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Integrating Planning of Maintenance and Continuous Production in an Oil and Gas Production System by the Use of Digital Twins

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Global Manufacturing Management
Submission date: June 2021
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Preface

This report is a master's thesis in Production Management as part of the Global Manufacturing Management study program at the Department of Mechanical and Industrial Engineering at the Norwegian University of Science and Technology (NTNU). This master's thesis is part of a multidisciplinary project between the Production Management and Reliability, Availability, Maintainability and Safety (RAMS) research groups at NTNU where the common topic is regarding digital twins across disciplines. The master's thesis focuses on the production management perspective of a digital twin and is investigating the integration of production and maintenance planning from a production management point of view. The study was conducted during the spring semester of 2021 and the initial motivation for the study was derived from the BRU21 research project and the Specialisation Project conducted in the autumn semester of 2020 at NTNU. The master's thesis has been written under the supervision of Professor in RAMS, Jørn Vatn, at the Department of Mechanical and Industrial Engineering.

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Aksel Gustavsen Bøhn

Abstract

This thesis investigates how mathematical models can serve as a basis for integrating production and maintenance planning in digital twins and cyber-physical systems. The thesis considers production and maintenance planning in the offshore oil and gas industry, where maintenance is considered to be a significant operating cost. Integrating production and maintenance planning is challenging because the two disciplines generally conflict with each other. Decisions regarding the production plan influence the condition of the machines in the system, while decisions for when to perform maintenance impose restrictions for the production plan. Previous studies have not dealt with the capabilities of digital twins and cyber-physical systems for integrating production and maintenance. To address this, mathematical models have been derived in this thesis to define principles for how these models should interact in order to utilise the capabilities of digital twins and cyber-physical systems. The models were linked to existing research concerning concepts, frameworks, technologies, and tools for digital twins and cyber-physical systems to discuss how this can contribute to realising the mathematical models in a digital twin and cyber-physical system and how it can contribute to decision-making across the disciplines. The results reveal that the models must automatically gather data in real-time, exchange data between them and with other elements of the digital twin and cyber-physical system, and handle the dependency between the production plan and the condition of the machines. A recommendation for further work is suggested to include a stochastic process in the modelling of the condition to capture the uncertainty of the degradation process.

Keywords – Integration, production planning, maintenance planning, digital twin, cyber-physical system

Sammendrag

Denne avhandlingen undersøker hvordan matematiske modeller kan fungere som grunnlag for å integrere produksjons- og vedlikeholdsplanlegging i digitale tvillinger og cyber-fysiske systemer. Avhandlingen tar for seg produksjons- og vedlikeholdsplanlegging i olje- og gassindustrien, der vedlikehold anses å være en vesentlig driftskostnad. Integrering av produksjons- og vedlikeholdsplanlegging er utfordrende fordi de to fagene generelt er i konflikt med hverandre. Beslutninger angående produksjonsplanen påvirker tilstanden til maskinene i systemet, mens beslutninger om når man skal utføre vedlikehold gir begrensninger for produksjonsplanen. Tidligere studier har ikke tatt høyde for mulighetene digitale tvillinger og cyber-fysiske systemer bringer for å integrere produksjon og vedlikehold. For å løse dette har matematiske modeller blitt utledet i denne oppgaven for å definere prinsipper for hvordan modellene skal samhandle og utnytte mulighetene digitale tvillinger og cyber-fysiske systemer bringer. Modellene er blitt knyttet til eksisterende forskning angående konsepter, rammeverk, teknologier og verktøy for digitale tvillinger og cyber-fysiske systemer for å diskutere hvordan dette kan bidra til å realisere de matematiske modellene i en digital tvilling og et cyber-fysisk system, og hvordan dette kan bidra til beslutningstaking på tvers av fagområdene. Resultatene avslører at modellene må automatisk samle inn data i sanntid, utveksle data mellom dem og andre elementer i en digital tvilling og et cyber-fysisk system, samt håndtere avhengigheten mellom produksjonsplanen og maskinens tilstand. Et forslag til videre arbeid er å inkludere en stokastisk prosess i modelleringen av tilstanden for å fange usikkerheten ved nedbrytningsprosessen.

Nøkkelord – Integrering, produksjonsplanlegging, vedlikeholdsplanlegging, digital tvilling, cyber-fysisk system

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Abbreviations

CAD	Computer Aided Design
CPS	Cyber-physical systems
DT	Digital twin
ERP	Enterprise resource planning
IoT	Internet of Things
MES	Manufacturing Execution Systems
PDF	Probability density function
RFID	Radio Frequency Identification
RUL	Remaining useful life

1 Introduction

Industry 4.0 is a common term describing the ongoing fourth industrial revolution. By digital transformation and the use of modern technology, industrial companies enable further automation and integration of their operations, as well as increasing autonomous decision-making processes, and real-time monitoring of assets and processes (Lasi et al., 2014). An evolving concept as a result of Industry 4.0 is digital twins. A digital twin is a virtual model of a physical object or system which provides real-time information about a physical part (Lu et al., 2020). The digital twin (DT) is considered to be a prerequisite for the development of cyber-physical systems (CPS) (Uhlemann et al., 2017) which are systems that enable remote diagnosis, real-time control, transparency, predictability, and increased efficiency of a production system (Monostori, 2014). By utilising the principle of Internet of Things (IoT), sensors and software can be connected with each other and exchange data. This enables a real-time representation of an object through the virtual model. In manufacturing, a digital twin can, for example, represent a physical product, production line, or an entire factory, while in the oil and gas industry it can represent a specific component, an oil well, or an entire oil platform. A digital twin can monitor and evaluate how the physical object is performing and enables simulation and "what-if" analysis based on the actual real-time performance of the physical object (Boschert and Rosen, 2016). A challenge in industrial companies is the integration of production planning and maintenance planning – two disciplines that generally conflict with each other (Nourelfath and Châtelet, 2012). Production planning and control describe the activities an organisation performs to plan and control the production so that the organisation's demand is met. This involves ensuring the availability of equipment, raw material, and personnel, while also planning the desired output of the production that is needed to meet the demand (Jacobs et al., 2011). Maintenance planning, on the other hand, involves planning activities that aim to ensure the system's function and lifetime, as well as ensuring safety and human well-being. Planning maintenance includes, amongst other things, deciding when the maintenance should be performed, by whom, and with what type of equipment and material (Al-Turki, 2009).

Furthermore, there are three types of strategies that determine how the maintenance is performed, namely corrective, preventive, and predictive maintenance (Wang et al., 2015). Corrective maintenance is activities performed whenever a component or equipment runs to failure. This is considered to be a costly solution, not only in terms of the actual maintenance costs of running parts to a damaged state but also in terms of the cost of lost production. Preventive maintenance is planned maintenance activities that are done in a precautionary matter and often scheduled in specific time intervals. Predictive maintenance, often referred to as condition-based maintenance (Wang et al., 2015), involves regular monitoring of the actual mechanical condition, operating efficiency, and other indicators of the operating condition of machines and process systems (Mobley, 2004). This regular monitoring provides the required data to ensure the maximum interval between repairs and minimise the number and cost of unscheduled outages created by failures. Predictive maintenance measures parameters in the condition of the equipment to find the optimal time to carry out tasks that optimise the service life of machines and processes without increasing the risk of failure. Although predictive maintenance has been used in the industry for several years already, it is considered to have great potential in Industry 4.0 due to the accelerated use of technologies like big data and cloud computing (Li et al., 2016), improving the procedure of gathering and interpreting data.

This thesis aims to investigate how production and maintenance planning can be integrated by the use of digital twins and cyber-physical systems. Maintenance activities on production equipment use time that otherwise could be used for actual production while, on the other hand, avoiding maintenance activities in favour of running production can increase the risk of failure on equipment which could initiate downtime. For many production systems, there exist a trade-off between producing as much as possible and wearing out the components of the system (Verheyleweghen et al., 2019). According to Djurdjanovic et al. (2018), in order for modern manufacturing practices to move toward the standards of the fourth industrial revolution, advancements in maintenance and production operations decision-making are necessary. Previous research indicates that the practice of making maintenance and production decisions separately can be costly and that there are significant benefits for making these decisions in an integrated fashion (Aghezzaf and Najid, 2008). Moreover, Industry 4.0, digital twins, and cyber-physical systems are reckoned to be important concepts that can contribute to this matter, and help improve the planning and management of production and maintenance (García and García, 2019; Tao et al., 2019b). Digital twins and cyber-physical systems will contribute to more accurate planning and more efficient dispatching through real-time monitoring, analysis, evaluation and optimisation of the production and maintenance planning operation (Tao et al., 2019b), while Industry 4.0-related technologies is considered to have a significant impact on both production and maintenance management according to García and García (2019).

The importance of digital twins is increasingly recognised by both academia and industry, and many digital twin applications have been successfully implemented in different industries, including product design, production, prognostics and health management (Tao et al., 2019b). Another industry that has identified the opportunity to take advantage of digital twin applications is the oil and gas industry (LaGrange, 2019). As a result of lower oil prices, incentives have emerged to improve maintenance performance in the industry since maintenance costs are considered to be a significant operating cost (Norwegian Petroleum Directorate, 2020). Based on this, it will be of interest to investigate how the integration of production and maintenance planning can be carried out in the offshore oil and gas industry by the use of mathematical models in a digital twin and cyber-physical system.

1.1 Background

The purpose of this thesis is to develop mathematical models for integrating production and maintenance planning and investigating how such models can be used in a digital twin and cyber-physical system and utilise the capabilities of the digital twin concept. The problem is studied in light of offshore oil production. There have been several research papers that address the challenges of integrating production and predictive maintenance (Pan et al., 2011; Liu et al., 2018; Ghaleb et al., 2020a; Hafidi et al., 2020), however, these papers are not incorporating the digital twin concept and how it can improve the integration of production and maintenance planning in their research. Furthermore, the above-mentioned articles are studied in an industrial manufacturing environment, where the characteristics of production are different from the offshore oil and gas industry which is the scope of this thesis.

In the Norwegian oil and gas industry, there have been several investigations into the use of mathematical programming and optimisation (Haugland et al., 1988; Christiansen and Nygreen, 1993; Jonsbråten, 1998; Ulstein et al., 2007). Haugland et al. (1988) formulated a linear program for offshore oil production planning, which was gradually extended to a mixed-integer program. The model assumes that the wells are already drilled and that it only remains to find the production profiles which provides the optimum value of some given criterion, like the net present value of income. Christiansen and Nygreen (1993) described a planning model for the management of 130 oil-producing wells in the North Sea. The objective was to form a better basis for the decisions about which wells to produce from and which to shut down during a period. Jonsbråten (1998) presented a mixed integer programming model for optimal development of an oil field under uncertain future oil prices. A finite set of oil price scenarios with associated probabilities was provided. The work of Jonsbråten (1998) is based on the model presented by Haugland et al. (1988). Furthermore, Ulstein et al. (2007) developed an integer program for tactical planning of Norwegian petroleum production. The problem considered regulation of production levels from wells, splitting of production flows into oil and gas products, further processing of gas, and transportation in a pipeline network. More recently, Krishnamoorthy et al. (2016) considered a dynamic scenario-based approach for the daily production optimisation in the upstream oil and gas domain. Nevertheless, these papers do not consider maintenance as part of their optimisation problems, nor do they consider the digital twin concept or cyper-physical systems.

Regarding the integration of production and predictive maintenance in the oil and gas industry, some recent papers have been published by Verheyleweghen and Jäschke (2017), Verheyleweghen and Jäschke (2018) and Matias et al. (2020). Verheyleweghen and Jäschke (2017) proposed a framework for combined diagnostics, prognostics, and optimal operation of a subsea gas compression system while Verheyleweghen and Jäschke (2018) studied the optimisation of several wells subject to choke degradation. The paper proposed to integrate condition monitoring and prognostics into the production planning problem to reduce conservativeness by actively steering plant degradation and preventing violation of health-critical constraints. A model for predictive control approach that incorporates process monitoring was proposed in Matias et al. (2020). The model allows steering of plant degradation actively, preventing violation of health-critical constraints while optimising the economic production of the system.

However, none of the papers above studied the integration of production and maintenance by the use of digital twins and how the two disciplines can utilise the concept of digital twin and cyber-physical systems to improve operational performance. Rødseth et al. (2018) are the authors who are closest to address this gap. The authors investigated how estimating the remaining useful lifetime can help synchronise the production and maintenance planning with predictive maintenance capability and briefly discuss how Industry 4.0 trends relate to the maintenance part of the problem. A three-step approach for synchronising maintenance planning was proposed, consisting of (I) establish the initial maintenance plan, (II) modelling of RUL, and (III) synchronise the maintenance plan. Using real-life data about historical loads and speeds, the remaining useful life of the component under consideration can be calculated. However, the paper does not account for the use of digital twins, although some aspect of digitisation of maintenance is discussed, neither do the paper directly incorporate the production planning aspect in the problem or study how the planned production can influence the degradation of a component.

Therefore this thesis aims to investigate how production and maintenance planning can be integrated and synchronised by the use of digital twins, specifically address how digital twins can contribute to this matter, and investigate what concepts, frameworks, technologies, and tools that exist for this purpose.

1.2 Objectives

The main purpose of this thesis is to develop mathematical models that can serve as a basis for integrating production and maintenance planning in digital twins and cyber-physical systems for an offshore oil and gas production system. The aim is to investigate how the mathematical models should be structured and how they should interact with each other to improve the synchronisation between production and maintenance by utilising real-time data from the system and predicted degradation of a component. In that regard, the following research objectives have been determined:

1. Derive basic mathematical models for integrating production and maintenance.
2. Define principles for what the mathematical models in a digital twin and cyber-physical system should do in order to integrate production and maintenance.
3. Investigate what concepts, frameworks, technologies, and tools that must exist in a digital twin and cyber-physical system in order to support the integration of production and maintenance through existing research in the literature.
4. Discuss how digital twins can contribute to decision-making across the two disciplines production and maintenance.

The two first research objectives are linked to Chapter 3 which presents the development of the models and a numerical demonstration. The last two research objectives are linked to Chapter 4, where the derived models are linked to the existing literature on digital twins and cyber-physical systems to determine what concepts, frameworks, technologies, and tools that must be incorporated with the mathematical models to support the integration of production and maintenance planning.

1.3 Approach

This section presents the methodological approach for this thesis and describes the different methods that have been applied. The process behind the literature review is described, before mathematical modelling as a methodological approach is presented.

1.3.1 Literature Review

A literature review from the Specialisation Project, conducted during the fall semester of 2020, forms the basis of the literature for this thesis. Furthermore, the literature review has been extended during the spring semester of 2021 to include additional articles that are relevant to the research objectives for this thesis. The searches have been conducted in the following databases: Emerald, Science Direct, Springer, Scopus, and One Petro. Performed searches were done in all of the databases through Google Scholar, except for OnePetro which was only included for searches related to the oil and gas industry. Several facets were decided to provide precise searches, and relevant synonyms and terms were included. These are presented in Table 1.1.

Primarily searches were done by using a block search strategy (combining several facets with 'AND' or 'OR' operators). Furthermore, when highly relevant articles were found, cited by searches were performed to find additional relevant articles. Articles were decided to be relevant if the title, abstract, or keywords of the article included some of the search facets.

Facet	Related terms and synonyms
Integration	• Integrate, integrating • Synchronise, synchronisation, synchronising • Synchronize, synchronization, synchronizing • Coordination, coordinate, coordinating • Joint optimisation, joint optimization
Maintenance	• Predictive maintenance • Condition-based maintenance
Production	• Operation • Manufacturing
Planning	• Plan • Scheduling • Schedule
Industry 4.0	• Maintenance 4.0 • Digitisation • Cyber-physical system • Digital twin
Oil and gas	• Offshore • Petroleum • Remote operations

Table 1.1: Search words used in the literature review

Then the articles were skimmed to assess if they in fact were relevant to the thesis or not. Research articles that investigated the integration problem were rated highly, however, this criterion had to be looser when searching for literature that studied the integration problem in the context of oil and gas production or Industry 4.0. The reason for this is that there seem to be few or no articles that specifically address the integration problem in these contexts. The software JabRef has been used to manage all of the literature used in the thesis.

1.3.2 Mathematical Modelling

The main research approach in this thesis is mathematical modelling. The modelling is done in a conceptual domain, thus the need for real data has been non-existent. This thesis does therefore not rely on collected data from real life. Gaining access to data when working with modelling can be difficult but should not introduce problems as long as the researcher works in the conceptual domain (Karlsson, 2016). However, to demonstrate the mathematical models that have been derived in this thesis, certain data and input parameters have been required to run the model. Some of this data, for example, related to production rates in the oil sector and oil price, is assumptions based on what can be found in the literature and other sources of information. It has been highlighted in the actual section whenever such assumptions have been made in the demonstration of the model. Furthermore, data related to the degradation of the choke valve (Section 3.4) has been based on information found in the recommended practice article from DNV-GL (2015), which presents methods and concepts for managing sand production and erosion. Considering that the recommended practice article was developed in collaboration with several major actors in the oil and gas sector, it is reasonable to assume that the suggested data values in this article have realistic values.

As digital twins can be seen as a digital model of a physical asset, mathematical modelling is a suitable method for studying how this can enable integration of production and maintenance. Furthermore, production and maintenance planning is also areas of research that often is studied through the use of mathematical modelling. Several research methods for operations management is discussed by Karlsson (2016). The author defines axiomatic research as research that is primarily driven by the (idealised) model itself. The primary objective is obtaining solutions within the defined model and ensuring that these solutions provide insights into the structure of the problem. Axiomatic research generates an understanding of the behaviour of certain variables in the model, based on assumptions about the behaviour of other variables in the model (Karlsson, 2016). Additionally, it can generate an understanding of how to manipulate certain variables in the model, assuming desired behaviour of other variables in the model and assuming knowledge about the behaviour of the other variables in the model (Karlsson, 2016). Axiomatic research is primarily prescriptive, seeking to develop policies, strategies and actions to improve the results available in the literature and to find an optimal solution for a newly defined problem. Descriptive research, on the other hand, is seeking to analyse a model to understand and explain the characteristics of the model (Karlsson, 2016).

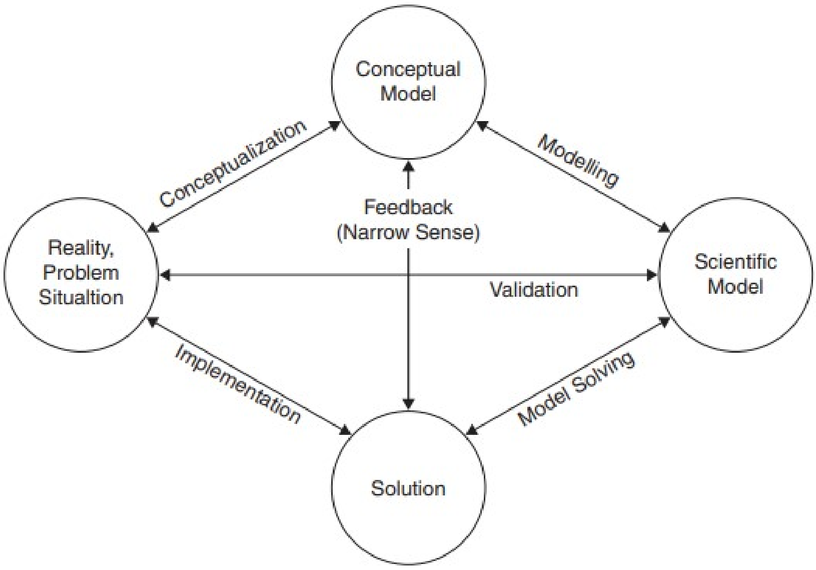


Figure 1.1: Research model from Karlsson (2016) based on Mitroff et al. (1974)

The research approach of this thesis can be described as axiomatic quantitative research, based on the definition presented by Karlsson (2016). Axiomatic quantitative research starts with a description of the operational process or the operational decision problem that is going to be studied. Relating this to Figure 1.1, this correlates with the conceptual model in the illustration. Karlsson (2016) emphasised that in axiomatic research, it is necessary to describe all assumptions that underlie the conceptual model. This has been done accordingly throughout Chapter 3. Furthermore, the work in this thesis contributes to the study of a new variant of the problem, using well-known solution techniques found in the literature, rather than studying a problem that has been studied before and applying new types of solution techniques that provides better results. The second phase of an axiomatic quantitative research approach is the specification of the scientific model of the process or problem. To perform either mathematical or numerical analysis, the scientific model should be presented in formal mathematical terms. Additionally, relationships in the model should be explained and related to earlier work in which similar relations have been developed (Karlsson, 2016). The relationships is explained in Section 3.2 and the relation to earlier work is described throughout Chapter 3.

The advantages of this research method are that it enables analysis of large complex situations from the real world without the need to interfere or interact with an actual system of the real world. It also facilitates discussion of "what if" type of questions, which is directly relatable to the capabilities of a digital twin. On the other hand, the results of a model are strongly dependent on the quality of the model and on the assumptions made. By making either many or unrealistic assumptions, one may risk that the model becomes distant from the real-life situation. In addition to this, mathematical models are often unique and tailor-made for the problem it aims to solve, thus making it difficult to generalise. Having said that, it will still allow for studying the interactions between production and maintenance planning and how a digital twin can enable optimisation and synchronisation between these two disciplines.

1.4 Outline

Below follows a description of the remaining structure of this thesis.

Chapter 2 - Theoretical Background: presents the fundamental theoretical definitions and concepts that production and maintenance planning is built upon, predictive maintenance, and remaining useful life and prognostics methods for maintenance, while also describing the characteristics of an oil and gas production system, Industry 4.0, digital twins and CPS, and mathematical modelling.

Chapter 3 - Mathematical Models for Digital Twins: presents the mathematical models that have been derived in this thesis, describing the problem and case under consideration and the three models that are considered to integrate production and maintenance.

Chapter 4 - Linking the Models to a Digital Twin and Cyber-Physical System: elaborates on how the digital twins are interpreted in the literature, forming the basis for discussing how the mathematical models relate to the various elements of a digital twin and cyber-physical system.

