices had to be made by the writer.

On one hand, an expert wanted to keep a descriptive format so that an in-depth answer could be given. On the other hand, one expert provided positive feedback on the multiple-choice format due to the simplification for data analysis afterwards. These different perspectives on which format was best suited could just be subjective options or related to industry value chain. The feedback material is not enough to perform any extensive analyzes, but it's worth speculating if service providers emphasize time and effectiveness, while operators are more focused on the result than time

A decision was made to keep the selective (multiple-choice) format as a response to the requirements "user-friendly" and "time efficient" derived in 4.3.1 Functional Requirements. Additionally, some adjustments were performed to satisfy the request of a descriptive answer option where suitable. As the example explained and illustrated in Figure 23. Furthermore, a comprehensive analysis has not been performed for each question to optimize answer alternatives / format due to time limitations and the need for a focused thesis scope. The answer format assigned to this model is for illustrative purposes and proposals for improvement and needs further research for validation.

5.3. Recommended Research

Based on the discussion above, further research should be performed to validate the updated self-assessment model. The main remarks are highlighted below with recommendations for future research.

1. Lack of industry involvement. To become a recognized version / replacement for the Analyses Module the industry needs to be more involved. It is therefore recommended that the new self-assessment model should be reviewed and tested by more industry experts (than until now) to secure industry validation.
2. The Maintenance Baseline Study is a complete self-assessment model where each module needs to be seen together with the other modules, i.e. output X is input to Y. Given this fact, updating one module will not be sufficient to assess the entire maintenance management system of companies. Thus, it is recommended that similar projects are conducted where state-of-the-art technology, as AI, is included in all MBS modules.
3. Explore different IoT Architectures. As discussed in 2.3.3 IoT Architecture and 5.2.3 Reference Architecture are there multiple IoT reference architecture described in the literature. The one used to formulate questions and questionnaire layout was chosen based on a relatively small literature review on the subject. Based on this, another IoT reference architecture could potentially be better suited for this application and it is recommended to examine this closer.
4. Answering format. Multiple-choice was selected to meet functional requirements such as, easy-to-use and time efficiency. However, industry feedback was split in their view of which format was most suitable. It is recommended to collect more feedback from the industry to gain knowledge if multiple-choice is the appropriate solution, and if yes, examine closer which quantification scale is best suited.

The self-assessment model developed in 4 Model Development could be used as inspiration for more projects where other modules are studied and revised to follow the technological change we have seen the last 10-15 years. One of the MBS intentions was exactly this; to be updated along with state-of-art technology and best practice. AI is state-of-art technology and will be considered as "best practice" of data analysis when implemented correctly.

6. Conclusion

The thesis objective was to develop an updated version of the Analyses Module in the Maintenance Baseline Study where state-of-the-art technology (i.e. AI) and maintenance strategies (i.e. predictive maintenance) was included in the assessment. Further, additional requirements to the self-assessment model as user-friendliness, time efficiency and accessibility was derived in 4.1 Mission Requirements as a measure to improve the assessment process. On this basis, together with theory presented 2 Theoretical Background, a new model was developed with process described and executed in 4 Model Development. The complete self-assessment model can be viewed in Appendix A - Complete self-assessment model including formatting, or by following the link below which leads to the on-line model. https://docs.google.com/forms/d/e/1FAIpQLScMRkh2UvQMdl4LMkrap6Uhlc25vfyS6aY1jh973ZrvKom5dg/viewform

The model is constructed to assess the work processes necessary to build a system where condition monitoring data are analyzed with AI, and where predictive maintenance principles lay the premise for this, through a strategized approach. Furthermore, goals such as improved usability have been met using an online format with multiple-choice and increased accessibility. Additionally, multiple-choice provides a time effective assessment where responses are summarized and available immediately after the assessment is finished. The new self-assessment model address important areas of asset knowledge, selection of appropriate condition monitoring equipment and analysis procedures, which are a necessity for a successful implementation of AI analytics.

The Maintenance Baseline Study intention was to continuously update guidelines according to "best practice" and technology advancement. Due to rapid technological development within computer science the MBS should have been updated to include AI. As a result of this incomplete update, the thesis objective was to develop an updated version of the Analyses Module in the Maintenance Baseline Study. With this basis, different maintenance strategies were discussed in 2.2 The evolution of maintenance, to get complete understanding of relevant domains. Additionally, the correlation between strategy development and opportunities provided by innovative technology were described. For example, condition monitoring has been an important enabler for predictive maintenance, but computer science is the technology that will bring maintenance to the next level. To understand the potential of AI, Big Data analysis and the visionary outlook in the industy, the concept of Industry 4.0 was studied along with enabling technologies and system structures. Section 2.3 Industry 4.0

provided a deeper understanding of how physical objects and cyber systems can be constructed with sensor technology and AI.

