

A decision making framework to achieve prescriptive maintenance in the FMCG production industry

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Preface

In your hands is my masters thesis on the development of a maintenance system that uses advanced analytics. I believe that the future of manufacturing will be in the use of data analytics, and therefore I'm happy that I was able to do research on this specific subject. Being able to do so at Heineken Global Supply Chain was even more interesting, because it can be challenging to improve such a traditional production process using new technologies.

This project would not have been possible without the help of multiple people. I would like to thank Nick for his supervision during the project, from a business and technical perspective, and Yusong for the support on the scientific content and technical aspects. Their enthusiasm for the subject helped me to gain insights in the world of predictive maintenance and smart manufacturing. Furthermore, Yeoseon and Mayank helped me with some specific parts of my research and were always open for questions, for which I am very grateful.

Hopefully you will enjoy reading my thesis and afterwards be convinced of the advantages of the use of analytics in the fast moving consumer goods industry.

*A.F.L. van de Loo
Delft, February 2019*

Abstract

In recent years, technologies such as artificial intelligence have enabled automated systems to provide more decision support for maintenance planning. Using high levels of analytics to determine optimal maintenance actions and moments is called prescriptive maintenance. Multiple prescriptive maintenance models have been proposed for different industries. However, none of these models or frameworks were designed for use in the FMCG industry. This industry seems to be lagging compared to the oil & gas, process and transport industries, but also in the FMCG sector there is a need for improved maintenance strategies. The FMCG industry however shows specific characteristics that disable the use of existing prescriptive maintenance systems. The dynamic behaviour of the large production environments in this industry need a more flexible, scalable and reliable system than the existing systems.

This research defines a framework that can successfully achieve prescriptive maintenance at a FMCG production plant, for a system consisting of multiple components. The focus in this case is on the prescriptive decision making based on input of diagnostic data and prediction of future component states. Based on existing prescriptive maintenance frameworks for multi-component systems a multi-layer approach is used where a distinction is made between component and system level. Such an approach is combined with an agent-based approach where agents can make decisions using appropriate decision making techniques found in literature.

This framework uses an intelligent agent-based approach to optimize maintenance planning on a component and system level. The agents act on different levels and negotiate to find an optimal system level result. An economic approach was used, where all impact of maintenance was translated to costs. The optimal maintenance strategy that is found will be the one with the lowest overall costs. The component level decision is made using a prediction of the remaining useful life of a component. After an optimization of maintenance type and time – using brute force search –, reinforcement learning is used to determine the optimal planning moment. On a system level, each new component level decision is evaluated by the system level agent and a system optimum is found using a brute force technique. During this optimization, the un-fixed maintenance moments may be replanned on a component level, by taking into account loss of functionality and economies of scale.

As prescriptive maintenance aims to increase operational efficiency and reduce costs, the effect of the framework on these KPIs was simulated and compared in a FMCG case study. It was found that, even if more failures are predicted than necessary, the intelligent planning of maintenance by this framework leads to a decrease of indirect costs. When a fully accurate prediction of the remaining useful life is used, this prescriptive maintenance system can also increase a systems operational efficiency and reduce maintenance costs next to the decrease of indirect costs. It can be concluded that the influence on overall production time was largest, which led to the decrease of the indirect costs of lost production. This could, for this specific system, be attributed to the fact that maintenance was planned in such way that simultaneous maintenance, and therefore system downtime, was prevented.

Although the case study showed promising results, room for improvements has been found. Firstly, the quality of the predictive algorithm proved to be essential to the functioning of the model. Testing this framework with a high quality prediction is therefore a recommendation for future research. An important factor that should be considered is the trade-off between accuracy and earliness of prediction. Furthermore, testing the framework with a more complicated system in the FMCG industry will show if this system is indeed scalable enough for the desired application.

Before this framework can be implemented in an industrial setting, the proper infrastructure has to be in place. This includes a well structured data collection system, software platform where the framework is placed and a clear human-machine interface. When these enablers are in place, the use of this framework could lead to improved efficiency, reduced costs and increased production time.

Contents

List of Abbreviations	ix
List of Figures	xi
List of Tables	xiii
1 Introduction	1
1.1 Background	1
1.1.1 Challenges in FMCG production	1
1.1.2 Maintenance in FMCG	2
1.1.3 Technological advancements	2
1.2 Research objective and scope	3
1.3 Research questions	3
1.4 Research approach	3
1.5 Thesis outline	4
2 Maintenance and technology	5
2.1 Maintenance interventions and strategies	5
2.1.1 Preventive maintenance	5
2.1.2 Predictive Maintenance	6
2.1.3 Prescriptive Maintenance	6
2.2 Maintenance methodologies	7
2.2.1 Reliability-centered maintenance (RCM)	7
2.2.2 Business centered maintenance (BCM)	7
2.2.3 Total Productive Maintenance (TPM)	8
2.2.4 Life cycle cost (LCC) approaches	8
2.2.5 Comparison of methodologies	9
2.3 Maintenance KPIs	10
2.3.1 Commonly used KPIs	10
2.4 Maintenance analytics	12
2.5 Decision making models	14
2.5.1 Decision making cycles	14
2.5.2 Markov Decision Processes	14
2.5.3 Maintenance decision models for multi-component systems	15
2.6 Architecture and decision making	16
2.6.1 Cyber-physical systems architecture	16
2.6.2 Decision making techniques	18
2.7 Multi-agent systems	19
2.8 Scientific gap	20
3 Prescriptive maintenance framework	23
3.1 Problem definition	23
3.1.1 FMCG Failure characteristics	23
3.1.2 Design requirements	25
3.2 Used methodologies	26
3.3 Proposed framework	26
3.3.1 Data collection	28
3.3.2 Component level analysis and prediction	28
3.3.3 Component level decision making and planning	29
3.3.4 System level decision making	30
3.3.5 Information transfer	31

3.4	Scope	31
4	Optimization and decision making	33
4.1	Level interaction	33
4.1.1	Scalability	33
4.1.2	Diversity	34
4.2	Component level	35
4.2.1	Component level agent functions	35
4.2.2	Quality of maintenance	35
4.2.3	Optimizing maintenance moment and intervention	36
4.2.4	Optimizing planning moment	37
4.2.5	Solving methods	38
4.2.6	Programming component agent functions	39
4.3	System level	39
4.3.1	System level agent functions	39
4.3.2	System level optimization	39
4.3.3	System level costs	40
4.3.4	Individual costs	40
4.3.5	Combined costs	40
4.3.6	Solving methods	41
4.3.7	Negotiation	41
4.3.8	Programming system agent functions	41
5	Case study	43
5.1	KPIs	43
5.1.1	Overall Equipment Effectiveness (OEE)	43
5.1.2	Maintenance costs	44
5.2	Hypothesis	44
5.3	Background	44
5.3.1	Production site	44
5.3.2	Equipment description	45
5.3.3	Requirements	48
5.4	Simulation setup	51
5.4.1	Scope of simulation	51
5.4.2	Simulation model	51
5.5	Model input	53
5.5.1	Diagnostics and prognostics	53
5.5.2	Cost functions	54
5.5.3	Reinforcement learning	55
5.6	Verification	55
5.7	Base case	58
5.8	Results and discussion	60
5.8.1	Component level decision	60
5.8.2	System level decision	61
5.8.3	Comparison to current situation	62
6	Conclusion & Recommendations	65
	Bibliography	67
A	Research paper	71
B	Cooling process	79

List of Abbreviations

ABAO	As-Bad-As-Old
AGAN	As-Good-As-New
AI	Artificial Intelligence
BCM	Business Centered Maintenance
CAM	Capital Asset Management
CAPEX	Capital Expenditures
CBM	Condition-Based Maintenance
CIBOCOF	Centrum voor Industrieel Beleid OnderhoudsConcept Ontwikkelings Framework
CM	Condition Monitoring
CPS	Cyber-Physical Systems
DPDA	Detect–Predict–Decide–Act
FMCG	Fast Moving Consumer Goods
ILS	Integrated Logistic Support
KPI	Key Performance Indicator
LCC	Life Cycle Cost
LSA	Logistic Support Analysis
MAS	Multi-Agent System
MDP	Markov Decision Process
MMS	Maintenance Management System
MTTF	Mean Time To Failure
OEE	Overall Equipment Effectiveness
OODA	Observe–Orient–Decide–Act
OpCo	Operating Company
OPI	Operational Performance Indicator
OPEX	Operational Expenditures
PDCA	Plan–Do–Check–Act
PLC	Programmable Logic Controller
PLI	Profit Loss Indicator
RCM	Reliability-Centered Maintenance
RUL	Remaining Useful Life
SCADA	Supervisory Control And Data Acquisition
SHE	Safety, Health and Environment
TPM	Total Productive Maintenance (<i>or</i> Management)
TTR	Time To Repair

List of Figures

2.1	The evolution of maintenance strategies	5
2.2	BCM approach (Waeyenbergh and Pintelon, 2002)	8
2.3	Key maintenance performance indicators in literature categorized by Galar and Kumar (2017)	10
2.4	Main contributions to LCC (Reina <i>et al.</i> , 2016)	12
2.5	Different levels of (maintenance) analytics (Kart <i>et al.</i> , 2013)	13
2.6	Decision making cycles	14
2.7	Example of a Markov Decision Process and its use	15
2.8	Multi layer approach of Verbert <i>et al.</i> (2017)	16
2.9	The 5C-architecture from Lee <i>et al.</i> (2015)	17
2.10	Approaches for control in multi-agent systems, adapted from (Duinkerken and Pang, 2017)	20
3.1	General classification of failures as defined by Heineken NL	24
3.2	Classification of failures by induced downtime for packaging line of Heineken Den Bosch, NL	24
3.3	Time-to-repair (TTR) analysis of two FMCG companies	25
3.4	Time-to-repair (TTR) analysis of two non-FMCG systems	25
3.5	High level overview of the proposed maintenance concept	27
3.6	Proposed framework to achieve prescriptive maintenance for a multi-component system	27
3.7	Visualization of a remaining useful life prediction (Verbert <i>et al.</i> , 2017)	29
3.8	Simplified visualization of component dependencies	30
4.1	Main scope of this research in the proposed framework	33
4.2	The structure of the agents on component- and system level	34
4.3	The structure of the decentralized system	34
4.4	Different maintenance qualities	36
5.1	Maintenance maturity levels used by Heineken	45
5.2	Vapor-compression refrigeration cycle	46
5.3	Simplified P&ID of the cooling system	46
5.4	GEA Grasso SP1 impression and specifications (Southern Sales and Service Ltd., 2018; Gresco Refrigeration Ltd., 2008)	47
5.5	BAC CXV evaporative condenser impression and specifications (BAC, 2011; Gresco Refrigeration Ltd., 2008)	47
5.6	Maintainable items of a compressor (SINTEF, 2002)	48
5.7	Frequency of compressor repairs versus repair time	49
5.8	ABC rating flowchart	50
5.9	Suggested periodic inspection and maintenance by manufacturer	50
5.10	Framework for prescriptive maintenance of the cooling system	51
5.11	Two different degradation models at the same time step	53
5.12	Comparison of degradation models	54
5.13	C_0 results for simulations with different time-step sizes	56
5.14	Costs of loss of functionality for different time-step sizes	56
5.15	Simulation run times for different time-step sizes	57
5.16	Operation of the compressor system	58
5.17	Prediction results for two situations in different compressors	60
5.18	Cost breakdown for two situations in different compressors	60
5.19	Maintenance planning on system level	61
5.20	Influenced components of life cycle costs	63

A.1	The evolution of maintenance strategies	72
A.2	High level overview of maintenance concept with scope highlighted in red	73
A.3	The structure of the decentralized system	73
A.4	Reinforcement learning loop	74
A.5	Cooling system used in case study	75
A.6	Maintenance planning on system level	75
A.7	Influenced components of life cycle costs	76
B.1	P&ID of cooling system, Bulmers Cider Plant, Hereford UK	80
B.2	P&ID of Grasso SP1 TB-5B compressor	81

List of Tables

2.1	Comparison of the four 'traditional' maintenance methodologies (1/2) (Waeyenbergh and Pintelon, 2002)	9
2.2	Comparison of the four 'traditional' maintenance methodologies (2/2) (Waeyenbergh and Pintelon, 2002)	9
2.3	Performance matrix of solving algorithms	18
5.1	Maintenance characteristics for three production facilities (averages in period 07-2017 – 06-2018)	45
5.2	Risk classification per category for the ABC rating	49
5.3	Probability of failure input for both failure modes	53
5.4	Failure cost specifications per failure	54
5.5	Maintenance cost specifications per intervention	55
5.6	Input parameters for reinforcement learning	55
5.7	95% Confidence interval of C_0 for different time-step sizes	55
5.8	Total downtime costs of the ammonia compressors in Hereford (excluding non-production days)	58
5.9	Total maintenance costs of the ammonia compressors in Hereford	58
5.10	OEE for the ammonia compressors in Hereford	59
5.11	Q-tables for two situations in different compressors	61
5.12	Comparison of amount of maintenance moments, scenario 1	62
5.13	Comparison of amount of maintenance moments, scenario 2	62
5.14	Cost comparison of current situation versus simulations	62
5.15	Efficiency comparison	63
A.1	Cost comparison of current situation versus simulations	76
A.2	Efficiency comparison	76

1

Introduction

The competition between Fast Moving Consumer Goods (FMCG) companies is higher than ever ([The P&G Company, 2018](#); [Unilever Group, 2018](#)). Therefore companies have to develop new ways of working to maintain their current position. Heineken for example, being the worlds second largest brewing company, defined '*Drive end2end performance*' as one of its strategy pillars, where the focus is on unnecessary costs and efficiency ([HEINEKEN Holding NV, 2018](#)). To reach this strategic goal, companies like Heineken strive to eliminate bad costs, drive functional efficiency, manage capital in a smart way and maximize the benefits of their global scale.

1.1. Background

As the name already suggests, the fast-moving consumer goods industry is characterized by its dynamic nature. FMCG products are generally of relatively low cost and sold on a regular basis to a large consumer group. As the targeted market is usually a large part of the whole population, this industry differentiates itself from other production industries by the large production volumes sold in small quantities ([Singh, 2014](#)).

FMCG is a category that includes, for example, food and beverages, personal care products and cleaning products. These products are usually available in local stores and supermarkets, as they are purchased very frequently by individual consumers. The FMCG industry consists of a small amount of large multi-national companies that produce a majority of products, but also some regional or local focused companies ([Unilever Group, 2018](#)). For these companies it is essential that they remain competitive to hold or increase their market share.

The main focus in the production facilities of large FMCG companies is a constant search to increase efficiency and reduce unnecessary operational expenditures (OPEX) and capital expenditures (CAPEX). Next to power consumption and raw material costs, maintenance is a large category of OPEX. In some cases maintenance can also be viewed as CAPEX, when it is considered as life extending investment or when equipment has to be replaced completely or partially. Maintenance is a key subject, as maintenance costs generally make up one of the largest parts of a plant's budget ([Efthymiou et al., 2012](#); [Behera and Sahoo, 2016](#)).

1.1.1. Challenges in FMCG production

The production efficiencies and costs are under heavy pressure in FMCG production industry. Many other manufacturing industries that faced the same challenges implemented management principles such as lean manufacturing. Where other industries were successful in this implementation, the FMCG production sector is lagging. Multiple issues causing this gap between manufacturing and the FMCG industry were identified by [Heymans \(2009\)](#).

For example, concepts as Make to Order (MTO) and Just in Time (JIT) require an extremely reliable production process, steady demands and low varieties (Heymans, 2009). Because the FMCG sector is a high-variety environment, these concepts need high reliability equipment and high-quality demand forecasts (Mahalik and Nambiar, 2010). An effective maintenance strategy is essential to ensure equipment reliability, and thereby equipment availability and productivity (Waeyenbergh and Pintelon, 2004). However, selecting a maintenance strategy for the FMCG sector is not straightforward.

Although the goal of maintenance mostly is to ensure reliability of production equipment during production time, the scheduling of maintenance activities reduces the operational time of equipment. Even if preventive maintenance actions prevent failures and therefore the need for more expensive corrective maintenance actions, it still affects the equipment availability. This is mostly the case in the high-volume FMCG production sector, but also to some extent in the pharmaceutical and automotive sector (Colledani *et al.*, 2018). In these sectors, the 24-hour operation does not create daily breaks in the production schedule where maintenance actions could be planned outside operational time.

1.1.2. Maintenance in FMCG

Currently, the maintenance strategies in a large part of big FMCG production companies are based on long existing maintenance concepts. Most production facilities have some sort of preventive maintenance system in place for certain equipment types. Mostly maintenance is planned according to running hours. This system can be compared to car service programs that have fixed mileages as maintenance indicators. In other cases however, maintenance is done only after equipment failure.

Also some equipment types, mostly in the utilities area, have been installed redundantly or with a larger capacity than required to prevent production loss in case of a breakdown. Loss of production because of an unplanned stoppage will inevitably lead to additional costs. These costs include overtime working of employees, emergency repair costs, loss of raw material and lost revenue. These costs are in some cases prevented by early replacement, which is in turn also economically inefficient (Verhagen and Boer, 2018).

Next to the additional costs that can be prevented by an effective maintenance strategy, research has shown that maintenance has an positive impact on productivity and profitability of production plants (Alsyounf, 2007; Waeyenbergh and Pintelon, 2002).

1.1.3. Technological advancements

The fast emerging technological achievements in knowledge discovery are changing the industry. Technologies such as big data, machine learning and internet of things created a new knowledge industry, and maintenance strategies should be adapted to the new standards. As the industry reaches a higher digital level, possibilities exist to collect huge amounts of data and information from processes in operation, maintenance and business (Karim *et al.*, 2016).

As a result of the technological advancements, many automated systems have been developed in the past decades. This leads to the fact that more data is gathered, stored and processed by separate systems. For maintenance, such data sources could be Maintenance Management Systems (MMS), Condition Monitoring (CM) and Supervisory Control and Data Acquisition (SCADA) systems (Schmidt *et al.*, 2017). The use of this data for decision making is a central part of new maintenance approaches. The increase in processing power has led to faster, cheaper and more extensive data analysis and processing opportunities. This creates options for the use of artificial intelligence for decision making in more complex systems, but also in more general day-to-day applications.

1.2. Research objective and scope

Typical FMCG companies have a large number of assets that require similar maintenance. Some manufacturers provide intelligent maintenance programs for individual assets, however they do not consider structural and functional similarities and dependencies between different assets. These individual systems are not designed to be extended with other equipment types or to be integrated in other systems or an infrastructure of a large FMCG company. Also, these systems are not making use of the scale advantage of having many similar equipment types worldwide.

Where in some industries extensive maintenance decision support is used, the FMCG sector is lagging. Technologies such as machine learning and internet of things are not widely used in the FMCG industry. In maintenance, such models and technologies could be used to extract useful information from all generated data, and improve maintenance decision making. Using artificial intelligence to decide on maintenance actions and moments is called prescriptive maintenance. There is not yet a prescriptive maintenance framework that is suitable for large companies in the FMCG-sector such as Heineken.

The main objective of the research therefore is to define a framework that can successfully achieve prescriptive maintenance at a FMCG production plant such as a beverage production company, for a system consisting of multiple components. The scope of this research will be the maintenance decision making within this framework. The maintenance decisions should therefore be made for a multi-component system, based on diagnostic and prognostic data of its individual components. To be able to determine such a decision making model, it should be clear what is needed to implement a maintenance system. Also, it is necessary to determine a framework that can best be used for this specific case.

1.3. Research questions

From the above mentioned objective, the following research question has been defined:

How to achieve prescriptive maintenance to increase functional efficiency and reduce costs in the FMCG industry?

To be able to answer this research question, it will be divided into smaller parts. Firstly it should be researched what the characteristics are of FMCG production companies and how maintenance can influence the efficiency and costs of these companies. Next, appropriate maintenance strategies and methodologies should be selected for this application. When focusing on the decision making in a maintenance concept, it should be researched what technologies would enable scale-up. Finally, it is interesting to see what the performance of a new strategy would be, compared to the current situation. These objectives are summarized in the following five sub questions:

- *How can maintenance influence the efficiency and costs of FMCG production companies?*
- *What maintenance strategies that can achieve an efficiency increase and cost reduction can be found in literature?*
- *What methodology is suitable to be used for a prescriptive maintenance strategy of a FMCG production company?*
- *What technology can be used for the decision making that enables the scale-up possibilities of the strategy?*
- *How does a prescriptive maintenance strategy perform compared to currently used strategies at a FMCG company?*

1.4. Research approach

Firstly, existing maintenance frameworks, technologies and methods in literature will be reviewed that may be suitable for this industry taking into account the found characteristics. Based on this research, a combination of Total Productive Maintenance and Life Cycle Cost methodologies are used in the design of a new maintenance concept. A multi-layer framework will be proposed that includes a predictive

part and a decision making part. In this framework, the decision making is the novelty of this research, because predictive methods already exist for some components used in this industry. The decision making part uses a multi-agent approach to provide maintenance decisions based on input from the predictive part. Then, a discrete-time simulation model will be created to assess the functioning of the framework in a case study. In this case study, data from a FMCG production plant will be used as input for the model to simulate an implementation. The performance of the framework will be evaluated by comparison with actual failures of the case system and recommendations will be made for further development of this approach.

1.5. Thesis outline

This thesis contains a literature review on maintenance methodologies, frameworks and implementations that can be used in a FMCG environment in chapter 2, followed by the the proposed maintenance framework in chapter 3. Then in chapter 4 the proposed approach for the maintenance decision making is discussed in detail. The last chapters include a case study to demonstrate the functioning of the framework followed by a conclusion.

2

Maintenance and technology

In literature, a number of approaches can be found for the selection of a maintenance strategy. A maintenance strategy is defined as the set of maintenance interventions and the structure in which these interventions are placed (Waeyenbergh and Pintelon, 2002). Existing strategies have changed over the years and new ones have been developed, as technological advancements lead to opportunities for automation or increased decision support (Karim *et al.*, 2016). Some sources provide guidance for the generation of such maintenance structures or frameworks. In the following paragraphs prior research on maintenance interventions and strategies is discussed and evaluated for suitability in the FMCG sector, including the success factors and examples of a maintenance concept implementation.

2.1. Maintenance interventions and strategies

Maintenance interventions are the interaction of a maintenance technician or operator with a piece of equipment to improve the state of that equipment. The moment on which the intervention is done and the type of intervention depend on the maintenance strategy that is selected for that specific equipment type. The maintenance interventions can be split into two main categories, namely corrective maintenance and preventive maintenance (Waeyenbergh and Pintelon, 2004).

Corrective maintenance is the category that mostly includes unplanned maintenance, which is necessary to restore the functionality of equipment after (unexpected) breakdown or failure. The maintenance is in this case called *reactive*. Reactive maintenance is generally more costly than other forms of maintenance (Smith, 1993). Reactive maintenance is the most straightforward maintenance strategy, as the only trigger is the failure of a component. More advanced maintenance strategies have evolved from this, and this evolution is shown in figure 2.1. These other strategies will be discussed in the following sections.



Figure 2.1: The evolution of maintenance strategies

2.1.1. Preventive maintenance

In contrast to reactive maintenance, preventive maintenance includes the *proactive* part of maintenance interventions. Preventive maintenance aims to prevent unexpected events that require maintenance by performing pre-planned actions. This planning may be based on the condition of the equipment,

expected life time or just random planning. [Wireman \(2004\)](#) defines several types of preventive maintenance, two of which are:

- Routine maintenance tasks such as cleaning, inspection, lubrication, tightening, etc.
- Proactive Replacements & Scheduled Refurbishing

These two examples of preventive strategies do not require an intelligent maintenance planning system, but are simply performed periodically or based on running hours of the equipment. More advanced preventive methods included predictive and prescriptive maintenance. These two are discussed in the following two sections.

2.1.2. Predictive Maintenance

In a predictive maintenance maintenance strategy, maintenance is planned according to the measured conditions of equipment and a prediction of the remaining useful life (RUL). In essence, predictive maintenance is a form of condition-based maintenance that also takes the expected life into account ([Niu and Jiang, 2017](#)). Predictive maintenance is generally most useful for equipment types which have comparable life cycles, and the remaining life can be predicted by extrapolating measurements using the historical data of the same equipment type. In contrast to predictive maintenance, other condition-based maintenance (CBM) strategies are best to be used if an item fails randomly or shows low failure predictability ([Kelly, 2006](#)).