Chapter 5 - Discussion: presents the discussions of the work carried out in this thesis. The two main parts of the thesis, Chapter 3 and 4, are discussed regarding how they support and answer the research objectives, in addition to discussing the challenges and limitations of the work. Suggestions for further work is also recommended in this chapter.

Chapter 6 - Conclusion: this chapter concludes the master's thesis.

Chapter 2 describes relevant theory and literature both regards to production management and reliability, availability, maintainability and safety. After this, Chapter 3 presents the derived mathematical models that demonstrate some of the challenges for integrating the different digital twins. Following this chapter, Chapter 4 evaluates and discuss the literature on digital twins and how it enables integration across disciplines. The aim is to link the derived mathematical models to the frameworks and methods that exists in the literature.

2 Theoretical Background

The theoretical background acts as a foundation for the work that has been carried out in this thesis. The following chapter presents theoretical definitions and concepts that production and maintenance planning is built upon, predictive maintenance, and remaining useful life and prognostics methods for maintenance. Following this, descriptions of the characteristics of an oil and gas production system, Industry 4.0, digital twins and CPS, and mathematical modelling is provided. The first part, Section 2.1, presents traditional production planning and control theory, describing how the production planning function typically is organised and describing production planning and control principles in the oil and gas industry. Section 2.2 introduces maintenance planning and scheduling and briefly describes the different maintenance strategies that exist. Section 2.3 describes predictive maintenance as this is seen as an important maintenance strategy in modern industry and for digital twins and cyber-physical systems. In relation to predictive maintenance, the concept of remaining useful life is typically applied together with prognostics methods for maintenance. This is presented in Section 2.4. General characteristics of an oil and gas production system are presented in Section 2.5 to understand the challenges and prerequisites for how integrated production and maintenance planning in the oil and gas industry should be conducted. Section 2.6 address the two relevant concepts for integrated production and maintenance planning in Industry 4.0, namely digital twins and cyber-physical systems. The last part, Section 2.7, presents theoretical principles in mathematical modelling.

2.1 Production Planning and Control

Production planning and control describe the activities an organisation performs to plan and control the production so that the organisation's demand is met. This involves ensuring the availability of equipment, raw-material and personnel, while also planning the desired output of the production that is needed to meet the demand. Production planning and control are defined by Jacobs et al. (2011) as:

> "... to manage efficiently the flow of material, to manage the utilisation of people and equipment, and to respond to customer requirements by utilising the capacity of our suppliers, that of our internal facilities, and (in some cases) that of our customers to meet customer demand." (Jacobs et al., 2011)

While a *plan* is a formalisation of what is intended to happen in the future, it does not guarantee that an event will actually happen. Unforeseen changes and differences occur, and *control* is the process of coping with these changes and differences (Slack et al., 2013). A common concept of planning general activities is the concept of planning horizons. The terms and descriptions may vary depending on the application area and industry, but in regards to production planning and control, the planning horizons can be classified into three levels (Jacobs et al., 2011; Slack et al., 2013):

- Strategic (long-term)
- Tactical (medium term)
- Operational (short term)

At the *strategic level*, production planning and control aim to provide information for decision-making on determining the capacity needed to meet the market demands. This is also the level where decisions regarding human resource capabilities, technology, and geographical locations take place (Jacobs et al., 2011). At the *tactical level*, production planning and control determines the product volume and mix that matches the supply and demand. This implies providing the exact material and production capacity needed to meet the demand by planning for the right quantities of material to arrive at the right time and place to support production and distribution. Furthermore, maintaining appropriate levels of raw material, work in process, and finished goods inventories in the correct locations are central tasks at this level, while planning of capacity requires determining employment levels, overtime possibilities, subcontracting needs, and support requirements (Jacobs et al., 2011). Lastly, the *operational level* is where the detailed scheduling of resources required to meet production requirements is conducted, which involves time, people, material equipment and facilities (Jacobs et al., 2011).

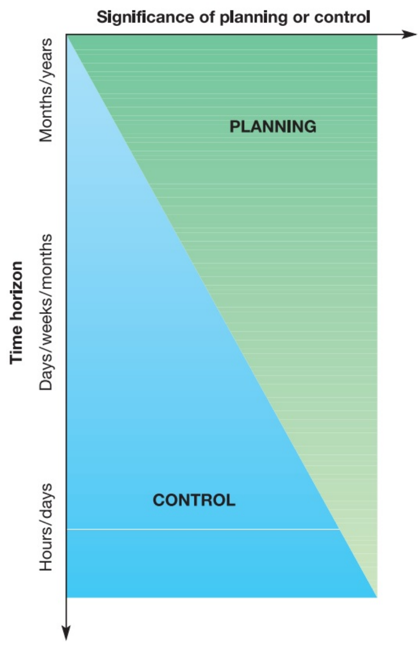


Figure 2.1: Relationship between planning and control (Slack et al., 2013)

The different levels of planning and how they interact with each other can also be described by the previously introduced terms planning and control. The two terms are separate but closely related activities (Slack et al., 2013). Long-term planning lies within the planning category, whereas the operational and short-term level lies within the control category, illustrated in Figure 2.1. A more detailed description of how processes in the supply chain fit with the different planning horizons is illustrated in the supply chain planning matrix in Figure 2.2, where production processes are highlighted in the red box. The matrix places plant location and production system in the long-term level, master production scheduling and capacity planning in the mid-term level, and lot-sizing, machine scheduling, and shop floor control at the short-term level.

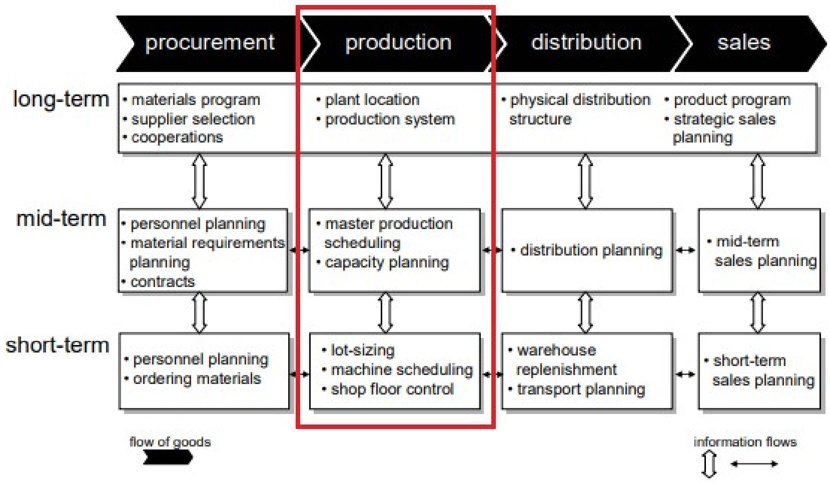


Figure 2.2: The supply chain matrix adapted from (Fleischmann et al., 2015)

2.1.1 The Difference Between Production Planning and Scheduling

When reviewing the literature at hand, it is important to distinguish between production planning and production scheduling. The two terms may sound similar, however, there are differences between the two although they both can be categorised as production planning. Strategic (long-term) planning decides the executive composition of the supply chain by determining capacity- and location-related decisions, while tactical (medium-term) planning make decisions regarding material requirements and desired output. Operational (short-term) planning is performed on a weekly or daily basis at a more detailed level to assign tasks and the sequencing of tasks that comes as a result of the tactical production plan. It is at this level that production scheduling is performed. Fleischmann et al. (2015) uses the term "scheduling" to describe activities in both the mid-term level (master production schedule) and short-term level (machine scheduling). Throughout this thesis, the term production planning are used to describe production planning activities that is performed at the tactical level, while production scheduling describes processes and activities at the operational level.

2.1.2 Production Planning and Control System

Production planning and control are organised in a system that is tightly linked with the planning horizons. The hierarchy is illustrated in Figure 2.3, while the linkage to the planning horizon and level of detail is illustrated in Figure 2.4.

The *production plan* is driven by the strategic business plan and concerns determining quantities of product groups that need to be produced in a period, desired inventory levels, resources of equipment, labour, and material needed in a period, and the availability of the needed resources. The level of detail is not high at this stage (Arnold et al., 2008). The *master production schedule* is based on the production plan and determines the quantity of each end item that is to be made. Whereas the production plan is based upon product families, the master production schedule is developed for individual end items (Arnold et al., 2008). *Material requirements plan* establishes when the components and parts are needed to make each end item. This involves determining what to order, how much to order, when to order, and when to schedule delivery (Arnold et al., 2008). *Purchasing and production activity control* represent the implementation and control phase of the production planning and

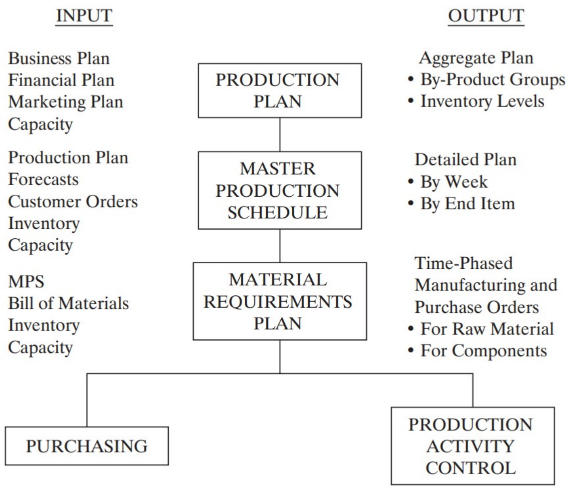


Figure 2.3: Hierarchy of production planning and control system (Arnold et al., 2008)

control system. Purchasing establishes and controls the flow of raw materials into the factory, while production activity and control plans and controls the flow of work through the factory (Arnold et al., 2008).

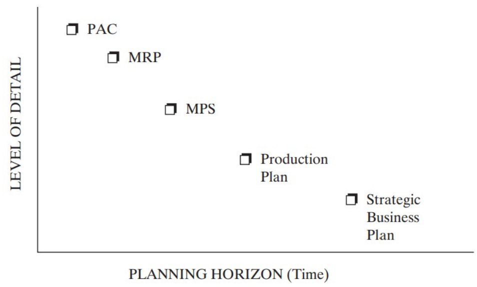


Figure 2.4: Level of detail versus planning horizon (Arnold et al., 2008)

To plan the production, five basic inputs need to enter the production planning and control system (Arnold et al., 2008):

- Product description - describes the product characteristics and features through drawings and specifications. The most common method is through a bill of material, that describes the components used to make the product and the sub-assemblies related to the product (Arnold et al., 2008).
- Process specifications - describes the necessary steps to make the finished product. Typically specifies what operations that need to be done, in what sequence, with what equipment, and how much time is required to complete each operation (Arnold et al., 2008).
- Time consumption - includes how much time is needed to perform operations, and how much time is needed to load and deliver the product to other stations of the system (Arnold et al., 2008).
- Available facilities - information regarding what plant, stations, equipment, and labour will be available at what time to process work (Arnold et al., 2008).

- Required quantities - based on demand forecasts, customer orders, orders to replace finished goods inventory, and the material requirements plan (Arnold et al., 2008).

2.1.3 Production Processes

Having presented the overall goal of production planning and control, planning horizons, and the difference between production planning and scheduling, the following section moves on to briefly describe some common production processes. Depending on what kind of products are produced, the different production processes that are used in manufacturing can be listed as follows (Arts et al., 2018):

- Continuous production
- Mixed model flow and assembly lines
- Job shop manufacturing
- Group technology / Cellular manufacturing systems
- On site manufacturing

Continuous production is often used in process industries and for bulk materials. Oil refineries, chemical products, and food processing are examples. The products are often liquids that can be packed in any amount desired (Arts et al., 2018). *Mixed model flow and assembly lines* include assembly processes found in the automotive industry and consumer electronics, as well as parts manufacturing systems that are based on a fixed and repetitive sequence of process steps that are basically identical for all products. This process is typically suitable for the manufacture or assembly of products that are sold in large volumes and low variety (Arts et al., 2018). *Job shops* are characterised by a highly functional process structure, where machines are grouped according to specific processes, like milling or drilling in a machine shop. Each product could have its own routing through the shop, which enables the system to handle large varieties of products. Job shops are generally suitable for small product quantities (Arts et al., 2018). *Group technology* groups the products based on similar production characteristics and consecutive process steps will happen in the same cell (Arts et al., 2018). *On-site manufacturing* is performed when realising complex infrastructural works (bridges, tunnels) or the completion of a major industrial facility. These works are often organised as a separate project. The main feature of on-site manufacturing is that the equipment and components needed to finish the product is transported to the product's site (Arts et al., 2018).

2.1.4 Production Planning and Control in Oil and Gas

Keeping the above in mind, the production process in oil and gas is considered to be continuous production. Similar to general production planning and control described previously in this chapter, production planning and control in oil and gas also involve different planning horizons. Bieker et al. (2007) studied the information flow in offshore oil production optimisation. In oil and gas, a typical production system is operated by periodically generating a production and injection plan. The production and injection plan will determine the production level of each well for a specific period, while also determining the injection of gas or water for the injection wells (Bieker et al., 2007). According to Bieker et al. (2007), the goal in optimising the production plan in offshore oil is typically to maximise the daily production rate of oil and to inject gas and water according to established rules provided by the reservoir planning. This implies that the wells that should produce must be prioritised and that the rate of production on each well must be determined. This is required since the available processing capacity is less than the combined flowing capacity of the wells (Bieker et al., 2007). Similarly to the manufacturing industry, the development of a petroleum field asset requires planning on several horizons (Gunnerud and Foss, 2010). On the strategic level (long-term horizon), reservoir planning is based on market conditions, field properties, and strategic considerations of the developing company. This level typically also include decisions related to the technology for an offshore field and involves deciding how to develop the subsea solution, whether to process the fluid onshore or offshore, and how to export the different produced products (Gunnerud and Foss, 2010). On the tactical level (medium-term horizon), also called tactical reservoir management, the goal is to extract as much oil and gas from the reservoir as possible, within the bounds of the strategic decisions. Decisions at this level involve deciding the drilling of new wells to reach a predefined production rate while at the later stage it can involve deciding whether to apply artificial lift technology to boost production (Gunnerud and Foss, 2010). On the operational level (short term) the goal will be to maximise daily production rates. However, production could be constrained by certain reservoir conditions related to the production equipment like, for example, a pipeline capacity or downstream water handling capacity. This results in the need to model both the subsea part and the surface part of the value chain. Decisions at this level involve deciding the production and injection rates, so-called artificial lift inputs and routing of well streams (Gunnerud and Foss, 2010).

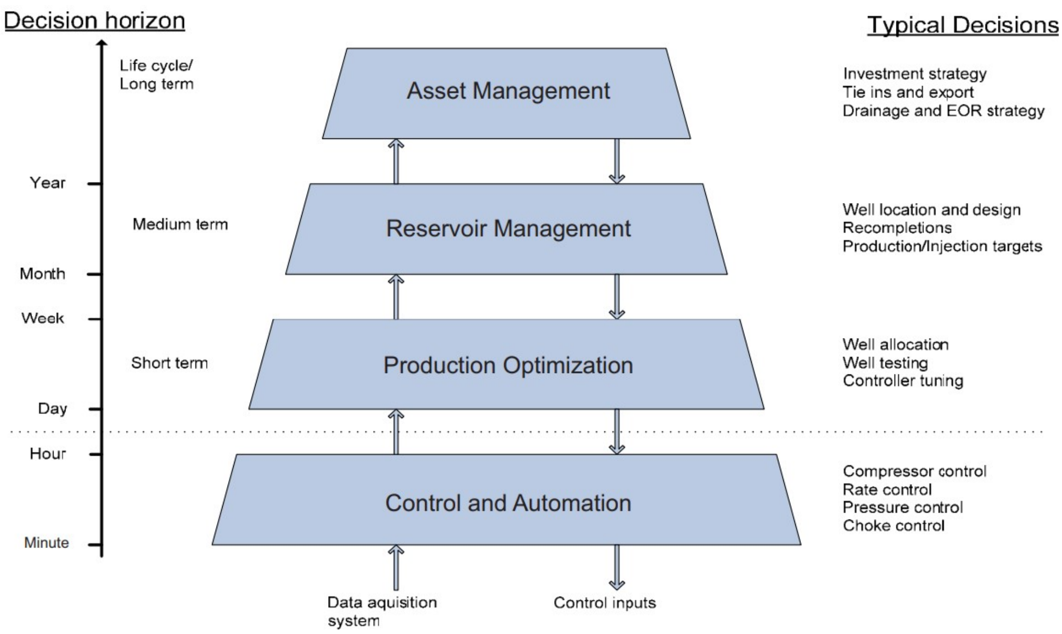


Figure 2.5: Multilevel control hierarchy for oil and gas (Foss and Jensen, 2011)

Similar structures and interpretations are found in the literature (Saputelli et al., 2002; Foss and Jensen, 2011). Saputelli et al. (2002) introduced a hierarchy of oil field operations that identifies various levels of detail and time scales for decision-making processes. The hierarchy has similarities with the production planning and control hierarchy discussed previously in this chapter. This hierarchy describes five levels: capacity planning design, operational planning, scheduling, supervisory control, and regulatory control. Additionally, Foss and Jensen (2011) presented a multilevel control hierarchy consisting of four levels: asset management, reservoir management, production optimisation, and control and automation. The hierarchy is illustrated in Figure 2.5, which illustrates that decisions on different time scales are closely related to each other. Decisions above the horizontal dotted line are semi-automatic because humans are involved in the decision-making. The vertical arrows indicate that the decisions on different layers influence each other. Typically, long-term optimisation imposes constraints on lower-level decisions to avoid a short-term production strategy harming long-term recovery (Foss and Jensen, 2011).

2.2 Maintenance Planning and Scheduling

So far, the principles of production planning and control has been presented. This section describe principles of maintenance planning and scheduling. Maintenance is the combination of all technical and associated administrative actions intended to maintain an item or system in, or restore it to, a state in which it can perform its required function (Dekker, 1996). Furthermore, the objectives of maintenance are described by Dekker (1996) as:

- Ensuring system function (availability, efficiency and product quality)
- Ensuring system life (asset management)
- Ensuring safety
- Ensuring human well-being

Similar to the theory of production planning and control described in Section 2.1, the process of maintenance planning and scheduling can also be divided into three basic levels depending on the planning horizon (Al-Turki, 2009):

- Long range (strategic) - yearly plans
- Medium range (tactical) - monthly plans
- Short range (operational) - daily and weekly plans

Although the terms are slightly different, the maintenance planning horizons can be interpreted in the same way as the planning horizons of production planning and control presented in Section 2.1. *Strategic* maintenance planning typically addresses four dimensions: (I) decisions regarding outsourcing or in-house maintenance, (II) organisation and work structure, (III) maintenance strategy, and (IV) selection of the support system (Al-Turki, 2009). *Tactical* maintenance planning decides how the maintenance organisation operates and provides details for major overhauls, construction jobs, preventive maintenance plans, plant shutdowns, and vacation planning. The plan balances the need for manpower over the period covered and estimates the required spare parts and material acquisition (Al-Turki, 2009). *Operational* maintenance planning determines the required elements to perform maintenance tasks. Required labour, equipment, and material are estimated and planned at this level (Al-Turki, 2009).

2.2.1 Maintenance Strategies

To achieve the objectives of maintenance, several maintenance strategies exist and are discussed in the literature. However, the definitions and classifications of the different methodologies are often used interchangeably and without precision. An example of this is made clear by comparing the works of Duffuaa and Raouf (2015) and Wang et al. (2015). The former suggests nine different strategies, while the latter, on the other hand, classifies the strategies in three classes: corrective maintenance, preventive maintenance, and predictive maintenance. The two different interpretations are presented in Figure 2.6 and 2.7. As the two figures illustrate, there are different interpretations of the maintenance methodologies and how they are classified. This is also a subject that is researched by Khazraei and Deuse (2011), who addressed the lack of a common taxonomy regarding maintenance types. However, in this thesis, the definition presented by Wang et al. (2015) is used.

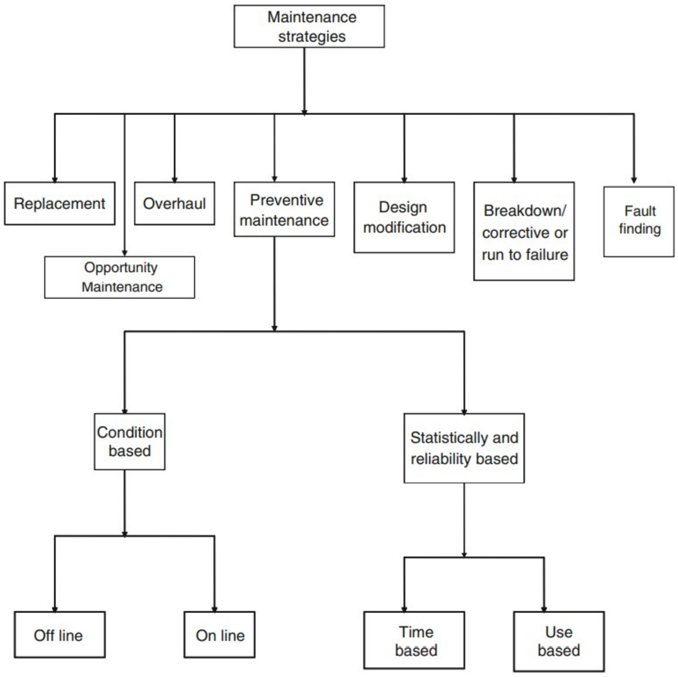


Figure 2.6: Maintenance strategies (Duffuaa and Raouf, 2015)

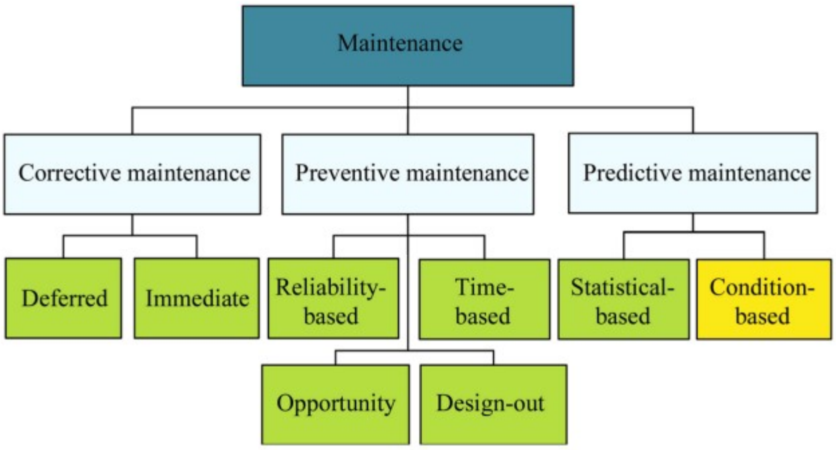


Figure 2.7: Classification of maintenance strategies (Wang et al., 2015)

The maintenance strategies and methods applied in various industries has gone through several phases throughout history (Eyoh and Kalawsky, 2018). While there was a time where maintenance activities were done to fix equipment when it broke (corrective maintenance) or were done in a precautionary matter (preventive maintenance), the modern methods rely on more structured and thoughtful strategies in addition to the two mentioned above. The two strategies are still in use in industries (Wang et al., 2015), but predictive maintenance has become a common maintenance strategy in modern maintenance management. Predictive maintenance is considered to have great potential in Industry 4.0 due to the accelerated use of technologies like big data and cloud computing (Li et al., 2016). The next section will present the theory regarding predictive maintenance.