With a good theoretical foundation, the new self-assessment model was developed through a five-step process. First, scope boundaries were determined with a system-of-systems chart to create a context for the model, and some constraints were set to form a realistic workload. The goal was to update the Analyses Module in a user-friendly, accessible format which included AI technology. Scope boundaries were set to the operations- and maintenance life cycle phase of an asset.

Secondly, a stakeholder analysis was performed to clarify needs, requirements, and criterions. This type of information is essential for building a system that complies with user needs and expectations. By splitting an asset into life cycle phases, all stakeholders in each can be identified in systematic matter. As scope boundaries were confined to the operation- and maintenance phase, this was the main focus. Next, key stakeholders (i.e. model users) were analyzed further to ensure that their needs, requirements, and criterions would be met.

Knowing the need for the Analyses Module to be updated and the needs of key stakeholders allowed a system breakdown to be performed to derive functional requirements. From a user perspective, user-friendliness, accessibility, and time effectiveness were found to be key criterions, while from a developer's perspective, evaluation of state-of-the-art technology was considered a key criterion to achieve the thesis objective. To meet these requirements the selection process identified Google Forms as the most suitable platform due to its accessibility and flexibility in development and automatic storage of answers.

Following a four-layer IoT architecture, the questions to assess a company's readiness to implement AI technology were formulated. With a focus on perception and computation, the model starts with assessing a company's fundamental asset knowledge, then moves to selection of condition monitoring equipment, and finally addresses how monitoring data is handled. The predictive maintenance framework together with ISOs condition monitoring designs cycle provided important reference guidelines when deriving questions that were self-evident, served a purpose and provided applicable answers.

The final stage of the development process was validation. The questionnaire went through an iterative process of review by domain experts and updated according to feedback. The process was performed to secure the models topical accuracy and value adding potential to the industry.

With that said, several recommendations have been put forward to further improve the model. The current format should be considered as a concept and needs to be developed further to achieve a higher degree of validation and industrial acceptance. Despite this, perhaps this updated version of the Analyses Module provides a small contribution towards increasing the industrial focus on AI and accelerating the transition into the digital era.

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Appendices

Appendix A - Complete self-assessment model including formatting

Self-Assessment Model for Intelligent Predictive Maintenance Analytics

* Required

1. Email address *

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Foundation	To perform data driven analytics one need to assess how technology can monitor and detect potential errors/deviation/failure modes. FMCA, FMSA and RCM analysis are foundation for selecting appropriate condition monitoring equipment. Question 1-4 relates to systems functional description, failure modes, symptoms and root causes that would help to select suitable condition monitoring strategy.

2. To what extent are assets evaluated for condition monitoring/ PdM?

Check all that apply.

	All (>80%)	All critical (>60%)	Some critical (>40%)	Few (>20%)	None (<20%)
Answer	☐	☐	☐	☐	☐

3. To what extent are failure modes and their causes as component faults analyzed?

Check all that apply.

	All (>80%)	All critical (>60%)	Some critical (>40%)	Few (>20%)	None (<20%)
Answer	☐	☐	☐	☐	☐

4. To what extent are fault symptoms registered in the management system and analyzed?
Note: Example of fault symptoms could be excessive vibration, reduced /increased pressure, reduced/increased flow, reduced/increased temperature, reduced/increased speed, etc.

Check all that apply.

	All (>80%)	All critical (>60%)	Some critical (>40%)	Few (>20%)	None (<20%)
Answer	☐	☐	☐	☐	☐

5. To what extent are descriptors defined by operation variables to evaluate (recognized) fault symptoms?
Note: Example of operation variables could be vibration, pressure, flow, temperature, speed og acoustics

Check all that apply.

	All (>80%)	All critical (>60%)	Some critical (>40%)	Few (>20%)	None (<20%)
Answer	☐	☐	☐	☐	☐

Selection of condition monitoring equipment	Correct condition monitoring equipment needs to be selected based on system variables and measurement technique which is best suited to detect / cover failure modes. Question 5-7 relates to selection of appropriate CM equipment.

6. To what extant is CM equipment installed/selected based on failure mode detectability?

Check all that apply.

	Always (>80%)	Often (>60%)	Sometimes (>40%)	Rarely (>20%)	Never (<20%)
Answer	☐	☐	☐	☐	☐

7. To what extent are multiple condition monitoring techniques considered when selection condition monitoring equipment?

Note: Data in this perspective could be vibration, temperature, acoustics, pressures, etc.