The basis for this maintenance strategy is the ability to predict upcoming failures. In the most basic approach, a maintenance engineer would assess the state of a component by inspection and decide when to perform maintenance based on his/her experience. By collecting more data of a component, the state can be better determined. When the amount of data becomes too large for a human to process, the use of computers is necessary to create an accurate prediction. In that case, technologies such as machine learning can be used to create more and better predictions ([Rødseth et al., 2017](#)).

2.1.3. Prescriptive Maintenance

The rightmost strategy shown in figure 2.1 is the prescriptive maintenance strategy. Prescriptive maintenance is the most advanced of these strategies. Prescriptive maintenance is the next step after preventive and predictive maintenance, that achieves pro-active and smart maintenance planning ([Matyas et al., 2017](#)). This definition of prescriptive maintenance will be used throughout the report.

Prescriptive maintenance aims to provide a decision of what maintenance to perform at what moment. It uses historical data and real-time information to provide a maintenance decision as output. This decision can be used to support human decision making to plan maintenance or in a completely automated maintenance planning system. This enables a smart maintenance planning to avoid failures, increase efficiency and machine availability ([Matyas et al., 2017](#)).

Four actions are needed to achieve prescriptive maintenance and to deliver a maintenance decision. These are:

1. Data acquisition and pre-processing
2. Data analysis
3. Prediction of future states
4. Maintenance decision making

Firstly, collecting useful data that can be used for maintenance decision making should be selected. This could be a combination of historical failure data, live operational data (e.g. PLC-data) and production planning. This data should be presented in a structured way before analysis can be performed. As the data is well structured, it can be analyzed to find correlations between the live data and historical

data using techniques such as machine learning.

Based on the data analysis, a prediction of the remaining useful life (RUL) can be made. This step can also be used to determine at what stage a decision should be made. Also this step may contain advanced analytical techniques as machine learning. The decision making step is what defines the 'prescriptive' part of prescriptive maintenance, as it aims to prescribe the optimal maintenance action based on the analyzed data and prediction of the future states.

In literature, multiple applications of prescriptive maintenance in industry can be found. [Verbert et al. \(2017\)](#) for example, proposes the use of prescriptive maintenance for a railway network. This network consists of multiple components with different failure characteristics. [Martinod et al. \(2018\)](#) and [Niu and Jiang \(2017\)](#) discuss the use of prescriptive maintenance for different applications in the transport industry. Other industries for which prescriptive maintenance frameworks have been proposed include the automotive ([Matyas et al., 2017](#)), process and oil & gas industries ([Galar and Kumar, 2017](#)). No prescriptive maintenance framework was found that was designed for the FMCG industry. It has not yet been researched if an existing framework could also be used in this specific industry.

2.2. Maintenance methodologies

The way that maintenance interventions and strategies are performed are based on maintenance methodologies. These methodologies are the frameworks that a company could use to implement a certain intervention or strategy. Many frameworks can be found in literature, and selecting one for a specific situation can be a challenge.

As it can be a challenge to select the most appropriate methodology for a specific situation, [Waeyenbergh and Pintelon \(2009\)](#) introduced the "Centrum voor Industrieel Beleid OnderhoudsConcept Ontwikkelings Framework" (CIBOCOF) to support decision making on the maintenance concept to be implemented. It can be used as a tool to select the right maintenance methodology and model from a large amount of models, without needing excessive time or knowledge to study each one. [Waeyenbergh and Pintelon \(2009\)](#) and [Waeyenbergh and Pintelon \(2002\)](#) argue that most maintenance methodologies are based on a four 'traditional' concepts. These concepts will be discussed in the following sections.

2.2.1. Reliability-centered maintenance (RCM)

The RCM concept was primarily designed as a methodology for preventive maintenance that could increase equipment availability and safety, while preventing unwanted additional costs. RCM selects the most appropriate strategies for the specific application based on reliability parameters. RCM is based on four main objectives, which are:

1. Preserve system function
2. Identify failure modes that could cause system malfunction
3. Prioritize the importance of the functions and their respective failure modes
4. Select only preventive maintenance tasks that are applicable and effective

The RCM methodology was for example recently implemented in a process plant ([Vishnu and Regikumar, 2016](#)). The outcome of such an implementation will be a selection of maintenance strategies for specific equipment types, based on the reliability. Such a methodology is most effective for a production environment where loss of production time is very costly compared to the maintenance itself ([Kelly, 2006](#)).

2.2.2. Business centered maintenance (BCM)

When following the BCM methodology, the production facility's maintenance strategy is driven by the overall business objectives, and not by the maintenance department itself. The goal of BCM is to

maximize the contribution of maintenance to profitability of the production facility. When the business objectives are set, they are translated into maintenance objectives to create a maintenance strategy for each single piece of equipment (Kelly, 2006; Waeyenbergh and Pintelon, 2002).

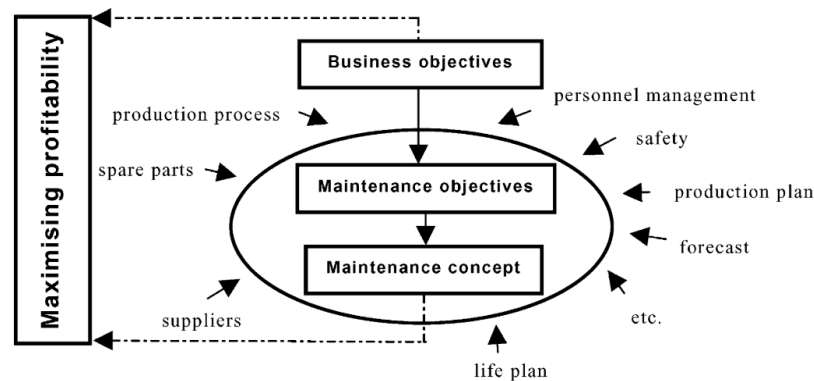


Figure 2.2: BCM approach (Waeyenbergh and Pintelon, 2002)

This approach is well structured, which can be attributed to the extensive and accurate research into each single piece of equipment. To be able to use this approach excessive technical, process and production data is needed that concerns each specific machine. The availability of this data might be a challenge. Another logical downside is the complexity of this detailed approach (Waeyenbergh and Pintelon, 2002). A schematic overview of this approach is shown in figure 2.2, where can be seen that many factors are taken into account, with the goal to maximize profitability.

2.2.3. Total Productive Maintenance (TPM)

TPM was originally designed in Japan in the 1950s to support the Total Quality Management strategy, and over the years evolved to a standard for plant maintenance. The goals of TPM are:

1. Improving equipment effectiveness
2. Improving maintenance efficiency and effectiveness
3. Early equipment management and maintenance prevention
4. Training to improve the skills of all people involved
5. Involving operators (occupants) in routine maintenance

The successful use of TPM would lead to full utilization of a company's assets. For that reason, TPM often is a prerequisite for Lean Manufacturing improvement strategies. Lean Manufacturing strives to eliminate waste from a process, and therefore would need full asset utilization (Wireman, 2004). Currently TPM is used by many large production companies, also in the FMCG industry (e.g. Heineken, Kraft-Heinz, Procter & Gamble and Unilever).

An example of an implementation of TPM in a FMCG company is Tsarouhas (2007). A step-wise approach was used which involve data collection, training employees, implementing new maintenance strategies and checking the results. This approach ensures a successful implementation of the most appropriate strategies.

2.2.4. Life cycle cost (LCC) approaches

The main goal of LCC approaches is to minimize the life cycle costs of the used equipment. Maintenance can be a key factor in firstly the life cycle length and also the associated costs. Therefore the

selection of maintenance strategies based on the life cycle costs is defined as a LCC approach.

Multiple methodologies that can be categorized as LCC approaches can be found in literature, such as terotechnology, capital asset management and integrated logistics support. Terotechnology emerged in the UK in the 70s in the pursuit of optimal LCC. The approach focuses on reliability and maintainability already from the design phase of the equipment or products. Terotechnology also takes installation, operation maintenance and replacement into account in order to include the full life cycle (Kelly, 2006).

Capital asset management (CAM) is closely related to terotechnology. It is a management methodology that involves design, procurement, use and maintenance of fixed assets (capital). Both CAM and terotechnology are not easy to implement due to uncertainty of demand forecast, product life and practical constraints as time and costs (Kelly, 2006; Waeyenbergh and Pintelon, 2002).

Integrated Logistics Support (ILS) can be defined as interactive approach to integrate support considerations in the design and provide support in the operational phase at minimum costs. Logistic Support Analysis is a structure that can be used to pre-plan all aspects of ILS to further reduce costs and increase efficiency (Waeyenbergh and Pintelon, 2002)

2.2.5. Comparison of methodologies

Tables 2.1 and 2.2 show a comparison of the discussed maintenance methodologies with advantages and disadvantages for each methodology. In chapter 3 a choice will be made on the most appropriate maintenance methodology for this research, based on this comparison.

	RCM	BCM
Advantages	Trace-ability Cost savings Rationalization Involves operators	Accuracy Integrated auditing
Disadvantages	Complexity Extensive need of data Only focused on reliability	Complexity Extensive need of data

Table 2.1: Comparison of the four 'traditional' maintenance methodologies (1/2) (Waeyenbergh and Pintelon, 2002)

	TPM	LCC-approaches
Advantages	Increased productivity Increased quality Increased SHE performance Involves operators	Complete scope LCC is main KPI Feedback to design phase Full integration
Disadvantages	Not purely maintenance No decision rules Costs and profit not accounted	Rather theoretical Challenging implementation (uncertainty) Less structured than others

Table 2.2: Comparison of the four 'traditional' maintenance methodologies (2/2) (Waeyenbergh and Pintelon, 2002)

2.3. Maintenance KPIs

When assessing the performance of maintenance strategies, appropriate key performance indicators (KPIs) have to be used. In literature, many different indicators can be found. [Galar and Kumar \(2017\)](#) performed a literature research on performance indicators that are used in a maintenance context. Each author has a different way in choosing and classifying the maintenance performance indicators. Next to the differences between authors, all agree on some KPIs that are vital for the management of maintenance ([Galar and Kumar, 2017](#)). The vital maintenance KPIs that are identified by most authors include number of breakdowns, mean time to failure (MTTF), availability, overall equipment effectiveness (OEE) and maintenance costs.

The found maintenance KPIs can mainly be split into two categories, namely the process indicators and the result indicators. The first of which can be described as category with leading indicators that monitor how the tasks are performed and how well the processes are designed, while the latter category includes the lagging indicators that monitor the results of the maintenance strategy. This structure with different KPIs is shown in figure 2.3.

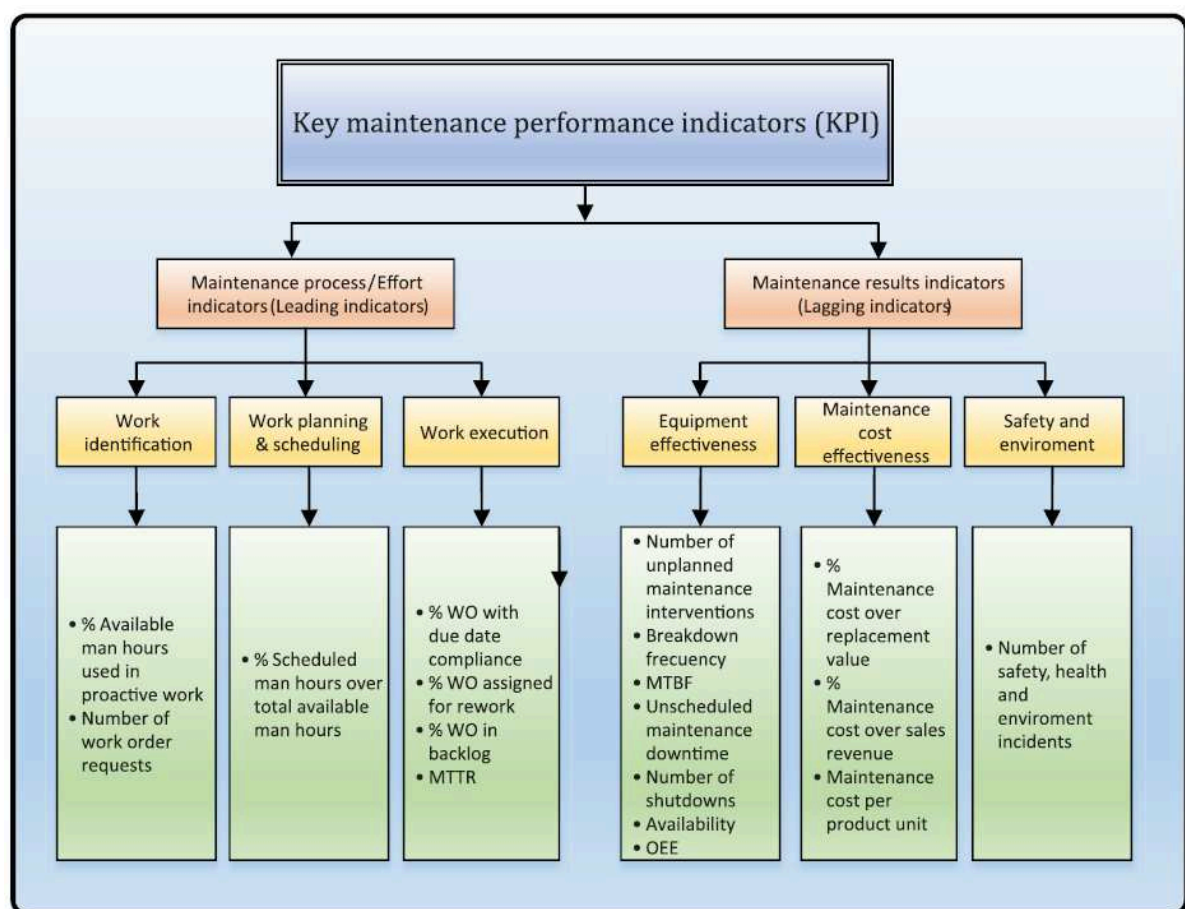


Figure 2.3: Key maintenance performance indicators in literature categorized by [Galar and Kumar \(2017\)](#)

2.3.1. Commonly used KPIs

The vital KPIs that were mentioned are commonly used in a maintenance context. These indicators can all be placed in the category of result indicators. This main category can again be split into three parts. These are equipment effectiveness, maintenance costs and safety, health and environment (SHE). What KPIs will be used in this research will be discussed in the case study in chapter 5, but this section already introduces the most commonly used ones.

Effectiveness indicators

Arguably, the number of breakdowns is the most basic, but important indicator for the functioning of a maintenance strategy. By comparing the numbers of two separate periods, an improvement of reliability can be measured. In parallel, the mean time to failure (MTTF) can be used. This indicator shows the average time a machine is able to operate before it fails. This KPI can be more easily compared than the number of breakdowns, as the period over which it is measured is not important to the comparison. A downside of MTTF however is that it generally has a high uncertainty, e.g. [Tsarouhas et al. \(2009a\)](#).

A more detailed KPI, with respect to the time that a machine can be used, is the availability. This KPI is defined as the degree to which a system would be able to perform a task, if the task is scheduled at a random moment. So the availability takes into account not only the downtime caused by failures, but also the time spent on preventive maintenance, planned production time and the duration of repairs ([Tsai et al., 2004](#)).

Availability is used as input for an even more inclusive KPI, namely Overall Equipment Effectiveness (OEE). OEE is used in the TPM methodology as a measure for the effectiveness of equipment. It includes the availability of the equipment, the performance efficiency and the quality rate. OEE can be defined by the following formula:

$$OEE = Availability \times Performance\ Efficiency \times Quality\ Rate \quad (2.1)$$

This measure is mostly used as a percentage of the highest possible value, but can also be expressed as costs or missed revenue depending on the target audience. Management is more interested in the financial implications, where maintenance departments strive to increase equipment effectiveness on itself ([Wireman, 2004](#)).

Cost indicators

Other important measures for the performance of maintenance strategies are the associated costs. As in all business applications, costs can be divided into direct and indirect costs. For maintenance, direct costs include the costs for the actual performing of maintenance such as spare-part costs and labour costs. Indirect costs include the costs associated with downtime and lost production ([Verbert et al., 2017](#)). To get more context aware cost KPIs, the costs can be divided by the equipment value, revenue or production volume. This way, costs can be compared between different production systems or even production facilities.

Another indicator to accurately assess the financial implications of maintenance is to calculate the total costs over the whole equipment life cycle ([Waeyenbergh and Pintelon, 2002](#)). One of the main pillars of the LCC is the maintenance costs pillar. An overview of the main contributions to LCC is shown in figure 2.4. A maintenance concept can, next to the maintenance cost pillar, also have influence on some operating costs such as lost production and utilities ([Reina et al., 2016](#)).

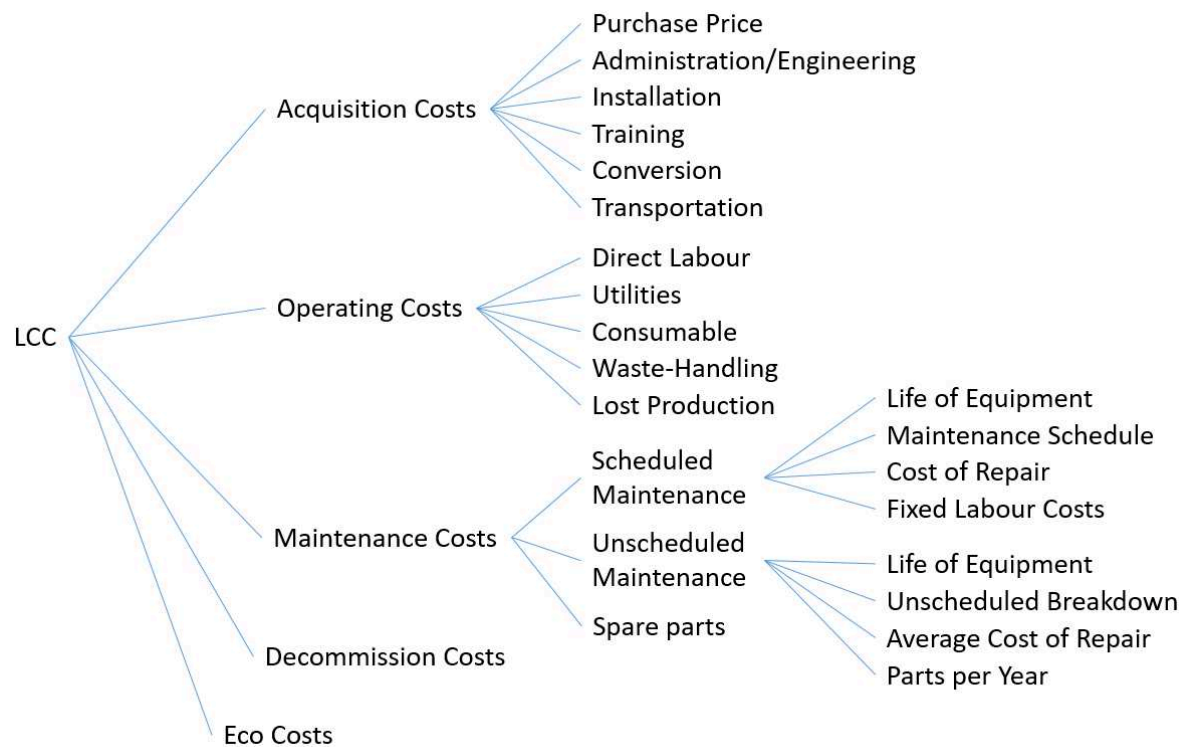


Figure 2.4: Main contributions to LCC (Reina *et al.*, 2016)

SHE indicators

The third category of lagging indicators are related to safety, health and environment. Failure of some types of equipment could lead to dangerous situations for employees or the environment. So preventing these failures will reduce the risk of certain SHE related incidents. In large production companies all accidents are recorded. The number of SHE related incidents caused by equipment breakdown can therefore be used as KPI and compared to previous periods to detect changes. Also the number of days without an accident or number of days of accident related leave can be used as comparable KPIs.

2.4. Maintenance analytics

The increasing intelligence of computer systems has created opportunities to analyze operational data and support maintenance decisions. The faster computer systems are able to analyze large amount of data, the less human input is needed for decision making.

The intelligence of systems can be divided into a number of levels. The level of intelligence can be defined as the capability to reach certain levels of analytics, which were defined by Kart *et al.* (2013). These levels are commonly used in a maintenance context (Karim *et al.*, 2016). These levels are visualized in figure 2.5, differentiating the extent of human input and the artificial input. The blue parts show the artificial analytics parts and the green parts show the human input.

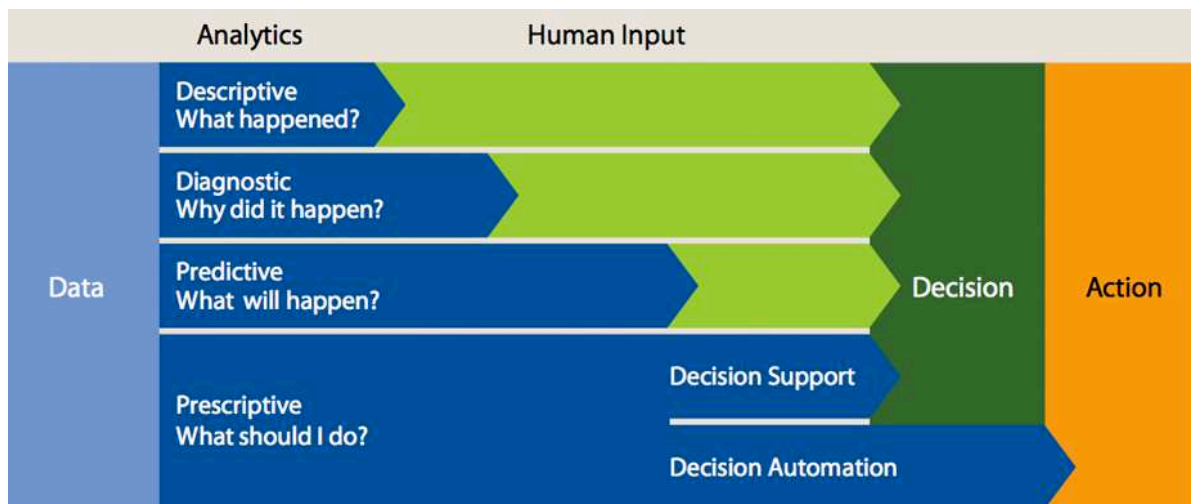


Figure 2.5: Different levels of (maintenance) analytics (Kart *et al.*, 2013)

A more detailed explanation of the different levels of analytics is given below:

- **Descriptive analytics**, where historical data is analyzed to see what has happened. In maintenance for example, a machine breakdown is analyzed by looking at operational parameters to find what part of the machine failed.
- **Diagnostic analytics**, the next step after descriptive analytics, aims to find the cause of the breakdown by analyzing operational data and can be used to determine the state of the equipment.
- **Predictive analytics**, can be used to predict if events will happen and at what point in time, by comparing historical data on reliability to diagnostic data concerning the current state. This way breakdowns can be prevented without using a predefined safety buffer, but by accurately predicting the upcoming (breakdown-) events.
- **Prescriptive analytics**, the final step in maintenance analytics aims to give optimal decision support to a human, or alternatively even making maintenance decisions independently by combining business-, operational- and financial data.

As previously stated, advanced analytical methods that use technologies such as machine learning have created opportunities to decrease human involvement in decision making. In many companies analytics are used to some extent, but transforming information into a (maintenance) decision is still mostly a human task. As Lee *et al.* (2014) and Lindström *et al.* (2017) describe, a prognostics-monitoring system can contribute positively on many levels, but some issues that prevent successful implementation are not yet resolved. These issues include two interesting topics:

- Most maintenance methods that use advanced analytics are designed for single equipment types or a small number of components, although they make up a larger system on which they structurally and functionally depend. It is also very common that there are many comparable equipment types in a company's portfolio.
- Health condition of machines are not taken into account during manager and operator interaction. This leads to interference of business and technical objectives when scheduling maintenance.

Multiple sources target one of the mentioned topics, but have not yet created a business aware maintenance concept for multi-component systems for the FMCG sector (Fan *et al.*, 2015; Prytz *et al.*, 2015; Liu *et al.*, 2018).

2.5. Decision making models

In the field of maintenance, decisions have to be made on the moment and type of maintenance for example. Structured approaches that lead to a decision are called decision making models. Multiple models have been proposed in literature that can be used for decision making in a maintenance context.