2.3 Predictive Maintenance

Predictive maintenance, often referred to as condition-based maintenance (Wang et al., 2015), involves regular monitoring of the actual mechanical condition, operating efficiency, and other indicators of the operating condition of machine and process systems (Mobley, 2004). This regular monitoring provides the required data to ensure the maximum interval between repairs and minimise the number and cost of unscheduled outages created by failures. It is a strategy that uses the actual operating condition of plant equipment and systems to optimise the total plant operation (Mobley, 2004). Predictive maintenance measures parameters in the condition of equipment to find the optimal time to carry out tasks that optimise the service life of machines and processes, without increasing the risk of failure. There are different methods of measuring the symptom of failures, which leads to the two groups of predictive maintenance: statistical-based predictive maintenance and condition-based predictive maintenance (Wang et al., 2015). Statistical-based predictive maintenance relies on statistical data from the continuous recording of the stoppages of machines and equipment to develop models for predicting failures. Condition-based predictive maintenance depends on continuous or periodic monitoring of the equipment's condition to detect the signs of failure and make maintenance decisions (Wang et al., 2015). When implementing a predictive maintenance strategy, several key techniques including sensors and signal processing techniques, feature extraction techniques, fault diagnosis and prognosis techniques and maintenance optimisation techniques should be taken into account (Wang et al., 2015). According to Wang et al. (2015), there are both advantages and disadvantages of predictive maintenance, summarised in Table 2.1.

Advantages	**Disadvantages**
• Equipment that requires maintenance is shut down only before imminent failure • Reducing the total time spent maintaining equipment • Reducing maintenance costs by avoiding catastrophic damage • Increasing availability and reliability of machines • Extending life of equipment and processes	• The skill level and experience required to accurately interpret condition monitoring data is high • The cost of the equipment needed for condition monitoring is often high

Table 2.1: Advantages and disadvantages of predictive maintenance (Wang et al., 2015)

To monitor the equipment's condition by the use of sensor technology, some predictive maintenance techniques have been classified by Selcuk (2016):

- Process parameter measurements
- Vibration analysis
- Oil analysis
- Thermal analysis
- Acoustic analysis
- Other

The different techniques have different application areas and different suitability (rotating equipment, electrical equipment, etc.) to detect various problems (crack detection, corrosion monitoring, etc.) and is not explained in detail in this thesis.

2.3.1 Predictive Maintenance System

Predictive maintenance as a maintenance strategy is described by both Jardine et al. (2006) and Xu et al. (2019). The latter can be viewed as a continuation of the concepts found in the former, aiming to provide an overview of the predictive maintenance system in the modern era of big data. In general, the predictive maintenance system consists of data acquisition and pre-processing, fault diagnostics, fault prognostics and maintenance decision-making, according to Xu et al. (2019). These activities are further described below.

Data acquisition describes the process and activities of collecting and storing relevant data from physical assets. It acts as a foundation for fault diagnostics and prognostics. The two types of data that is considered to be relevant for predictive maintenance are *event data* and *condition monitoring data* (Jardine et al., 2006). Event data provides information regarding what happened (e.g., installation, breakdown, overhaul, etc.), what caused the event, and what was done (e.g., minor repair, preventive maintenance, oil change, etc.) in relation to the event and to the targeted physical asset (Jardine et al., 2006). On the other hand, condition monitoring data are the measurements related to the health condition/state of the physical asset. Some examples of condition monitoring data are vibration data, acoustic data, oil analysis data, temperature, pressure, and so on (Jardine et al., 2006). The advance of Internet of Things technology enables these data to be captured and stored for further analysis (Xu et al., 2019). Jardine et al. (2006) also pointed out that event data and condition monitoring data are equally important, although people tend to put more emphasis on the collection of the condition monitoring data.

When it comes to data processing, the first step is to clean the data. This is an important step since data often contains errors. Data cleaning increases the chance that the data is free of errors before further analysis and modelling. Data errors are caused by many factors, where one example is human errors, while for conditioned monitoring data, data errors may be caused by sensor faults (Jardine et al., 2006). After the data has been cleansed, the data can then be analysed. A variety of models, algorithms, and tools are available in the literature to analyse data for better understanding. The models, algorithms and tools used for data analysis depend mainly on the types of data collected (Jardine et al., 2006).

Fault diagnostics focus on detection, isolation and identification of faults when they occur. Machine fault diagnostics is a procedure of mapping the information obtained in the measurement space or features in the feature space to machine faults in the fault space (Jardine et al., 2006). There are two main approaches in fault diagnostics, which are statistical approaches and artificial intelligence approaches. The process of fault diagnostics is outside of the thesis' scope, and is not described further.

Moving on to the concept of fault prognostics, it can be defined as "*the ability to predict the future condition of a machine based on the current diagnostic state of the machinery and its available operating and failure history data*" (Byington et al., 2002). According to Jardine et al. (2006), prognostics is superior to diagnostics in the sense that prognostics can prevent faults or failures, and if not, prepare spare parts and human resources for the problems, and thus save extra unplanned maintenance cost. On the other hand, prognostics cannot completely replace diagnostics since in practice there are always some faults and failures which are not predictable. Besides, similar to other prediction techniques, prognostics cannot be 100 per cent sure to predict faults and failures (Jardine et al., 2006). The next section of this chapter presents different methods related to fault prognostics in maintenance.

2.4 Remaining Useful Life and Prognostics Methods for Maintenance

In the research literature, Peng et al. (2010), Sikorska et al. (2011), An et al. (2013), and Gao et al. (2015) studied the different prognostics methods for maintenance. In this section, remaining useful life is described before two statistical approaches, the Wiener process and Gamma process, are presented.

2.4.1 Remaining Useful Life

The remaining useful life (RUL) is often used as an indicator that describes the remaining time before a component no longer is useful or productive. The remaining useful life of a component or system is more precisely defined as the length from the current time to the end of useful life (Si et al., 2011). The remaining useful life is a random variable that depends on the current age of the component, the operation environment and the observed condition monitoring or health information. It is often used in relation to predictive maintenance as it can contribute to the planning of maintenance activities, spare parts provision, and the profitability of the owner of an asset (Si et al., 2011).

The random variable of the remaining useful life at time t_j (age or usage) can be denoted as $RUL(t_j)$, such that

$$\mathrm{RUL}(t_j) = inf\left\{h : Y(t_j + h) \in S_L \middle| Y(t_j) < L, Y(s)_0 \leq s \leq t_j\right\}, \tag{2.1}$$

where

$Y(t_j)$	= the current condition of the system
$Y(t_j + h)$	= the future health state of the system
S_L	= the set of failed (or unacceptable) states of the item

2.4.2 Methods

In the literature, the remaining useful life prediction methods can be roughly classified into physics-based and data-driven prediction methods where data-driven methods have received the most attention (Wang et al., 2018). However, a more specific classification is presented by Gao et al. (2015), distinguishing between physics-based, data-driven, and model-based prediction methods. The required knowledge and data needed to establish the model is the factor that distinguished the various methods. The classification of the different prognostics methods is illustrated in Figure 2.8

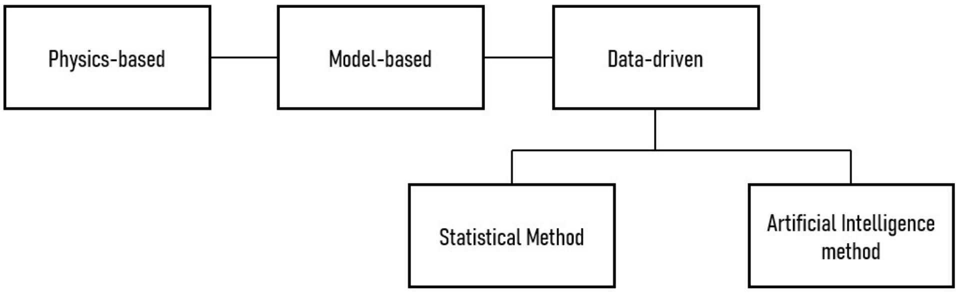


Figure 2.8: Illustration of prognostics methods based on Gao et al. (2015)

According to Gao et al. (2015), physics-based approaches estimates the remaining useful life using a mathematical representation of the physical behaviour of the degradation processes. The drawback is that the method requires detailed knowledge of the system behaviour which for most manufacturing systems is rarely available. In addition to this, physics-based models need to determine the coefficients or parameters involved experimentally which makes the models application-specific (Gao et al., 2015). Model-based methods utilise probability distribution for its formulation. Based on the relevant physical mechanisms, state evolution models and measurement models that relate sensor output to the underlying machine states are established (Gao et al., 2015).

Data-driven methods utilise information extracted from historical data to numerically establish a relationship between the current damage state and the future state. The data-driven methods can be further categorised to artificial intelligence approaches and statistical approaches (Gao et al., 2015). Artificial intelligence approaches use past data to train the model, which in turn is used for prediction. For instance, an artificial neural network provides an estimate based on historical data rather than a physical understanding of the failure mechanism. On the other hand, statistical approaches assume that system performance degradation follows a statistical distribution (Gao et al., 2015). This thesis considers the Gamma process to be most relevant for the problem in Chapter 3, but the Wiener process is also included to demonstrate an alternative approach.

Wiener Process

The Wiener process is often also called "Brownian motion with drift" and can generally be described as a type of regression model. Nevertheless, they have specific properties which distinguish them from regression models (Si et al., 2011). The Wiener process can be used to model the path of degradation processes where successive and accumulative fluctuations in degradation can be observed. However, as the Wiener process originally was designed to model the non-monotonic motion of small particles, it is not suitable in modelling degradation which is monotone (Gao et al., 2015). The Wiener process is widely discussed in literature (Si et al., 2011; Gao et al., 2015) and can be expressed as follows:

$$Y(t) = \lambda t + \sigma B(t), \tag{2.2}$$

where

λ = drift parameter
$\sigma > 0$ = diffusion coefficient
$B(t)$ = standard Brownian motion

The definition of the RUL at time t_i can be represented by the first time passage (FPT) of $\{Y(t), t \geq t_i\}$ crossing threshold w as $X_{t_i} = inf\{x_{t_i} : Y(t_i + x_{t_i} \geq w | Y(t_i \leq w\}$. In the literature, it is known that the PDF (probability density function) of the first passage time of the Wiener process is the inverse Gaussian distribution (Si et al., 2011).

Gamma Process

The Gamma process is commonly used to model stochastic deterioration in maintenance optimisation problems. Because Gamma processes are well suited for modelling the temporal variability of deterioration, they have proven to be useful in determining optimal inspection and maintenance decisions (van Noortwijk, 2009). When a degradation process is monotonic and evolving in only one direction, a Gamma process is a suitable model to apply. Examples of this type of degradation are wear-processes, fatigue crack propagation, corrosion, crack growth, erosion, and degrading health index, among others (van Noortwijk, 2009; Si et al., 2011). In these cases, the deterioration is supposed to take place gradually over time in a sequence of tiny positive increments. The advantage of using a Gamma process for degradation modelling is that the mathematical calculations are relatively straightforward (van Noortwijk, 2009; Gao et al., 2015). On the other hand, the Gamma process is only appropriate to characterise a monotonic degradation process, and due to its independent increment property, the estimation of a future state is independent of the historical behaviour. Furthermore, the noise involved in the Gamma process that is used to quantify the estimation uncertainty must follow the Gamma distribution. These assumptions limit the application of the Gamma process for degradation modelling (Gao et al., 2015).

Considering that $Y(t) = X(t)$, degradation measures can be considered to be directly accessible, without any additional nose. Then, the Gamma process can be defined as (Barros, 2018):

$$X(t_2) - X(t_1) \sim f_{\alpha_{(t_2-t_1)}}, \beta(x) = \frac{x^{(\alpha(t_2-t_1)-1)} e^{-x\beta} \beta^{\alpha(t_2-t_1)}}{\Gamma(\alpha(t_2-t_1))} I_x \geq 0 \tag{2.3}$$

where

α = Shape parameter, $\alpha \geq 0$
β = Scale parameter, $\beta \geq 0$

and $X(t_2) - X(t_1)$ denotes the increments of degradation $I(t_2 - t_1)$.

Furthermore, the mean of all the paths $E[X_t]$ can be calculated as:

$$\mathrm{E}[X_t] = \mathrm{E}[X_t - X_0] = \frac{\alpha}{\beta} t \tag{2.4}$$

and the variance among the paths Var $[X_t]$ as:

$$\mathrm{Var}[X_t] = \mathrm{Var}[X_t - X_0] = \frac{\alpha}{\beta^2} t \tag{2.5}$$

2.5 Oil and Gas Production System

This section presents general characteristics of an oil and gas production system to understand the challenges and prerequisites for how integrated production and maintenance planning in the oil and gas industry should be conducted.

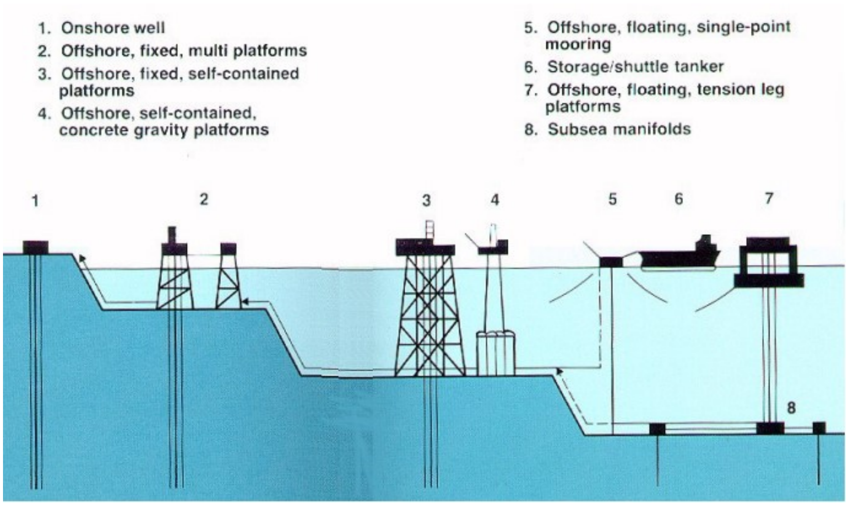


Figure 2.9: Oil and gas production facilities (Devold, 2006)

In an offshore oil and gas production system there is a range of different structures that are used depending on size and water depth. From floating production facilities, where all the topside systems are located on a floating structure with dry or subsea wells, to subsea production systems that are located on the seafloor (Devold, 2006). The different types of oil and gas production systems are illustrated in Figure 2.9. What is common for all of the different systems is that they consist of wellheads, wells and choke valves, which is presented in the following section.

2.5.1 Wellhead, Wells and Choke Valves

A wellhead can be installed both on the topside structure of an offshore installation or located underwater on a special sea bed template. To maintain the pressure for maximising the production, a wellhead could also be an injection well that injects water or gas back into the reservoir. The wellhead consists of equipment that regulates and monitors the extraction of hydrocarbons from the underground formation and is mounted at the opening of the well. The wellhead consists of three components: the casing head, the tubing head, and the "Christmas tree". The Christmas tree is composed of several valves, among these is the choke valve (Devold, 2006). Figure 2.10 illustrates how the wellhead and Christmas tree fits together in an oil production system.

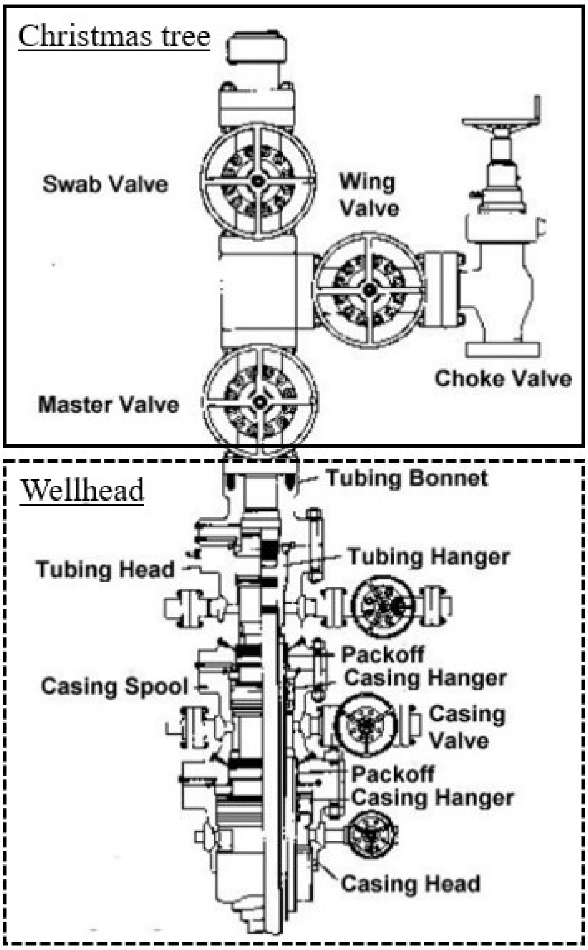


Figure 2.10: Illustration of wellhead and Christmas tree, adapted from Devold (2006)

Choke valves are normally located on top of each well (Gola and Nystad, 2011) and controls the flow rates, protects the equipment from pressure fluctuations (Nystad et al., 2010), and generally has a capacity of extracting 40,000 oil barrels per day according to Tattersall (2016). Furthermore, the choke valve is the first and only piece of equipment in the subsea system that controls the start-up, operation, and shutdown processes of the well. When export storage capacity is reached, wells might be shut off temporarily or production switched to other wellheads, which makes start-up and shutdown considerations for subsea choke valves vital in oil production systems (Tattersall, 2016).

Due to sand that is carried along with the oil and gas water mixture during the extraction process, choke valves are subject to erosion. Because of decreasing reservoir pressure and increasing sand extraction, it is common for the choke valve erosion process to increase toward the end of the well-life (Nystad et al., 2010). According to Nystad et al. (2010), an increase in the production can be obtained by reducing the downstream pressure at choke valves, which will increase the flow rate, but it will also increase the erosion as more sand passes through the choke valve at higher velocity. Having described characteristics of oil and gas production in this section, the topics of the next section are Industry 4.0, digital twins, and cyber-physical systems.

2.6 Industry 4.0, Digital Twins, and CPS

Industry 4.0 describes the ongoing fourth industrial revolution where digital technologies and smart manufacturing are key aspects. Nine emerging technologies are considered to be the foundation of Industry 4.0: big data and analytics, autonomous robots, simulation, horizontal and vertical system integration, the industrial Internet of Things, cyber-security and cyber-physical systems, the cloud, additive manufacturing, and augmented reality (Rüßmann et al., 2015). Although many of the technologies are connected to each other, the two technologies that are considered to be relevant for integrating production and maintenance planning in this thesis are cyber-physical Systems and digital twins. This section presents concepts and definitions in regards to these two technologies.

2.6.1 Cyber Physical Systems

According to Lee (2008), cyber-physical systems are *"integrations of computation with physical processes, where embedded computers and networks monitor and control the physical processes, usually with feedback loops where physical processes affect computations and vice versa"*. Another, yet quite similar definition, is found in Rajkumar et al. (2010): *"Cyber-physical systems are physical and engineered systems whose operations are monitored, coordinated, controlled and integrated by a computing and communication core."*. Cyber-physical systems are applied in various areas, such as process control, advanced automotive systems, and manufacturing (Lee, 2008) and the expectations of cyber-physical systems is that they enable remote diagnosis, real-time control, transparency, predictability and increased efficiency of a system (Monostori, 2014). A five-levelled structure of developing and deploying a cyber-physical system for a manufacturing application is presented by Lee et al. (2015). The "5C architecture" is illustrated in Figure 2.11 and further described below.

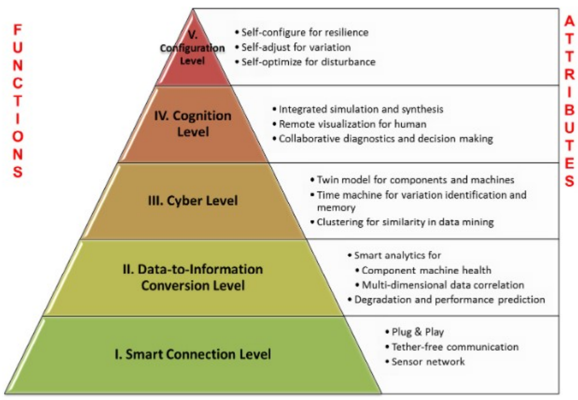


Figure 2.11: The 5C architecture of a CPS (Lee et al., 2015)

- **Smart Connection:** The first step in developing a cyber-physical system is gathering accurate and reliable data from machines and their components. The data could either be measured by sensors or obtained from existing software like an enterprise resource planning (ERP) system. Seamlessly gathering the data is essential, as well as selecting the correct type of sensors that will be used.
- **Data-to-information conversion:** The gathered data needs to be inferred to meaningful information through smart analytics for component machine health and degradation and performance prediction. By calculating health value, estimated

remaining useful life, and so on, the second level of CPS architecture brings self-awareness to machines.