Check all that apply.

	Always (>80%)	Often (>60%)	Sometimes (>40%)	Rarely (>20%)	Never (<20%)
Answer	☐	☐	☐	☐	☐

8. To what extant are sensors installed to monitor the performance and health of company assets?

Note: Performance and health data could be vibration, temperature, pressure, flow etc.

Check all that apply.

	All (>80%)	All critical (>60%)	Some critical (>40%)	Few (>20%)	None (<20%)
Answer	☐	☐	☐	☐	☐

ICT Platform	To accomplish the intention of the computation layer all acquired condition monitoring data should be routed and stored on a common platform enabling immediate access to real-time and historical data. Questions 8-11 relate to the current information and commutation technology (ICT) platform, the infrastructure and to ascertain if data are stored in a structured manner that facilitates advanced AI/ML analytics.

9. Which information and communication platform/software (ICT) is used by your company? Specify program / software.

Check all that apply.

- ☐ ERP System
- ☐ CMMS Program
- ☐ SCADA System

Other: ☐ ________________

10. Is condition monitoring data automatically stored? *

If yes, please specify where data is stored in "Other"

Mark only one oval.

- ◯ Yes *Skip to question 11*
- ◯ No *Skip to question 12*

Data Storage

11. Where is data stored?

Check all that apply.

- [ ] EPR System
- [ ] CMMS Program
- [ ] SCADA System
- [ ] External Database
- [ ] Local Database
- Other: [ ] ______________________

Data Classification

12. Is condition monitoring data classified and stored accordingly? *

Mark only one oval.

- ◯ Yes *Skip to question 13*
- ◯ No *Skip to question 14*

Classification Requirements

13. What classification requirements are used to organize the data? *

Check all that apply.

- [ ] Asset Tag no.
- [ ] Data format (e.g. vibration, temperature, pressure, etc.)
- [ ] Time
- [ ] Data
- Other: [ ] ______________________

Inspection Data

14. Are reports (maintenance, inspection, repairs, etc.) stored on the same platform and with the same classification requirements? *

Mark only one oval.

- ◯ Yes *Skip to question 16*
- ◯ No

Inspection Reports

15. Specify platform or location, and classification rules for storage.

____

____

____

____

____

Data Evaluation

Databases with historical information of asset failures (maintenance reports, inspection reports, repairs, etc.) could have a lot of value used correctly. The problems with this data are human interaction and lack of standards / procedures when reporting performed tasks and asset condition. The result is huge variation in data quality. However, such historical reports together with CM data has the potential to be valuable inputs as training sets to AI/ML algorithms.

16. Has the company established requirements related to data format and quality?

Check all that apply.

- ☐ Yes
- ☐ No
- Other: ☐ ________________

17. Has the company a work process to evaluate data quality?

Check all that apply.

- ☐ Yes
- ☐ No
- Other: ☐ ________________

18. Has the company a work process to evaluate data value?

Check all that apply.

- ☐ Yes
- ☐ No
- Other: ☐ ________________

19. Has the company started the data cleaning process of historical logs to meet established requirements to format and quality?

Check all that apply.

- [ ] Yes
- [ ] No
- [ ] Other: ______________________

Data Analysis

When analyzing condition monitoring data, or events in general related to maintenance, the company needs to have a work processes where an analysis is initiated based on requirements set by the management. Further, there should be a procedure from initiation to finished report, where necessary resource is available to conduct analysis of desired quality.

20. To what extant has specific requirements been established to initiate an analysis when operation parameters indicate nonconformance from an asset?

Check all that apply.

	All (>80%)	All critical (>60%)	Some critical (>40%)	Few (>20%)	None (<20%
Answer	☐	☐	☐	☐	☐

21. Is the analysis initiated automatically? *

Mark only one oval.

- ◯ Yes
- ◯ No *Skip to question 23*

Automatically Initiated

22. Elaborate how and through which channels the analysis is initiated.

____

Not Automatically Initiated

23. Specify how an analysis is initiated and on what terms.

____

Data Analysis with AI and ML	One of most significant changes from today's analysis norm and analysis performed in the vision of Industry 4.0 is the shift from single parameter analysis to multivariable analysis (i.e. Big Data). To improve output accuracy, e.g. RUL, prognostic analysis is performed by combining several different data inputs (vibration, temperature, acoustics, historical failures, etc.). Further, the analysis output is combined with enterprise data (e.g. spare parts inventory, available resource, future demand, planned production shut down, etc.) to optimize production, maintenance planning and execution of maintenance activities. .