2.5.1. Decision making cycles

As a basis for many decision making models for humans and machines the "Observe–Orient–Decide–Act" (OODA) model for situational awareness is used. This model was first introduced by military strategist [Boyd \(1996\)](#) and was originally designed to optimize human decision making in stressful situations. Later, many frameworks have been derived from the OODA-model in other contexts. Maintenance decision making is one of the fields where these model can be used. This model is structured as a cycle, as can be seen in figure 2.6a. Each time a decision has to be made, at least one full cycle should be made.

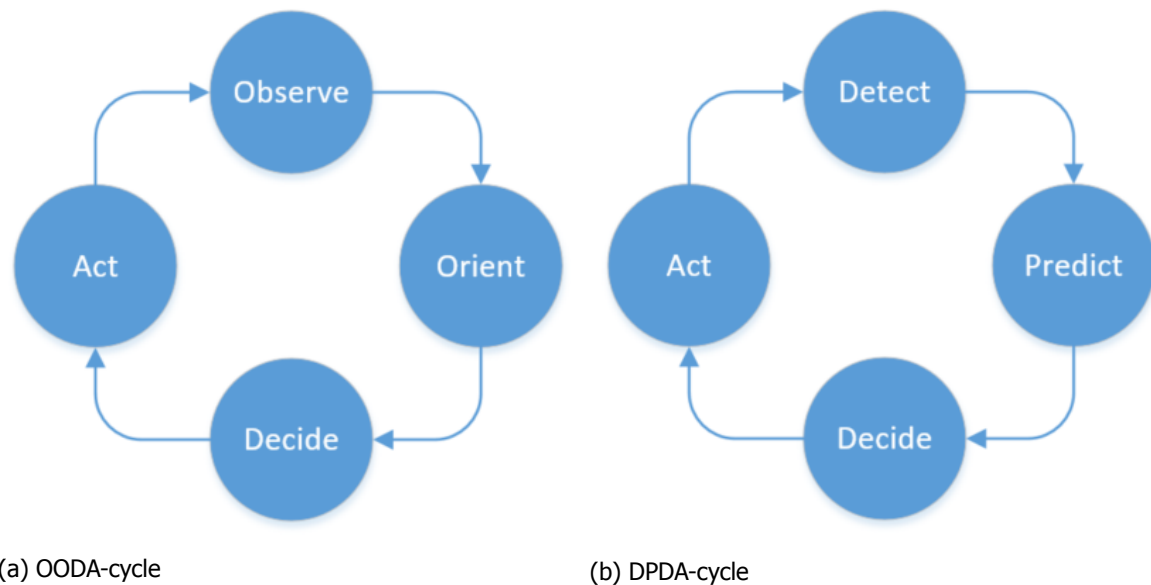


Figure 2.6: Decision making cycles

The "Detect–Predict–Decide–Act" (DPDA) cycle is directly derived from the OODA-cycle and also consists of four phases: *Detect* specific situations; *Predict* future (undesired) events; *Decide* on recommendations that should be provided; *Act* on the decision or recommendation by adapting the operational system ([Engel et al., 2012](#)). This approach is visualized in figure 2.6b. Where the OODA-cycle is most appropriate for human decision making, the DPDA-cycle can also be used for automated decision making systems. Both cycles are widely used and accepted as decision making model. A maintenance strategy that uses technologies such as data mining, machine learning and operational research can be implemented by using a DPDA-cycle ([Bousdekis et al., 2017](#)).

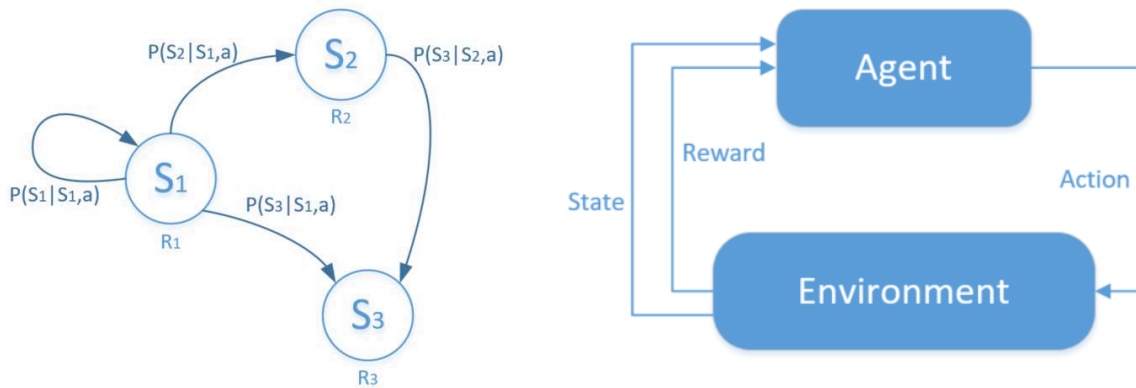
2.5.2. Markov Decision Processes

Markov Decision Processes (MDPs) are a subclass of discrete-event models that are useful for decision making in fields such as robot control, manufacturing and traffic signal control, where there is need for sequential decision making based on uncertain state transitions ([Negenborn et al., 2005](#)), as also might be the case in a maintenance system.

A MDP can be defined by a set of states, actions, rewards and transition probabilities. An example of a MDP is shown in figure 2.7a. The circles represent the states and the arcs between them represent the transitions between two states. If a certain state S_n is reached, a reward R_n is gained. The tran-

sition probabilities between states are defined by the target state, origin state and the action a that is performed.

For example, a MDP can be used to model the interaction of an agent to its environment, such as shown in figure 2.7b. By performing an action, the agent interacts with its environment and subsequently receives a new state and the associated reward.



(a) Example of a MDP with three states

(b) Agent interaction described as MDP

Figure 2.7: Example of a Markov Decision Process and its use

At the basis of a MDP stands the Markovian property. This property is that the past states are not needed to solve the problem, but the current state suffices. This means that only the necessary information of each state is saved. This property makes a MDP very useful for a prescriptive maintenance system where the current state of a component suffices to make maintenance decisions.

Next to these advantages, the main advantage of a MDP is that optimal actions can be performed even if sub-optimal direct results are found when an action is performed. Simple planning will just decide on direct results, even if that is not the optimal solution. Therefore a MDP is an effective solution to program decision making in a stochastic environment, where the result of an action is not fully certain (Pradeep and Noel, 2018).

2.5.3. Maintenance decision models for multi-component systems

For some specific cases of multi-component systems, maintenance decision frameworks have been defined. Such frameworks exist for multiple types of systems, for example in the transport sector. Verbert *et al.* (2017) proposes a multi layer approach for the specific case of maintenance of a railway system. This multi-layer approach is structured in a system layer and a layer for multiple individual components, as seen in figure 2.8.

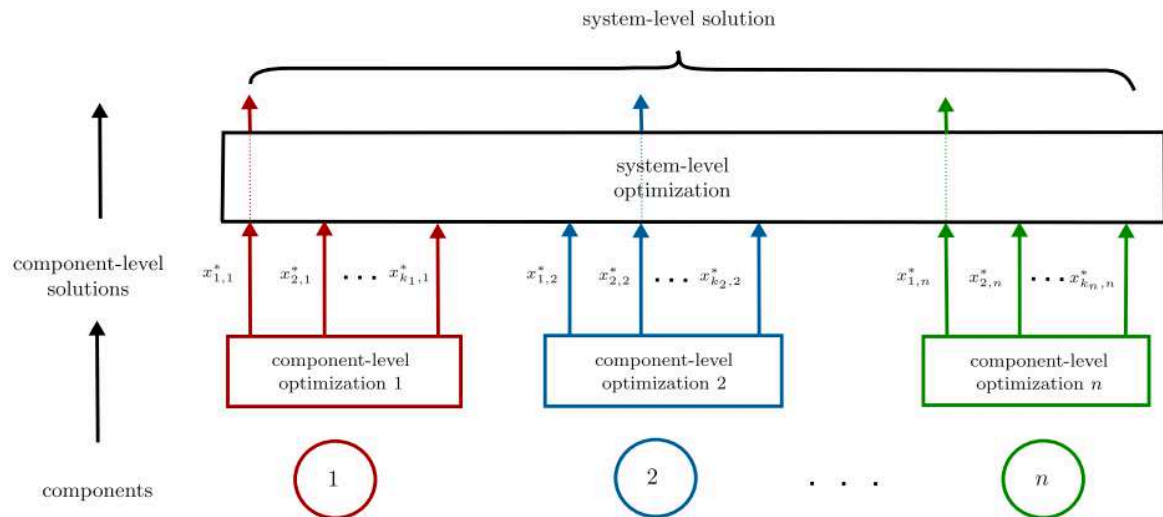


Figure 2.8: Multi layer approach of Verbert et al. (2017)

In this approach, multiple near optimal solutions of the component level are determined by using a Markov Decision Process and shared with the system layer. In that layer a decision is made for the overall maintenance solution. This multi-layer approach is used as a basis for the proposed framework in this research, as can be seen in chapter 3.

Another approach is proposed by Martinod et al. (2018), where a clustering approach is used to find the optimal system solution. Both these decision models follow a centralized approach, where there is unidirectional communication to the system level. This creates a robust system, but in general centralized structures are less scalable compared to a distributed system (Burness et al., 1999).

2.6. Architecture and decision making

By connecting the physical world to computer systems, the amount of gathered data has enormously increased. Generally, this data is too extensive or too complex for humans to process. In recent years however, artificial intelligence (AI) is used to be able to collect, analyze and process this huge amount of available data. The use of this 'big-data' in the field of maintenance is also increasing, mainly due to the evolving AI technologies that create possibilities to reach a higher level of maintenance analytics, as discussed in section 2.4. AI methods as machine learning can be applied using technologies such as artificial neural networks, neuro-fuzzy systems and random forest (Rødseth et al., 2017).

2.6.1. Cyber-physical systems architecture

To be able to make maintenance systems intelligent, physical systems must be connected to the computational systems that provide the analytics. Combinations of a physical system and the artificial intelligence technologies that enable the interaction with the physical world by computation, communication and control are named cyber-physical systems (CPS) (Baheti and Gill, 2011). The structure of these systems is discussed in this section.

Lee et al. (2015) proposed the 5C-architecture for implementation of CPS. The architecture consists of five levels, as can be seen in figure 2.9. This architecture provides a structure for the connection between maintenance concepts and maintenance infrastructure such as sensors, components, machines and support systems.

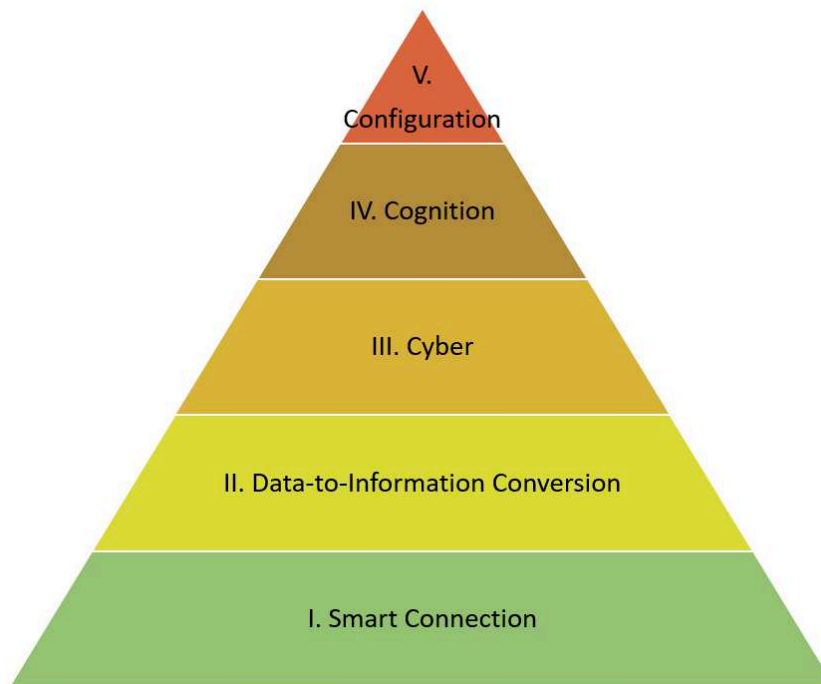


Figure 2.9: The 5C-architecture from [Lee et al. \(2015\)](#)

Each level in the 5C-architecture corresponds to a different operational or business level and can be characterized by certain capabilities:

- I. At the basis of CPS stands the data acquisition layer. This level includes sensors which enable condition monitoring of equipment and business data from enterprise systems.
- II. To extract information from the gathered data, it must be converted. As example, data can lead to information on health of machines and components, creating a self-aware environment.
- III. When multiple similar machines are connected, a comparison can be made between those machines on performance and degradation. This level acts as the information hub to provide better insight of the total system.
- IV. When the knowledge that was acquired in the previous levels is presented in a proper way, decisions can be prioritized and optimized. This level should include the human machine interface of a maintenance system for example.
- V. A total CPS can perform actions itself to avoid errors and failures in the future. This is the most evolved level of this architecture.

A successful intelligent maintenance framework should at least include step I to IV, namely the data acquisition, data processing, equipment connection and communication. CPS is a widely accepted approach for the connection of equipment to analytics. This architecture can therefore be used for the maintenance framework discussed in this research. How this architecture is used for this research will be discussed in chapter 3.

2.6.2. Decision making techniques

Multiple techniques can be used to solve the decision models described in section 2.5. Widely accepted techniques include the following:

1. Brute force approaches
2. Heuristics
3. Dynamic programming
4. Reinforcement learning

Brute force approaches that simply compute all possibilities and selects the best option in the complete set. This approach can be used when the number of possibilities is small. Examples of such methods are depth-first and breadth-first search (Doyle, 1997). When the problem is extended to a more complicated system, other methods such as heuristics may have to be used.

Heuristics are an improved version of brute force methods. Heuristics use problem specific knowledge to find the best solution. This is mostly done by finding the best possible state that leads to a target solution (Potdar and Thool, 2014). However, it is not guaranteed that the optimal solution is found. Examples of heuristic methods are best-first and A^* approaches.

Also, there are some methods that can be used for specific problems. Dynamic programming and reinforcement learning are methods that both can solve specific problems such as Markov Decision Processes, that are discussed in section 2.5.2. The main difference between them is that reinforcement learning can be used when the objective and reward functions are not known a priori, and in dynamic programming these functions are needed find a solution.

To decide what technique is most suitable for the specific problems in this research, a multi-criteria analysis is done. A number of categories of criteria have been defined to be used in the selection of a suitable method. These are:

- Application, describing whether the method is most suitable for a specific problem or not
- Efficiency, which is based on the number of evaluations, the running time and memory usage
- Reliability, consisting of success rate, number of violations and percentage of solutions found
- Quality of solution, based on repeatability and computational accuracy

A performance matrix of these methods is shown in table 2.3. The solving techniques are rated per category using a scale of 1 (lowest) to 5. Because the number of parameters is expected to be reasonably small and will not affect the scalability, efficiency is weighed with factor 1, while reliability and quality are weighed with factor 2. The scores were based on Pradeep and Noel (2018); Potdar and Thool (2014); Doyle (1997). The analysis shows highest scores for brute-force approaches and reinforcement learning.

Method	Application	Efficiency	Reliability ($\times 2$)	Quality ($\times 2$)	Σ
Brute force approach	All	1	4	5	19
Heuristics	All	3	3	3	15
Dynamic programming	MDP	4	3	2	14
Reinforcement learning	MDP	3	4	4	19

Table 2.3: Performance matrix of solving algorithms

Brute force approach

The brute force approach – or brute force search – can be used if the efficiency is not a strong requirement. It is a very general optimization technique, where the solution is found by simply evaluating all possible options. Brute force approaches can best be used when the number of possibilities is small, to prevent long running time. When the problem is extended to a more complicated system, other methods may have to be used.

The implementation of this approach is the easiest compared to the other approaches. For a minimization problem for example, a loop through all options and a if-statement would suffice to reach the minimum value. The application of this approach will be discussed in section 4.2.5.

Reinforcement learning (RL)

In recent years, technologies have been developed that can mimic the learning process of humans. Such processes are called machine learning. This technology enables computers gain experience and to improve current ways of working. Computers are, unlike humans, less limited in their processing power and ability to store large amounts of data.

Machine learning (ML) in general is a big category of technologies and methods in the field of AI. There are many different ways that machine learning can be used in a maintenance context. Next to the prediction of failures as described in section 2.1.2, machine learning methods can be used in decision making. By letting a computer run a large number of scenarios, the statistically best results for a specific situation can be determined. Reinforcement Learning is such a ML-technique that can be used for decision making. Due to faster and cheaper processors techniques such as these can be more used for more applications. Either they can be used in more advanced systems that were to complex before or they can be used more easily and cheaper in less advanced systems (Sharp *et al.*, 2018).

Reinforcement learning is most effective when a markov decision process has to be solved. RL is a machine learning technique that is able to learn using delayed rewards. This means that that when deciding, not the immediate reward is chosen if the long term reward is higher. This approach is in contrast to other machine learning methods such as convolution neural networks, which train on a immediate reward.

Another characteristic of RL is that both the system response and the desired behaviour are unknown beforehand. As in all MDPs, the agent computes the value function by interacting with the environment or system in a step-wise approach, such as shown in figure 2.7b. After each step, the reward calculated and the computed value function is updated according to the experience gained in that step. The agent performs steps until a terminal state is reached.

This step-wise process is repeated for a number of episodes. The results of the episodes are combined, and after an agent has collected a sufficient number of experiences, the reward associated to actions can be estimated accurately (Negenborn *et al.*, 2005). The application of this approach will be discussed in section 4.2.5.

2.7. Multi-agent systems

Next to the decision making approaches for multi component systems such as discussed by Verbert *et al.* (2017) and Martinod *et al.* (2018), agent based approaches exist that use a different structure. A multi-agent system (MAS) is a collection of independent components that make observations and decisions to reach a common or individual goal. The best way for agents to share information depends on the structure of the problem (Harbers *et al.*, 2007).

Multi-agents systems are used to divide the responsibilities of decision making for a certain system between multiple agents. This way, the flexibility and scalability of decision making is increased so that it can be used to control or simulate complex problems and systems with many interacting entities (Houston *et al.*, 2017).

There are four principal ways which can be used to control multi-agent systems, namely hierarchical, coordinated, cooperative or non-cooperative [Duinkerken and Pang \(2017\)](#). A basic overview of these approaches is shown in figure 2.10. The three rightmost options are all distributed, while the leftmost structure is centralized.

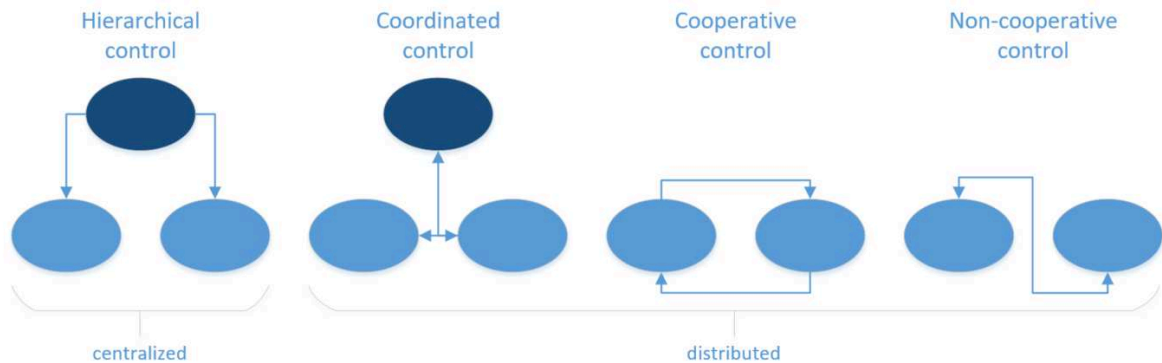


Figure 2.10: Approaches for control in multi-agent systems, adapted from ([Duinkerken and Pang, 2017](#))

The choice of control structure depends on the nature of the goal, i.e. common or individual, complexity of the decision making, the functional relationships of the agents and the characteristics of the environment. In contrast to centralized communication, a hierarchical control structure is not inefficient by definition. It can even be the most efficient control structure, because the priorities and goals are very clear ([Dellaert, 2007](#)).

Hierarchical control systems are designed to divide the decision making responsibilities among individual agents, while keeping assuring that the final decision is made centrally. However, hierarchical controlled systems might not be capable to cope with changing environments. Cooperative control structures on the other hand are better suited to handle instabilities and uncertainties that might be caused by disturbances in and outside the system. Also, a distributed structure could reduce computational loads by fully dividing the problem that needs to be solved ([Li and Zheng, 2016](#)).

However, agents in a distributed control structure usually do not have a global overview of the system and connect to only a small number of sensors or other agents, which could lead to more uncertainty on the system level. This is especially the case if an agent predicts the evolution of a system, such as in model predictive control approaches ([Li and Zheng, 2016](#)).

From the above mentioned reasons it can be concluded that for a system with low expected disturbances, such as a prescriptive maintenance system, a hierarchical control structure is most appropriate to ensure that the system priorities are taken into account.

2.8. Scientific gap

As described in section 2.1.3, multiple prescriptive maintenance models have been proposed for different industries. However, none of these models or frameworks were designed for use in the FMCG industry. This industry seems to be lagging compared to the oil & gas, process and transport industries for example. Also, it has not been researched if the existing prescriptive maintenance methods can be used in other fields such as the FMCG industry ([Rødseth et al., 2017](#)).

Currently, the used maintenance concepts in many FMCG companies do not fully use the potential of the technological advancements of the past decades, as operational data is mostly just used to control processes but not as guide for maintenance operations. Technologies such as machine learning, which can be used for prediction of failures and prescription of maintenance actions, are not widely used in the FMCG industry. In maintenance, such models and technologies can be used to fully extract useful

information from all generated data, and improve maintenance decision making.

For a prescriptive maintenance system, prescriptive analytics should be used. Although the analytics methods have strongly improved over the last years, these systems are designed for single equipment types or individual components (Lee *et al.*, 2014; Lindström *et al.*, 2017). In such systems, such as described by Liu *et al.* (2018), the system dependencies of the components are not taken into account, where maintenance decisions for multi-component systems made at a higher level will lead to a decrease of maintenance costs (Verbert *et al.*, 2017). For multi-component maintenance systems in the FMCG industry, scalability is a strong requirement. Especially because big FMCG companies generally have many equipment types for which such a maintenance system could be used. A system that could make use of this scale advantage would deliver a significant contribution to literature (Lindström *et al.*, 2017).

A new maintenance framework that helps to achieve prescriptive maintenance in the FMCG industry would deliver a significant contribution to fill the scientific gap that is sketched above. Such a new framework, based on the findings of this literature research, will be proposed in the next chapter.

3

Prescriptive maintenance framework

This chapter contains the proposed prescriptive maintenance framework. This new framework was designed while taking the found literature of chapter 2 and the design requirements into account. These requirements will firstly be discussed, followed by selection of used methodologies and the proposed framework itself.

3.1. Problem definition

As the goal of this research is to define a framework for a prescriptive maintenance system such as described in section 2.1.3, it should be able to make maintenance decisions based on input gathered from the system. These decisions should ensure the needed production targets are met, for the lowest possible total costs. These total costs include direct and indirect costs, as discussed in section 2.3. To make the framework useful for the FMCG industry, also some other design requirements have to be met. These are based on the specific characteristics that can be found in this industry. These characteristics will be discussed in the following section.

3.1.1. FMCG Failure characteristics

In literature, some research can be found on failures of production equipment in the FMCG sector. This research however is mostly equipment specific, however some shared characteristics can be found in many FMCG production companies. These shared properties can mostly be found in the packaging and utilities areas.

In the packaging environment specific failure characteristics can be observed. For instance, in the packaging facilities of Heineken a clear pattern in failure downtime and occurrence can be found throughout the 170 breweries. Figure 3.1 shows a classification of failures in packaging based on the downtime per failure. A division can be seen between minor stoppages that can be easily resolved, shown in orange, and breakdowns that require a more time consuming intervention, shown in purple. The 'two-peak'-shape that can be distinguished means that failures can be classified into one of the two categories.