- **Cyber:** This level acts as a central information hub, where information from every connected machine in the network is gathered. By having significant amounts of data from the network, specific analytics can be used to extract additional information regarding the status of individual machines. These analytics enables the possibility of comparing the performance of a single machine with other machines in the network, as well as similarities between machine performance and historical information can be measured to predict the future behaviour of the machinery.
- **Cognition:** The presentation of the acquired information to expert users supports the decision-making process. Since comparative information and individual machine status is available, a decision on the priority of tasks to optimise the maintaining process can be made. This level requires proper info-graphics to transfer the acquired information to the users.
- **Configuration:** The configuration level is the feedback from cyberspace to physical space and acts as supervisory control to make machines self-configure and self-adaptive for resilience and variations.

2.6.2 Digital Twins

A digital twin is generally defined as a virtual representation of a physical product, process or item. It can be applied in several areas like health care (Bruynseels et al., 2018), manufacturing (Tao et al., 2019b), and oil and gas (LaGrange, 2019). A digital twin for manufacturing systems consists of a virtual representation of a production system that can run on different simulation disciplines which are characterised by the synchronisation between the virtual and real system, by using sensor data, connected smart devices, mathematical models, and real-time data elaboration (Negri et al., 2017). Similar characteristics are valid for the oil and gas industry as well. According to Sharma et al. (2017), in order to prioritise future investment decisions and maximise the performance of an existing asset in an offshore oil and gas context, a data-driven system approach is required. The digital twin may be utilised to manage the asset throughout its lifecycle as it integrates real-time sensor data, inspection results, physics models, and equipment performance data with advanced analytics for the entire asset to drive the data-driven decision-making process (Sharma et al., 2017). Some benefits of a digital twin in the oil and gas industry are identified by the paper to be able to analyse production rates and identify system bottlenecks, and analyse equipment failure rates and optimise maintenance programs. The integrating capabilities of a digital twin in oil and gas is illustrated in Figure 2.12.

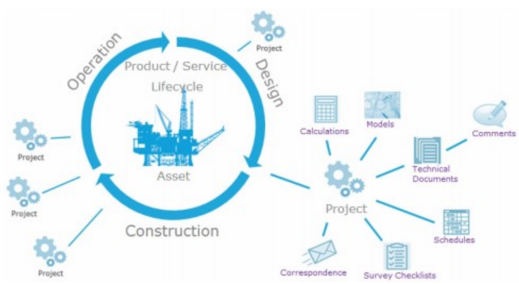
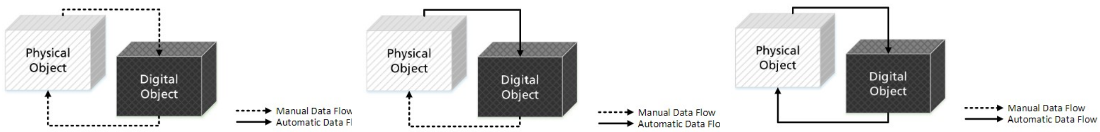


Figure 2.12: The integrating capabilities of a digital twin in oil and gas (Sharma et al., 2017)

The digital twin aims to represent the physical asset to simulate and reflect their state and behaviours through modelling and simulation analysis, and to predict and control their future states behaviours through feedback (Tao et al., 2019a). In terms of production planning, a digital twin enables the production plan to be simulated, evaluated, and improved in a virtual world. As the digital twin is able to collect real-time data from the physical twin, the production plan can be improved and equipment can be adjusted accordingly if there are any differences from the optimal plan (Qi and Tao, 2018).

Kritzinger et al. (2018) presents three data integration levels of a digital twin, where the integration levels differ based on the amount of data integration between the physical and digital counterpart. The three levels of integration are digital model, digital shadow and digital twin, illustrated in Figure 2.13a, 2.13b, and 2.13c. The authors distinguish between these three levels because some digital representations are modelled manually and are not connected with any physical object in existence, while others are fully integrated with real-time data exchange.



(a) Digital model **(b)** Digital shadow **(c)** Digital twin

Figure 2.13: Three levels of data integration in a digital twin (Kritzinger et al., 2018)

A *digital model* is a model that represents a physical object without automatically exchanging data between the physical and digital object. The digital representation might include a description of the physical object, simulation models, or mathematical models. The lack of automatic data exchange implies that a change in the state of the physical object has no direct effect on the digital object and vice versa. A *digital shadow* behaves slightly different to this, as a change in the state of the physical object leads to a change of state in the digital object, but not vice versa. The data exchange is only partially automatic. A *digital twin* will represent a physical object with automatic data exchange between the physical and digital object. This implies that a change in the state of the physical object directly leads to a change in the state of the digital object and vice versa (Kritzinger et al., 2018).

2.6.3 Difference between Cyber-Physical Systems, Internet of Things and Digital Twins

Although a digital twin depends on a physical asset in the physical space, a digital twin is only limited to the digital model itself. While a cyber-physical system, on the other hand, is characterised by both a physical asset and a digital twin (Lu et al., 2020). Furthermore, digital twin differs from Internet of Things as this refers to connections between a network of physical assets through which data can flow between themselves. Internet of Things does not include the idea of digital models in cyberspace (Lu et al., 2020). The difference between cyber-physical systems, digital twins and Internet of Things and their relationships is illustrated in Figure 2.14.

These relationships and differences implies that the digital twin is a prerequisite for the development of cyber-physical systems (Uhlemann et al., 2017) and it can be argued that this

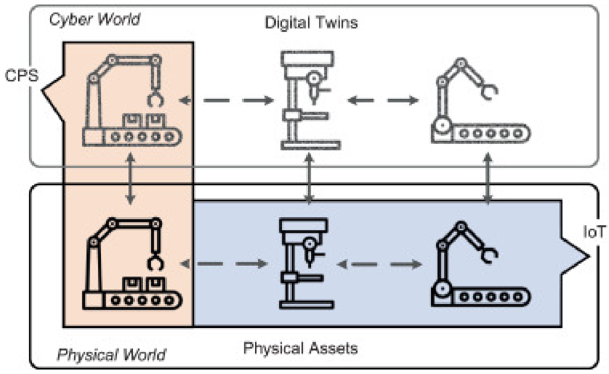


Figure 2.14: Relationship between digital twins, CPS, and IoT (Lu et al., 2020)

is also supported by Lee et al. (2015) where the twin model for components and machines is seen as an attribute for the cyber level in a cyber-physical system (see Figure 2.11). However, this standpoint is not shared by Tao et al. (2019a). While the authors agree that both cyber-physical systems and digital twins enable precise and better management and operation of the physical world, and that cyber-physical systems focus more on computing, communication and collaboration capabilities, and that digital twins focus more on virtual models, the digital twin is not specifically seen as a prerequisite for a cyber-physical system by the authors.

2.7 Mathematical Modelling

Chapter 3 describe the mathematical models that have been developed in this thesis, therefore basic concepts and theory related to mathematical modelling is presented in this section. Mathematical models are models in which mathematical relationships are to be expressed through functions and which allows for capturing the reality of a system within a mathematical framework (Sánchez, 2020). A system, situation, process, or another entity is modelled by mathematical expressions and a mathematical model typically consists of parameters, variables, constraints, and an objective function. *Parameters* are the symbolic representation of real-world data. In the literature, it can also be referred to simply as *data* and can describe values in the model like, for example, costs. The variables of the model represent the unknown or the quantities in the model that vary. The *decision variable* is the quantities that must be determined by the decision-maker (Hart et al., 2017), while variables that the decision-maker is unable to determine is called stochastic variables. A *constraint* is a restriction imposed upon the values of the decision variables by the characteristics of the problem under study. Lastly, the *objective function* is a function of the decision variables and represents the function that the mathematical model should either maximise or minimise (Bradley, 1977).

In general, a distinction between deterministic and probabilistic models are made (Vatn, 2020). In models where all the quantities can be said to be known, the model is deterministic (Nocedal and Wright, 2006) and a deterministic model is primarily used to describe relations between physical quantities and other real-world observables (Vatn, 2020). A probabilistic model is a model that enables the analyst to apply the law of total probability efficiently when expressing uncertainty by probability calculus (Vatn, 2020). A probabilistic model is not a model of the world, but it is a model used to express uncertainty regarding observables in the real world. In addition to this, models that depend on unknown quantities like, for example, future demand or future oil prices is said to be stochastic. In a situation where unknown quantities must be modelled, the quantities can be incorporated in the model by using different scenarios of the uncertain value, along with the probabilities of each scenario (Nocedal and Wright, 2006). In mathematical modelling, there are several different types of programming. The following subsections will focus on linear programming, mixed-integer programming, and nonlinear programming.

2.7.1 Linear Programming

Linear programs have a linear objective function that is to be maximised or minimised, and there are linear constraints that may include both equalities and inequalities (Nocedal and Wright, 2006). The objective function $Z()$ is typically a function of the decision variables $x_j, j = 1,...,n$. Furthermore, m restrictions regarding linear combinations of the decision variables are assumed. All decision variables and some parameters have to be non-negative (Vatn, 2020). A linear programming problem on the standard form can be written as:

$$\text{Maximise}: Z = c_1x_1 + c_2x_2 + ... + c_nx_n \tag{2.6}$$

Subject to the constraints:

$$\begin{aligned} a_{11}x_1 + a_{12}x_2 + ... + a_{1n}x_n &= b_1 \\ a_{21}x_1 + a_{22}x_2 + ... + a_{2n}x_n &= b_2 \\ &\vdots \\ a_{m1}x_1 + a_{m2}x_2 + ... + a_{mn}x_n &= b_m \\ x_1 \geq 0, x_2 \geq 0, ..., x_n &\geq 0 \\ b_1 \geq 0, b_2 \geq 0, ..., b_m &\geq 0 \end{aligned}$$

In canonical form, the linear programming problem can be written as:

$$\text{Maximise}: Z = cx \tag{2.7}$$

$$\begin{aligned} \text{Subject to}: Ax &= b \\ x &\geq 0 \\ b &\geq 0 \end{aligned}$$

For linear models, a common solution approach is the simplex method. This is an algorithm that searches through the feasible region to find the optimal solution (Winston and Albright, 2016). In Microsoft Excel, the Simplex LP Solver is used to solve linear models, including models where some or all of the decision variables are restricted to be binary or integer (Winston and Albright, 2016).

2.7.2 Mixed-Integer Programming

A mixed-integer program is a linear program where some of the decision variables can only take integer values (Richards and How, 2005). In many situations, the solution of a linear program can result in non-integer solutions which can be unsuitable for situations where the solution must have an integer value. A mixed-integer linear program can be written as:

$$\text{Maximise} : Z = cx \tag{2.8}$$

$$\begin{aligned} \text{Subject to} : Ax &= b \\ x &\geq 0 \\ b &\geq 0 \\ x_j \text{is an integer for } j &\in I \end{aligned}$$

2.7.3 Non-linear programming

Nonlinear programming problems are optimisation problems where the objective or the constraints are nonlinear functions of the decision variables (Winston and Albright, 2016; Vatn, 2020). These problems are often more realistic than linear models but they are also more difficult to solve (Winston and Albright, 2016). One solution for nonlinear problems is to take the derivatives of the objective function and search for roots in the set of equations obtain. Newton's method is one method for finding successively better approximations to the roots of a real-valued functions but requires calculation of all the derivatives and the method may converge slowly or fail to converge. Therefore other approaches are usually required (Vatn, 2020).

In order to solve smooth nonlinear problems, Generalised Reduced Gradient method in Microsoft Excel can be used. This is a gradient based method that calculates numerically or analytically the gradient of the objective function (Vatn, 2020). For non-smooth nonlinear problems, genetic algorithms is a suitable approach. The approach is inspired by natural selection, aiming to construct and breed a population for candidate solutions points (Vatn, 2020). More simply stated, a genetic algorithm provides a method for intelligently searching an optimisation model's feasible region for an optimal solution (Winston and Albright, 2016). In Microsoft Excel, the evolutionary solver utilises genetic algorithms to optimise the solution (Winston and Albright, 2016; Vatn, 2020).

3 Mathematical Models for Digital Twins

In this chapter, the mathematical models that have been developed in this thesis is presented. First, a description of the problem and the case is presented in Section 3.1. Section 3.2 describe the three models and how they interact with each other. The mathematical model that considers the production aspect is presented in Section 3.3, the model that considers the condition aspect is presented in Section 3.4, and the model that considers the maintenance aspect is presented in Section 3.5. Section 3.3, 3.4 and 3.5 starts with a description reference to anchor articles that contains a description of the general characteristics of the problem so that the work of this thesis is clearly positioned in the scientific literature (Karlsson, 2016). Section 3.6 concludes the chapter providing a numerical demonstration of the mathematical models.

3.1 Problem Description and Case Description

The driving force of offshore oil production can be said to be the reservoir pressure (Haugland et al., 1988). The reservoir pressure determines the maximum amounts of oil that are possible to produce. As an oil field matures, the reservoir pressure decreases (Haugland et al., 1988; Höök et al., 2014; Verheyleweghen and Jäschke, 2018) and so will the production levels. This implies that the production from each well must be below a level determined by the pressure near that well (Haugland et al., 1988). Additionally, the amount of produced oil will also depend on the capacities of receiving the oil when it reaches the surface. The produced oil must either be processed at the offshore facility or it must be transported to a processing plant (Haugland et al., 1988). These characteristics of oil production mentioned above can be translated into mathematical constraints. Recall from Chapter 2.7 that a constraint is a restriction imposed upon the values of the decision variables by the characteristics of the problem under study.

One way to reduce the pressure drop in the reservoir is to start producing from other wells in the system or change which wells are producing to increase the rate of production. As a reservoir matures, the pressure in the reservoir will decrease over time which again means that the production rate also will decrease. To restore the pressure in a well, the well can be shut down for a certain period. However, changing which wells to produce from will cause more sand production in the wells. This will result in increased erosion levels and thus increased degradation of the choke valve. Erosion of chokes and bends may be a problem if the sand production from the reservoir is high, and it is not uncommon to have choke replacement frequencies of 3-4 months in the offshore industry (Verheyleweghen and Jäschke, 2018). Thus, there is a trade-off between maximising the production and minimising the degradation of the equipment.

The degradation of components in an offshore environment is inevitable. To counter this, maintenance can be performed to restore the state of the component to "as good as new". Offshore maintenance actions are costly due to the requirement of vessels and specialised equipment like remotely operated vehicles (Markeset et al., 2013) and it requires planning ahead of the activity. Because of this, maintenance actions will have both a lead time that must be accounted for when planning production and maintenance, as well as a maintenance related cost. It may be worth noting that the sand production generally tends to increase as the field matures and reservoir pressure decreases (Verheyleweghen and Jäschke, 2018).

The models in this thesis aim to decide the optimal changing of wells to maximise the profit, without exceeding a determined threshold for degradation. By integrating production and maintenance by the use of a digital twin and cyber-physical system it should be possible to control when the maintenance must be performed in a better way. A digital twin can gather data on the component by the use of sensors and enable "what-if" analyses based on alternative production plans. By conducting such analyses, the synchronisation of when to shut down wells for maintenance could be improved by determining the appropriate time to shut down so that the maintenance activity can be coordinated with a predetermined maintenance window.

3.1.1 Case Description

In this thesis, a fictional case scenario based on real-life characteristics of an oil production system is considered. The case considers an offshore production facility, with a set of wells that are allocated to this facility only. A planning horizon of 12 months is applied, which can be considered to be tactical production planning as discussed in Section 2.1. Furthermore, the case considers the system to consist of two wells. The choke valve is found between the reservoir and the topside facility and is used to control the flow from the wells in the system (Gunnerud and Foss, 2010).

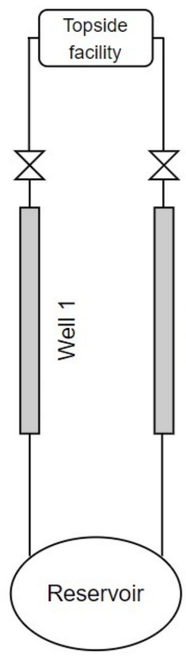


Figure 3.1: Simplified case illustration

3.2 Model Description

This section describes the three models, hereby referred to as digital twins (DT), developed in this thesis. They are referred to as digital twins because they are considered to be able to incorporate capabilities of digital twins. The motivation for considering these three models is based on Vatn (2018) and lectures on digital twins in the subject TPK4161 - Supply Chain Analytics at NTNU. There might be that other perceptions on how to model these disciplines are more suitable. The three underlying models are named:

- Production DT
- Condition DT
- Maintenance DT

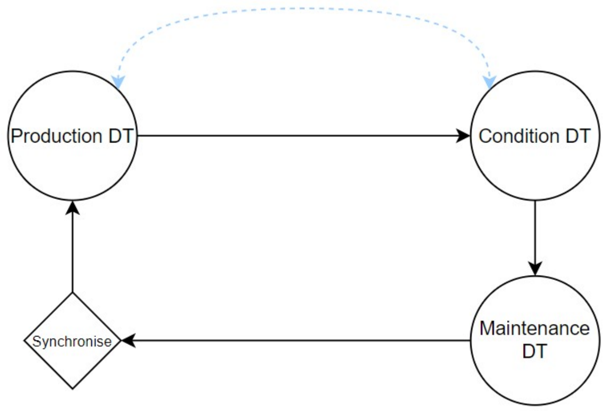


Figure 3.2: Overview of the relationships between the models

Figure 3.2 illustrates how the models relate to each other. The Production DT optimises the well-scheduling and provides a production plan during the selected time horizon. Therefore, the Production DT must gather cost data related to the production, as well as other parameters that are related to producing oil and operate the wells. The result of the Production DT will be an optimised production plan of the wells based on relevant cost parameters. The output of the Production DT will form a production profile that will act as an input to the Condition DT.

The Condition DT should describe the condition of the selected component, in this case, a choke valve, based on the production profile determined by the Production DT. The Condition DT should take into account any uncertainties related to the condition and degradation of the component. The data regarding the production load should be extracted from the Production DT, and the Condition DT should be able to “search” for data from the Production DT. This is illustrated by the light blue and dashed arrow. The predicted degradation from the Condition DT will act as an input for the Maintenance DT.

The Maintenance DT determines when maintenance should be done based on the condition of the choke valve. Therefore, the Maintenance DT needs information regarding the condition of the choke valve and a determined maintenance safety threshold that should initiate a maintenance action. The predicted degradation from the Condition DT is thus coupled with the maintenance safety threshold.

Since the aim of the integrated models is to plan the production based on the condition of the component, which again is dependent on the production plan, a synchronisation step is required. The reason for this is that the mathematical formulations in the Production and Condition DT are not independent. Due to this interconnectivity, changes on one part have an impact on the other. This dependency is difficult to model in an optimisation problem.

3.3 Production DT

This section contains the mathematical model for the Production DT and starts with a description of the scientific work that the model is based upon. First off, Haugland et al. (1988) simplified the time aspect of the problem under consideration. In reality, the production profile for each well should be a continuous function of time, but such functions are difficult to handle in optimisation algorithms. Therefore, the authors divided the lifetime of the field into a finite set of periods, and within each period they assumed the production rate to be constant. The paper also discusses two types of capacities in the system. Reservoir capacity, which is a maximum capacity of production output that depends on the reservoir pressure, and receiving capacity, which is the capacity of how much oil can be stored on the topside facility before transportation. Similar capacities and constraints are discussed by Gunnerud and Foss (2010), who stated that there are capacity limits on the production equipment, like wells, valves and pipelines, in addition to a constraint that originates from the downstream part of the value chain, like the capacity to handle gas and water.

Ortíz-Gómez et al. (2002) presented three mixed integer multi-period optimisation models of varying complexity for the oil production planning in the wells of an oil reservoir. The study aimed to find the oil flow rates and operation/shut-in times of the wells, considering the oil production demands for each period of time. What is interesting to consider from this paper is the behaviour of production and well pressure and how these two influence each other. As previously mentioned, the driving force for the oil production from a well is the pressure difference between the reservoir and the wellbore. When the well is open to flow at the beginning of the operation, oil can be extracted because of the pressure difference between the wellbore and the wellhead. As the operation time increases, the wellbore pressure decreases which also causes an oil flow from the reservoir to the well. Because of the resistance to the oil flow between the reservoir and the wellbore, the wellbore pressure decreases over time when oil is produced from the well (Ortíz-Gómez et al., 2002). These characteristics are also briefly discussed by Haugland et al. (1988). Furthermore, Ortíz-Gómez et al. (2002) stated that when the production from a well is increased or decreased by opening or tightening valves on the production platform, the pressure in the well will decrease or increase. In addition to this, if the well is shut-in, the wellbore pressure will increase because of the effect of oil flow from the reservoir to the well. In their optimisation problem, the authors assume that the pressure of the wellbore is the same as that of the reservoir when the well has just been drilled or when it has been shut-in for a significant period of time.