24. To what extant is performance- and condition monitoring data used to determine diagnosis and prognosis when an analysis is initiated?

Check all that apply.

	Always (>80%)	Often (>60%)	Sometimes (>40%)	Rarely (>20%)	Never (<20%
Answer	☐	☐	☐	☐	☐

25. To what extent is multivariable data used when determine diagnosis and prognosis?

Note: Multivariable data analysis is when analysis is performed by combining different data input. Data inputs in this perspective could be obtain from multiple sources as vibration, temperature, acoustics, pressures, etc.

Check all that apply.

	Always (>80%)	Often (>60%)	Sometimes (>40%)	Rarely (>20%)	Never (<20%
Answer	☐	☐	☐	☐	☐

26. To what extant is enterprise data used to plan maintenance activities when a diagnosis and prognosis is determined?

Note: Enterprise data is typically spar part availability, future production, planned shutdowns, available resources, etc

Check all that apply.

	Always (>80%)	Often (>60%)	Sometimes (>40%)	Rarely (>20%)	Never (<20%
Answer	☐	☐	☐	☐	☐

Appendix B - Mail correspondence with Expert no.1

Fra: Alexander Carlsen <ale.carlsen@stud.uis.no>
Sendt: torsdag 4. juni 2020 15.53
Til: [redacted]
Emne: Spørreskjema - "A Self-assessment model for intelligent predictive maintenance analytics"

Hei [redacted]

Takk for sist!

Håper alt går bra og du har fått deg noen dager på kontoret de siste ukene.

Har du vært så heldig, eller er det fortsatt hjemmekontor hele tiden?

Jeg tar deg ordet og sender over første utkast av spørreskjemaet for *«A Self-assessment model for intelligent predictive maintenance analytics»* som er tittelen på oppgaven min.
Det er 42 spørsmål med ulike svaralternativet.
Jeg har valgt å dele skjemaet inn i 1. organisasjon, 2. Asset og 3. Teknologi. med tilhørende underkategorier.

Ta den tiden du trenger, ikke hold tilbake og kommenter på det du møtte ønske 😊

Best Regards
Alexander Carlsen
Student no. 251299
Tel. (+47) 95 96 85 00

Alexander Carlsen

From: [redacted]
Sent: mandag 8. juni 2020 14:28
To: Alexander Carlsen
Subject: SV: Spørreskjema - "A Self-assessment model for intelligent predictive maintenance analytics"

Hei Alexander

Jeg synes du har klart å lage et skjema som vil kunne være forståelig for enhver i industrien. Har et par tanker jeg ønsker å dele med deg.

En av forskjellen mellom den tradisjonelle «Vedlikehold 3.0» og «Vedlikehold 4.0» er at en tidligere gjorde analyser av enkelte parameter, som for eksempel kun vibrasjon. I sammenligning, så ønsker en fra et «Vedlikehold 4.0 perspektiv» å kombinere flere ulike parametere i multivariable analyser (big data) eksempelvis (vibrasjon, temperature av lager, akustikk, og prosess trykk og temperatur). Videre, kombinere resultatene av en slik analyse med «enterprise level data» som er e.g. varelager, fremtidig produksjon, tilgjengelige ressurser i fremtiden, osv (dette er referert i spørsmål 27?). Til slutt, vil en gjøre dette for å identifisere det tidsintervallet som har minst innvirkning på produksjon og dermed mest konstnadseffektivt. Derfor lurte jeg på om det vil kunne være en ide å lage et spørsmål som omhandler bruken av data i analysene. Er dagens analyse basert på en enkel parameter analyse (dermed Vedlikehold 3.0) eller en multivariabel analyse (Vedlikehold 4.0).

I tillegg, som vi diskuterte sist, så er typisk SAP-systemer preget av menneskelig interaksjon over flere tiår og dermed er kvaliteten varierende (som vil basere seg på yrkeserfaring og kompetanse osv). En av utfordringen i olje og gass er at selskapene har mye data, men de er usikker på verdien av denne dataen. Dermed er mange svært konservative når det gjelder deling av data. Uansett, det vil kanskje være interessant å ha et spørsmål om hvorvidt selskapene har startet det som gjerne sees på som en «data cleaning» prosess for å undersøke nytten av dataen i en eventuell fremtidig algoritme / maskin læring.
For eksempel, et spørsmål som handler om selskapene loggfører tilstandsdata, og et spørsmål om hvordan de anser kvaliteten og nytteverdien av denne dataen? Eneste grunnen til dette, er at jeg vet det er flere selskaper som har nevnt dette med data kvalitet, som har vist seg å være svært dårlig eller ikke brukende. Om dette er gjeldende for alle, kan ikke jeg vite, men dersom dette er tilfelle for alle, så vil det kunne være et fint funn (av flere) i analysen din. Dette er kun umiddelbare tanker jeg har og trenger nødvendigvis ikke å være interessante å ha med i skjemaet ditt.