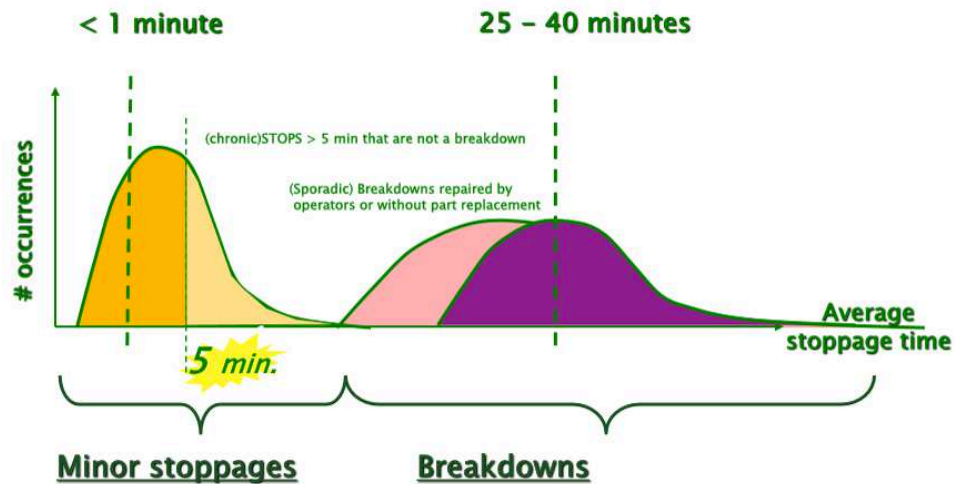


Figure 3.1: General classification of failures as defined by Heineken NL

When analyzing actual failure data of a packaging line of Heineken Den Bosch for example, this division can indeed be observed. The failures are ordered to induced downtime and graphed in figure 3.2. The light green bars indicate the frequency of the failures and the dark green bars show the downtime in minutes.

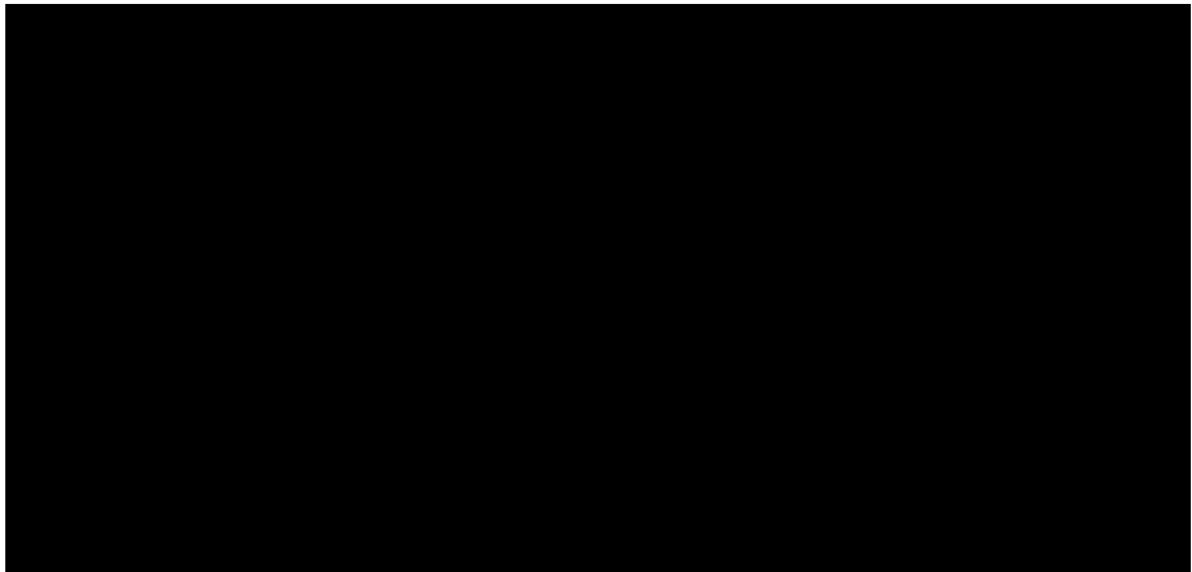


Figure 3.2: Classification of failures by induced downtime for packaging line of Heineken Den Bosch, NL

The same 'two-peak'-shape was identified by [Liberopoulos and Tsarouhas \(2005\)](#) and [Tsarouhas et al. \(2009b\)](#) in other FMCG companies – an automated pizza production line and a juice bottling plant –, as can be seen in figures 3.3a and 3.3b respectively. In these cases, time of lost production and the time-to-repair (TTR) were considered. The TTR indicates the time from failure to finished repair and therefore equals indicator of downtime caused by a failure that was used in the previous examples. The same shape can be identified in other cases, such as [Tsarouhas \(2009\)](#).

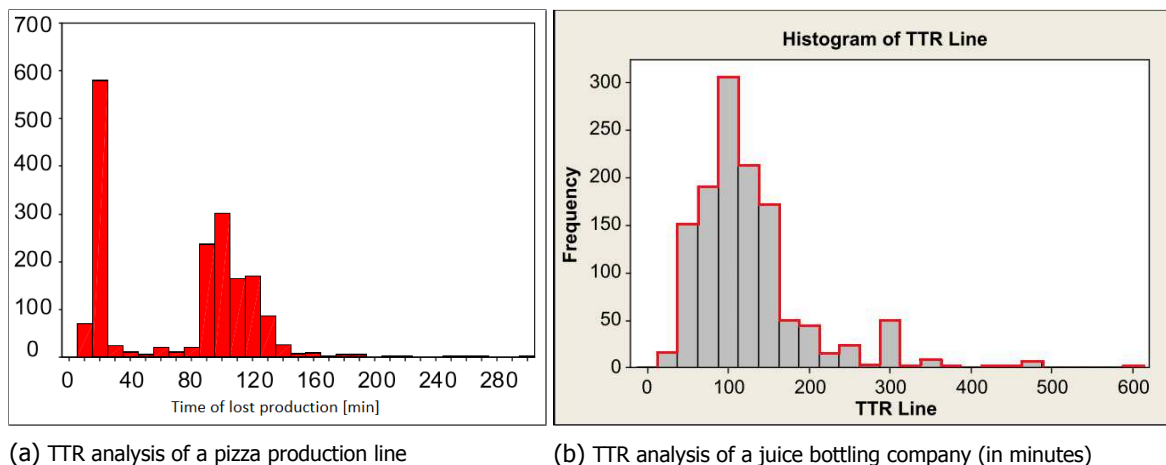


Figure 3.3: Time-to-repair (TTR) analysis of two FMCG companies

These histograms confirm the statement that a division can be made between minor stoppages and breakdowns. An explanation that could further increase the gap between the two peaks was found by [Liberopoulos and Tsarouhas \(2005\)](#). In the FMCG industry high volume products are produced of which many are subject to quality deterioration during stoppages. Due to this fact, during stoppages that cost more time, semi-finished products have to be removed or checked which costs additional time.

For comparison, two TTR graphs of other industries and equipment types are shown in figure 3.4. The first histogram of in figure 3.4a shows the TTR analysis of a different type of manufacturing industry, namely a plastic injection moulding company ([Hauw Sen et al., 2017](#)). Figure 3.4b shows the TTR histogram of lift doors in the London Underground ([Houston et al., 2017](#)). These histograms show that the 'two-peak'-shape observed in the FMCG industry is not necessarily a usual shape for other manufacturing industries or equipment types. Other shapes can also be identified in other sectors, such as [Horváth and Gaál \(2008\)](#).

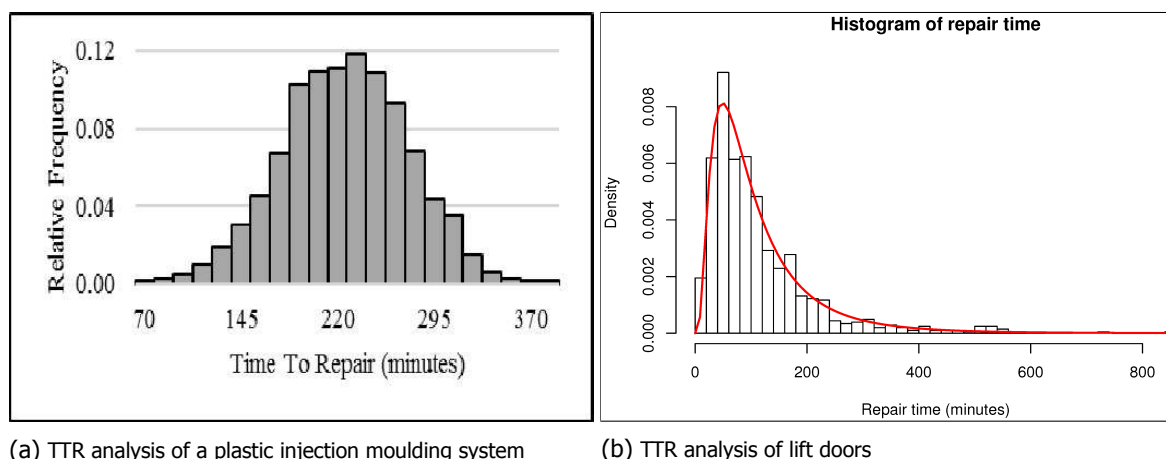


Figure 3.4: Time-to-repair (TTR) analysis of two non-FMCG systems

3.1.2. Design requirements

From the characteristics discussed in the section above, it can be concluded that the system should be able to cope with the fast changing environment, and therefore must frequently collect and process new data. Also it should be scalable from a production system to a factory scale, while allowing for multiple diverse equipment types, because interacting components may be found in all areas of a production facility. Thirdly, for a successful implementation a applicable setup should be used for the connection of the framework to equipment and end-users, as the maintenance actions are performed

by maintenance personnel.

Based on the above mentioned challenges, the following concrete design requirements have to be taken into account:

1. Able to prescribe maintenance actions based on dynamic input from system
2. Minimization of total costs (direct and indirect) for system, while productivity is ensured
3. Scalable enough for use in complete FMCG production plant
4. Able to handle diverse equipment types
5. Include the full information cycle from data gathering to information transfer

3.2. Used methodologies

Many general maintenance methodologies can be found in literature, as was stated in section 2.2. Here, the four 'traditional' methodologies were described and compared. To be able to reach the research goal, while taking the design requirements into account, some parts of methodologies have been selected for the design of a new framework.

Based on the information in tables 2.1 and 2.2 it was decided to use both TPM methodologies and LCC-approaches as foundation for the framework. A reason to select these two methodologies is to ensure the focus on both productivity and costs, mentioned by design criterion 2. Were the focus of TPM is to improve productivity by making systems more efficient, the LCC approach can be used to minimize costs of the whole life cycle. As the life cycle costs stand central to this approach, all direct and indirect cost-aspects that are shown in figure 2.4 can be included depending on the scope.

Also, both TPM and LCC methodologies include the operator and maintenance personnel in the process, which is an important part of design requirement 5. An additional advantage is that TPM is used by many large FMCG production companies, which creates synergy between the proposed framework and the existing methodologies. The step-wise approach of the TPM methodology will enable a successful implementation.

The disadvantages of TPM that are shown in table 2.2 can be overcome when appropriately addressed. Where the TPM methodology is not purely maintenance, this research uses the parts that are applicable for use in a maintenance context. The novelty of this research can be found in the decision making, that is lacking in the methodology itself. Lastly, the combination with a LCC approach will ensure that costs and profits are considered.

A disadvantage of LCC approaches during the time of the comparison (in 2002) was the uncertainty of factors used in the decision making. The new technologies that were discussed in section 2.6 can solve challenges in uncertainty, e.g. the use of ML and advanced analytics. These technologies will ensure that decisions can be made by the framework so that design criterion 1 will be satisfied.

The remaining design requirements 3 and 4 will be met by also including another methodology. As discussed in section 2.7, a multi-agent approach is able to provide the scalability and the flexibility needed for a prescriptive maintenance framework for the FMCG production industry. Given the limited uncertain behaviour of the components in such as system and to ensure the common goal is reached, a hierarchical control structure is proposed. The recent advances in technology prevent that such a structure will lead to computational capacity issues.

3.3. Proposed framework

The proposed concept is based on the DPDA approach discussed in section 2.5.1, because this is a proven decision model for maintenance strategies (Bousdekis *et al.*, 2017). In contrast however, a

distinction is made between component- and system level decision making, resulting in a multi-layer approach such as proposed by Verbert *et al.* (2017). This approach makes the framework applicable for multi-component systems.

The framework that results is schematically shown in figure 3.5. The overall process can be split into five sections, namely the data collection, the component level prediction, the decision making on respectively component and system level, and finally the information transfer. The third and the fourth block are both in the 'decide'-step of the DPDA approach.

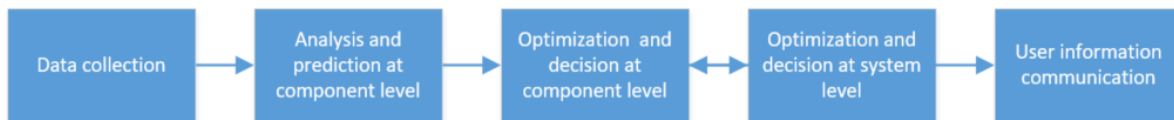


Figure 3.5: High level overview of the proposed maintenance concept

An agent-based approach will be used for the components and system decision making. This decision will be further discussed in section 4.1.1. A hierarchical control structure is chosen for the multi-agent system, as discussed in section 2.7. As can be seen in figure 3.5, between the two decision steps the arrow is pointing to both sides. This indicates that the information transfer is happening in both directions. This way, agents are able to negotiate to reach the systems optimal state. Figure 3.6 shows how this approach is used for a multi-component system.

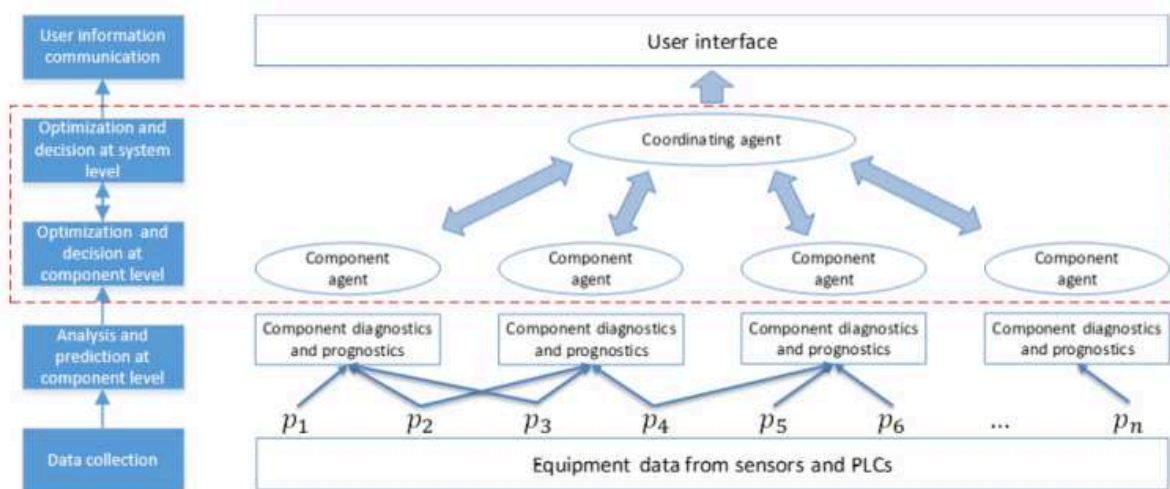


Figure 3.6: Proposed framework to achieve prescriptive maintenance for a multi-component system

The values p_1 to p_n represent the parameters from the system that are used for the component level diagnostics and prognostics. The output of this step is in turn used as input for the component decision making by each component agent. The component agents negotiate with the coordinating agent to reach the optimal system solution. The exact structure for this negotiation will be discussed in detail in section 4.1.

The design of this framework aligns with the 5C-architecture by Lee *et al.* (2015) shown in figure 2.9, where the level I is the data collection, level II the diagnosis and prediction on component level, level III is the information transfer between the agents and level IV is the information transfer to the end-user. Level V can be seen as the continuous improvement that happens in the prediction layer.

3.3.1. Data collection

What most FMCG production facilities have in common is the controlling of operational systems using Programmable Logic Controllers (PLCs). These controllers use input from measurements to control equipment automatically. The input that is used by the PLCs is in many cases already stored in historians for diagnostic use after failures. As the PLC-input is used for the automatic control, all critical parameters for operation are measured. The data collection is, in this case, equal to data collection for diagnostic and predictive analytics (Kart *et al.*, 2013). This framework however uses a higher level of analytics in the following layers.

To enable a truly scalable solution, the data collection layer must be designed so that it can be accessed by all entities that require specific data from different components of a system. This could for example be realized by cloud storage of data, where to all decision making entities are connected. Data would be uploaded to a cloud-environment directly from the PLC where it is stored. From there, the needed parameters can be extracted by systems that require them using only one connection.

In some specific cases, where PLC-data does not provide enough information, it might be interesting to gather additional data. For example, vibration data could be collected by a dedicated sensor to be used for a diagnosis on the state of a certain component. Data from such individual sources can also be uploaded and stored in the same cloud-environment.

3.3.2. Component level analysis and prediction

Using the input from the data collection layer, the current state of a component can be diagnosed. As described in level II of the 5C-approach, this layer converts data to information that can be used for further analysis. With the results of the diagnosis, a prediction of future states on component level can be made. Such predictions are already available for many equipment types (Niu and Jiang, 2017; Glawar *et al.*, 2018). The prediction can have the form of a remaining useful life (RUL)-prediction. Predicting the RUL is the main goal of predictive maintenance, and also serves as input for the decision making of a prescriptive maintenance system. The determination of the RUL is visualized in figure 3.7.

The goal of this step is to give a prediction on when a component will fail. By comparing live operational data to historical degradation models of the same component type, the degradation of the component can be predicted with a certain probability. In figure 3.7, $d_i(\tau_c)$ is the degradation level at the current time τ_c , where the dots represent the measured degradation. The degradation model, which is linear in this example, is used to extrapolate the degradation to determine the moment of failure to a specific certainty.

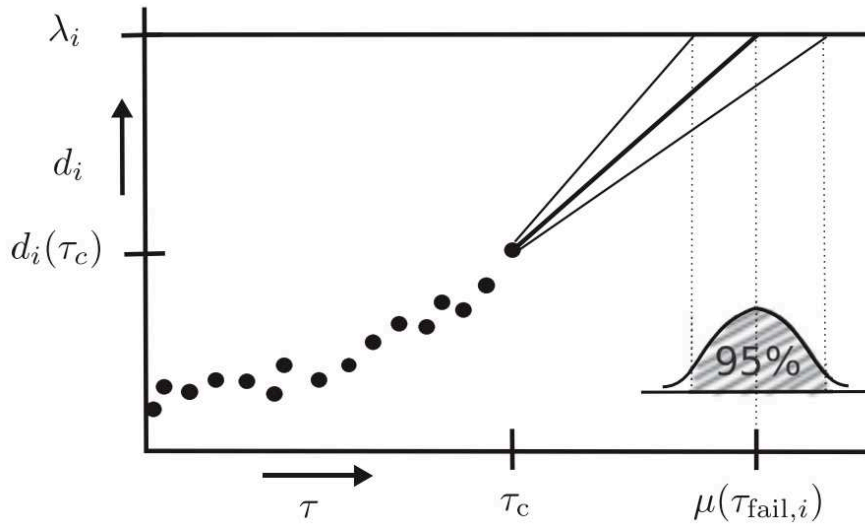


Figure 3.7: Visualization of a remaining useful life prediction (Verbert et al., 2017)

The rise of machine learning has provided faster and more intelligent approaches to create degradation models. Large amounts of data can be used to train algorithms that predict future states of equipment. This creates an opportunity to use this framework for many more equipment types. Each equipment type could have a unique degradation model so, depending on the system, many degradation models might have to be made.

3.3.3. Component level decision making and planning

As stated at the start of this chapter, a distinction is made between decision making on the individual component level and the overall system level. This section will introduce the first part, the decision making and planning of tasks at a component level. In different words, this decision is the prescriptive analytics part on component level. This decision will be made by an agent that is dedicated to the specific component. The goal of this agent is to find the optimal maintenance action and moment for the component it is dedicated to. So the output from this level should be two decisions:

1. The type of maintenance required by the component
2. The optimal time for the component to perform the maintenance

The first decision, concerning the *type of maintenance*, refers to the action that is needed to bring the level of degradation of the component back to (near) its original value. As this maintenance framework is aimed at the FMCG industry, two types of maintenance are considered, namely minor and major maintenance. This division corresponds to the 'two-peak' shape discussed in section 3.1.1.

The second decision, on the *optimal maintenance moment*, refers to the moment that leads to the minimum total costs. In short, that means the lifetime of the component needs to be maximized, failure should be prevented and downtime during planned production time should be minimized, all on the component level.

Leading from this, the optimal maintenance moment depends on the prediction of the degradation of the component, and the cost functions that are corresponding to the component type. The optimal moment to plan the maintenance moment is not that straightforward however. A trade-off should be made between the accuracy and earliness:

- The accuracy of the prediction increases with time, so the longer one waits before planning the maintenance action, the more accurate the prediction of the degradation is.
- The earlier the the maintenance action is planned, the better a maintenance schedule can be created, e.g.:
 - Time to get spare parts and personnel to the component to perform maintenance before failure
 - Preventing of system downtime due to failure during planned production time by planning maintenance in out-of-service windows
 - Early information to the system level optimization will create a better system level result

To illustrate, predictions that are made too early to be accurate are useless, and off course planning maintenance seconds before failure is neither useful.

To summarize, the goal of this step is therefore to determine the type of maintenance needed, the optimal time that the maintenance action should be performed, and additionally at what time the maintenance action should be planned, for a component that the specific agent is dedicated to.

3.3.4. System level decision making

Where the previous step concludes with a best case scenario for each single component, in this step a optimal maintenance planning for the whole system is provided. The optimal system level planning could off course be different than a simple combination of the different component plannings. Reasons for this include constraints of working hours and availability of maintenance personnel, planned production times, inter-component dependence and budget.

When the combination of all optimal individual component solutions is not equal to the optimal system value, a new solution will be searched. The optimization variable used to find the optimal solution is the moment of maintenance, as the type of maintenance depends on the degradation of the component and should not be changed.

Also included in this step will be the interdependence of components. If components are structurally dependent, they all have to be stopped when maintenance has to be performed. This creates opportunities to combine maintenance interventions of multiple components to reduce the total downtime caused by those maintenance interventions. On the other hand, some components might be maintained while others are still running, which prevents loss of system functionality while a component is maintained.

A simplified example of component dependencies can be seen in figure 3.8. If component 1 would require maintenance, component 2 would also have to be shut down. However, component 3 would still be able to continue operation. So if components are placed in parallel, total loss of functionality can be prevented, and if components are dependent in series, the downtime can be used to maintain multiple components.

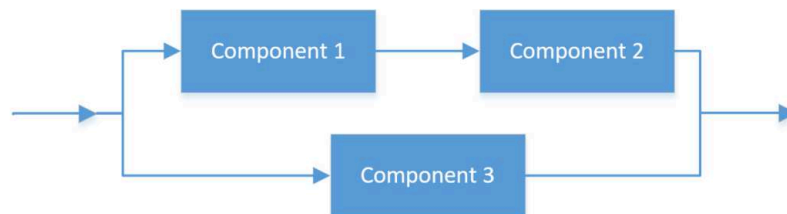


Figure 3.8: Simplified visualization of component dependencies

To be able to reach the best possible outcome for the whole system, an agent-based approach is used where the component level agents will negotiate with a coordinating agent that acts on a system level. The structure that is used for this negotiation will be discussed in detail in section 4.1.

3.3.5. Information transfer

The last step in this framework is the information transfer. The knowledge that is created by this framework is useless if it is not well interpreted. In the design of the information transfer the end user must always be kept in mind. In this case, the end user is a maintenance engineer or equipment operator who has the objective of performing maintenance tasks.

The information or knowledge that is required by the maintenance engineer can be split into three categories, namely:

- **When** should a maintenance task be performed?
- **What** actions should be taken to complete the task?
- **How** should these actions be taken?

The 'When' and 'What' questions are at the core of what this prescriptive maintenance framework will deliver. The 'How' question is outside of the scope of this research and should – at least for now – be answered using the knowledge from experience of the maintenance personnel, or a maintenance guide or manual.

3.4. Scope

The proposed framework consists of five steps, each of which are described in the previous section. To limit the scope, the focus of this research is on the two decision making steps and the interaction between them. It is chosen not to focus on the other steps for now, but in literature multiple methods have been found that can contribute to the steps that will not be discussed in detail.