Lang and Zhao (2016) studied an oil well production scheduling problem for the light load oil well during petroleum field exploitation. The problem the authors studied had the following characteristics that made it difficult to be modelled and solved. Firstly, the problem contained both the discrete variables to determine the oil well's on and off status, and the continuous variables to determine the oil production of oil wells. Secondly, during the oil production, not only minimum up and downtime constraints, but also the mutual influence relations between the pressure of oil well bottom and oil production was considered

Indices:	
T	Set of time periods
t	Period
W	Set of wells
i	Well number
Parameters:	
P_o	Price of oil
O_i	Operating cost for well i
d_f	Decreasing factor of production
$Q_{i,t}$	Production rate in well i in period t
$Q_{\max}$	Maximum production rate from one well
Decision variable:	
$W_{i,t}$	Whether to produce from well i in period t or not

Table 3.1: Notation for Production DT

Moving now on to consider the Production DT derived in this thesis, where the notation for the model is provided in Table 3.1. The decision variable for the problem, $W_{i,t}$, is to decide whether to produce from well i in period t or not. The production rate, Q, is assumed to decrease over time with a decreasing factor, d_f. This can then be considered to be the production profile. As stated by Haugland et al. (1988), the production profile for each well should be a continuous function of time, but this is difficult to handle in optimisation problems. Thus, the lifetime of the field is divided into a finite set of periods, and within each period the production rate is assumed to be constant, similarly to the work of Haugland et al. (1988). In addition to this, the decreasing factor is introduced to capture the aspect that the production rate of a well is decreasing over time as discussed by both Haugland et al. (1988) and Ortíz-Gómez et al. (2002). Furthermore, it is difficult to solve and model both the discrete variables to determine the oil well's on and off status, and the continuous variables to determine the oil production of oil wells (Lang and Zhao, 2016), therefore, the only possibility to influence the production rate in this problem is by deciding which wells to produce from. The production rate can be reset to an upper level by shutting down the well for a certain period. This will increase the pressure in the well as discussed by Ortíz-Gómez et al. (2002). The rate and speed at which the pressure increases after a well is shut depends on several conditions and requires complex formulas that are not considered in this problem. It is reasonable to assume that the pressure needs a certain time to recover to desirable levels and that the production rate will not return completely to the maximum production rate. However, the pressure, and thus the production rate, is considered to be reset immediately back to the upper level after a well is shut down. As discussed in the introduction to this chapter (Section 3.1), starting up a well after it has been shut down will generate significant amounts of sand production in the well, thus resulting in a considerable increase in the degradation of the choke valve. This degradation process is modelled in Section 3.4. The upper production rate level of the model can be considered to be a capacity in the same matter as discussed by both Haugland et al. (1988) and Gunnerud and Foss (2010). However, a receiving capacity is not included in the model in order to minimise the complexity. Furthermore, the oil price is assumed to be fixed during the planning horizon. In a real-life situation, the price of oil is constantly changing. To prevent unnecessary complexity in the model, the oil price is considered to be fixed and deterministic. In addition to this, an assumption is made that there is a fixed operational cost of running a well in a period.

The decision variable, considered to be deciding which wells to produce from, is determined by using boolean operators:

$$\mathrm{W}_{i,t} = \begin{cases} 1, & \text{produce from well } i \text{ in period } t \\ 0, & \text{don't produce from well } i \text{ in period } t \end{cases} \tag{3.1}$$

Considering that there are no previous periods at the start of the planning horizon, the production rate in the first period, $Q_{i,1}$, can be expressed as:

$$Q_{i,1} = Q_{\text{max}} \cdot W_{i,1} \tag{3.2}$$

For the remaining periods of the planning horizon, the production rate $Q_{i,t}$, is:

$$\mathrm{Q}_{i,t} = \begin{cases} \mathrm{Q}_{i,t-1} \cdot d_f & \text{if } \mathrm{W}_{i,t-1} = 1 \ \wedge \ \mathrm{W}_{i,t} = 1 \\ \mathrm{Q}_{\text{max}} & \text{if } \mathrm{W}_{i,t-1} = 0 \ \wedge \ \mathrm{W}_{i,t} = 1 \\ 0, & \text{otherwise} \end{cases} \tag{3.3}$$

Equation 3.3 can in practice be translated to the following: if the well is scheduled to produce in the previous period ($\mathrm{W}_{i,t-1} = 1$) and the well is scheduled to produce in the current ($\mathrm{W}_{i,t} = 1$), then the production rate, $\mathrm{Q}_{i,t}$, is equal to the previous production rate times the decreasing factor ($\mathrm{Q}_{i,t-1} \cdot d_f$). If the well has been shut in the previous period ($\mathrm{W}_{i,t-1} = 0$), but is scheduled to produce in the current ($\mathrm{W}_{i,t} = 1$), then the production rate, $\mathrm{Q}_{i,t}$ is equal to the maximum production rate, Q_{max}. Otherwise, the production rate is 0. Additionally, equation 3.3 makes the problem at hand into a nonlinear problem. This means that the problem can not be solved as a linear program or mixed-integer program. However, the problem can be optimised using the evolutionary solver in MS Excel for non-smooth nonlinear problems, as presented in Section 2.7.3.

The sum of operational cost is expressed as:

$$\sum_i \sum_t W_{i,t} \cdot O_i \tag{3.4}$$

and the sum of income is expressed as:

$$\sum_i \sum_t Q_{i,t} \cdot P_o \tag{3.5}$$

The objective function, which is to maximise the profit, can then be written as:

$$\text{Maximise} \sum_i \sum_t Q_{i,t} \cdot P_o - \sum_i \sum_t W_{i,t} \cdot O_i \tag{3.6}$$

Subject to the logical constraint that the assignment of wells must be a binary value:

$$W_{i,t} = \text{binary} \quad \forall \quad t \in T,\ i \in W \tag{3.7}$$

Considering only these aspects, the optimisation problem is straightforward although there are "if" statements involved, however, the condition of the choke valve must be included to the decision process.

3.4 Condition DT

Machines and components will suffer increasing wear with increased age and usage due to degradation which causes low reliability. Pan et al. (2011) introduced the concept of a machine's remaining maintenance life to describe the degradation of a machine. The paper also introduced the concept of effective age to describe a machine's health status, which has a corresponding relationship with the health index. Similarly, Liu et al. (2018) proposed an integrated decision model that coordinates predictive maintenance decisions based on prognostics information by considering health status and dummy age subjected to machine degradation. None of these papers models the degradation process based on the production load. This thesis aims to describe the degradation based on the production load in order to investigate how the synchronisation of production and maintenance can be improved. Zied et al. (2011) studied combined production and maintenance plans for a manufacturing system satisfying random demand. The authors first determined an optimal production plan which minimised the average total inventory and production cost before using this production plan and taking deterioration into account to derive an optimal maintenance schedule that minimised the maintenance cost. A similar approach was conducted by Ayed et al. (2012), who established a production plan before integrating the effect of the machine degradation introducing a unitary degradation cost. Then, the optimal production plan was obtained by minimising the sum of costs. Wang et al. (2019) proposed a joint production planning and condition-based maintenance model, where the degradation is modelled as a stationary Gamma process.

Another model that considered the production load is found in the work of Verheyleweghen and Jäschke (2018), who used an erosion model from DNV-GL (2015) when optimising oil production of several wells subject to choke degradation. The formula is based on various constants and a parameter for sand production. The sand production rate was assumed to be proportional to the overall mass flow rate from the reservoir which corresponds to the production rate. Furthermore, the paper assumed that the health state of the plant is known at any given time, meaning that real-time erosion monitoring systems are installed and working. Similar assumptions can be made in a digital twin and cyber-physical system, which enables continuous monitoring of a component through the use of sensor technology. In this thesis, the intention was to first introduce a deterministic erosion model from DNV-GL (2015) that describes the erosion that occurs as a result of sand production in the well, before applying this model with a Gamma process to account for uncertainties in the degradation. The Gamma process is suitable to model gradual damage monotonically accumulating over time in a sequence of tiny increments, such as wear, fatigue, corrosion, crack growth, and erosion, among others (van Noortwijk, 2009) and has been applied in several scientific articles that integrate production and maintenance (Kallen and van Noortwijk, 2005; Cheng et al., 2018; Cholette et al., 2019; Wang et al., 2019). Unfortunately, several attempts have been made to apply this procedure in the work of this thesis, but the erosion model presented in DNV-GL (2015) is complex and without access to data regarding geometric factors of the choke valve and other operational conditions it has proved to be difficult to achieve plausible and realistic values from the model. This is discussed further in Chapter 5. Therefore, a simplification of the degradation model has been made in order to demonstrate the interactions between the mathematical models. The intended erosion model is still included in the thesis to illustrate the possibilities of incorporating a physical erosion model with a stochastic degradation process.

3.4.1 Erosion Model

In DNV-GL (2015), recommended practice regarding managing sand production and erosion is presented. The document was developed in cooperation with several major oil and gas operators. One of the models was applied in Verheyleweghen and Jäschke (2018) and is presented below:

$$\frac{dE}{dt} = \frac{K \cdot F(\alpha) \cdot U_p^n}{\rho_t \cdot A_t} \cdot G \cdot C_1 \cdot GF \cdot \dot{m}_{\text{sand}} \cdot C_{\text{unit}} \tag{3.8}$$

where

A_t	= Area exposed to erosion
C_1	= Model/geometry factor
C_{unit}	= Unit conversion factor
$\frac{dE}{dt}$	= Erosion rate in mm/year
$F(\alpha)$	= Function characterising ductility of material
G	= Corrections function for particle diameter
GF	= Geometry factor
K	= Material erosion constant
$\dot{m}_{\text{sand}}$	= Sand production rate
n	= Velocity exponent
ρ_t	= Density of target material
U_p	= Particle impact velocity

The function characterising ductility of the material, $F(\alpha)$, depends on the material properties of the system. Ductility is the ability of a material to change shape without fracture (Koch et al., 1999). The function has an angle dependency for whether the material is ductile or brittle. The corrections function for particle diameter, G, is defined as:

$$G = \frac{d_p \cdot \beta \cdot (1.88 \cdot log(A) - 6.04)}{D_{\text{pipe}}} \tag{3.9}$$

where d_p is the particle diameter and D_{pipe} is the pipe diameter. In this function, β and A are dimensionless parameters:

$$A = Re \cdot \frac{tan(\alpha)}{\beta} \tag{3.10}$$

$$\beta = \frac{\rho_p}{\rho_f} \tag{3.11}$$

where Re is the Reynolds number of the flow, α is the particle impact angle, ρ_p is the particle density, and ρ_f is the fluid density.

Furthermore, the sand production rate is assumed to be proportional to the overall mass flow rate from the reservoir:

$$\dot{m}_{\text{sand}} = SR \cdot \dot{m}_r \tag{3.12}$$

where SR corresponds to the sand rate parameter and $\dot{m}_r$ is the flow rate from the reservoir.

This erosion model describes the degradation of the choke valve that is caused by erosion due to sand production in the wells. However, there are other random factors (like the size of sand, environmental conditions, etc.) that influence the degradation. Therefore, a stochastic model should be applied to account for uncertainties in the degradation of the choke valve and other random factors that induce variation in the degradation rate. The Gamma process has been presented in Section 2.4.2. As discussed initially in Section 3.4, attempts have been made to apply this approach in the work of this thesis without success. Because of this, and in order to be able to demonstrate the models from this thesis, a simplified deterministic degradation model is applied in the Condition DT.

3.4.2 Simplified Degradation Model

The simplified degradation model is based on calculated erosion rates in case examples presented in DNV-GL (2015). An erosion rate of 0,21 millimetres per ton of sand has been chosen. This way, the predicted degradation during a period can be calculated based on the sand production in the valve. The degradation can then be expressed as follows:

$$DE_{i,t} = ER \cdot m_{i,t} \cdot 0.001 \text{ton/kg} \tag{3.13}$$

where ER is the erosion rate of 0,21 mm/ton and $m_{i,t}$ is the amount of sand produced in the well. The parameters are multiplied with a conversion factor to express the erosion as mm/kg instead of mm/ton. An assumption that the sand production is proportional to the production rate, $Q_{i,t}$, is made. Then the amount of sand produced, $m_{i,t}$, can be expressed as follows:

$$m_{i,t} = Q_{i,t} \cdot SR \tag{3.14}$$

where $m_{i,t}$ is the amount of produced sand in well i in period t, and SR is a sand rate parameter similar to the assumption made in DNV-GL (2015) and Eq. 3.12.

To capture the assumption that sand production will jump whenever a well is opened for production after it has been shut down, as described in Section 3.1, an increasing factor, i_f, is introduced. The production of sand in the well based on the sand jumps can then be expressed in the following way:

$$\mathrm{M}_{i,t} = \begin{cases} m_{i,t} & \text{if } \mathrm{W}_{i,t-1} = 1 \ \land \ \mathrm{W}_{i,t} = 1 \\ m_{i,t} \cdot i_f & \text{if } \mathrm{W}_{i,t-1} = 0 \ \land \ \mathrm{W}_{i,t} = 1 \end{cases} \tag{3.15}$$

If the well has been producing in the previous period and is producing in the current period, then the sand production is equal to the sand production from Eq. 3.14. If the well has been shut down in the previous period but is scheduled to produce in the current period, then the sand production based on jumps, $M_{i,t}$ is equal to the sand production from Eq. 3.14 multiplied with the increasing factor, i_f.

3.5 Maintenance DT

In Pan et al. (2011), predictive maintenance operations are performed based on the machine's condition, and a health index is introduced to represent the machine's health status. When a maintenance operation is completed, the machine's condition is restored to be "as good as new". When a machine's condition reaches a certain level, it will break down and require maintenance. By introducing a safety threshold, a predictive maintenance operation will be triggered before the machine's condition reaches a breakdown state. A similar approach was used by Liu et al. (2018), who introduced a dummy age of the machine to demonstrate the effect of maintenance actions. The lifetime of the machine will increase with time, and the dummy age of the machine will decrease by adopting maintenance actions. Depending on the state of the machine in a certain period, various maintenance actions can be performed to reduce the dummy age of the machine. In this model, the concept of a health index or dummy age of the machine is not introduced. Instead, the model consider that the degradation must be below a determined maintenance safety threshold. If the degradation level exceeds the maintenance safety threshold, a maintenance activity is scheduled and the degradation is reset.

Indices:	
$MA_{i,t}$	Maintenance activity
ML	Maintenance safety threshold
$DE_{i,t}$	Degradation level

Table 3.2: Notation for Maintenance DT

The notation for the Maintenance DT is provided in Table 3.2. Whether a maintenance activity occurs in a given period or not can be written as:

$$\mathrm{MA}_{i,t} = \begin{cases} 1 & \text{if } DE_{i,t} > ML \\ 0, & \text{otherwise} \end{cases} \tag{3.16}$$

Going above the maintenance safety threshold and thus replacing or maintaining the choke valve, should also reset the degradation level. In other words, the choke valve begins a new degradation process after a maintenance activity. Furthermore, an assumption is made that the time to carry out maintenance is negligible.

So far, the mathematical formulation of the models has been described in the previous sections and relevant research literature has been presented to justify choices made in the model. The next section will demonstrate the mathematical models for the fictional case, presented in 3.1.

3.6 Numerical Demonstration

In this section, a demonstration of the models is carried out, using assumed values for the parameters that act as input data. The values have been chosen to the best of the author's ability to reflect a real-life situation. Recall the objective function (Eq. 3.6) from Section 3.3, repeated below. This is the objective that is to be maximised, subject to the constraints and parameters that have been determined.

$$\text{Maximise} \sum_{i}\sum_{t} Q_{i,t} \cdot P_o - \sum_{i}\sum_{t} W_{i,t} \cdot O_i \tag{3.6}$$

Table 3.3 presents the values that have been applied to the production model to establish a production plan and to decide which wells that should produce and when they should be shut down to recover the pressure in the well.

Parameter	Value
P_o	550 [NOK/barrel]
O_i	1.500.000 [NOK/period]
$Q_{\max}$	30.000 [barrels/period]
d_f	0.9

Table 3.3: Input parameters

The oil price has been set to 550 NOK per barrel and represents a typical oil price during the spring of 2021. The operational cost per period has been difficult to determine without knowledge of the typical economic perspective of drifting an oil well and has thus been set arbitrary to the value of 1.500.000 NOK per period. These two parameters are part of the objective function (Eq. 3.6). Furthermore, an oil well can typically produce between 500-5000 barrels of oil per day (Ranger Minerals, 2020). Assuming that there are 30 days in a month and that the mean production rate is 1000 barrels per day, the maximum production rate, $Q_{\max}$, has been set to 30.000 barrels per month. The decreasing factor of the production rate has been set to 0.9. These parameters are used in Equation 3.2 and 3.3.

	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
$W_{1,t}$	1	1	1	0	1	1	1	1	0	1	1	1
$W_{2,t}$	1	1	1	0	1	1	1	0	1	1	1	1

Table 3.4: Optimised well scheduling

Table 3.4 and 3.5 presents the optimised solution based on the constraints established in Section 3.3 and the parameters from Table 3.3. Table 3.4 represents the decision variables from Equation 3.1, while Table 3.5 represents the calculated production rates based on Equation 3.2 and 3.3. Note that, in Table 3.4, both wells are scheduled to be shut down in period T4, while well 2 is scheduled to be shut down in period T8 and well 1 in period T9.

	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
$Q_{1,t}$	30000	27000	24300	0	30000	27000	24300	21870	0	30000	27000	24300
$Q_{2,t}$	30000	27000	24300	0	30000	27000	24300	0	30000	27000	24300	21870
Total	60000	54000	48600	0	60000	54000	48600	21870	30000	57000	51300	46170

Table 3.5: Calculated production rates

A graph illustrating the production rate over time is presented in Figure 3.3. This solution provides the maximised objective function with a profit of 262.347.000 NOK. The objective function was solved using the evolutionary solver in Microsoft Excel. Since there are scheduled shutdowns of the wells in periods T4, T8 and T9, these would be appropriate periods to perform maintenance activities. However, the optimisation must still account for the degradation and the condition of the choke valve to ensure that the choke valve is not running to failure.

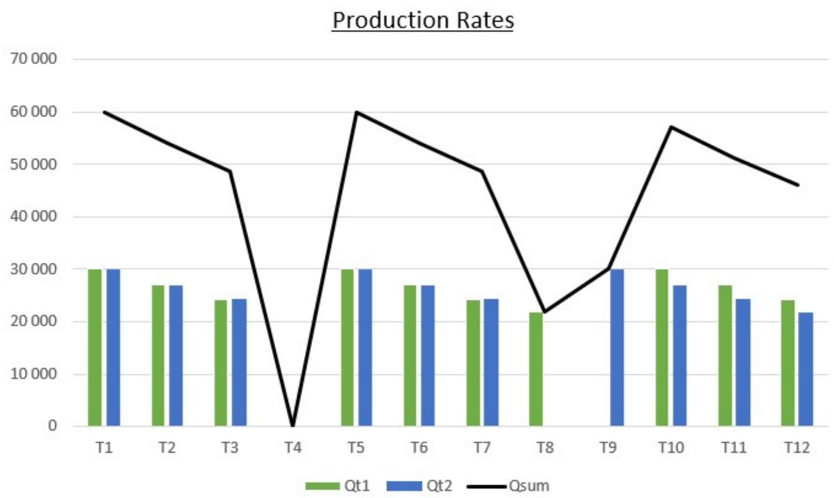


Figure 3.3: Graph of production rates (Qt1: production in well 1, Qt2: production in well 2, Qsum: total production)

Erosion model

Arianti (2018) performed a study on estimating sand production in oil reservoirs. The results reveal that at an oil rate of 1000 barrels per day, the calculated sand production in well 1 was 0.005 lb/barrel, well 2 was 0.007 lb/barrel, well 3 was 0.005 lb/barrel, and well 4 was 0.002 lb/barrel. Based on this, the sand production rate is assumed to be 0.005 lb/barrel. Converting this to kilograms, the sand production rate becomes ≈ 0.0023 kg/barrel. Now, the sand rate parameter, SR, for Equation 3.14 has been determined. Furthermore, the increasing factor, i_f, for Equation 3.15 has been set to 3 to represent the sand jumps. Using the production rates from Table 3.5, the following sand production is calculated, using Equation 3.14:

	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
$m_{1,t}$	68	61	55	0	207	61	55	50	0	207	61	55
$m_{2,t}$	68	61	55	0	207	61	55	0	207	61	55	50

Table 3.6: Sand production

Notice that for both wells the sand production has a significant increase in T5 due to the sand jumps, while well 2 has another jump in T9 and well 1 another in T10. The estimated sand production from Table 3.6 can now be used as a parameter in the simplified erosion model (Eq. 3.13).

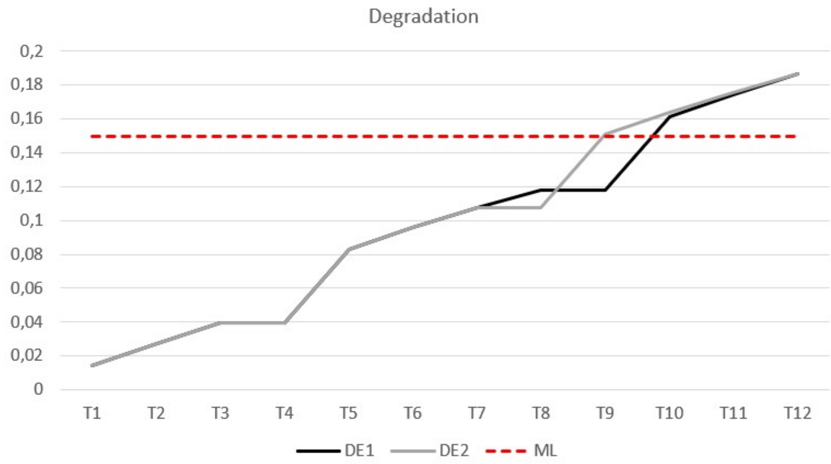


Figure 3.4: Graph of degradation (DE1: degradation in well 1, DE2: degradation in well 2, ML: maintenance safety threshold)

The predicted degradation based on the production load and the sand jumps is illustrated in Figure 3.4. The degradation of well 1 is coloured in black, and the degradation of well 2 is coloured in grey. The maintenance safety threshold, which in this demonstration is set to 0,15 mm, is coloured in red. The figure illustrates that the condition of the choke valve for well 1 exceeds the maintenance safety threshold in T10, while the condition of the choke valve for well 2 exceeds the maintenance safety threshold in T9. This implies that a maintenance activity should be scheduled for these periods. It can be disadvantageous to perform maintenance activities separately and consecutively as this will typically initiate a set-up cost for shipping personnel, equipment, and replacement parts to the production facility. This has not been accounted for in the models of this thesis and is discussed further in Chapter 5.

Because of this, and because the mathematical formulations in the Production and Condition DT are not independent, as discussed in Section 3.2, a re-optimisation of the production plan so that the choke valves reach the maintenance safety threshold in the same period is required. To do this, some adjustments to the mathematical model are done. In the re-optimisation, the production rates from Table 3.5 is considered to be constraints, from now on referred to as the production capacity, expressed in Equation 3.17.

$$Q_{i,t} \leq PC_{i,t} \tag{3.17}$$

Additionally, the new decision variable is to decide how much to produce, $Q_{i,t}$ during the time horizon without exceeding the production capacity, and not to decide which wells to produce from as in the initial problem. The objective function is still to maximise the profit. Furthermore, another constraint is introduced, expressing that the degradation cannot exceed the maintenance safety threshold (Eq. 3.18).

$$DE_{i,t} \leq ML \tag{3.18}$$

This way, the scheduling plan of the wells performed in the initial problem remains the same, but the production rates are optimised with respect to the maintenance safety threshold and the production capacity. The re-optimised production rates are provided in Table 3.7. It is worth noting that the production rates after re-optimisation are lower than the initial production rates from Table 3.5, confirming that the optimised solution is within the constraint of the production capacity.