Uansett, så synes jeg at du har klart å laget et forenklet skjema som vil være forståelig for hvem som helst.

Mvh,
[redacted]

Appendix C - MoM from Expert no. 2

Minutes of Meeting

Friday 12.06.2020

Topic: Feedback on self-assessment questionnaire

Medium: Telephone

Attendances:

[redacted] ConocoPhillips

Alexander Carlsen, Student, UiS

After reaching out to the industry for feedback "Expert no. 2" at ConocoPhillips was quick to review and contact writer to provide inputs. Below are notes of his comments which, in his opinion, would improve the questionnaire revision 1.

1. Concentrate about one phase of the product life cycle.
2. Clear changes from questions with answer alternative (yes/no) to descriptive.
3. More Descriptive answer opportunities
4. Question needs to be self-evident, i.e. all abbreviations must be explained.
5. What is the meaning of intelligent analytics?
   (needs to clear that it is AI and ML algorithms that are the intended meaning)
6. Reduced questionnaire to 20-25 Question. Max 40 min time to complete assessment.
7. For which companies? Operators or service?

To summarize:
The questionnaire should focus on one area of the life cycle, be self-evident (abbreviations and questions) and simplified (reduce amount of questions).

Some comments, e.g. on abbreviations explanation are addressed in the thesis, however, Sukhvir did not have access to this while reviewing questionnaire. This should be available for everyone who will use the final self-assessment model.

Appendix D - MoM from Expert no. 3

Minutes of Meeting

Friday 24.06.2020

Topic:	Feedback on self-assessment questionnaire revision 1 / 2a
Medium:	Microsoft Teams

Attendances:

[redacted], Business Manager, Apply

Alexander Carlsen, Student, UiS

"Expert no. 3" received revision 1 (containing 47 questions) on the 12th June but was not free for a meeting before the 24th. In this period the questioner had been updated so the meeting started with going through the latest revision get Mr. Raza up to date.

During the session following notes/comments from "Expert no. 3" were taken:

1. Good that answers are alternative are quantified. This makes is easier to analyze the responses to the questionnaire.
2. A bit small target group when relating AI/ML to maintenance. The combination of data science, informatic and maintenance can make it problematic for "any" operational or maintenance engineer to understand the context all questions. Make sure that questions are as clear and intuitive as possible.
3. Revision 1 has to many questions but looks like that has been addressed.

After the session "Expert no. 3" asked for revision 2a so that he could have look at the last revision.

To summarize:

Answer alternative where answer is quantified are positive and makes the analysis process easier later. Could be difficult for al operational or maintenance engineer to perform the self-assessment due to the subject. In general, changes made from revision 1 was needed.

Appendix E - Feedback external review no. 3

From: Alexander Carlsen <ale.carlsen@stud.uis.no>
Sent: onsdag 24. juni 2020 22:16
To: [redacted]@conocophillips.com>; [redacted]@yahoo.com' [redacted]@yahoo.com>
Subject: RE: [EXTERNAL]Master Thesis on readiness assessment of PdM analytics

Dear [redacted]

First of all I will to thank you for our conversation and your input om my thesis.

After your feedback have I changes several questions and reduced the questionnaire to a total of 22 questions.

It you have time, and still are willing to help me, I would really appreciate if you could take a quick review on the last revision attached.

All feedback will be received with gratefulness!

Thanks for all your help so far! 😊

Best Regards
Alexander Carlsen
Student no. 251299
Tel. (+47) 95 96 85 00

Alexander Carlsen

From:	[redacted]@conocophillips.com>
Sent:	fredag 26. juni 2020 12:01
To:	Alexander Carlsen
Cc:	Idriss El-Thalji
Subject:	RE: [EXTERNAL]Master Thesis on readiness assessment of PdM analytics
Attachments:	Master Thesis - Self-assesment model_Question Proposal_rev 4.docx

Alexander,

It has become much better. Work little bit more on making it more focused. All abbreviations must be explained. CM can be read as condition monitoring as well as corrective maintenance.

Have made some suggestions. Implement if you and your supervisor agree.

Have a nice weekend.

[redacted]