For example, multiple methods can be found for data collection and analysis for a maintenance framework, e.g. Schmidt *et al.* (2017); Karim *et al.* (2016); Lee *et al.* (2014). Predictive algorithms exist for many types of equipment that are used in a FMCG environment, such as compressors and pumps. Also for human-machine interfaces and dashboards multiple studies have been performed, such as Yigitbasioglu and Velcu (2012); Okoh *et al.* (2017); Wallach *et al.* (2017). As discussed, the focus of the next chapter will be on the novel approach to optimization of maintenance actions and decision making for this specific framework. This scope is visualized in figure 4.1.

4

Optimization and decision making

As it was stated in the previous chapter, the main scope of this research is the optimization and decision making process of the proposed prescriptive maintenance framework, as seen in figure 4.1. This chapter will focus on both the optimization and decision on component and system level, and additionally the interaction between the two levels. The used approach is partly based on [Verbert et al. \(2017\)](#) and [Martinod et al. \(2018\)](#), who propose a maintenance concept for multi-component transport systems such as a railway system or urban aerial rope-way transport systems. In contrast however, this research proposes the use of an agent based approach to be compatible with the more dynamic environment of a FMCG production company. Also, the proposed approach uses more suitable solving methods for systems with many components, in order to ensure scalability.



Figure 4.1: Main scope of this research in the proposed framework

4.1. Level interaction

In the design of the decision making framework, there are multiple ways of structuring the elements of the framework and the information flows between them. Due to this interaction between elements, the framework can be seen as a control system. For this research the goal is to design a framework that is scalable and flexible enough for the desired application, namely maintenance planning for the FMCG production sector. This section elaborates on the advantages and disadvantages of certain control approaches, and ends with the proposed setup.

4.1.1. Scalability

As discussed in section 2.7, a hierarchical structure consists of a single coordinating element and a set of other elements which only communicate with the coordinating element. Hierarchical control systems are designed to divide the decision making responsibilities among individual agents, while keeping assuring that the final decision is made centrally. In the context of maintenance for a FMCG production plant for example, this could be used for an equipment type with a limited number of components.

Agents in a distributed control structure usually do not have a global overview of the system and connect to only a small number of sensors or other agents, which could lead to more uncertainty on the system level. This is especially the case if an agent predicts the evolution of a system, such as in model

predictive control approaches (Li and Zheng, 2016).

From section 2.7 it can be concluded that for a system with low expected disturbances, such as a prescriptive maintenance system, a hierarchical control structure is most appropriate to ensure that the system priorities are taken into account. Such a structure is schematically shown in figure 4.2.

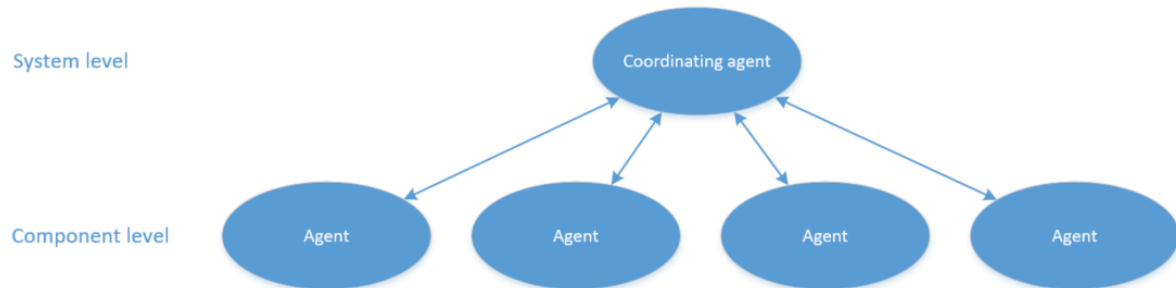


Figure 4.2: The structure of the agents on component- and system level

Also, a multi-agent approach performs better than classic control approaches, as it comes to negotiation. Agents in a multi-agent system behave as entities with self-interest. In a classic distributed system, the elements are assumed to have the same common goal.

This intelligent approach is a more flexible approach to multi-component maintenance systems, as the agents can negotiate to reach the system optimum. Such an approach is necessary in a FMCG environment, where maintenance interventions with short duration should be effectively scheduled along with more time consuming interventions. Using intelligent agents, a part of the decision making is transferred from the coordinating agent to the agent on the component level.

4.1.2. Diversity

The centralized structure sketched in figure 4.2 is suitable for a system with a limited number of components that are similar. Diversity of components could cause problems in such a structure, whereas a decentralized approach would be able to handle diverse components (Truong *et al.*, 2016).

In a partly decentralized approach, agents do not just communicate with one coordinating agent, but instead with intermediate agents which in turn communicate with the central coordinating agent. This creates a structure as shown in figure 4.3. Intermediate agents would take the role of the coordinating agent for certain parts of the system, such as a group of similar components. This way, the central agent will not have to consider all optimization results on component level, which reduces the needed processing power and time, and enable diversity between different groups.

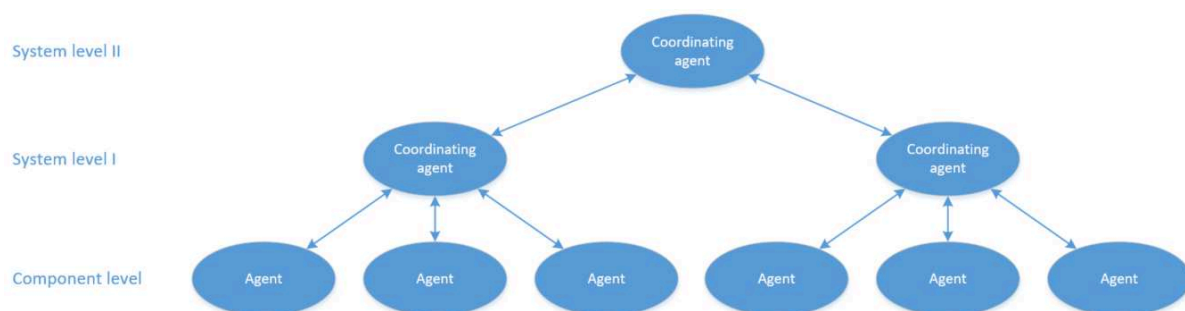


Figure 4.3: The structure of the decentralized system

The coordinating agents on the different system levels will have the same task. They should find the

optimal combination of maintenance task on their system level. This way, the optimal maintenance of groups of components can be considered effectively, as well as maintenance on component level. An additional advantage of decentralized control is the increased stability of the system. A problem in one of the planning agents would not affect the whole system, but just the section in which it is placed.

To conclude, in order to create a scalable framework which can be used for a diverse set of equipment, a decentralized intelligent agent structure is proposed for the prescriptive maintenance system in a FMCG production environment.

4.2. Component level

Now that the basic structure is defined, the intelligence of the component level agents will be discussed. The decision making on component level can be split into two parts. In the first part a decision is made on the needed maintenance intervention and optimal maintenance moment, depending on the information that is available at that moment. In the other step it is decided if this particular moment is the optimal moment to really plan the maintenance. By weighing the risks of planning maintenance at a later moment and having more information, the maintenance is planned or the decision is postponed. In this section, these two parts are discussed in detail.

4.2.1. Component level agent functions

Agents on this level of the framework have a set of four functions. The first agent function is to import the prediction from the diagnostics and prognostics algorithm. Being assigned to one specific component, the agent will then use the input and its own information to determine the optimal maintenance action and moment for that time-step. Additionally, the component level agent determines whether the determine maintenance action should be planned now, or if the planning should be postponed. Lastly, if the agent decides to plan the maintenance action, it communicates to the coordinating group agent what the type, moment and costs are for the maintenance action.

The exact methods used for these functions can be found in the rest of this section.

4.2.2. Quality of maintenance

Based on [Martinod et al. \(2018\)](#), three types of results of maintenance actions are used. These results are shown in figure 4.4. $(1 - \alpha)$ is the factor that represents the reduction of the degradation level or the increase of reliability, and R represents the factor of reliability where $R = 1$ defines the as-good-as-new reliability.

- After as-good-as-new maintenance the reliability of the part is equal to the nominal value. This behaviour can be observed when a part is replaced with a new one. The effect on reliability is shown in figure 4.4a. $\alpha = 0, R = 1$
- Mostly however, a maintenance action will not fully restore the reliability to the nominal value, but to somewhere between the old and as-good-as-new state. Such an action can be called imperfect maintenance ([Van Horenbeek and Pintelon, 2013](#)). The effect is shown in figure 4.4b. $0 < \alpha < 1, \text{unchanged} < R < 1$
- Thirdly, when maintenance is performed without influencing the reliability of the component, as-bad-as-old maintenance is performed. This could be the effect of corrective maintenance, providing a ad-hoc solution to a problem without increasing reliability ([Martinod et al., 2018](#)). This is shown in figure 4.4c. $\alpha = 1, R = \text{unchanged}$

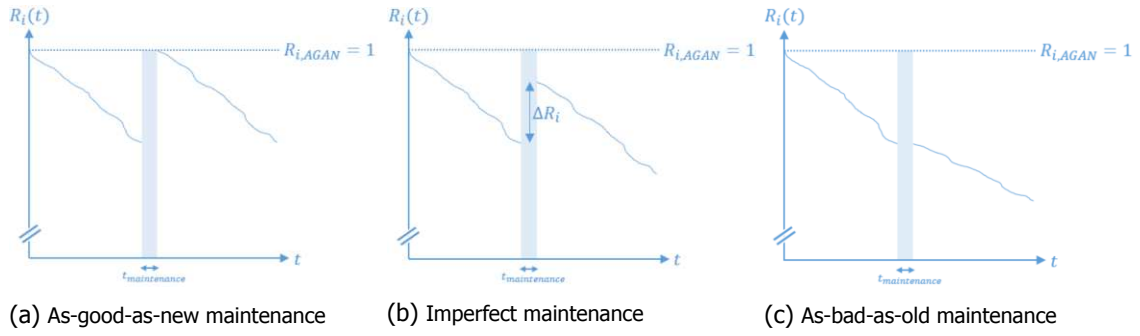


Figure 4.4: Different maintenance qualities

The quality of maintenance, resembled by the increase in reliability, depends mostly on two factors. These factors are a tactical factor and an operational factor. The tactical factor depends on the conditions of the maintenance, such as the type of maintenance. For example, major maintenance will have a more positive influence on reliability compared to a minor maintenance intervention. The operational factor, on the other hand, depends on the intervention itself. This factor can for example be influenced by the expertise of the engineer, tools that are used and the technical support given by the company.

For each maintenance intervention that is used in the prescriptive maintenance model, the value for α must be defined. When considering major and minor maintenance, in general $\alpha_{major} < \alpha_{minor}$. Namely, a major maintenance intervention should lead to a larger increase of reliability than a minor intervention. Considering this enables the agents to make long term decisions on the type of maintenance to be planned.

The definitions that were introduced in this section will be used in the simulation of the proposed maintenance framework, which will be discussed in chapter 5.

4.2.3. Optimizing maintenance moment and intervention

The optimization on component level to determine the appropriate maintenance intervention and the optimal maintenance moment is done using an economic approach. All possible effects of a maintenance strategy are modeled as costs, including costs such as the risk costs and costs of downtime. The equations shown in this section are based on [Verbert et al. \(2017\)](#), who proposed them for use in a prescriptive maintenance system for railway infrastructure. The equations – although slightly altered – can also be used for this research, as the multi-component approach is comparable.

The optimization of the maintenance type and moment are formalized as follows:

$$(a^*, t^*) = \arg \min (C_d(a, t) + C_i(a, t) + C_r(a, t)) \quad (4.1)$$

where $C_d(a, t)$ are the direct costs, $C_i(a, t)$ the indirect costs and $C_r(a, t)$ the costs associated with the risk of performing maintenance too late for maintenance intervention a performed at time t . The associated costs of optimal action and time (a^*, t^*) are:

$$costs = \min (C_d(a, t) + C_i(a, t) + C_r(a, t)) \quad (4.2)$$

If necessary, the algorithm calculates the costs of the possible maintenance actions on available maintenance times at each time-step. The maintenance action and time of the associated lowest overall costs are determined. These total costs are defined by the three costs components used in equation 4.2. Following the LCC-approach discussed in section 2.2.4, the maintenance costs are divided by the lifetime of the equipment. This means that postponing maintenance will make is less costly per unit of time.

Direct costs

The direct costs of the considered maintenance intervention depend mostly on the type of action. To translate these costs into the life cycle cost approach, where the life-time of the component is taken into account, the costs will be expressed as costs per unit of time. This is shown in equation 4.3.

$$C_d(a, t) = \frac{c_d(a)}{t + t_{main}} \quad (4.3)$$

where $c_d(a)$ are the direct costs of maintenance intervention a , t is the time of the maintenance moment counted from the decision moment and t_{main} is the time since the last maintenance intervention.

Indirect costs

Similarly to the direct costs, the indirect costs will also be expressed per unit of time. However, the indirect costs of a maintenance intervention depend on both the maintenance action and the moment. For example, when maintenance has to be performed during planned production, the costs related to downtime will be higher than outside of operation hours. This relation is shown in equation 4.4.

$$C_i(a, t) = \frac{c_i(a, t)}{t + t_{main}} \quad (4.4)$$

where $c_i(a, t)$ are the indirect costs of performing maintenance action a at time t .

Risk costs

The risk costs are divided in two parts, namely the risk of performing maintenance too late and the risk of performing the wrong maintenance action. These risks are combined in equation 4.5.

$$C_r(a, t) = \sum_{j \in \{1, \dots, n\}} P(H = f_j) \times p(t_{fail} < t | H = f_j) \times C_{fail,j} \quad (4.5)$$

where $P(H = f_j)$ is the probability mass function of the health state, $p(t_{fail} < t | H = f_j)$ is the chance that the component will fail before t , $C_{fail,j}$ the additional costs of failure of type j .

4.2.4. Optimizing planning moment

The second step of the component level optimization will optimize the moment that maintenance is planned. When an optimum is found in the previous step, this is done based on the information that is available at that time. It might be possible that with more accurate information another maintenance moment is more suitable. The trade-off between waiting for more information or planning ahead to avoid breakdowns depends on the risk and possible gains. This problem is stated as a markov decision process (MDP), of which an explanation can be found in section 2.5.2.

The state that is evaluated contains the information needed to decide whether to plan the maintenance or to postpone the decision and wait for more accurate information. The state is shown in equation 4.6 below.

$$state = [costs, Pf, ttf, t^*, a^*, D, F] \quad (4.6)$$

where $costs$ are the costs of the maintenance plan that is evaluated, Pf is the probability of failure at the considered moment, ttf is the predicted time to failure, t^* is the planned maintenance moment, a^* is the planned maintenance action, D is a variable that shows if maintenance is planned and F shows if the component has already failed.

The model will reconsider the planning moment until either D or F indicates that a terminal state is reached. The system level decision may reset the variable D , which would lead to the reactivation of the component optimization step. This creates the feedback from the system level to the component level.

4.2.5. Solving methods

To solve equation 4.1, equation 4.7 and the MPD discussed in section 4.2.4 above, multiple techniques could be used. Using the multi-criteria analysis in section 2.6.2, the reinforcement learning (RL) approach was chosen to solve the MDP. For the optimization of maintenance type and time a brute force approach was selected, as this is easy to implement, it will definitely find the best solution and the number of possible solutions is limited by the number of maintenance interventions and available time-slots.

To learn on the actions and find the optimal solution, the RL algorithm needs to solve the exploration versus exploitation trade-off. Exploration is done in the form of trying random actions, to discover the underlying MDP. Exploitation is following the optimal policy that the algorithm has found so far, to maximize its rewards.

The RL algorithm used in this case is Q-learning. This algorithm stores the policies that have been found so far in a Q-table, hence the name. The Q-table stores the value Q, which is the quality of an action for a specific state. The Q-value is updated each iteration step using the weighted average of the old value and the reward found in the new state. The weight of the old rewards compared the new rewards, which is called the learning rate, determines the trade-off between exploration and exploitation.

The MDP for this specific application is a finite Markov decision process. The horizon of the problem is the predicted failure moment, as the maintenance must be planned in advance or the component will fail. These two options are the terminal states as included in the system-state shown in equation 4.6. The rewards for reaching the terminal states are shown below. If no terminal state is reached, there is no reward for that step. Also, as a finite horizon is considered, future rewards are not discounted (Verbert et al., 2017).

- The reward for planning the maintenance moment is defined as the utility during the time between decision and maintenance, minus the costs of maintenance: $R = u_{t-t_0} - C^*$ for $D = 1$
- The reward for a failure of the component is a penalty, thus a negative reward specific for failure of the component: $R = -R_{penalty}$ for $F = 1$

In this case of prescriptive maintenance planning, before the failure or breakdown, the immediate reward is not always known. For example, the final reward of extending the life-time of a component will only be known when it's replaced. For that reason, reinforcement learning will be used to decide whether to plan or to postpone the decision on the component level.

4.2.6. Programming component agent functions

As discussed in section 4.2.5 above, a brute force approach is used to find the optimal values a^* and t^* in equation 4.1. This is programmed as follows:

The component level agents firstly assess what the optimal maintenance action is. Each maintenance action is linked to a predefined failure mode within the agent. For each failure mode, the agent reads the time-to-failure from the prognostic input. The agent determines which failure mode has the shortest time-to-failure by comparing them using temporary variables. The maintenance action that is linked to the failure mode with the lowest time-to-failure is selected as the optimal maintenance action a^* .

When the optimal action a^* is determined, the agent will find the maintenance moment t^* for which the costs are lowest. The agent calculates the costs for all possible maintenance moments and compares them using temporary variables. The maintenance moment with the lowest costs *costs* is selected as the optimal maintenance moment t^* . After determining these optima, the *state* used for the next step is updated with a^* , t^* and *costs*.

Following the optimization of the maintenance action and moment, a RL-approach will be used to decide whether to plan or to postpone planning. This is programmed as follows:

After reading the RL starting parameters and creating an empty Q-table, a predefined amount of episodes is simulated. Each episode contains a number of steps and is finite, as it will maximally run until the time of failure. Firstly, the start-state is stored as a temporary variable which is used for a single episode. In each step in the episode, an action is chosen that will be simulated that step. The two possible actions are to plan or to postpone. This choice will be made based on previous experiences, the learning rate and partly a random choice. Choosing an action will lead to a certain reward, depending on the consequences of that action. The Q-table will be updated after each step.

The episode will end if one of the two terminal states is reached. These terminal states are either failure of the equipment or a decision to plan the maintenance. After the running the predefined number of episodes, the best scoring action for that specific state will be chosen based on the scores stored in the Q-table. If the choice is to plan maintenance, the *state* will be updated.

4.3. System level

When the agent at the component level has decided to plan a maintenance intervention, this is communicated to the associated system level agent. This agent will consider this maintenance intervention on a system level, thus combining different component level decisions.

4.3.1. System level agent functions

The functions on the system levels are equal to each other, but different to the functions of the component level agents. The system level agents have a set of four functions. Firstly, they collect proposed maintenance interventions from the component level agents or lower level system agents. They calculate the system level costs of their sub-agents and check for overlapping or nearby maintenance interventions that are already planned. They then can challenge their sub-agents to reconsider the maintenance options. Lastly, the system level agents communicate their optimal planning to a higher level system agent or to a user interface.

These functions will be discussed in detail in the following sections, including the precise methods.

4.3.2. System level optimization

When optimizing on the system level, not the actual result of the minimization of the system level costs is of most interest, but how this minimum is achieved. Therefore the goal is to find the input arguments of the minimum, which is the set of maintenance actions X for which the total costs on system level

are lowest. Equation 4.7 is used to find the arguments of the minimum. Only the actions that have not been planned yet are subject to minimization. The equations used in this section are based on Verbert *et al.* (2017).

$$X_{opt} = \arg \min_{X_{proposed}} C_{SL}(X_{proposed}, X_{fixed}) \quad (4.7)$$

where:

- X_{opt} is the set of optimal maintenance actions for the whole system;
- $X_{proposed}$ is the set of maintenance actions for the components that are proposed but not yet planned;
- X_{fixed} is the set of maintenance actions that have already been planned.

4.3.3. System level costs

To reach the minimal total cost on the system level, the system level costs C_{SL} will be minimized. C_{SL} for a strategy X is defined in equation 4.8.

$$C_{SL}(X) = C_0(X) - C_{EOS}(X) - C_{DT}(X) + C_{LF}(X) \quad (4.8)$$

This includes the total costs of all separate component maintenance costs, the economies of scale advantage, the downtime costs and a term that incorporates functionality losses. These components are discussed in the following paragraphs.

4.3.4. Individual costs

The total costs of all individual maintenance interventions of n components combined will form the basis of the system level costs. The total individual costs are shown in 4.9.

$$C_0(X) = \sum_1^n C_{l,ind} \quad (4.9)$$

4.3.5. Combined costs

In addition to the individual maintenance costs, components that are part of one system will have influence on each other. For the case of maintenance costs this influence can be determined in three parts, namely the economies of scale, combined downtime costs and costs of loss of functionality.

Economies of scale

The direct maintenance costs at component level are split into three parts to be able to add the effect of economies of scale.

$$c_d(a) = c_{d,1}(a) + c_{d,2}(a) + c_{d,3}(a) \quad (4.10)$$

In equation 4.10, the first part $c_{d,1}(a)$ equals the direct costs of maintenance per component that do not depend on economies of scale. $c_{d,2}(a)$ are the costs that can be shared between the components that undergo the same maintenance action a at the same moment. And lastly, $c_{d,3}(a)$ are the costs that can be shared between all components that are maintained at the same time, even if the maintenance actions are different.

$$C_{EOS}(X) = \sum_{l \in T} \sum_{a \in A} \beta_{1,(a,t)}(X) c_{d,2}(a) + \sum_{l \in T} \beta_{2,t}(X) c_{d,3} \quad (4.11)$$

Equation 4.11 shows the economies of scale advantages, where $\beta_{1,(a,t)}(X)$ is the number of components (minus one) on which maintenance action a is performed at time t for strategy X , and $\beta_{2,t}(X)$ is the number of components (minus one) on which maintenance is performed at time t for strategy X .

Combined costs of downtime

To calculate the costs of induced downtime, the indirect costs per component are also split into two parts, see equation 4.12.

$$c_i(a) = c_{i,1}(a) + c_{i,2}(a) \quad (4.12)$$

The first part $c_{i,1}(a)$ includes the indirect costs related to downtime, and $c_{i,2}(a)$ includes other indirect costs that may be applicable. The costs on system level of downtime loss can then be defined, shown in equation 4.13.

$$C_{DT}(X) = \sum_{t \in T} \beta_{2,t}(X) c_{i,1}(t) \quad (4.13)$$

Combined costs of loss of functionality

When the simultaneous maintenance of multiple components induces additional loss of functionality, these costs should also be involved in the optimization. For example, maintaining a back-up machine while the primary machine is already being maintained will lead to loss of functionality. This effect can be incorporated into the optimization by grouping components. If only components of a single group are maintained, no additional loss of functionality will be present. This is shown in figure 4.14.

$$C_{LF}(X) = \sum_{t \in T} f_{LF}(\mathbf{X}_t(X)) \quad (4.14)$$

In this equation f_{LF} is the penalty cost function for a set of groups $\mathbf{X}_t$ that are subject to maintenance at the same time.

4.3.6. Solving methods

To select the solving method used in the system level optimization the same multi-criteria analysis was used as in section 4.2.5. As the number of maintenance interventions that will be evaluated is relatively low, a brute force approach will also be used for this optimization.

4.3.7. Negotiation

For each new entry of a component level decision, the system level determines the system level costs. It can be the case however that changing the time of maintenance on component level would cause a local cost-increase, but decrease the costs at system level. For this reason, negotiation is possible between the agents on component and system level.

What will be the optimal decision depends on the system dependencies of each component. These dependencies are discussed and shown in figure 3.8.

The system level agent will challenge the component level agent to perform maintenance on the nearest, already planned, maintenance moment or alternatively just outside the planned maintenance moment. This could lead to a cost decrease because of economies of scale, or a costs increase due to loss of functionality. Of these situations, the optimal value will be used and added to the fixed set.

4.3.8. Programming system agent functions

This section explains the programming of the system level agent functions. When calculating C_{SL} , the equations 4.9 to 4.8 are used such as described in section 4.3.2.

The system level agent will be active if a new maintenance action is proposed by a component level agent. Firstly, the proposed time and duration of the maintenance action is read. The system level costs C_{SL} are calculated based on the prior and new information, and stored as a temporary variable. Next, the component level agent is challenged to calculate the individual costs for two other moments. These two moment are the closest maintenance moment in the list of planned maintenance X_{fixed}

and, if there already is overlap with another maintenance action in this list, just outside that other maintenance action.