	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
$Q_{1,t}$	29999	27000	24300	0	21137	26998	24296	21870	0	13796	26998	24298
$Q_{2,t}$	29998	26998	24300	0	5545	26998	24298	0	29377	26998	24299	21865
Total	59997	53998	48600	0	26682	53996	48593	21870	29377	40794	51297	46163

Table 3.7: Re-optimised production rates

A graph illustrating the production rates after re-optimisation is presented in Figure 3.5. The re-optimised solution provides the maximised objective function with a profit of 234.751.719 NOK.

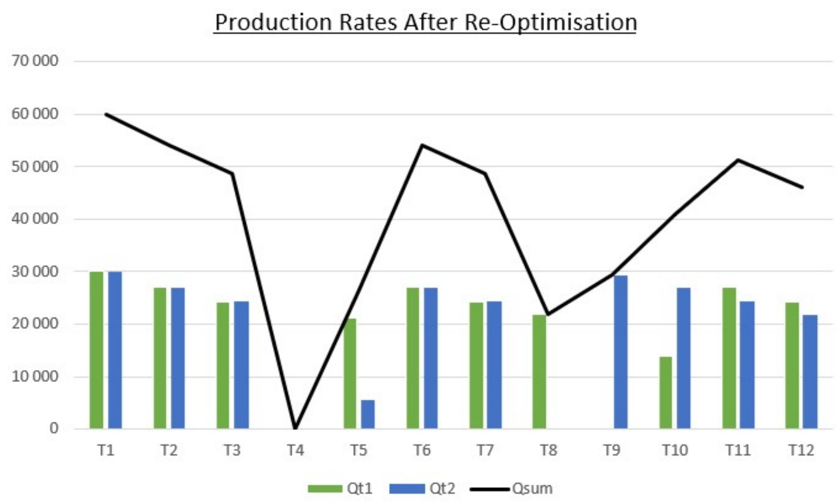


Figure 3.5: Graph of re-optimised production rates (Qt1: production in well 1, Qt2: production in well 2, Qsum: total production)

Based on the re-optimised production rates, the calculated degradation rates is presented in Figure 3.6.

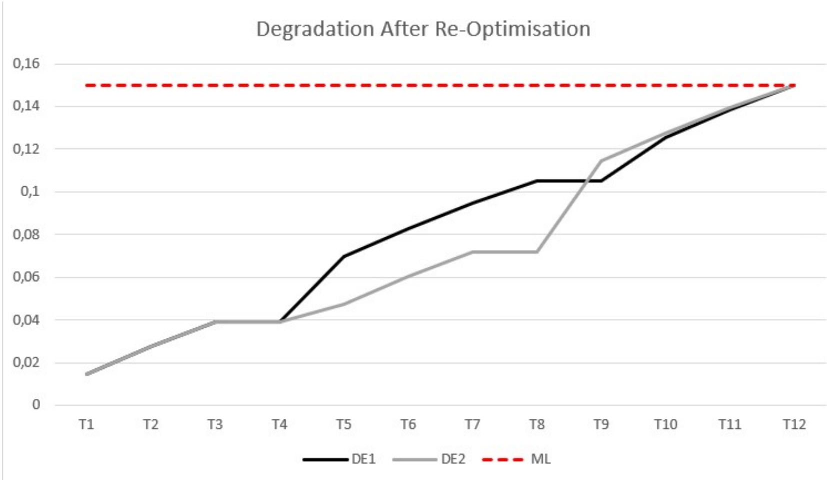


Figure 3.6: Graph of calculated degradation after re-optimisation (DE1: degradation in well 1, DE2: degradation in well 2, ML: maintenance safety threshold)

As illustrated in the graph, the re-optimised solution synchronises the degradation rate so that they reach the maintenance safety threshold approximately in the same period. This initiate a maintenance activity for the choke valve in well 1 in period T12 from the Maintenance DT, $MA_{1,12} = 1$. The condition of well 2 at T12 is in fact 0,14999 mm, resulting in not performing any maintenance activity for the choke valve in well 2 in period T12. It is reasonable to assume that a maintenance activity would be conducted in reality also for the choke valve for well 2 in this period since the condition of the valve is close to the maintenance safety threshold.

This concludes this section which has demonstrated the use of the mathematical models to integrate and synchronise the production and maintenance plan of two oil wells with associated choke valves.

4 Linking the Models to a Digital Twin and Cyber-Physical System

The following chapter is related to research objective 3 and 4. The chapter begins with an elaboration of how digital twins are interpreted in the literature in Section 4.1. This forms the basis for discussing how the mathematical models from Chapter 3 relate to the various elements of a digital twin in the succeeding sections, which are data gathering in Section 4.2, connectivity in Section 4.3 and virtual space in Section 4.4. The chapter is finalised with a discussion on how digital twins can contribute to decision-making in Section 4.5.

4.1 Frameworks

Several interpretations and classifications of what a digital twin is composed of exist in the literature. Greaves (2015) stated that the digital twin consists of three main elements: physical products in real space, virtual products in virtual space, and the connections of data and information that ties the virtual and real product together. A similar interpretation is presented by Zheng et al. (2018), who considered a digital twin system to consist of three main components: the physical space, the digital space, and an information processing layer that connects the two spaces. Additionally, Lu et al. (2020) stated that at the technical core, the development of digital twin needs three components: (1) an information model that abstracts the specifications of a physical object, (2) a communication mechanism that transfers bi-directional data between a digital twin and its physical counterpart, and (3) a data processing module that can extract information from heterogeneous multi-source data to construct the live representation of a physical object. A more comprehensive interpretation is found in the work of Qi et al. (2019), who extended the interpretation by Greaves (2015) so that the digital twin consists of five elements: physical entities, virtual models, services, digital twin data, and connections. While Redelinghuys et al. (2019) on the other hand presented a connection architecture for a digital twin consisting of physical twin, local data repositories, IoT gateway, cloud-based information repositories, and emulation and simulation.

The importance of data is discussed in the majority of the research papers in the literature, thus there seem to be a unison understanding in the literature that data forms the basis of digital twins. Furthermore, there is also an agreement on distinguishing between the physical part and the virtual part in a digital twin system. Although they are defined in different ways, the connectivity between the physical and virtual space is also addressed. Nevertheless, the need for a standardised framework or architecture for developing digital twins, defining what types of elements it consists of and how these elements should interact with each other, is evident and is also emphasised by Lu et al. (2020). According to Shao and Helu (2020), a digital twin manufacturing framework (ISO 23247) is under development by the International Organisation for Standardisation which is at the approval stage before publishing.

Based on the elements that are emphasised in the literature and due to the lack of a standardised framework, the tools, technologies, concepts and frameworks have been investigated considering the following structure:

- Data gathering
- Connectivity
- Virtual Space

4.2 Data Gathering

Data gathering have been highlighted in Section 2.3.1 as an important aspect for predictive maintenance, but it is also considered to be a fundamental layer of digital twins and cyber-physical systems. This section presents the findings in the literature regarding data gathering in digital twins and cyber-physical systems and aims to view this data gathering aspect in the light of production planning and predictive maintenance.

Cachada et al. (2018) considered three different ways to collect data in an intelligent and predictive maintenance system: automatic data collection is automatically gathered data that are stored in a database; semi-automatic data collection is when the data is automatically recorded in a database but has to be manually transferred to the system's database; manually data collection is when the information is manually inserted by a worker. The mathematical models in this thesis have not considered the data gathering aspect. In an ideal solution, systems for data gathering should be linked with the models so that the majority of the data input for the models are automatically gathered. Considering the capabilities of a digital twin and cyber-physical system, it should be possible to automatically gather the required data for the models, thus significantly lowering the need for semi-automatic and manual data collection. Nevertheless, some parameters in the models could be dependant on manual data collection, like the maintenance safety threshold, which in many cases is determined by expert knowledge.

The aspect of data gathering is also discussed by Lee et al. (2015). Unlike Cachada et al. (2018), Lee et al. (2015) considered data gathering related to cyber-physical systems. The first step includes gathering accurate and valid data from the machines and the components under consideration, before translating the data into meaningful information for decision-making and analysis (Lee et al., 2015). Furthermore, Lee et al. (2015) suggested that estimating remaining useful life and degradation and performance prediction are examples of methodologies for this purpose, bringing self-awareness to the machines. The Condition DT from Chapter 3 can be considered to belong to this category, acting as a conversion of condition data and performance data to a predicted outcome of degradation.

When this step is done, the data can be gathered in a central information hub (Lee et al., 2015). Connecting several machines from the production system provides information to the cyber level and a network of machines can be formed. By doing this, analyses can be performed to extract additional information on the status of the machines in the network. This way, the performance of a single machine can be compared with other machines in the network. Additionally, historical information and similarities between the machine performance can be measured to predict the future behaviour of the machines (Lee et al., 2015).

For production and maintenance management, several important data sources should be collected in a digital twin and cyber-physical system. From the production management perspective, it is necessary to have data related to the planning of production but also data related to the actual production and its performance. These types of data are relevant for the Production DT presented in Section 3.3. For maintenance management, data related to the condition of machines and maintenance activities are required, which are relevant for the Condition and Maintenance DT presented in Section 3.4 and 3.5.

4.2.1 Data Gathering for the Production DT

Agostino et al. (2020) proposed a digital twin approach for production planning and control using current cyber-physical systems state data in real-time. Considering the data integration in digital twins, proposed by Kritzinger et al. (2018) and initially discussed in Section 2.6.2, a digital twin of a production system must have continuous real-time data updates to successfully represent the physical twin. In order to do this, data regarding current machine status, current job and processing times must be collected, while also feeding the physical twin with data linked to the production schedule (Agostino et al., 2020). In an existing production system, relevant data for the digital twin can be collected from already existing systems like a manufacutring execution system (MES) or an ERP system. These systems typically possess data regarding machine status and production jobs (Agostino et al., 2020). Similar data systems for oil and gas should be able to provide production-related data to the digital twin. Furthermore, Agostino et al. (2020) discussed the production-related data in light of job shop manufacturing by gathering data on job and processing times, which does not apply to the case of oil and gas production. Instead, data regarding flow, pressure, and temperature in the well can be considered to be production-related data for an oil and gas production system.

Gathering production-related data was also discussed by Qi and Tao (2018). The authors suggested three data sources for digital twins in a manufacturing environment, namely manufacturing resources data, management data from information systems, and internet data. Firstly, manufacturing resource data consists of equipment data collected from the production system (considering real-time performance and operating condition), material and product data related to performance, inventory, costs and so on, while the environmental data describes factors like temperature, humidity and air quality (Qi and Tao, 2018). Secondly, management data from the manufacturing information systems include data regarding order dispatch, material distribution, marketing and sales, demand, finances and so on (Qi and Tao, 2018). Lastly, internet data includes user data collected from E-commerce platforms and social networks providing insight into consumer behaviours and demand patterns, while information from public data sources also can be used (Qi and Tao, 2018).

4.2.2 Data Gathering for the Condition and Maintenance DT

Moving on to the maintenance-related data, Spendla et al. (2017) stated that predictive maintenance utilises actual operating condition of equipment, material, and systems to optimise the manufacturing operation. This includes utilising a combination of vibration monitoring, process parameter monitoring, thermography, tribology, and visual inspection to obtain the actual operating conditions of critical components in the production system. Moreover, Paprocka (2018) presented a model of maintenance planning and production scheduling consisting of a data collection module that collects information on past failure modes in a database to take appropriate preventive actions and to avoid faults in the future. While the author does not consider Industry 4.0-related technologies, the principles of data collection are still relevant for gathering maintenance-related data in a digital twin. By gathering accurate data on failure-free operation time, repair times, failure modes, and faults, a better understanding of how the machine operates in a given environment is obtained. The gathered information can then be used to schedule inspections and to determine the scope of maintenance work (Paprocka, 2018). This will over time lead to a reduction of expensive repairs and increase failure-free operation time and lifespan of the machine.

Gathering data for digital twin and cyber-physical systems is emphasised broadly in the literature. The data forms the basis for the other elements of the system, and new technologies from Industry 4.0, like sensor technology, big data and cloud computing, enables better data acquisition procedures and abilities to analyse the data. Combining this with the real-time data acquisition ability of a digital twin, better decision-making on production and maintenance should be accomplished. The next subsection presents the methods, tools and technologies for data gathering in a digital twin and cyber-physical system.

4.2.3 Methods, Tools and Technologies for Data Gathering

Cai et al. (2017) presented techniques for sensor data integration and information fusion to build digital twins. The characteristics of a machine are extracted through sensor data to build a digital twin which reflects the actual status of its physical counterpart. Although their work considered a milling machine tool, the overall concept of data acquisition is relevant for other industries and production systems. As described in the two previous sections, a digital twin and cyber-physical system must collect data related to production and to the condition and maintenance aspect of a machine. This is also considered by Cai et al. (2017), who included the key machining parameters describing the manufacturing process for the production-related data which was obtained from a machine controller. Furthermore, the sensor data, which are relevant for the condition and maintenance of a machine, are collected from a variety of sensors used in machining monitoring and analysis. Cai et al. (2017) provided examples of sensors that are relevant for monitoring a milling machine tool, such as an electrical current sensor for power measurement, an accelerometer sensor for vibration measurement, a dynamometer for force measurement, and an acoustic emission sensor. The sensor data are obtained from a sensory data acquisition device. Similarly for oil and gas production systems, Bhowmik (2019) demonstrated the conceptual design of a digital twin for subsea pipelines and considered relevant sensor tools, such as acceleration from a motion sensor, absolute tension and compression from a subsea strain gauge, current profile from an acoustic dropler current profiler, wave data from a wave radar, subsea pressure sensor, and subsea temperature sensor.

Lee et al. (2015), Qi and Tao (2018) and Agostino et al. (2020) proposed that data can be acquired either by direct measures from sensors in the system or indirectly from data systems like an ERP system or a MES. In addition to this, Liu et al. (2020) considered technologies related to data gathering to be sensors, cameras, scanners and radio frequency identification (RFID) tags. However, the authors do not explicitly state what kind of sensors and technologies that should be applied. Considering the elaboration of tools and technologies so far in this section, it is reasonable to assume that sensors are a key technology for gathering data and that choosing the type of sensors depends on the production system and the machines in the system. Additionally, one must consider what type of data (production or condition/maintenance-related) that should be gathered.

4.2.4 Summary of Data Gathering

Returning now to the work of Cai et al. (2017), they consider the data to be gathered through a machine controller, sensors, and a sensory data acquisition device before the data is organised at a gateway. After this, the data can be stored in a database. Figure 4.1 is adapted to include data systems such as ERP and MES, and external data regarding oil prices, demand, and so on. Cloud storage is also introduced to the figure, based on findings that are presented in the next section (4.3).

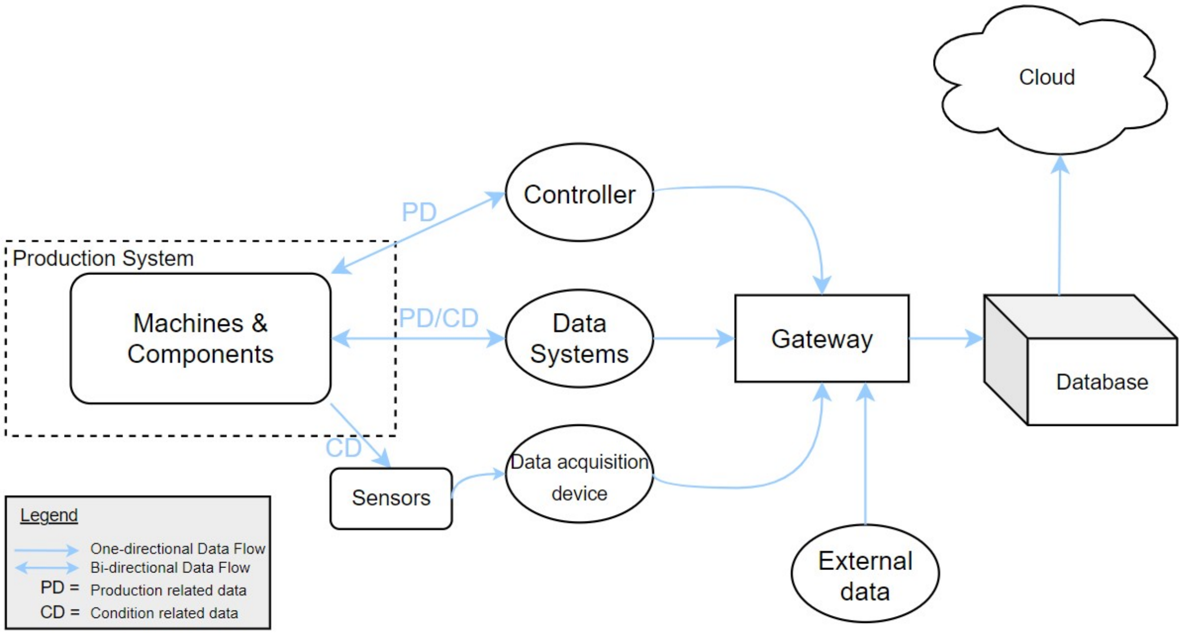


Figure 4.1: Data gathering, adapted from Cai et al. (2017)

The figure illustrates how the production and condition-related data are gathered, and by which technologies and devices. When the data is gathered, it should be stored in a database before it is uploaded to the cloud. After this, the digital twins should extract the relevant data from the cloud storage for usage in the virtual models. The exchange of data and the connectivity within the digital twin is the topic for the next section.

4.3 Connectivity

In this thesis, connectivity is interpreted as the systems and networks that enable the extraction of data from the physical world, as well as the exchange of data between the various elements and models of a digital twin and cyber-physical system. In addition to this, the connectivity aspect involves connecting the physical and virtual space in a bi-directional way. The extraction of data has already been discussed in the previous section using machine controllers and data systems for production and maintenance. However, the gathered data must be transferred to a database and be exchanged between the virtual models of the digital twin. This can be done using Internet of Things technology, communication networks and protocols, and cloud computing, among others.

Zheng et al. (2018) stated that the physical objects are separated and distributed in different places and that they need to be connected by Internet of Things technology, while Lu et al. (2020) suggested that a communication network is critical for enabling digital twins. The reason for this is that the state synchronisation between a digital twin and its counterpart in the physical space relies on bi-directional and real-time data communication. State changes to a physical object are detected by sensors and transmitted to its digital twin in cyberspace. In this regard, industrial communication protocols can help collect data from physical devices (Lu et al., 2020). The digital twin should continuously pull real-time sensor and system data to represent the real-time state of the physical entities (Qi et al., 2019). In addition to this, Internet of Things and cloud computing are necessary for the data exchange between the physical and digital world, but also for exchanging data within the virtual models and systems (Qi et al., 2019). Lastly, the various elements of the digital twin constantly interact with each other through the connections between them (Qi et al., 2019).

The connection architecture by Redelinghuys et al. (2019), which consists of a local data layer, an IoT gateway layer, cloud-based databases, and a layer of emulations and simulations, provides a more detailed elaboration on the connectivity aspect of digital twins. The architecture aims to establish communication between the physical twin and the digital twin, in addition to communicating with the digital twin and the outside world. The architecture, inspired by the 5C architecture by Lee et al. (2015), illustrates the data flows from the physical system or physical twin to the cloud, where it is stored in an information repository accessible in cyberspace (Redelinghuys et al., 2019). The first layer consists of the physical devices, like actuators and sensors, which can provide or consume signals exchanged with the local controller or data acquisition device located at the second layer, representing the data source for the physical twin (Redelinghuys et al., 2019).

The third layer contributes with a communication interface between the physical twin and the other layers. The fourth layer is called the IoT gateway and corresponds with the second level of the 5C-architecture from Lee et al. (2015), involving translating the data to meaningful information as presented in Section 2.6.1 and discussed in Section 4.2.1. The fifth layer represents the cloud-based information repository, which consists of cloud services that store historical information from the fourth layer. This information can be accessed from the sixth layer and be beneficial for decision-making by evaluating the current state of the physical twin (Redelinghuys et al., 2019). Hosting these repositories in the cloud enhances the availability, accessibility, and connectivity of the digital twin (Redelinghuys et al., 2019). The sixth and last layer involves emulation and simulation and connects the third, fourth and fifth layers. Redelinghuys et al. (2019) suggested equipping this layer with a user interface or dashboard that connects the user to real-time and historical information about the physical twin. Furthermore, emulation and simulation software should be implemented, allowing the user to interact with the layer, in addition to a graphical 3D representation of the physical twin.

4.3.1 Tools and Technologies

The tools and technologies that enable connectivity in a digital twin and cyber-physical system must exchange and transmit the data within the system. Furthermore, the gathered data must be stored and interpreted. Liu et al. (2020) considered several technologies that contribute to integrating the physical world and the digital world, specifically big data, Internet of Things, artificial intelligence, cloud computing, edge computing, 5G networks, and wireless sensor networks.

Incorrect or duplicated data must be removed by so-called data cleansing before it is integrated and stored for exchange and sharing within the digital twin and cyber-physical system. Afterwards, the real-time data can be analysed and mined based on cloud computing (Qi and Tao, 2018). Furthermore, data mapping and data fusion contributes to understanding the gathered data, where the most common data mapping technology used in the literature is XML, according to Liu et al. (2020). In summary, big data contribute to collecting and interpreting the data that is to be used in the system, thus enabling a better understanding of the real world.