When the component agent returns the individual costs, the C_{SL} for these options are calculated and compared to the stored value. The action that leads to the lowest overall C_{SL} will be selected and added to the X_{fixed} list. This process is repeated every time a component level agents proposes a new maintenance action to be planned.

5

Case study

The goal of this chapter is to demonstrate the functioning of the proposed framework and to show improved performance compared to currently used methods. A hypothesis has been constructed to assess the framework based on selected of KPIs. To test the hypothesis, a simulation model of the framework is designed and verified. The simulation model is based on a real life system used by Heineken at one of its production locations. The results of the simulations will be shown and discussed at the end of this chapter.

5.1. KPIs

The success of a maintenance strategy or concept depends on specific business requirements and the production system itself. To be able to measure the performance of maintenance, relevant key performance indicators (KPIs) should be identified and used ([Komonen et al., 2010](#)). In this section the KPIs are discussed which are used in this case study. An overview of KPIs used in a maintenance context was discussed in section [2.3](#).

When comparing the simulation of a new maintenance strategy to actual performed maintenance, the process indicators cannot be used as real KPIs. The simulation of a new strategy will use a different approach, directly leading to a change in the process. On the other hand, the result indicators that are produced by a simulation can give a good view of the implications of such a new strategy.

The result indicators are divided into three parts, namely equipment effectiveness, maintenance costs and safety, health and environment (SHE). Of these three, the first two can be accurately produced by a simulation, as the SHE indicators can also depend on specific situations, equipment use and operator experience. For that reason, equipment effectiveness and maintenance costs are considered to be appropriate KPIs to assess the performance of a new maintenance strategy. The next two sections describe methodologies used for these KPIs.

5.1.1. Overall Equipment Effectiveness (OEE)

OEE is used by TPM to measure the performance of equipment. OEE is computed by using equation [2.1](#) and reducing the 100%-scores that a system theoretically has by subtracting the 'six big losses'. These six losses are:

1. equipment failure
2. set-up and adjustment
3. idling and minor stoppages
4. reduced speed

- 5. defects in process
- 6. reduced yield

where the first two are availability losses, the second pair are efficiency losses and the third pair are quality losses (Waeyenbergh and Pintelon, 2002).

5.1.2. Maintenance costs

The financial indicators for a successful maintenance system can be looked at from different perspectives. The reduction of unexpected breakdowns decreases the normally expensive emergency repairs. Increased operational time would have a positive effect on the production. Maintenance staff would be more able to actually do maintenance when the planning is taken out of their hands. Reducing maintenance intervals/unnecessary repairs would decrease maintenance costs and spare part costs. Therefore, in this case study, the average life cycle costs are taken into account to compare the base case to the simulation of the proposed framework.

5.2. Hypothesis

The goal is to assess the performance of the proposed maintenance framework compared to the performance of the current maintenance concept. The performance will be measured using the two selected KPIs, namely OEE and life cycle costs. This leads to the following hypothesis:

If the proposed maintenance concept is implemented at Heineken, it will increase the OEE and reduce the life cycle costs for the selected equipment type.

The hypothesis will be tested in this chapter using a simulation model for the equipment type that is discussed in the following section.

5.3. Background

The system that is considered in this case study is the cooling system of one of Heineken's production locations in the United Kingdom. Heineken is one of the largest beverage production companies and the second largest beer producer worldwide. This section includes some background of the production site where the equipment is located and a description of the equipment itself.

5.3.1. Production site

The cooling system that is used for this case study is located at the Bulmers Cider Plant in Hereford, UK, which is one of the production locations of Heineken UK. To show that currently no successful maintenance strategy is used at this specific site, some background is given on the maintenance maturity of this production facility.

Heineken differentiates three levels of maturity in maintenance to classify production facilities. These three levels can be characterized by three measures, namely asset condition, asset performance and maintenance costs. The relation between these measures and levels is visualized in figure 5.1.

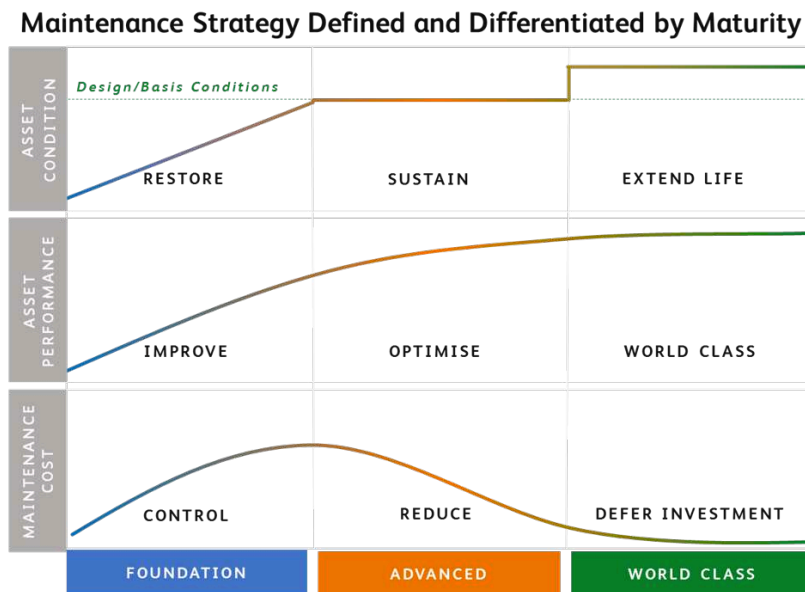


Figure 5.1: Maintenance maturity levels used by Heineken

Table 5.1 below shows some characteristics of this specific plant, for the period of July 2017 to June 2018. These numbers indicate that the maturity of the maintenance strategy in Hereford is in the

[illegible]

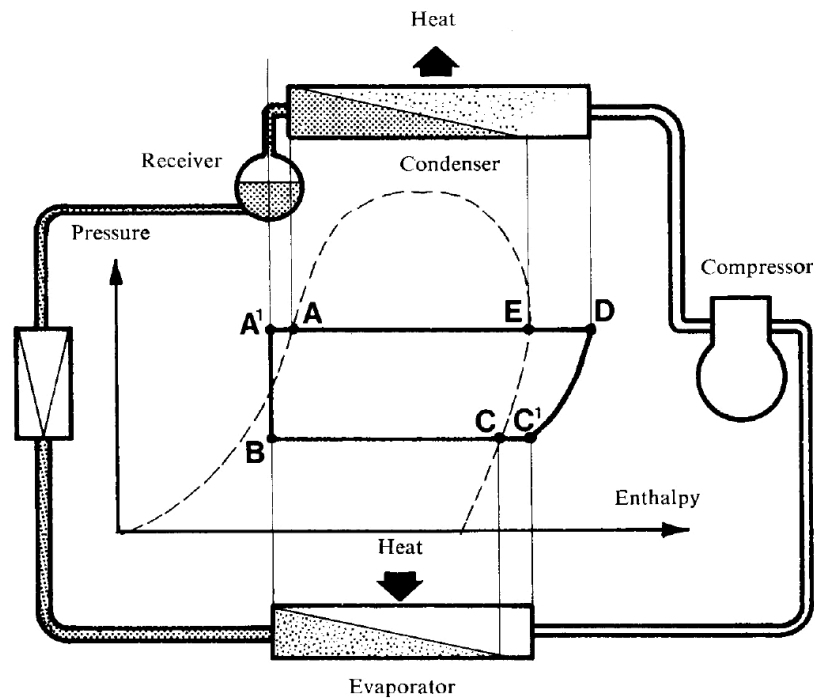


Figure 5.2: Vapor-compression refrigeration cycle

A vapor-compression system consists of four main parts, namely a compressor, a condenser, an expansion valve and an evaporator. The heat is extracted from a connected system by the evaporator, and transferred to another by the condenser.

In the case used for this research, the cooling system consists of three compressors, two condensers, one expansion valve and two heat exchangers acting as evaporators. The piping and instrument diagram (P&ID) can be found in figure B.1 and a more detailed view of the compressor system can be found in B.2, both in appendix B. A very simplified version of the P&ID is shown in figure 5.3.

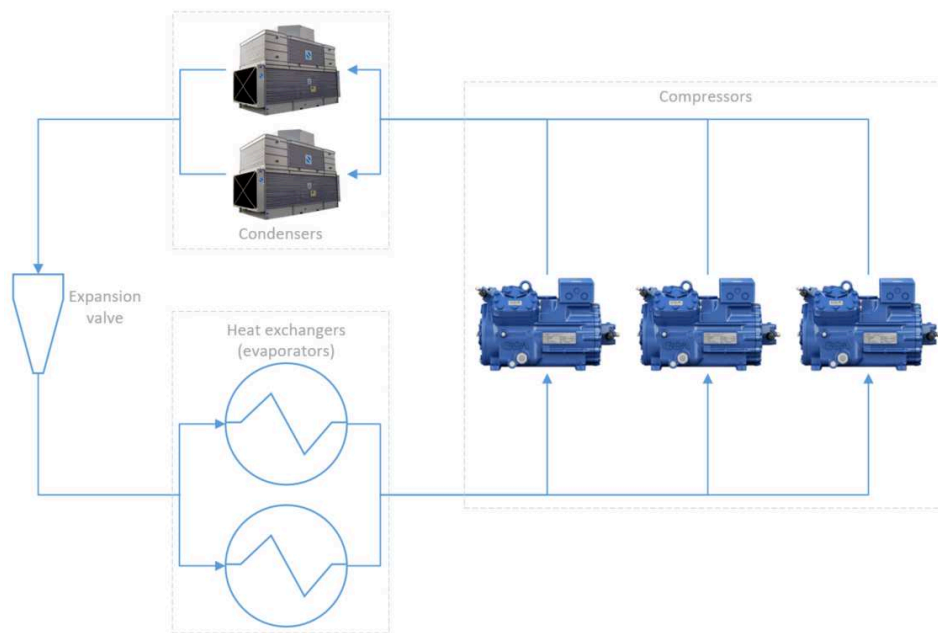
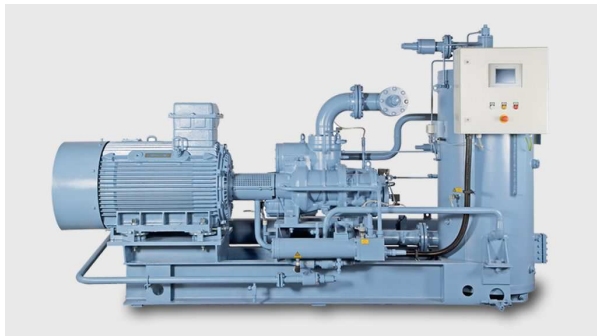


Figure 5.3: Simplified P&ID of the cooling system

To show the modular approach of the maintenance decision framework, the three ammonia compressors of the cooling system will be used as components in the multi-component system. The suitability of these machines for this case study will be discussed in section 5.3.3.

The three ammonia compressors used in cooling system in Hereford are all GEA Grasso SP1 TB-5. The specifications of these compressors can be found in figure 5.4b. Apart from the screw compressor itself, the compressor package consists of an electric motor and a lubrication system with an oil pump, cooler and separator. An impression of the packages used in Hereford can be found in figure 5.4a.



(a) Impression of SP1 compressor package

Grasso SP1 T-5A compressor unit specification (Phase 1)

	Design Conditions	Average Conditions
Compressor	SP1 TB-5A	SP1 TB-5A
No. of compressors	3	3
Refrigerant	R-717	R-717
Design evaporating temp.	-6°C	-6°C
Design condensing temp.	+32°C	+20°C
Operating speed r.p.m.	3600	3600
Duty	1540 kW	1269 kW
Power consumption	307 kW ¹⁾	210 kW ¹⁾
COP	5.0	7.45
Dimensions(LxWxH)	3500 x 1500 x 2000 mm	3500 x 1500 x 2000 mm

1) The given power consumption is the compressor shaft power consumption only and does not include losses in motor and electrical panel.

(b) Specifications of SP1 TB-5

Figure 5.4: GEA Grasso SP1 impression and specifications (Southern Sales and Service Ltd., 2018; Grenco Refrigeration Ltd., 2008)

Also the condensers will be used in this case study to show the scalability of the framework with different equipment types. The suitability of these condensers for this case study was checked in the same way as for the compressors in section 5.3.3. An impression and the specifications can be found in figure 5.5.



(a) Impression of a CXV evaporative condenser

BAC Condenser Specification

Duty (each)	2070 kW
Quantity	2
Manufacturer	BAC
Model	CXV-481
Design Wet bulb temp.	+21°C
Design Condensing temperature	+32°C
Fan power consumption	3 x 11 kW
Water pump power consumption	1 x 4.5 kW
Pan heater	1 x 8 kW
Unit dimensions (LxWxH)	5520 x 3610 x 4790 mm
Unit operational weight	14150 kg

(b) Specifications of BAC CXV-481

Figure 5.5: BAC CXV evaporative condenser impression and specifications (BAC, 2011; Grenco Refrigeration Ltd., 2008)

5.3.3. Requirements

To be suitable for use in this case study, the system and included equipment have to comply to a number of requirements:

- The system should have the complexity of a multi-component system, by contain components that are interdependent in some way
- The system should be or consist of one or more critical equipment type(s) (e.g. failure leads to production loss, safety or environmental hazard)
- The system should have a clear current maintenance strategy and expenses, enabling an accurate comparison between current situation and simulation

The following sections will show the systems compliance to the set requirements.

System complexity

As can be seen in the overview in figure 5.3, this system consists of multiple components which are operationally dependant on each other. The three identical ammonia compressors are placed in parallel, and are attached to the same input and output pipes, connected to the heat exchangers and the condensers respectively. The compressors are defined as being a component in a larger system which is the cooling system.

The compressors each consist of a set of maintainable items that can cause a failure and could require maintenance. SINTEF (2002) listed these items in the Offshore Reliability Data Handbook (OREDA), which is shown in figure 5.6.

COMPRESSOR					
Power transmission	Compressor unit	Control and Monitoring	Lubrication system	Shaft seal system	Miscellaneous
• Gearbox • Bearing • Seals • Lubrication • Couplings • Instruments	• Antisurge system • Casing • Cylinder liner • Instruments • Shaft seals • Radial bearing • Thrust bearing • Interstage seals • Valves & piping • Piston⁴ • Packing • Rotor w/impellers	• Instruments • Cabling, junction box etc. • Control unit • Actuating device • Monitoring • Internal power supply • Valves	• Reservoir w/heating system • Pump w/motor • Filter • Cooler • Valves & piping • Oil • Instruments • Seals	• Buffer gas system • Dry gas seal • Instruments • Overhead tank • Reservoir • Scrubber • Pump w/motor/gear • Filter • Valves • Seal gas • Seal oil	• Base frame • Cooler • Valves • Magnetic bearing control system • Piping • Purge air • Silencers

Figure 5.6: Maintainable items of a compressor (SINTEF, 2002)

SINTEF (2002) also defined a list of failure modes for compressors, including associated average repair times. This list was based on data of 131 industrial type compressors, sampled for an aggregated operational time of 2.4253×10^6 hours. When plotting the frequency of failures to the associated repair times, shown in figure 5.7a, a FMCG-like 'two-peak' shape can be seen. In this graph, in which emergency repairs have been ignored, it is seen that roughly two types of plan-able maintenance interventions can be distinguished. These two types of maintenance interventions, namely minor and major maintenance, will be used for this case study. The average repair times for these interventions

are 4 hours and 18 hours respectively.

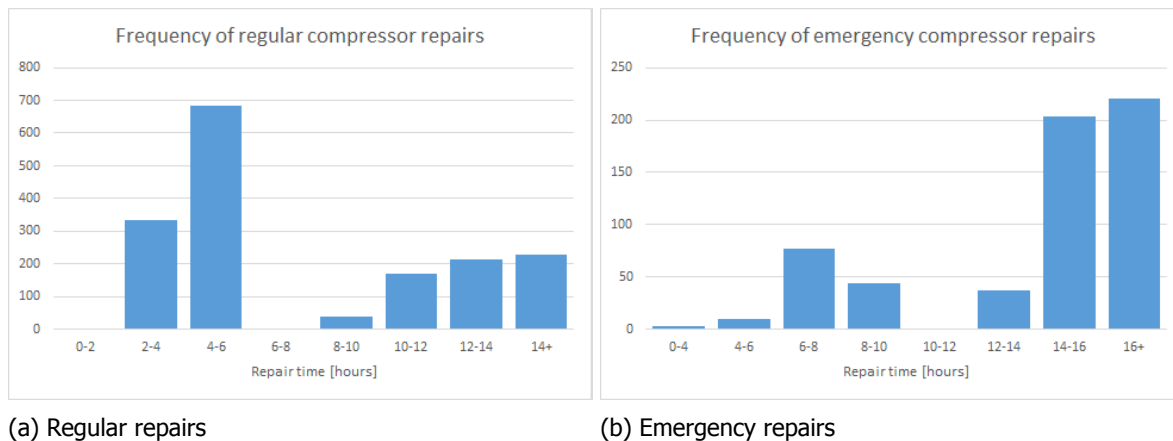


Figure 5.7: Frequency of compressor repairs versus repair time

Critical equipment analysis

The site in Hereford uses, like many production companies, the ABC-analysis for criticality assessment of equipment. Factors that are taken into account in the ABC-analysis include health & safety, environment and product quality. This analysis results in a classification of the equipment in one of three classes of failure seriousness. These classes are:

- A; failure could lead to critical situations
- B; failure will lead to moderate issues
- C; the effects of the failure will be negligible

Firstly, all factors are independently evaluated, as shown in table 5.2. The highlighted effects could be the result of a failure of the ammonia compressors at the Hereford site. Then the flowchart shown in figure 5.8 is followed to result in the final equipment classification. This specific equipment type is classified in category A, which defines it as a critical equipment type.

Risk category	A	B	C
Environment	External impact	Internal impact	No impact
Safety	Death or permanent	Temporary or disease	No accidents
Quality	Customer perceived	Batch rejection	No impact
Working time	24 hours/day	8-24 hours/day	< 8 hours/day
Delivery	Whole plant	Production line	No impact
Frequency	Higher than average	0.7 – 1× average	< 0.7× average
Maintainability (MTTR)	Longer than average	0.7 – 1× average	< 0.7× average

Table 5.2: Risk classification per category for the ABC rating

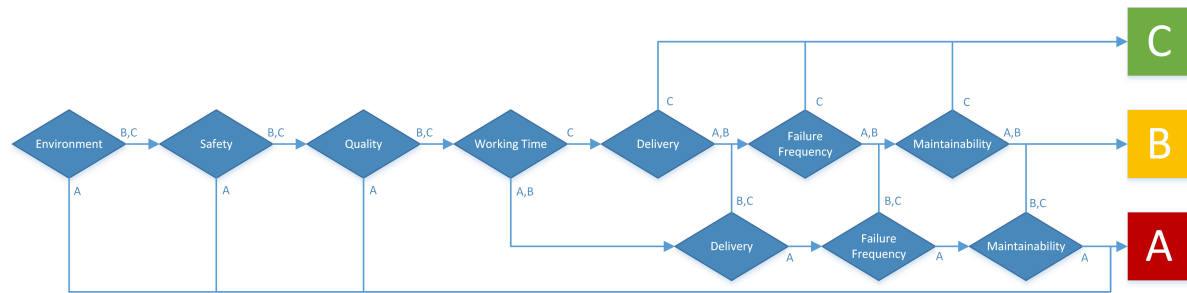


Figure 5.8: ABC rating flowchart

Current level of maintenance

Currently, for the selected equipment type a preventive maintenance system is in place. The equipment manufacturer supplied suggested planned inspection and maintenance intervals, as can be seen in figure 5.9. The maintenance department strives to comply to this suggestion. In any case the annual overhaul is planned during the full stop of the production facility each January.

EQUIPMENT	INSPECTION / MAINTENANCE	UNDERTAKEN	FREQUENCY	ATTENTION
Compressor & System	Operational Inspection	Operators	Daily (to 72 hours max)	Pressure & Temperature
				Logs. Noise & Vibration
	Major Inspection/ Maintenance	Operators or maintenance specialist	3 Monthly	Drive & guard condition
			6 Monthly	Check operation of safety cut outs
				Check drive alignment
		Maintenance specialist	Annually or to manufacturer Recommendations.	Check foundation bolts
				Top and/or bottom overhaul & maintenance.

Figure 5.9: Suggested periodic inspection and maintenance by manufacturer

The daily operational inspections do not require shutdown of the equipment, whereas the other inspections do require turning of the machine.

Next to the planned maintenance, some unplanned maintenance has to be performed when the compressor system fails or indicates a fault. Diagnostic analytics are performed after some of these failures to find their cause. This is currently the highest level of intelligence used in the maintenance planning for the ammonia compressors.

5.4. Simulation setup

This case study follows the steps shown below to create a trustworthy simulation and accurate results:

1. Definition of the scope and simulation model for the specific case of the cooling system discussed in this case study, shown in section 5.4.1 and 5.4.2.
2. Input of diagnosis and prognosis for the simulation, shown in section 5.5.1.
3. Compare system response for different time-step sizes to verify that the simulation approximates the model. Determine how parameters influence the results. Shown in section 5.6.
4. Comparison of the simulation results to actual the actual situation, shown in section 5.8.

5.4.1. Scope of simulation

For this specific case study, the model that is proposed in this thesis is fitted to the cooling system of the Bulmers Cider Plant. An overview of this model is shown in figure 5.10. This model contains the compressors and condensers of the cooling system discussed in section 5.3.2. The structural and process dependencies can be viewed in the P&ID in figure 5.3 and appendix B for more detail.

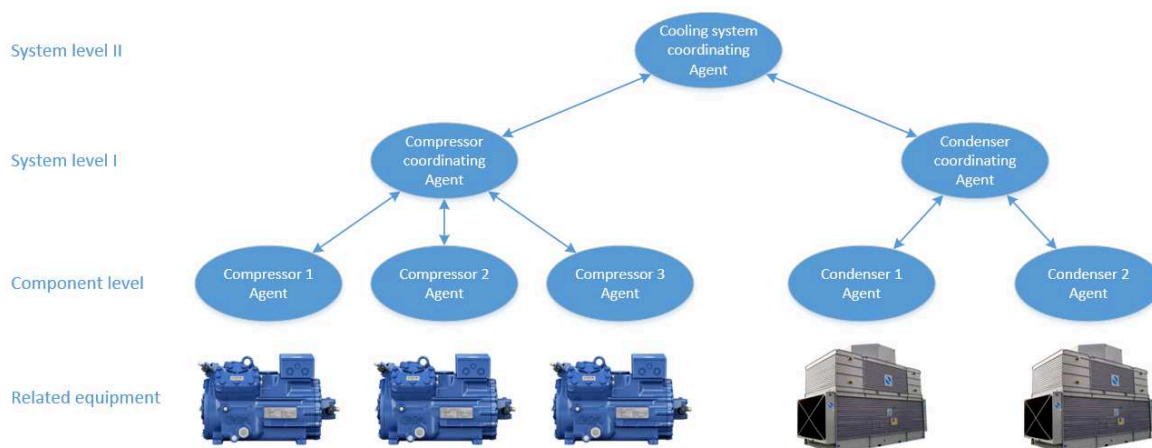


Figure 5.10: Framework for prescriptive maintenance of the cooling system

From the process functions of the different components two groups can be defined that are suitable for this case study. The compressors are grouped, as simultaneous maintenance of two or more compressors will lead to system downtime. For the condensers, simultaneous maintenance could also lead to system downtime.

5.4.2. Simulation model

Winsberg (2018) defines a computer simulation as a program that uses a step-wise approach to re-search the behaviour of a mathematical model. The step-wise approach is programmed in the way shown below, in the form of a discrete-time simulation model. The mathematical model is contained by the agents on component and system level, as discussed in sections 4.2.3 and 4.3.2 respectively.

Firstly, the system and component agents are named and the individual input parameters are defined. The time-step size for the simulation is selected, where each step represents a moment that maintenance can be planned. The simulation is performed by looping through all the steps, the number of which will be 1 year divided by the time-step size. Each step, the system and component agents are activated with a step-command. These step-commands on agent level are shown below. After the simulation, the run time and costs are stored for analysis.

Component level step

Each step the component level agents are activated. When the step-command is called, the agent firstly reads the input containing the probability of failure of its component for that time step. In the simulation, this diagnostic information is stored in a .csv-file for each agent separately. The exact contents of the .csv-file and the generation of a prognosis are discussed in section 5.5.1.

Using the diagnosis and prognosis input, the agent functions discussed in section 4.2.6 are performed. When a major maintenance intervention is performed, it is assumed that the component is restored to a as-good-as-new state. For minor maintenance actions, imperfect maintenance is assumed with $\alpha = 0.1$, which means that the quality of maintenance is 90%. This methodology is explained in section 4.2.2.

If maintenance is already planned but not yet performed when the step-command is called, the agent will wait for the maintenance intervention without planning a new maintenance moment.

System level step

Each step also the system level agents are activated. When activated, the system agent firstly updates the available maintenance moment according to the time-step size and a predefined maximum value. This makes sure that no maintenance actions are planned too early or too late. This is followed by the system level agent function discussed in section 4.3.8.

If no new maintenance action is proposed by any of the component level agents, the system level agent will perform no action when the step-command is called.

5.5. Model input

To be able to run the model, multiple categories of input are needed. First of all, the diagnostics and prognostics of the component degradation are needed. Additionally, for each component or system a set of cost functions has to be defined. This section discusses the used inputs for the model and the associated sensitivity of the model.

5.5.1. Diagnostics and prognostics

Input from the component diagnostics for the model should include the current health state of the component regarding the possible failure modes. These depend on the chance that the correct failure mode is selected and what the implications are of that failure mode. The prognostics consist of a prediction of the remaining useful life for the component, based on the health state.

For the means of this simulation, this input is slightly different than what it would be when the model is fully implemented in a production environment. The input for the simulation consists of a list with probabilities of failure for a specific time step. This list is structured as shown in table 5.3.

Step	Pf_{minor}	Pf_{major}
0	0.00	0.00
1	0.01	0.00
2	0.02	0.00
3	0.01	0.00
n	$Pf_{minor}(n)$	$Pf_{major}(n)$

Table 5.3: Probability of failure input for both failure modes

For this simulation, the input from the probability of failure is used to determine the time-to-failure which is used as the remaining useful lifetime. This time-to-failure will only be considered if the failure probability is above a preset limit, to prevent unnecessary computation of inaccurate predictions. The time-to-failure will be predicting using a degradation model. Such a model can be learned from previous experiences of failures. For this research, two degradation models will be considered. These two degradation models are an exponential, shown in figure 5.11a, and linear, shown in figure 5.11b.

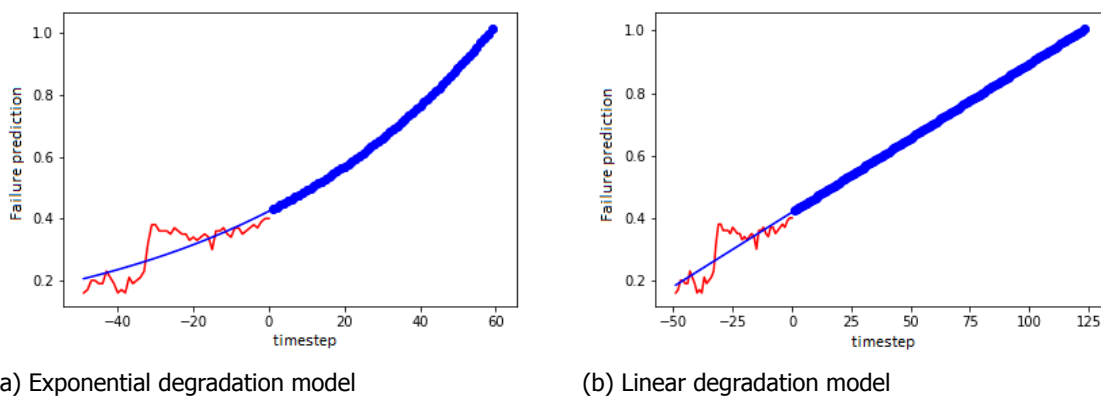


Figure 5.11: Two different degradation models at the same time step

Both these degradation models are compared to the real failures to assess the suitability for this specific equipment type. This comparison is shown in figure 5.12. It can be seen that the exponential degradation model performs better than the linear model, with a mean error of 22 steps versus 56 and a much larger deviation. Therefore the exponential model will be used for this case study to predict

the remaining useful life.

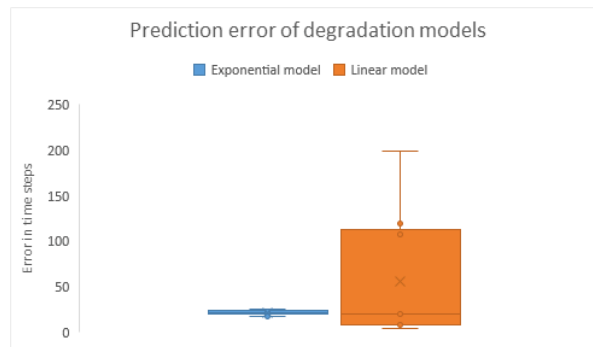


Figure 5.12: Comparison of degradation models

5.5.2. Cost functions

The cost functions can be split in a set for component level costs and a set for system level costs.

- Cost of failure C_{fail} for each failure mode
- Cost of wrong maintenance decision C_{wrong} for each failure mode
- Direct and indirect maintenance costs per maintenance action ($c_d(a)$ and $c_i(a)$, split into the necessary parts 1, 2 (and 3)). *Direct costs* consist of the spare-part costs, material costs (e.g. detergent, lubrication) and the personnel costs (duration of maintenance x wage x people). *Indirect costs* consist of costs related to downtime and write-off of maintenance equipment.
- Plan or postpone parameters (maximum utility u_{max} , discounting rate δ and failure penalty α)
- The cost function for loss of functionality f_{LF} (system level)

Failure costs

The direct costs largely consist of two parts, namely personnel costs and material costs. The hourly personnel costs for maintenance are based on the median hourly contract costs for maintenance technicians in the United Kingdom defined by [National Careers Service \(2018\)](#), namely €39/hour.

For failures, the costs are not equal to the planned maintenance costs. As can be seen in figure 5.7b, the repairs on average cost more time. Also material costs could be higher due to emergency deliveries of spare parts, but for this example the spare parts are assumed to be in stock. The costs of failure are shown in table 5.4.

	Failure requiring minor intervention	Failure requiring major intervention
Total costs	€1483	€3462
Material costs	€1171	€2643
Personnel costs	8 hours × €39/hour = €312	21 hours × €39/hour = €819

Table 5.4: Failure cost specifications per failure

Maintenance costs

The indirect maintenance costs – the costs related to downtime – do not depend on the time of day in this case, as during the 24-hour operation the downtime costs are constant. For this specific system, downtime of a single compressor will not directly impact the production process. However, when two or more compressors are down at the same time, production will be influenced. This can be included in the model as loss of functionality f_{LF} . The costs of one hour of lost production time is calculated using the average revenue per hectoliter multiplied by the average produced volume per

The costs for planned maintenance are shown in table 5.5.

	Minor maintenance intervention	Major maintenance intervention
Direct costs	€1327	€3345
Material costs	€1171	€2643
Personnel costs	4 hours × €39/hour = €156	18 hours × €39/hour = €702
Indirect costs	€0	€0
Downtime costs	4 hours × €0/hour = €0	18 hours × €0/hour = €0

Table 5.5: Maintenance cost specifications per intervention

5.5.3. Reinforcement learning

The input parameters for the reinforcement learning algorithm, that is used to solve the MDP, discussed in section 2.6.2 are shown in table 5.6. The penalty is the monetary cost of a major failure, the utility equals the avoided personnel costs, which are calculated per hour, and the learning rate is defined as 0.99 to stimulate exploration. A detailed explanation of the learning rate is given in section 2.6.2.

Parameter	Value
Utility u	39
Penalty $R_{penalty}$	3462
Learning rate	0.99

Table 5.6: Input parameters for reinforcement learning

5.6. Verification

To be certain that the simulation results approximate the theoretical results of the model, the simulation model has to be verified. This can be done by checking whether and at what rate the output of the simulation converges to a stable solution as the time steps are decreased in size, so the discretization resolution gets finer (Winsberg, 2018).

For this purpose, simulations are done using time-step sizes of 60, 30, 15, 10 and 5 minutes. For these different time-step sizes the total individual costs C_0 and 95% confidence interval are determined using Student's t-distribution. As can be seen in table 5.7, 10 simulation runs provided a stable solution for all these step sizes, with increasing stability for smaller time-step sizes. Therefore it is assumed that the model will provide stable results for other step sizes as well, in the same trend. The confidence interval (CI) is used as shown in equation 5.1, and means that for 95% of new measurements the true mean is expected to be inside the given interval.

$$Pr(\text{Sample Mean} - CI < \mu < \text{Sample Mean} + CI) = 0.95 \quad (5.1)$$

Time-step size [min]	95% confidence interval [%]
5	3.9 %
10	4.4 %
15	4.6 %
30	4.9 %
60	4.1 %

Table 5.7: 95% Confidence interval of C_0 for different time-step sizes

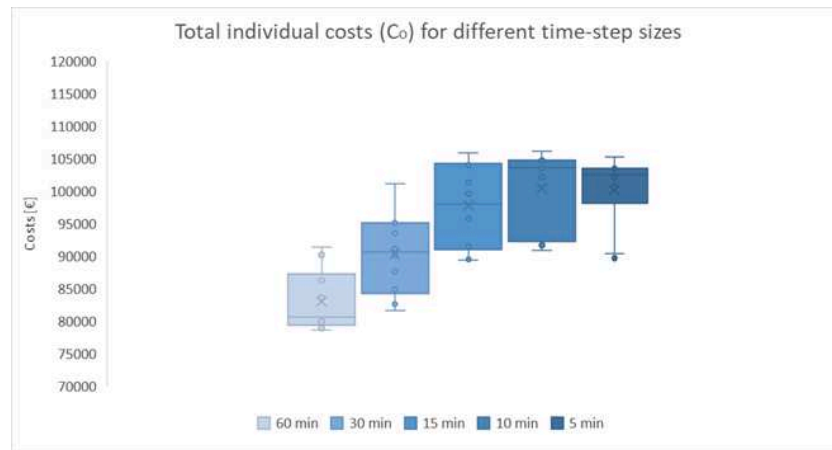


Figure 5.13: C_0 results for simulations with different time-step sizes

When looking at the results for the total individual costs, it can be observed that the costs converge when the step size is decreased. Using the definition of Winsberg (2018), it can be assumed that the simulation model approximates the solution of the mathematical model. This convergence can be attributed to the fact that more maintenance actions are rescheduled, which leads to higher individual costs, but lower loss of functionality. To prove this, the costs due to loss of functionality are shown in figure 5.14.

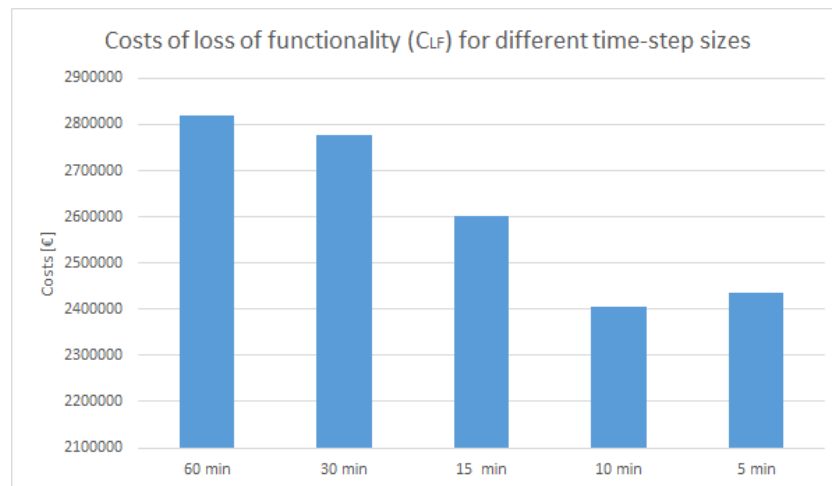


Figure 5.14: Costs of loss of functionality for different time-step sizes

The run time of the simulation on the other hand increases when the step size is decreased, which can be attributed to the increased number of needed computations. This is shown in figure 5.15. But it should be noted that the run times for the smallest step size is still acceptable for this simulation at an average of 290 seconds.

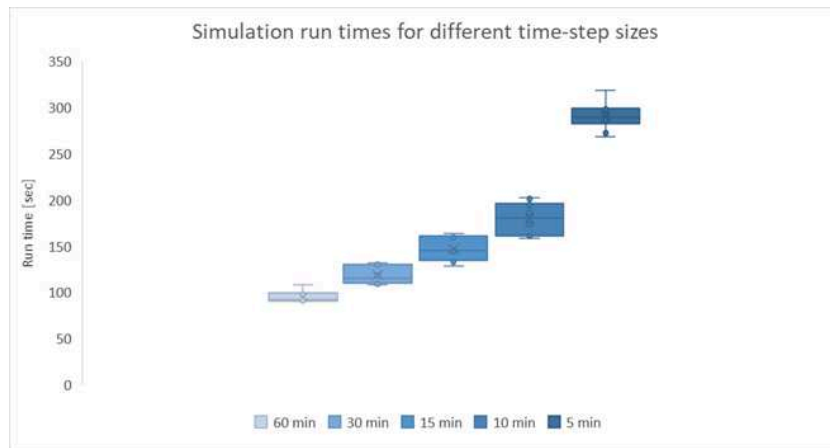


Figure 5.15: Simulation run times for different time-step sizes

5.7. Base case

To be able to compare the results from the simulation to the current situation, a base case was defined. This base case shows the actual performance of the system during the period of 01-07-2017 to 01-07-2018. Figure 5.16 shows the supply of current to the three compressors to visualize the operation of the system in total. The trend of the operation of the ammonia compressors is visualized with the red-dotted line.

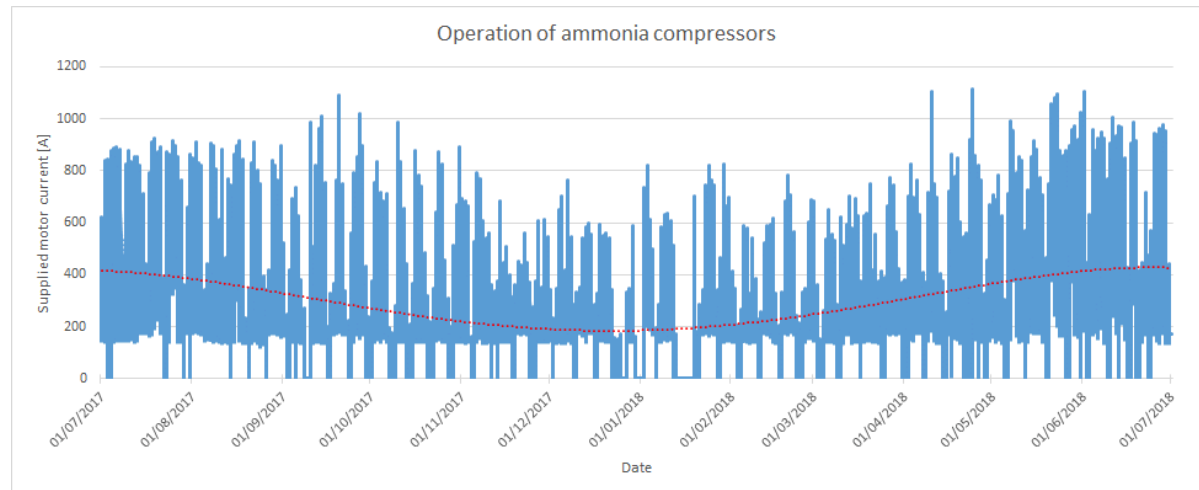


Figure 5.16: Operation of the compressor system

The trend-line shows a seasonal pattern, which can be attributed to two main aspects. Firstly, the production demand is lower in winter and therefore less cooling is required. And secondly, the average temperature in the UK is lower in winter, which also results in less energy consumption of the cooling process. In this off-season, a yearly full stop of the plant is scheduled for large maintenance activities. Also, during the holidays the employees have some time off.

Therefore, no production was planned during Christmas, New-Years Day and during a planned stop of the whole plant between 14-01-2018 and 19-01-2018. Downtime during these periods is not considered to have effect on the revenue, and will therefore be excluded in the downtime costs calculation in table 5.8. This table shows the downtime hours of planned and unplanned maintenance for both the whole system as individual compressors. As can be seen, the failure of individual compressors did not lead to any downtime costs.

Downtime costs		Duration [hours]	Costs
System	Planned	28.4	€1,177,000
	Unplanned	7.5	€311,000
Individual	Planned	137.0	€-
	Unplanned	78.4	€-
Total costs			€1,488,000

Table 5.8: Total downtime costs of the ammonia compressors in Hereford (excluding non-production days)

The direct costs of maintenance for the ammonia compressors in Hereford are shown in table 5.9.

Maintenance costs	Interventions	Costs
Planned	21	€41,993
Unplanned	15	€26,203
Total		€68,196

Table 5.9: Total maintenance costs of the ammonia compressors in Hereford

The OEE for the ammonia compressors in the selected period is shown in table 5.10. The approach discussed in section 5.1.1 was used.

Equipment	OEE [%]
Compressor 1	96.0
Compressor 2	96.3
Compressor 3	96.4
Average	96.3

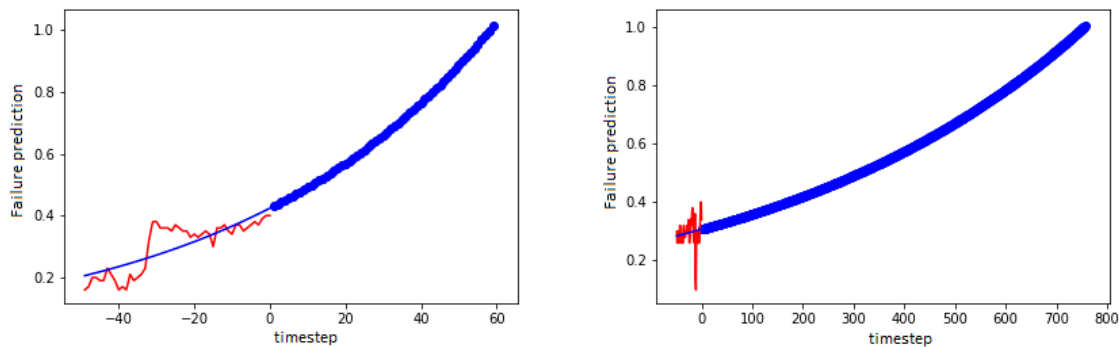
Table 5.10: OEE for the ammonia compressors in Hereford

5.8. Results and discussion

This section shows the results of the simulation of the framework. A breakdown is shown of two individual situations to clarify the functioning of the framework and discuss the differences between the situations. For this case the step-size was five minutes, so every five minutes the prediction is updated and maintenance can be planned.

5.8.1. Component level decision

At a certain timestep, the prediction for compressor 3 shows an upcoming failure. This prediction is shown in figure 5.17a. The algorithm determined that it is a minor failure that is coming up, by having compared a high amount of minor failures in the past. The same is shown for another situation for compressor 1 in figure 5.17b.



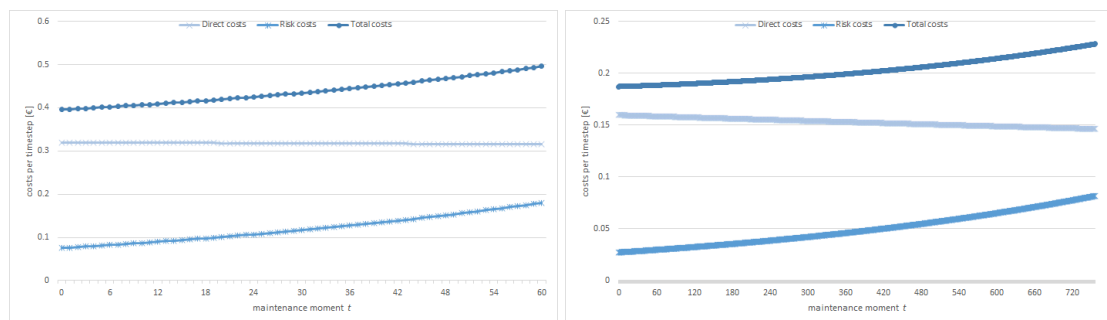
(a) Prediction result for compressor 3 at timestep 4147 (b) Prediction result for compressor 1 at timestep 18275

Figure 5.17: Prediction results for two situations in different compressors

The prediction in figure 5.17a shows that a component of compressor 3 will have a minor fault in around 5 hours from the current time step (5 minute steps). This prediction will be used to plan maintenance moment. To compare, another prediction for compressor 1 – with a longer RUL-prediction – is also discussed.

Maintenance decision

First the optimal maintenance moment is determined for the minor maintenance interventions that are needed to prevent the failures from happening. Using the cost functions described in section 4.2, we find the cost functions that are shown in figures 5.18a and 5.18b.



(a) Breakdown of total costs for compressor 3 at step 4147 (b) Breakdown of total costs for compressor 1 at step 18275

Figure 5.18: Cost breakdown for two situations in different compressors

The two costs functions show a similar shape, which can also be seen in other research such as Verbert *et al.* (2017). However, it should be noted that for the case of compressor 1 (in figure 5.18b), extending the maintenance decision leads to a smaller increase in risk costs, compared to the situation of compressor 3 (in figure 5.18a). This is caused by the longer RUL-prediction of compressor 1.

Planning decision

Continuing with these two situations, a decision must be made on whether to plan the maintenance at the current time step, or wait for a new (improved) prediction. This decision is made using reinforcement learning. This decision making is visualized using the Q-tables that were created in the process. They are shown in tables 5.11a and 5.11b for both situations.

Step	Plan	Postpone
0	-31216	-31112
1	-34084	-34152

(a) Q-table for compressor 3 from step 4147

Step	Plan	Postpone
0	-502	0
1 ...567	...	...
568	-476	-100
569	-3928	-3563
570	-4384	-3911
571	-3804	-3827

(b) Q-table for compressor 1 from step 18275

Table 5.11: Q-tables for two situations in different compressors

It should be noted that the numbers shown in the Q-tables are not real costs, but merely ratings used in the decision process. In the situation of compressor 1, the decision is made to plan maintenance after one step, as the risk-costs increase quickly each timestep. This can be seen in table 5.11a, where the green value indicates the best options. In the other case, waiting for a later moment seems to be a better option for 570 steps, as only in step 571 the maintenance is planned (see table 5.11b).

5.8.2. System level decision

On the system level it can be seen that simultaneous maintenance is prevented by the negotiation of the agents. Simultaneous maintenance would cause loss of functionality, and these indirect costs outweigh the direct maintenance costs of performing maintenance at a sub-optimal moment on component level. An example of this is shown in figure 5.19, where compressor 1 is maintained earlier to prevent overlap with compressor 3 in the maintenance planning.

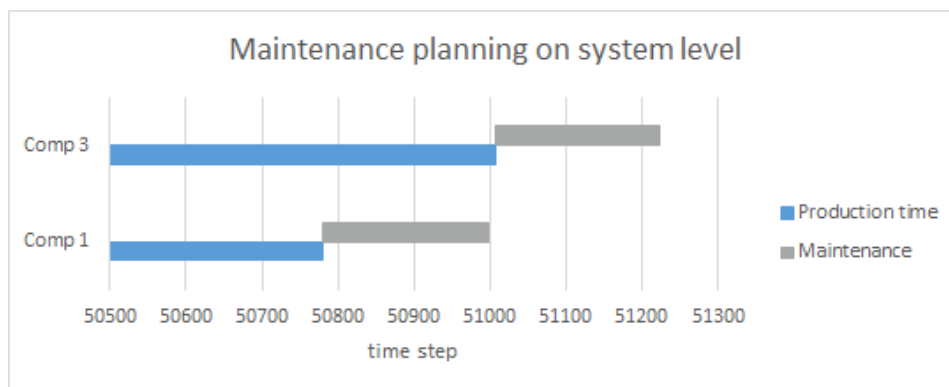


Figure 5.19: Maintenance planning on system level

5.8.3. Comparison to current situation

The result of the full simulation are compared to the base-case of the current maintenance strategy. Therefore, this section includes the results that show the acceptance or rejection of the hypothesis stated in section 5.2.

	Current situation	Scenario 1
Number minor interventions	27	41
Number major interventions	9	13

Table 5.12: Comparison of amount of maintenance moments, scenario 1

When comparing the number of maintenance interventions planned in the simulations of the discussed scenario to the current situation in 5.12, it can be seen that actually more maintenance interventions are planned than necessary. More RUL-predictions were made than the number failures that occur in reality, so this unexpected result is likely influenced by the prediction. To check whether it is actually caused by the quality of the prediction algorithm, a test is done using a dummy set with accurate predictions (predictions with pre-knowledge). These simulations will be referred to as 'Scenario 2' in the following section.