Edge computing refers to the enabling technologies allowing computation to be performed at the edge of the network. Since data is increasingly produced at the edge of the network it is more efficient to also process the data at the edge of the network (Shi et al., 2016). Therefore, edge computing is an ideal method to pre-process the collected data to reduce the network burden (Liu et al., 2020) and to improve the response time and reliability (Shi et al., 2016). This is beneficial in a digital twin and cyber-physical system that must update large amounts of data in real-time. Furthermore, the acquired data from sensors of the physical twin must be stored and be easily accessible through the internet. Due to the large volumes of data that may be stored, cloud-based storage is considered an attractive choice by Redelinghuys et al. (2019).

The next topic to address is the technologies that enable the transfer and transmitting of data throughout the digital twin and cyber-physical system. General technologies like Internet of Things, 5G and protocol technologies are frequently mentioned in the literature. In addition to this, software and systems that connects the devices and digital models in the system are required. More specifically, Qi et al. (2019) stated that PTC Thingworx, an Internet of Things software, can act as a gateway between sensors and the digital models to connect the various smart devices to the Internet of Things ecosystem. Furthermore, Mindsphere, a cloud-based Internet of Things operating system from Siemens, enables the connections between products, plants, systems, and machines.

On the other hand, Redelinghuys et al. (2019) suggested that the connections between the physical twin and its corresponding digital twin may rely on internet-enabled connections. The paper considers OPC Unified Architecture (OPC UA) to be a functional tool for this matter, in addition to exchanging data with various controllers and data acquisition devices. According to the authors, OPC UA is striving towards becoming the international standard for horizontal and vertical communication in manufacturing and automation. As an example, some OPC UA servers provide access to more than 150 device drivers (Redelinghuys et al., 2019), which makes it a suitable tool in digital twins and cyber-physical systems where the number of devices could potentially be high.

5G technology is also pointed out as an enabler for real-time data transmission (Liu et al., 2020). 5G is an abbreviation for the fifth-generation mobile network aiming to provide improved speed, reliability, and latency. Qi et al. (2019) also considered communication technology, unified communication interfaces and protocol technologies to enable the data exchange in a digital twin and cyber-physical system. Lastly, another aspect of connectivity is the human interactions with the digital twin in both physical and virtual space. This can be accomplished by utilising technologies like Virtual Reality and Augmented Reality (Qi et al., 2019). This enables visualisation of the physical part and is relevant for the oil and gas industry where the distance between the decision-maker and the production facility may be large.

4.3.2 Summary of Connectivity

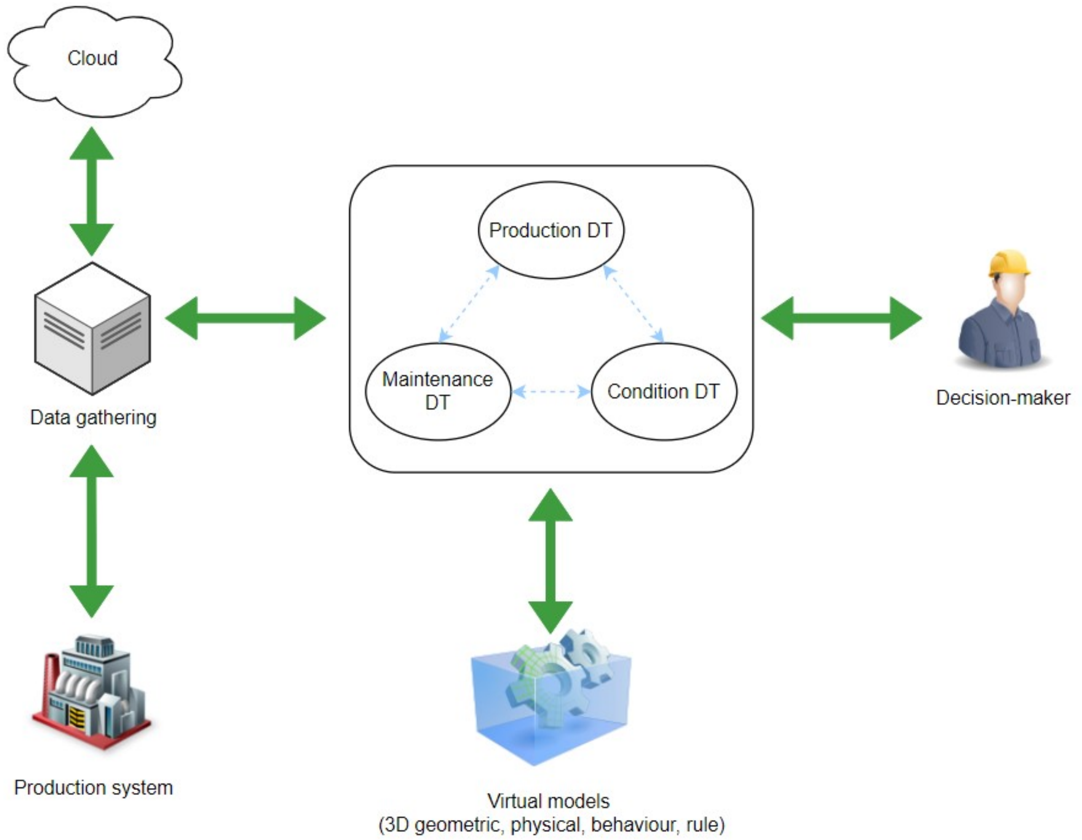


Figure 4.2: Connectivity in a digital twin and cyber-phsyical system

Figure 4.2 illustrates the aspect of connectivity. The left hand side of the figure illustrates the data gathering aspect from Figure 4.1. The connectivity aspect should link the data gathering with the virtual space, consisting of the Production, Condition, Maintenance DT, and the other virtual models that exists in the system. The virtual models is the topic for Section 4.4 and is further elaborated there. The virtual models are included in the figure to illustrate the interactions between the mathematical models and the other virtual models that exists in the system. Lastly, the decision-maker interacts with the mathematical and virtual models to support decisions, which is discussed in Section 4.5.

4.4 Virtual Space

So far, the data gathering aspect has been presented, which forms the basis of digital twins and cyber-physical systems, before the connectivity aspect was presented. The last element of a digital twin, the virtual space, is considered to be the core of digital twins (Liu et al., 2020).

Zheng et al. (2018) considered the virtual space to consist of two parts: a virtual environment platform and a digital twin application subsystem. The former establishes a unified 3D virtual model for different applications (e.g. product maintenance application and plant operation application) and provide an operating environment for an algorithms library. There are interactions between the two parts, and the latter receives various virtual models (e.g. workflow model, simulation model, etc.) from the former. The digital twin application subsystem should store the various models, methods, and historical data that are created during operation into the virtual environment platform. Furthermore, Zheng et al. (2018) suggested that the modelling of physical objects is available by obtaining the attributes of the virtual model from a database and that the feedback of 3D models should be stored in the database by using corresponding interfaces.

Tao and Zhang (2017) and Qi et al. (2019) also discussed the virtual space in terms of models. These virtual models should replicate the physical entities by reproducing the physical geometries, properties, behaviours, and rules. The authors consider four different virtual models: 3D geometric models, physics models, behaviour models, and rule models. The first type should describe a physical entity by its shape, size, tolerance, and structural relation. The second type should reflect physical situations, like deformation, delamination, fracture, and corrosion, based on physical properties such as speed, wear, and force. The third type should describe the behaviours, like state transition, degradation, and coordination, in addition to the effects on the entities from potential changes in the external environment. By following rules extracted from historical data or expert knowledge, the last type of models should equip the digital twin with logical abilities, like reasoning, judgement, evaluation, and autonomous decision-making.

Based on the types of models in the virtual space described above, this section is divided into four subsections concerning the following types of models:

- Geometric 3D models - visualising the processes and the components in the system
- Physical models - models of the physical properties and the loads on the physical entity
- Behavioural models - describing the behaviours of the physical entities
- Rule models - models of the rules that exists for the physical entity

4.4.1 Geometric 3D Models

One of the capabilities of digital twins is that they enable the visualisation of the behaviour and relations of the real-world system in virtual space. Combining this with real-time data from the physical world, the digital twin formulates real-time parameters, conditions, and dynamics for analysation and optimisation. In order to capture these characteristics and visualise them in real-time, geometric 3D models must be developed for the system. Geometric 3D models are built to describe shapes, sizes, positions, tolerance, and relations of the physical entities (Qi et al., 2019; Tao and Zhang, 2017).

This type of models is often discussed concerning digital twins. Combining this with real-time data from the system, the entity's performance can be visualised and analysed in real-time. Geometric 3D models are not within the scope of this thesis. However, it is important to highlight the capabilities of a digital twin to visualise, for example, a component and how it performs in real-time, which is highly relevant for the offshore industry where the decision-maker can be located far from the operational environment. With a digital twin, the decision-maker can still obtain a picture of how the system performs while also having the possibility to simulate the system's performance for other scenarios, for example, a new production plan.

Linking this to the case of this thesis, a corresponding geometric 3D model of the oil production system, including the reservoir, wells, choke valve, and the topside facility similar to the case illustrated in Figure 3.1, could be developed. Connecting the geometric 3D model to the gathered data and the other virtual models enable the visualisation in real-time of how the physical part performs.

4.4.2 Physical Models

Physical models are required to capture the physical processes of the physical twin. Qi et al. (2019) stated that the physical models should provide information regarding accuracy (e.g., dimensional tolerance, shape tolerances, position tolerance, and surface roughness), material (e.g., material type, performance, heat treatment requirement, hardness, etc.), and assembly information (e.g., mating relationship and assembly order). This way, information about entity features and constraints of the system is added to the virtual space. It is also worth mentioning that the material information is dependent on the material used in the production system and that assembly information is only relevant in a production system where assembling parts is a step in the production.

Tao and Zhang (2017) also explained the physical models, stating that the physical properties, such as function, capacity, torque and wear, and the loads on the physical entity, such as stress, resistance, and temperature, are provided to the geometric 3D models to form the physical model. This way the physical model can analyse physical processes such as deformation, cracking, and corrosion. Aivaliotis et al. (2019) presented a methodology for enabling digital twin using advanced physics-based modelling in predictive maintenance. According to the authors, a physics-based model refers to "*a simplified description, especially a mathematical one, of a system or process, to assist calculations and predictions consisted of a hierarchical structure of components and sub-components representing physical phenomena and connection lines among them to represent the actual physical coupling*".

More explicitly said, the physical models should capture the physical development of the machines in the system. In the case of this thesis, a physical model was required to describe the degradation and condition of the machine. This corresponds to the Condition DT, presented in Section 3.4, describing the physical behaviour of the choke valve based on the production load. Although it was simplified into being purely a deterministic model, the Condition DT illustrates its purpose in a digital twin and cyber-physical system and demonstrates the interactions it has with the Production DT and Maintenance DT. In order to become more predictive and describing the degradation process more realistically, the Condition DT should be developed by, for example, using a physical erosion model together with a probabilistic degradation model, as mentioned in Section 3.4. The model must utilise the equipment and environmental data discussed in Section 4.2.1, and the condition and maintenance related data in Section 4.2.2.

4.4.3 Behavioural Models

As presented initially in Section 4.4, behavioural models should describe the behaviours of a physical entity, like state transition, degradation, and coordination, in addition to the effects on the entities from potential changes in the external environment (Qi et al., 2019; Tao and Zhang, 2017). To represent the physical behaviour, several models must exist in the system, like a problem model, state model, dynamics model, and an evaluation model. To develop such models, finite state machines, Markov chains, and ontology-based modelling methods can be applied. When it comes to state modelling, this includes a state diagram, describing the dynamic behaviours of an entity, and an activity diagram, describing the required activities to complete an operation. Lastly, dynamics modelling deals with rigid body motion, elastic system motion, high speed rotating body motion, and fluid motion (Qi et al., 2019).

The Production DT would be tightly linked to a behavioural model since the Production DT influence how the production system behaves. It would be unprecise to categorise the Production DT as a behavioural model, as it is an optimisation model that aims to determine the production plan. It is the author of this thesis' understanding that the Production DT would influence a behavioural model based on what Tao and Zhang (2017) and Qi et al. (2019) defines as behavioural models. However, the Production DT should still be considered as an optimisation model. With that being said, introducing a behavioural model in the case of this thesis would result in having a model that describes how the machines in the production system behave and react based on what is determined by the Production DT.

4.4.4 Rule Models

In order to enable decision support, models describing rules are also needed. The rules are extracted from historical data, expert knowledge, and predefined logic. This way, the digital twin is equipped with an ability to reason, judge, evaluate, optimise, and predict outcomes and scenarios (Qi et al., 2019). The Maintenance DT presented in Section 3.5 is considered to be a variant of a rule model. The Maintenance DT determines when maintenance activities should be performed, based on the rule that the degradation should not exceed the predetermined maintenance safety threshold. The maintenance safety threshold can be determined by extracting historical data for which degradation level the choke valves typically fails, or it can be determined by expert knowledge.

4.4.5 Tools and Technologies

Many different tools and technologies may be applied when developing the various models in a digital twin and cyber-physical system and is dependent on the intended usage. The physical twin requires a corresponding geometric 3D model combined with real-time data that can act as the digital replica of the system or component under consideration. For this purpose, Computer-Aided Design (CAD) software like SolidWorks and NXCad can be applied. In addition to this, 3D MAX, AutoCAD, and CATIA are also software that supports this objective (Tao and Zhang, 2017). Additionally, Fuller et al. (2020) considered Simulink and Twin Builder as tools for enabling the visualisation and architecture modelling of digital twins.

For the physical models, Qi et al. (2019) presented that the finite element analysis software by ANSYS can be used to define the real-time boundary conditions for the geometric models by utilising sensor data. Then, the performance degradation or the wear coefficient can be incorporated into the models. In addition to this, the paper stated that Simulink enables physics-based modelling using multi-domain modelling tools. Multi-domain modelling involves components belonging to different engineering domains (Tiller, 2001), like mechanical, hydraulic, and electrical components (Qi et al., 2019).

The tools for behaviour modelling are used to establish a model responding to external factors and improves the simulation performance of the digital twin. Qi et al. (2019) provided an example where the motion control system of a CNC machine tool can be designed based on the PLC platform CoDeSys. Regarding the rule models, Qi et al. (2019) provided an example of utilising the machine learning ability by PTC's Thingworx upon the HP EL20 edge computing system. This way, a digital twin can learn rules and recognize deviating characteristics of the operation by monitoring sensors to automatically learn the normal state of machine under consideration while it is running.

Redelinghuys et al. (2019) chose Siemens Tecnomatix PS as the software for emulation and simulation due to its suitability for visualising the physical twin in real-time and allowing for the integration of the physical system with the virtual space. In addition to this, it enables the simulation, analysis, and optimiastion of production systems and logistics processes. The next section concludes Chapter 4, presenting digital twins for decision-making where simulation and optimisation are considered as tools for this matter.

4.5 Digital Twins for Decision-Making

So far, this chapter has discussed concepts, frameworks, technologies, and tools of the various elements of a digital twin and cyber-physical system, and linked the mathematical models to these elements. García and García (2019) considered decision-making and decision support to be central capabilities of digital twins and cyber-physical systems. Decision-making is a key factor for industrial enterprises as they require decisions regarding design, engineering, planning, communication, controls, and operations (Kuehn, 2019)

One method for improving decision-making by the use of digital twins is simulation (Kuehn, 2019). However, Qi et al. (2019) does not consider simulation to be a type of model, but rather to be a function of the models in the digital twin and cyber-physical system. That is, the various models in the system can be simulated to analyse possible outcomes and "what-if" scenarios. Liu et al. (2020) stated that digital twin simulation enables the virtual model to interact with physical entities bi-directionally in real-time. The difference from the traditional simulation procedure is that digital twin simulation uses real-time data of the physical system that are collected and recorded from physical space via Internet of Things (Liu et al., 2020). This is also supported by Shao et al. (2019), who considered digital twin simulation to use real-time sensor data as inputs before it updates some of the parameters of a manufacturing process or equipment. Lastly, Kuehn (2019), stated that the planning, optimisation, and operation of industrial enterprises requires modern data and simulation-driven multi-criteria decision approaches.

In the case of production planning and predictive maintenance, it would be valuable to simulate how a production plan will influence degradation and vice versa. One example could be that during a period where the oil prices have increased, it would be of interest to produce more oil to increase the profits. Simulating how this increase in production affects the degradation will be beneficial and can support the organisation in preparing for possible outcomes. It could also be used to simulate and analyse the cost-benefit of whether producing hard and running the components to failure is profitable due to the increased oil price. In addition to this, since stochastic processes introduce random variables, simulation is a helpful tool to achieve a more precise prediction of when the component will fail. Running a large set of simulations can result in more precise estimations while incorporating the real-time data acquisition ability of digital twins as time goes by can update the prediction to account for new data regarding the condition and actual production in the well.

Additionally, optimisation models can also contribute to the decision-making process between production and maintenance planning. The models derived in this thesis has demonstrated one situation where integrated production and maintenance planning can contribute to the decision-making process. The further realisation of optimisation models for digital twins will take advantage of the data gathering aspect and real-time data acquisition that can be linked with the optimisation models, in addition to the connectivity aspect that enables connection between the virtual models. Using the gathered data enables better estimation of the parameters that are used in the model, as well as being able to automatically update these parameters in real-time. This is further discussed in Section 5.1. The connectivity to the other models enables real-time updates and visualisation of the process, which can support the decision-maker by notifying and visualising unforeseen changes that occurs. For example, after some time it may turn out that the condition of the component has degraded faster than predicted. The connectivity between the virtual models in combination with the real-time data updating can notify the decision-maker of the development who can re-adjust and re-optimise the production plan accordingly.

5 Discussion

The discussions of the work carried out in this thesis is presented in this chapter. The two main parts of the thesis, Chapter 3 and 4, are discussed regarding how they support and answer the research objectives in Section 1.2, in addition to discussing the challenges and limitations of the work. This is done respectively in Section 5.1 and 5.2 before recommendations for further work is proposed in Section 5.3.

5.1 The Mathematical Models

The mathematical models in this thesis has been derived to support the following research objectives:

1. Derive basic mathematical models for integrating production and maintenance.
2. Define principles for what the mathematical models in a digital twin and cyber-physical system should do in order to integrate production and maintenance.

The aim of the mathematical models developed in this thesis has been to demonstrate how integrating production and maintenance planning can be integrated to make better decisions regarding when to do maintenance based on the planned production load, and to decide how hard the production should be, based on the predicted degradation of the component under consideration. Several researchers have emphasised the benefits and potential cost savings of making decisions on production and maintenance in an integrated fashion (Aghezzaf and Najid, 2008). For the case of oil and gas production, maintenance costs are considered to be a significant operating cost (Norwegian Petroleum Directorate, 2020), thus making the integration of production and maintenance planning an interesting topic for research in this industry. While previous research has focused on integrating production and maintenance planning purely by developing mathematical models (Pan et al., 2011; Liu et al., 2018; Ghaleb et al., 2020a; Verheyleweghen and Jäschke, 2018; Matias et al., 2020), this thesis has studied the integration problem in light of utilising digital twins and cyber-physical systems.

By deriving basic mathematical models, a foundation for discussing how these models would fit in a digital twin and cyber-physical system was made. In addition to demonstrating and defining principles for how the models should interact with each other and how they should communicate. By implementing these models in a digital twin and cyber-physical system, this interaction and communication can be enabled. It should also improve the optimisation by gathering relevant and accurate data that can be updated in the model in real-time, enabled by the digital twin and cyber-physical system. In addition to this, the defined principles should contribute to deciding what kind of technologies and tools that must be utilised to support the mathematical models in a digital twin and cyber-physical system. However, in order to investigate and discuss how these models can be linked and implemented in a digital twin and cyber-physical system, assumptions and choices have been made to prevent the complexity of the models, which is discussed in the following subsections.

5.1.1 Challenges with the Production DT

The work carried out in this thesis has pointed out some difficulties in modelling the integration of production and maintenance planning, which could prove to be useful for further research. Firstly, for the Production DT in Section 3.3, the model considers only two production wells. In reality, it is reasonable to assume that the number of wells in an oil production facility will be higher. However, Krishnamoorthy et al. (2016) considered a network of two wells, while Verheyleweghen and Jäschke (2018) considered three wells in their work. Therefore, it is reasonable to assume that considering two wells in the case of this thesis did not affect the purpose of demonstrating how production and maintenance planning can be integrated.

Furthermore, some of the input parameters in the Production DT have been decided arbitrarily, like the declining production factor, d_f, in Eq. 3.3 and the operating cost, O_i, in Eq. 3.4. The reason for this was the lack of real-life data. Considering the capabilities of a digital twin and cyber-physical system, it should be able to gather these data and automatically implement them in the models as discussed in Section 4.2 and 4.5. This should contribute to better parameter estimation as well as continuous updating of the parameters. The declining production rate factor could, for example, have been determined based on historical data, while the operating cost could have been extracted from an existing data system within the organisation.

An assumption that the production rate returns to full capacity after just one period of being shut down was made. As mentioned in Section 3.3, the rate and speed at which the pressure increases after a well has been shut depends on several conditions and requires more advanced formulas that are not considered in this problem. This assumption was made to demonstrate that changing which wells to produce from can both be advantageous and disadvantageous. The advantage of shutting down a well is that the pressure is restored and more oil can be produced when it is reopened. However, this comes at a cost in terms of lost production, which has not been included in the model. On the other side, the disadvantage of shutting down a well to restore the pressure is that this initiates increased degradation in the well when it is reopened. This interaction and trade-off between production and maintenance is the core of the problem that has been studied in this thesis and the models have been derived in order to investigate this particular interaction.

5.1.2 Challenges with the Condition DT

In Section 3.4, which describes the Condition DT, the difficulties using the erosion model presented in DNV-GL (2015) was briefly mentioned. The model requires sufficient data on the physical dimension of the oil well and the choke valve, in addition to data regarding the particle impact velocity, particle density and density of the target material among others. The recommended practice regarding managing sand production and erosion in DNV-GL (2015) does include some values for these parameters, and attempts were made to use these values. Unfortunately, the calculated values turned out to be significantly lower than what one would expect for a realistic value for erosion. The reason for this could be as simple as that the erosion model was calculated incorrectly, or that the amount of sand production presented in Table 3.6 were unrealistic, thus resulting in an imprecise value for the parameter $\dot{m}_{\text{sand}}$ in Eq. 3.8. Therefore, the simplified erosion model in Section 3.4.2 was used to demonstrate the erosion.

In addition to this, the Condition DT as presented in this thesis do not incorporate the aspect of uncertainty through stochastic processes as originally intended, thus failing to grasp the ability to be predictive in a correct manner. The intention was to use the Gamma process, presented in Section 2.4.1, to account for uncertainties in the degradation, and not to model the degradation deterministically as done in the Condition DT. The model considered the remaining useful life to be equal to the maintenance safety threshold. Due to the uncertainties that in reality applies to a degradation process, there is a possibility that the choke valve could still function after passing the maintenance safety threshold. Introducing the Gamma process and a failure threshold in addition to the maintenance safety threshold could have enabled further investigation of this problem. The failure threshold would have a greater value than the maintenance safety threshold, and if the degradation level lies between these thresholds, the risk of failure is high. When the degradation level has exceeded the maintenance safety threshold, estimations of the failure probability could have been included in the model, incorporating additional costs of running the production in this risky state.

Figure 3.4 illustrates the deterministic degradation process. The degradation is synchronised to hit the maintenance safety threshold in the same period, illustrated in Figure 3.6. If the degradation had been modelled as a stochastic process, like the Gamma process, uncertainty would have been introduced to the problem which indicates a robust plan, where the outcomes are affected by uncertain data. In order to deal with this situation, stochastic programming is required. One approach for this would have been to introduce two scenarios. In the demonstration of the models, one could consider that in period T6 the degradation is either above or below the mean degradation value. In this period, a decision must be made on how hard the production should be from period T6 and onwards. By doing this, two decision stages can be introduced. Stage 1 for period T1-T5 and stage 2 for period T6-T12. One situation in this scenario is the consequence of, for example, running hard in the first stage which may result in the component degrade faster, thus limiting the flexibility in the production plan for stage 2 as the condition of the component is close to the maintenance safety threshold.

5.1.3 Challenges with the Maintenance DT

Moving on to the Maintenance DT, presented in Section 3.5, the model considered the tactical planning horizon, thus considering periods of months. It is unlikely that a whole month of shutting down production would be required to perform maintenance or replace the choke valve. Therefore, the models should ideally be able to optimise the production down to the operational planning horizon of weeks or days. Furthermore, the Maintenance DT should also be able to reset the degradation level after a period of a maintenance activity. This was difficult to model without increasing the complexity of the model. In order for the model to be used for real-time decision-making, this feature must be incorporated in the model.

5.1.4 Discussion on the Re-Optimisation Procedure

Lastly, a re-optimisation procedure was introduced in the numerical demonstration in Section 3.6. This was done to demonstrate how the maintenance activity could be synchronised because having formulas that are not independent complicates the mathematical modelling and optimisation, as mentioned in Section 3.2. The explanation behind the independency is that the production plan is dependant on the degradation level of the component, while the degradation over time is dependant on the planned production. Kuehn (2019) proposed multi-criteria decision-making processes as a solution to handle this challenge, which is an interesting topic for further research. In addition to this, maintenance cost was neither included. Therefore the model is unable to capture the ability to determine whether running hard and replacing the component earlier would be as profitable as relaxing the production and performing maintenance in a later period. Without comparing the result with another alternative that explicitly accounts for the maintenance cost, it is difficult to determine whether or not it is more profitable to synchronise the maintenance activity as done in Section 3.6. However, assuming that there is a set-up cost for performing maintenance, it is reasonable to assume that synchronising the maintenance to the same period should generate cost savings.

Section 5.1 has discussed what the results of the derived mathematical models implies. The models must automatically gather data in real-time, exchange data between them and with other elements of the digital twin and cyber-physical system, and handle the dependency between the production plan and the condition of the machines. The assumptions, simplifications, and weaknesses of the models have also been discussed. However, considering the understanding that axiomatic research produces knowledge about the behaviour of certain variables in the model, based on assumptions about the behaviour of other variables in the model, from Karlsson (2016), provided in Section 1.3.2, indicates that it can be justified to make assumptions in mathematical modelling. Especially bearing in mind that the aim has been to demonstrate the possibilities and interactions between the models and how this would fit into a digital twin and cyber-physical system. If these models were to be tested in an actual system, then the requirements of replicating real life in a more precise manner would be higher. It is reasonable to assume that by the use of Industry 4.0 technology and digital twins and cyber-physical systems, it is possible to grasp these real-life characteristics.

5.2 Capabilities of Digital Twins

Chapter 4 presented concepts, frameworks, technologies, and tools that must exist in a digital twin and cyber-physical system and supports the following research objectives:

3. Investigate what concepts, frameworks, technologies, and tools that must exist in a digital twin and cyber-physical system in order to support the integration of production and maintenance through existing research in the literature.
4. Discuss how digital twins can contribute to decision-making across the two disciplines production and maintenance.

By utilising the presented concepts, frameworks, technologies and tools, the digital twin is seen as an enabler for better decision-making across the whole supply chain. The reason for this is first and foremost due to the data gathering aspect of a digital twin and cyber-physical system. Since decisions typically are made based on the amount of information that exists, it is reasonable to assume that data gathering is a significant contributor to decision-making. By gathering data from relevant elements of the system, the information grounds for the decision-maker is massively improved. However, the decision-making capabilities of a digital twin and cyber-physical system is not solely due to the ability to gather data, but also the ability to transform this data into meaningful information and visualising them in the virtual space. By having a digital visualisation of the entire production system, the ability to analyse and improve several elements of the production process is possible. Furthermore, the virtual representation enables simulation and optimisation of scenarios without interfering with the performance of the physical entity. In addition to this, by the use of real-time data and continuous updating of the system, real-time decisions can be made based on how the system is performing. Considering unforeseen situations that may occur during operation, this ability of digital twins is valuable in a decision-making context. This is also supported by Ghaleb et al. (2020b), who stated that the use of real-time information can significantly improve scheduling decisions.

The results of this thesis contributes to the understanding of how mathematical models relates to the existing frameworks and ideas of a digital twin and cyber-physical system. Since digital twins and cyber-physical systems are considered to be enablers for improved production and maintenance planning (García and García, 2019; Tao et al., 2019b), in combination with the fact that mathematical models are often used to optimise the production and maintenance plan (Budai et al., 2008), it forms a basis for further development of mathematical models for production and maintenance planning in a digital twin and cyber-physical system. Digital twins and cyber-physical systems are potentially important facilitators for making decisions across disciplines due to their ability to gather, interpret and visualise data from different perspectives. Section 4.2.1 and 4.2.2 presented the data gathering of respectively production-related data and maintenance-related data. This access of data from different disciplines is important for both developing models that integrate production and maintenance planning, but also for making decisions for both disciplines in an integrated fashion. Qi et al. (2019) also discussed this, and stated that "*the future modelling technologies are characterised by multidisciplinary and multifunctional synthesis*" and that "*the DT modelling process is an interdisciplinary synthesis process, which involves mechanical science, hydraulics, aerodynamics, structural mechanics, fluid mechanics, acoustics, thermals, electromagnetism, and control theory*". This has also been demonstrated in this thesis, where the mathematical models consist of principles related to production management and maintenance management, as well as fluid and mechanical science through the intended erosion model from DNV-GL (2015).

The thesis has presented concepts, frameworks, technologies, and tools that exists in the literature for utilising digital twins and cyber-physical systems. However, the technologies and tools mentioned are discussed in general. For instance, the thesis has not explicitly stated what tools and technologies that can support the optimisation models of production and maintenance planning. Complex real-life problems will require optimisation software, like MATLAB, Gurobi, or CPLEX, and these software must be able to communicate with the digital twin and cyber-physical system to gain access to the gathered data and interact with the other virtual models. In addition to this, the technical aspect of developing a digital twin system around mathematical models has not been considered. The technical execution of connecting the automatic data gathering to the models and achieve real-time updating of the models will be important to realise the capabilities of the digital twin and cyber-physical systems.

5.3 Further Work

As previously mentioned, the mathematical models in Chapter 3 has not incorporated the stochastic behaviour of a degradation process of a choke valve. The intention was to combine the physical erosion model in Section 3.4.1 with the Gamma process presented in Section 2.4.2. The work in this thesis was unsuccessful in executing this approach, and introduced a deterministic simplified degradation model in Section 3.4.2 instead. Incorporating a stochastic process to the modelling is a natural extension for further work of this thesis. The significance of not including a stochastic process has been discussed in Section 5.1.3, where the consequence of not including this was highlighted to be the possibility that the choke valve could in fact function after exceeding the maintenance safety threshold.

Furthermore, the technical execution of implementing the models in a digital twin and cyber-physical systems, connecting sensors, automatic data gathering, and other virtual models has not been the aim of this thesis, but will be an interesting study to consider for realising the capabilities of the digital twins and cyber-physical systems. Challenges in modelling the production planning aspect has been discussed in 5.1.1, where the limitation of choosing some parameters arbitrarily was discussed. It should be possible to solve these issue by implementing the models in a digital twin and cyber-physical system, due to the capabilities they posses for automatic gathering of real-time data. In order to this, appropriate concepts, frameworks, technologies, and tools must be chosen for the system, which have been presented in Chapter 4 of this thesis.

In section 5.1.4 the re-optimisation procedure was discussed, emphasising the challenges in modelling the production and degradation in the same optimisation problem as these two elements are not independent. One approach for meeting this challenge was proposed by Kuehn (2019), proposing multi-criteria decision-making processes as a possible method for this challenge. Furthermore, it is reasonable to assume that more advanced programming in combination with real-time and automatically data flow can be utilised to model this independency more efficiently.

6 Conclusion

This thesis aimed to derive mathematical models for integrating production and maintenance and to define principles for what the mathematical models in a digital twin and cyber-physical system should do in order to integrate production and maintenance. Production and maintenance planning is often studied through the use of mathematical modelling. Therefore, the mathematical models were derived based on previous research and were presented and demonstrated in Chapter 3. The demonstration of the models considered a fictional case scenario based on real-life characteristics of an oil production system. The case considered a production system consisting of two oil wells with associated choke valves that suffer degradation over time. The objective was to determine a production plan that accounts for the condition of the choke valve to plan maintenance activities in a synchronised manner. Throughout Chapter 3, principles for what the mathematical models in a digital twin system should do in order to integrate production and maintenance was defined. The models' ability to interact and communicate with each other was highlighted and it can be concluded that this interaction and communication can be enabled by implementing the models in a digital twin and cyber-physical system. The models must gather data automatically and in real-time, exchange data between them and other elements of the digital twin and cyber-physical system, and handle the dependency between the production plan and the condition of the machines.

Furthermore, by deriving these mathematical models, a foundation for discussing how the models would fit in a digital twin and cyber-physical system was made, and concepts, frameworks, technologies, and tools for digital twins and cyber-physical systems was discussed. The defined principles of what the mathematical models should do contribute to deciding what kind of technologies and tools that must be utilised to support the mathematical models in a digital twin and cyber-physical system. How digital twins can contribute to decision-making across production and maintenance has also been discussed, highlighting data gathering as a significant contributor to this matter. In addition to this, the capabilities of a digital twin and cyber-physical system to translate data into meaningful information and visualising them in the virtual space was also pointed out as a valuable capability for decision-making. These aspects should also improve the optimisation of the models by gathering relevant and accurate data that can be updated in the model in real-time.

While some of the challenges that occurred in the work of the thesis limit the real-life applicability of the results, the thesis provides new insight into how mathematical models in a digital twin and cyber-physical system can contribute to the interactions between production and maintenance, which in the case scenario of this thesis involves the trade-off between shutting down the production to restore pressure in an oil well or starting production in a well which leads to increased degradation rate. The challenges discussed in Chapter 5 has guided the directions for further research, which is recommended to be to include a stochastic process in the modelling of the condition, among others.

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Appendix

A1 Notations for The Production DT

Indices:	
T	Set of time periods
t	Period
W	Set of wells
i	Well number
Parameters:	
P_o	Price of oil
O_i	Operating cost for well i
d_f	Decreasing factor of production
$Q_{i,t}$	Production rate in well i in period t
$Q_{\max}$	Maximum production rate from one well
Decision variable:	
$W_{i,t}$	Whether to produce from well i in period t or not

A2 Equations for The Production DT

$$\mathrm{W}_{i,t} = \begin{cases} 1, & \text{produce from well } i \text{ in period } t \\ 0, & \text{don't produce from well } i \text{ in period } t \end{cases} \tag{3.1}$$

$$Q_{i,1} = Q_{\max} \cdot W_{i,1} \tag{3.2}$$

$$\mathrm{Q}_{i,t} = \begin{cases} \mathrm{Q}_{i,t-1} \cdot d_f & \text{if } \mathrm{W}_{i,t-1} = 1 \ \wedge \ \mathrm{W}_{i,t} = 1 \\ \mathrm{Q}_{\max} & \text{if } \mathrm{W}_{i,t-1} = 0 \ \wedge \ \mathrm{W}_{i,t} = 1 \\ 0, & \text{otherwise} \end{cases} \tag{3.3}$$

$$\sum_i \sum_t W_{i,t} \cdot O_i \tag{3.4}$$

$$\sum_i \sum_t Q_{i,t} \cdot P_o \tag{3.5}$$

$$\text{Maximise} \sum_i \sum_t Q_{i,t} \cdot P_o - \sum_i \sum_t W_{i,t} \cdot O_i \tag{3.6}$$

$$W_{i,t} = \text{binary} \quad \forall \quad t \in T, \, i \in W \tag{3.7}$$

A3 Equations for The Simplified Degradation Model

$$DE_{i,t} = ER \cdot m_{i,t} \cdot 0.001\text{ton/kg} \tag{3.13}$$

$$m_{i,t} = Q_{i,t} \cdot SR \tag{3.14}$$

$$\mathrm{M}_{i,t} = \begin{cases} m_{i,t} & \text{if } \mathrm{W}_{i,t-1} = 1 \wedge \mathrm{W}_{i,t} = 1 \\ m_{i,t} \cdot i_f & \text{if } \mathrm{W}_{i,t-1} = 0 \wedge \mathrm{W}_{i,t} = 1 \end{cases} \tag{3.15}$$

A4 Notations for The Maintenance DT

Indices:	
$MA_{i,t}$	Maintenance activity
ML	Maintenance safety threshold
$DE_{i,t}$	Degradation level

A5 Equations for The Maintenance DT

$$\mathrm{MA}_{i,t} = \begin{cases} 1 & \text{if } DE_{i,t} > ML \\ 0, & \text{otherwise} \end{cases} \tag{3.16}$$

A6 Spreadsheet of Optimisation

Oil price	kr 550	
Operational cost	kr 1 500 000	
Max prod rate	30 000	
Decline in prod	0,9	
Sand rate	0,0023	
Sand jump	300 %	
Erosion rate	0,21	mm/ton
kg to tonn	0,001	
ML	0,15	

	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
Q_{t1}	30 000	27 000	24 300	0	30 000	27 000	24 300	21 870	0	30 000	27 000	24 300
Q_{t2}	30 000	27 000	24 300	0	30 000	27 000	24 300	0	30 000	27 000	24 300	21 870
Q_{sum}	60 000	54 000	48 600	0	60 000	54 000	48 600	21 870	30 000	57 000	51 300	46 170
Well 1	1	1	1	0	1	1	1	1	0	1	1	1
Well 2	1	1	1	0	1	1	1	0	1	1	1	1
Cost	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
Well 1	kr 1 500 000	kr 1 500 000	kr 1 500 000	kr 0	kr 1 500 000	kr 1 500 000	kr 1 500 000	kr 1 500 000	kr 0	kr 1 500 000	kr 1 500 000	kr 1 500 000
Well 2	kr 1 500 000	kr 1 500 000	kr 1 500 000	kr 0	kr 1 500 000	kr 1 500 000	kr 1 500 000	kr 0	kr 1 500 000	kr 1 500 000	kr 1 500 000	kr 1 500 000
Sum	kr 3 000 000	kr 3 000 000	kr 3 000 000	kr 0	kr 3 000 000	kr 3 000 000	kr 3 000 000	kr 1 500 000	kr 1 500 000	kr 3 000 000	kr 3 000 000	kr 3 000 000
Income	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
Well 1	kr 16 500 000	kr 14 850 000	kr 13 365 000	kr 0	kr 16 500 000	kr 14 850 000	kr 13 365 000	kr 12 028 500	kr 0	kr 16 500 000	kr 14 850 000	kr 13 365 000
Well 2	kr 16 500 000	kr 14 850 000	kr 13 365 000	kr 0	kr 16 500 000	kr 14 850 000	kr 13 365 000	kr 0	kr 16 500 000	kr 14 850 000	kr 13 365 000	kr 12 028 500
Sum	kr 33 000 000	kr 29 700 000	kr 26 730 000	kr 0	kr 33 000 000	kr 29 700 000	kr 26 730 000	kr 12 028 500	kr 16 500 000	kr 31 350 000	kr 28 215 000	kr 25 393 500
Profit	kr 30 000 000	kr 26 700 000	kr 23 730 000	kr 0	kr 30 000 000	kr 26 700 000	kr 23 730 000	kr 10 528 500	kr 15 000 000	kr 28 350 000	kr 25 215 000	kr 22 393 500
SumProfit	kr 262 347 000											
SandProd	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
m_1	69	62,1	55,89	0	207	62,1	55,89	50,301	0	207	62,1	55,89
m_2	69	62,1	55,89	0	207	62,1	55,89	0	207	62,1	55,89	50,301
Degradation	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
DE_1	0,01449	0,027531	0,0392679	0,0392679	0,0827379	0,0957789	0,1075158	0,11807901	0,11807901	0,16154901	0,17459001	0,18632691
DE_2	0,01449	0,027531	0,0392679	0,0392679	0,0827379	0,0957789	0,1075158	0,1075158	0,1509858	0,1640268	0,1757637	0,18632691
ML	0,15	0,15	0,15	0,15	0,15	0,15	0,15	0,15	0,15	0,15	0,15	0,15

Figure A6.1: Spreadsheet of optimisation

A7 Spreadsheet of Re-Optimisation

Oil price	kr 550
Operational cost	kr 1 500 000
Max prod rate	30 000
Decline in prod	0,9

	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
Q_{t1}	29 999	27 000	24 300	0	21 137	26 998	24 296	21 870	0	13 796	26 998	24 298
	<=	<=	<=	<=	<=	<=	<=	<=	<=	<=	<=	<=
	30 000	27 000	24 300	0	30 000	27 000	24 300	21 870	0	30 000	27 000	24 300
Q_{t2}	29 998	26 998	24 300	0	5 545	26 998	24 298	0	29 377	26 998	24 299	21 865
	<=	<=	<=	<=	<=	<=	<=	<=	<=	<=	<=	<=
	30 000	27 000	24 300	0	30 000	27 000	24 300	0	30 000	27 000	24 300	21 870
Q_{sum}	59 997	53 998	48 600	0	26 682	53 996	48 593	21 870	29 377	40 794	51 297	46 163
Well 1	1	1	1	0	1	1	1	1	0	1	1	1
Well 2	1	1	1	0	1	1	1	0	1	1	1	1
Cost	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
Well 1	kr 1 500 000	kr 1 500 000	kr 1 500 000	kr 0	kr 1 500 000	kr 1 500 000	kr 1 500 000	kr 1 500 000	kr 0	kr 1 500 000	kr 1 500 000	kr 1 500 000
Well 2	kr 1 500 000	kr 1 500 000	kr 1 500 000	kr 0	kr 1 500 000	kr 1 500 000	kr 1 500 000	kr 0	kr 1 500 000	kr 1 500 000	kr 1 500 000	kr 1 500 000
Sum	kr 3 000 000	kr 3 000 000	kr 3 000 000	kr 0	kr 3 000 000	kr 3 000 000	kr 3 000 000	kr 1 500 000	kr 1 500 000	kr 3 000 000	kr 3 000 000	kr 3 000 000
Income	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
Well 1	kr 16 499 557	kr 14 849 781	kr 13 364 993	kr 0	kr 11 625 596	kr 14 849 167	kr 13 362 753	kr 12 028 287	kr 0	kr 7 587 798	kr 14 849 067	kr 13 363 931
Well 2	kr 16 498 802	kr 14 849 077	kr 13 364 770	kr 0	kr 3 049 732	kr 14 848 838	kr 13 363 663	kr 0	kr 16 157 191	kr 14 848 711	kr 13 364 512	kr 12 025 493
Sum	kr 32 998 359	kr 29 698 858	kr 26 729 763	kr 0	kr 14 675 328	kr 29 698 004	kr 26 726 416	kr 12 028 287	kr 16 157 191	kr 22 436 509	kr 28 213 579	kr 25 389 424
Profit	kr 29 998 359	kr 26 698 858	kr 23 729 763	kr 0	kr 11 675 328	kr 26 698 004	kr 23 726 416	kr 10 528 287	kr 14 657 191	kr 19 436 509	kr 25 213 579	kr 22 389 424
SumProfit	kr 234 751 719											

Figure A7.1: Spreadsheet of re-optimisation, part 1

Sand rate	0,0023			SandProd	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
				m_1	68,99814671	62,09908292	55,88997024	0	145,8483816	62,09651536	55,88060292	50,30010805	0	95,19237514	62,09609655	55,88552988
Sand jump	300 %			m_2	68,99499033	62,0961421	55,8890388	0	38,26027803	62,09513932	55,88441058	0	202,6993111	62,09461039	55,88796101	50,28842627
				Degradation	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
				DE_1	0,014489611	0,027530418	0,039267312	0,039267312	0,069895472	0,08293574	0,094670667	0,10523369	0,10523369	0,125224088	0,138264269	0,15000023
Erosion rate	0,21	mm/ton		DE_2	0,014488948	0,027529138	0,039265836	0,039265836	0,047300494	0,060340474	0,0720762	0,0720762	0,114643055	0,127682923	0,139419395	0,149979965
kg to tonn	0,001			ML	0,15	0,15	0,15	0,15	0,15	0,15	0,15	0,15	0,15	0,15	0,15	0,15
ML	0,15															
				Maintenance activity												
					T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
				MA_1	0	0	0	0	0	0	0	0	0	0	0	1
				MA_2	0	0	0	0	0	0	0	0	0	0	0	0

Figure A7.2: Spreadsheet of re-optimisation, part 2