	Current situation	Scenario 2
Number minor interventions	27	27
Number major interventions	9	9

Table 5.13: Comparison of amount of maintenance moments, scenario 2

In table 5.13 it can be seen that for scenario 2, the framework behaves as expected. The cause of the over-prediction of failures can be attributed to the quality of the predictive algorithm used for this case study. The decision making algorithm can therefore be considered to be working. The financial results of both simulations are shown in table 5.14.

	Current situation	Scenario 1	Difference	Scenario 2	Difference
Total direct costs	€68,196	€97,892	€29,696	€65,934	€2,262
Total indirect costs	€1,488,000	€304,000	€1,184,000	€418,000	€1,070,000

Table 5.14: Cost comparison of current situation versus simulations

As can be seen in table 5.14, both simulations lead to a big reduction of system downtime – 2 or more compressors down at the same time – and therefore indirect cost. Interesting is that the simulation with fewer interventions shows more system downtime. This fact can be attributed to the prediction horizon of the dummy set, which leads to a delayed prediction of the remaining useful life.

Next to the financial implications of the false predictions, they could lead to a decrease in trust of the maintenance personnel in the prescriptive framework. As the personnel is the end-user of such a system, it is vital that they are positive that they can rely on the provided maintenance planning.

When going back to the LCC costs overview shown in figure 2.4, it can be concluded that the prescriptive maintenance approach has influence on the cost components shown in figure 5.20. The repair costs per intervention of scheduled maintenance and fixed labour costs will not be influenced. But other components, such as life of equipment, maintenance schedule, number of unscheduled breakdowns and used parts are changed by this strategy.

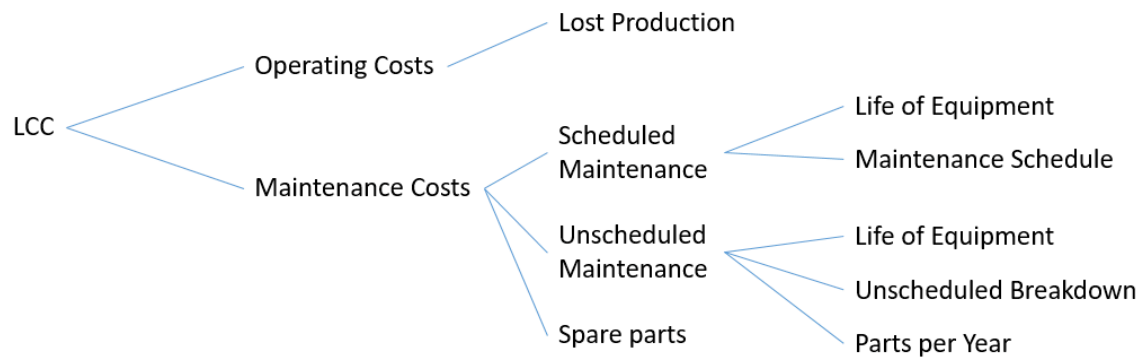


Figure 5.20: Influenced components of life cycle costs

The influence on OEE is shown in table 5.15. It can be seen that efficiency of the system was slightly increased by the prescriptive maintenance approach, when using the high quality prediction.

	Current situation	Scenario 1	Scenario 2
OEE [%]	96.3	96.0	96.5

Table 5.15: Efficiency comparison

The results in this section show that the maintenance costs can be reduced and the efficiency can be increased, by implementing the prescriptive maintenance framework that is proposed in this research.

6

Conclusion & Recommendations

The goal of this research was to define a framework that can successfully achieve prescriptive maintenance at a FMCG production plant, for a system consisting of multiple components. In this framework, the focus was on the prescriptive decision making based on input of diagnosis and prediction of component states.

It was found that the FMCG industry shows specific characteristics that disable the use of existing prescriptive maintenance systems. The dynamic behaviour of the large production environments in this industry need a more flexible, scalable and reliable system than the existing systems. In literature survey however, some methodologies have been found that might be combined to create a suitable prescriptive maintenance framework for this specific industry. Existing prescriptive maintenance frameworks for multi-component systems use a multi-layer approach where a distinction is made between component and system level. Such an approach was combined with an agent-based approach where agents can make decisions using appropriate decision making techniques found in literature.

This framework uses an intelligent agent-based approach to optimize maintenance planning on a component and system level. The agents act on different levels and negotiate to find an optimal system level result. An economic approach was used, where all impact of maintenance was translated to costs. Therefore the optimum maintenance strategy that is found will be the one with the lowest overall costs. The component level decision is made using a prediction of the remaining useful life of a component. After an optimization of maintenance type and time – using brute force search –, reinforcement learning is used to determine the optimal planning moment. On a system level, each new component level decision is evaluated by the system level agent and a system optimum is found using a brute force technique. During this optimization, the un-fixed maintenance moments may be replanned on a component level, by taking into account loss of functionality and economies of scale.

As prescriptive maintenance aims to increase operational efficiency and reduce costs, the effect of the framework on these KPIs was simulated and compared in a FMCG case study. This case study was done using a cooling compressor system in a beverage production facility of Heineken UK. It was found that, even if more failures are predicted than necessary, the intelligent planning of maintenance by this framework leads to a decrease of indirect costs. When a fully accurate prediction of the remaining useful life is used, this prescriptive maintenance system can also increase a systems operational efficiency and reduce maintenance costs next to the decrease of indirect costs. It can be concluded that the influence on overall production time was largest, which led to the decrease of the indirect costs of lost production. This could, for this specific system, be attributed to the fact that maintenance was planned in such way that simultaneous maintenance, and therefore system downtime, was prevented.

Although the case study showed promising results, room for improvements has been found. Firstly, the quality of the predictive algorithm proved to be essential to the functioning of the model. Testing this framework with a high quality prediction for all involved components is therefore a recommendation for future research. An important factor that should be considered is the trade-off between accuracy

and earliness of prediction. Furthermore, testing the framework with a more complicated system in the FMCG industry will show if this system is indeed scalable enough for the desired application.

Before this framework can be implemented in an industrial setting, the proper infrastructure has to be in place. This includes a well structured data collection system, a software platform where the framework is placed and a clear human-machine interface. When these enablers are in place, the use of this framework could lead to improved efficiency, reduced costs and increased production time.

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Decision making framework to achieve prescriptive maintenance in the FMCG production industry

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Abstract

In recent years, technologies such as artificial intelligence have enabled computer systems to provide decision support for maintenance planning. Using advanced analytics to determine optimal maintenance actions and moments is called prescriptive maintenance. Multiple prescriptive maintenance models have been proposed for different industries. However, none of these models or frameworks were designed for use in the FMCG industry. This industry seems to be lagging compared to the oil & gas, process and transport industries for example. The goal of this research is to define a framework that can achieve prescriptive maintenance at a FMCG production plant. This research focuses on the decision making for maintenance on multi-component systems using technologies such as machine learning. The proposed framework uses an intelligent agent-based approach to optimize maintenance planning on a component and system level. The agents act on both levels and negotiate to find an optimal system level result. A life-cycle cost approach was used, where all impact of maintenance was translated to costs and thereafter minimized. As prescriptive maintenance aims to increase operational efficiency and reduce costs by artificial decision making, the effect of the framework on these KPIs was simulated and compared in a FMCG case study. This case study was done using a discrete-time simulation of a cooling compressor system in a beverage production facility. It was found that, given a high-quality prediction of the remaining useful life, this prescriptive maintenance framework can increase a systems operational efficiency and reduce maintenance costs. However, the largest improvement could be seen in the overall production time of the system, as maintenance was planned in such way that loss of functionality was prevented.

Introduction

The competition between Fast Moving Consumer Goods (FMCG) companies is higher than ever ([The P&G Company, 2018](#); [Unilever Group, 2018](#)). Therefore companies have to develop new ways of working to maintain their current position. Because the FMCG sector is a high-variety environment, these new concepts require high reliability equipment and high-quality demand forecasts ([Mahalik and Nambiar, 2010](#)). An effective maintenance strategy is essential to ensure equipment reliability, and thereby

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equipment availability and productivity (Waeyenbergh and Pintelon, 2004), and also a way to reduce costs (Alsyouf, 2007).

Typical FMCG production companies have a large number of assets that require maintenance. The moment and type of maintenance that is performed depend on the maintenance strategy that is selected for a specific equipment type. Chosen maintenance strategies can be split into two main categories, namely corrective maintenance and preventive maintenance (Waeyenbergh and Pintelon, 2004). Corrective maintenance is the category that mostly includes unplanned maintenance, which is necessary to restore the functionality of equipment after (unexpected) breakdown or failure. The maintenance is in this case called *reactive*. Reactive maintenance is generally more costly than other forms of maintenance (Smith, 1993). Reactive maintenance is the most straightforward maintenance strategy, as the only trigger is the failure of a component. More advanced maintenance strategies have evolved from this, and this evolution is shown in figure A.1.



Figure A.1: The evolution of maintenance strategies

In contrast to reactive maintenance, preventive maintenance includes the *proactive* part of maintenance interventions. Preventive maintenance aims to prevent unexpected events that require maintenance by performing pre-planned actions. This planning may be based on the condition of the equipment, expected life time or just random planning. In a predictive maintenance strategy, maintenance is planned according to the measured conditions of equipment and a prediction of the remaining useful life (RUL) (Niu and Jiang, 2017). The rightmost strategy shown in figure A.1 is prescriptive maintenance. This is the most advanced of these strategies. Prescriptive maintenance is the next step after preventive and predictive maintenance, that achieves pro-active and smart maintenance planning (Matyas et al., 2017). Prescriptive maintenance aims to provide a decision on the type of maintenance and the moment it is performed. This decision is made using a combination of historical data and real-time information. The decision can be used to support human decision making to plan maintenance or in a completely automated maintenance planning system.

Some manufacturers provide intelligent maintenance programs – including prescriptive maintenance – for individual assets, however they do not consider structural and functional dependencies between different assets. These individual systems are not designed to be extended with other equipment types or to be integrated in other systems or an infrastructure of a large FMCG company. Where in some industries intelligent maintenance decision support is used, the FMCG sector is lagging (Heymans, 2009). There is not yet a prescriptive maintenance framework that is suitable for this sector. Therefore the research question that has to be answered is: *How to achieve prescriptive maintenance to increase functional efficiency and reduce costs in the FMCG industry?*

This research proposes a multi-agent framework to achieve prescriptive maintenance at a FMCG production plant, for a system consisting of multiple equipment types, using total productive maintenance and life-cycle costs methodologies. In this new approach, flexibility and scalability are central in the design of the framework. The functioning of the framework is demonstrated in a case study, where a discrete-time simulation is used of a cooling system of a FMCG production plant. This framework is presented in the following section. After that, the setup and results of the case study are discussed, followed by a conclusion and recommendations for future research.

Agent-based maintenance planning framework

As the goal of this research is to define a framework that can achieve prescriptive maintenance, this framework should be able to provide maintenance decisions based on input gathered from a production system. These decisions should ensure the needed production targets are met, at the lowest possible

total costs. These total costs include both direct and indirect costs (Galar and Kumar, 2017). To make the framework useful for the FMCG industry, some other design requirements have to be met. Firstly, the system should be scalable enough for use in single a production system up to factory scale, allowing for multiple diverse equipment types. Also, for a successful implementation an applicable setup should be used for the connection of the framework to equipment and end-users.

The proposed framework can be split into five sections, namely the data collection, the component level prediction, the decision making on respectively component and system level, and finally the information transfer. This process is loosely based on the "Detect–Predict–Decide–Act" cycle from Bousdekis *et al.* (2017). The main scope of this research is the optimization and decision making process of the proposed prescriptive maintenance framework. This scope is shown in figure A.2.

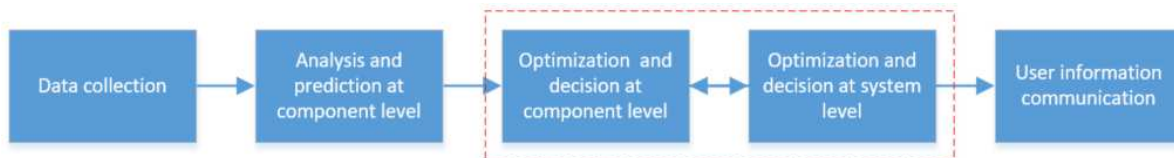


Figure A.2: High level overview of maintenance concept with scope highlighted in red

The decision making process on component and system level and the interaction between the two levels are partly based on Verbert *et al.* (2017) and Martinod *et al.* (2018). In contrast however, this research proposes the use of an agent based approach to be compatible with the more dynamic environment of a FMCG production company in terms of flexibility. Also, the proposed approach uses more suitable solving methods for systems with many components, in order to ensure scalability.

A multi-agent approach will be used for the components and system decision making. This intelligent approach is a more flexible approach to multi-component maintenance systems, as the agents can negotiate to reach the system optimum. Such an approach is necessary in a FMCG environment, where maintenance interventions with short duration should be effectively scheduled along with more time consuming interventions. Using intelligent agents, a part of the decision making is transferred from the coordinating agent to the agent on the component level. Using a hierarchical approach however, it is assured that the system level optimum is found.

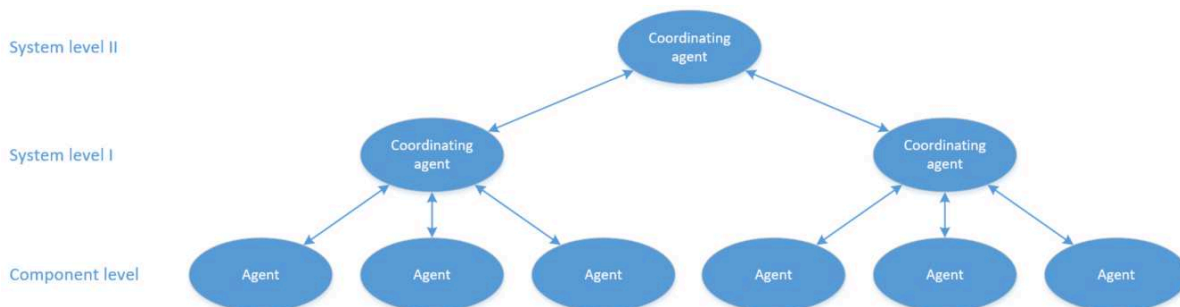


Figure A.3: The structure of the decentralized system

In a partly decentralized approach, agents do not just communicate with one coordinating agent, but instead with intermediate agents which in turn communicate with the central coordinating agent. This creates a structure as shown in figure A.3. Intermediate agents would take the role of the coordinating agent for certain parts of the system, such as a group of similar components. This way, the central agent will not have to consider all optimization results on component level, which reduces the needed processing power and time, and enable scalability of the framework (Truong *et al.*, 2016).

On the component level a decision is made on the required maintenance intervention and moment. This decision is made using a prediction of the remaining useful life (RUL). To make this decision an optimization is done based on life cycle costs (LCC) of the equipment. This cost function of the maintenance type and moment is shown in equation A.1. For a more detailed view into the cost

functions see [Verbert et al. \(2017\)](#).

$$(a^*, t^*) = \arg \min (C_d(a, t) + C_i(a, t) + C_r(a, t)) \quad (\text{A.1})$$

In this optimization $C_d(a, t)$ are the direct costs of the maintenance intervention mostly caused by labour costs and spare part costs. $C_i(a, t)$ are the indirect costs caused by downtime of the component and $C_r(a, t)$ the costs associated with the risk of performing maintenance too late. Following the LCC-approach, the maintenance costs are divided by the lifetime of the equipment.

After an optimal value is found, a decision is made whether to plan the maintenance or wait for a potentially better planning moment. This is done using a Markov Decision Process (MDP) defined by the state in equation A.2 and is solved using Reinforcement Learning (RL). The state includes the costs of the selected maintenance intervention, probability of failure Pf , predicted time to failure t_{tf} , maintenance time t^* and action a^* , and two terminal states D and F .

$$\text{state} = [\text{costs}, Pf, t_{tf}, t^*, a^*, D, F] \quad (\text{A.2})$$

RL is a machine learning technique that is able to learn using delayed rewards. This means that when deciding, a trade-off is made between immediate and long term reward based on the desired functionality.

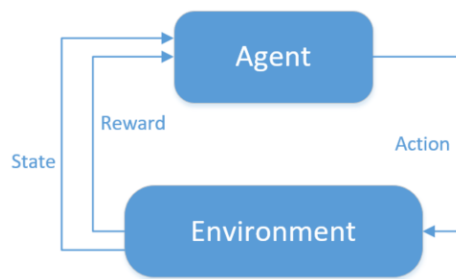


Figure A.4: Reinforcement learning loop

Another characteristic of RL is that both the system response and the desired behaviour are unknown beforehand. The agent computes the value function by interacting with the environment or system in a step-wise approach. This approach can be seen in figure A.4. After each step, the reward is calculated and the computed value function is updated according to the experience gained in that step. After an agent has collected a sufficient number of experiences, the reward associated to actions can be estimated accurately ([Negenborn et al., 2005](#)). This approach is chosen as it performs better than conventional search methods such as dynamic programming.

The MDP for this specific application is a finite Markov decision process. The horizon of the problem is the predicted failure moment, as the maintenance must be planned in advance or the component will fail. These two options are the terminal states as included in the system-state shown in equation A.2.

On the system level, equation A.3 is used to find the arguments of the minimum total costs. Only the maintenance interventions that have not yet been planned are subject to minimization.

$$X_{opt} = \arg \min_{X_{proposed}} C_{SL}(X_{proposed}, X_{fixed}) \quad (\text{A.3})$$

In this equation, $X_{proposed}$ is the set of maintenance actions for the components for which it has not yet been planned and X_{fixed} is the set of maintenance actions that have already been planned. The cost functions for this approach can again be found in [Verbert et al. \(2017\)](#).

For each new entry of a component level decision, the system level determines the system level costs. It can be the case however that changing the time of maintenance on component level would cause a local cost-increase, but decrease the costs at system level. For this reason, negotiation is possible between the agents on component and system level. The system level agent challenges the component level agent to perform maintenance on the nearest, already planned, maintenance moment or alternatively just outside the planned maintenance moment. This could lead to a change in costs due to economies of scale, or due to loss of functionality. Of these situations, the optimal value will be used and exported as the suggested maintenance action.

Case study

To demonstrate the proposed framework, discrete-time simulations are done for a cooling installation of Bulmers Cider Plant in Hereford, UK. This system uses a vapor-compression refrigeration cycle to provide cooling to the production of cider. A simplified P&ID of this system is shown in figure A.5. Similar types of cooling installations are used on many FMCG production sites. The KPIs that will be evaluated in this case study are the costs of maintenance and the overall equipment effectiveness (OEE), because these two indicators show the most important effects of a maintenance concept (Galar and Kumar, 2017).

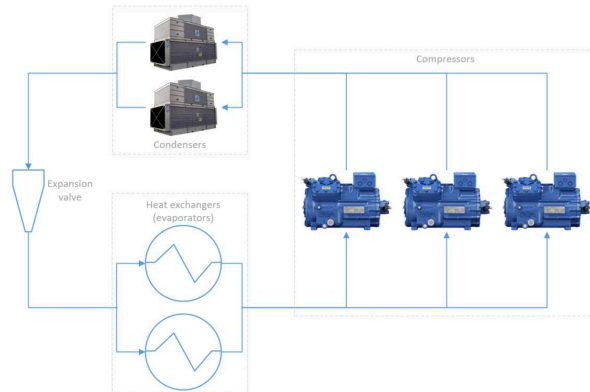


Figure A.5: Cooling system used in case study

Two types of failures and corresponding interventions are considered in this study, namely minor and major. The average maintenance durations that were used are taken from SINTEF (2002). The indirect costs of maintenance are defined as the missed revenue due to system downtime, and will be charged if two or more compressors are unable to operate at the same time for any reason.

To verify the simulation model, simulations are done using time-step sizes of 60, 30, 15, 10 and 5 minutes. For these different time-step sizes the total individual costs C_0 and 95% confidence interval are determined using Student's t-distribution. 10 simulation runs provided a stable solution for all these step sizes, with increasing stability for smaller time-step sizes. It is assumed that this also holds for other time-step sizes.

Results and discussion

On the component level it is observed that postponing the maintenance decision leads to a smaller increase in risk costs if the RUL is determined long before the failure. This shows that the component level decision making behaves as expected, where early knowledge creates more opportunities to plan maintenance in an efficient way. The RL-algorithm postpones the planning of maintenance if it is not immediately necessary and better options might present itself.

On the system level it can be seen that simultaneous maintenance is prevented by negotiation of the agents. Simultaneous maintenance would cause loss of functionality, and these costs outweigh the direct maintenance costs of performing maintenance at a sub-optimal moment on component level. An example of this is shown in figure A.6, where compressor 1 is maintained earlier to prevent maintenance overlap with compressor 3.

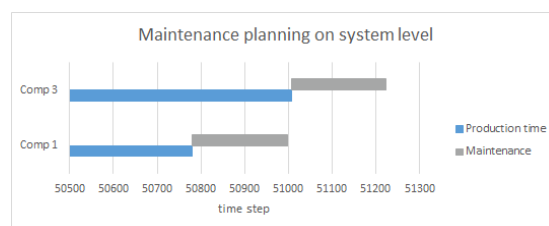


Figure A.6: Maintenance planning on system level

When comparing the number of maintenance interventions planned in the simulation to the current situation, it was observed that actually more maintenance interventions are planned than necessary. To check whether it is caused by the quality of the prediction algorithm, a scenario is added using a dummy set with accurate predictions (predictions with pre-knowledge) which will be referred to as 'Scenario 2'. With this dummy prediction the framework behaves as expected. The cause of the over-prediction of failures can therefore be attributed to the quality of the predictive algorithm used for this case study and the decision making framework can be considered to be working. The financial results of both scenarios are shown in table A.1, and the influence on OEE is shown in table A.2.

	Current situation	Scenario 1	Difference	Scenario 2	Difference
Total direct costs	€68,196	€97,892	€29,696	€65,934	€2,262
Total indirect costs	€1,488,000	€304,000	€1,184,000	€418,000	€1,070,000

Table A.1: Cost comparison of current situation versus simulations

	Current situation	Scenario 1	Scenario 2
OEE [%]	96.3	96.0	96.5

Table A.2: Efficiency comparison

As can be seen in table A.1, both simulations lead to a big reduction of system downtime – 2 or more compressors down at the same time – and therefore indirect cost. Interesting is that the simulation with fewer interventions – scenario 2 – shows more system downtime than the first scenario. This fact can be attributed to the limited prediction horizon of the dummy set, which leads to a late prediction of the remaining useful life and less possibilities to optimize. It can also be seen that the efficiency of the system was slightly increased by the prescriptive maintenance approach, when using the high quality prediction.

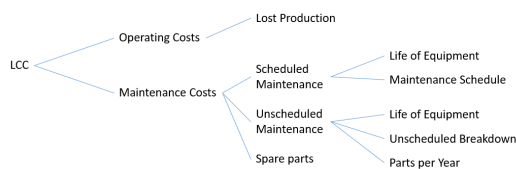


Figure A.7: Influenced components of life cycle costs

The prescriptive maintenance approach shows influence on the cost components of the LCC costs overview shown in figure A.7. The repair costs per intervention of scheduled maintenance and fixed labour costs will not be influenced. Other factors, such as life of equipment, maintenance schedule, number of unscheduled breakdowns and used parts are changed by this strategy.

These results show that the maintenance costs can be reduced and the efficiency can be increased, by using the prescriptive maintenance framework that is proposed in this research.

Conclusion and recommendations

The goal of this research was to define a framework that can successfully achieve prescriptive maintenance at a FMCG production plant, for a system consisting of multiple components. In this framework, the focus was on the prescriptive decision making based on input of diagnosis and prediction of component states.

This framework uses an intelligent agent-based approach to optimize maintenance planning on a component and system level. The agents act on different levels and negotiate to find an optimal system level result. A life-cycle cost approach was used and therefore the optimum maintenance strategy that is found will be the one with the lowest overall costs. The component level decision is made using a prediction of the remaining useful life of a component. After an optimization of maintenance type and time – using brute force search –, reinforcement learning is used to determine the optimal planning moment. On a system level, each new component level decision is evaluated by the system level agent and a system optimum is found using a brute force technique. During this optimization, the un-fixed maintenance moments may be replanned on a component level, by taking into account loss of functionality and economies of scale.

As prescriptive maintenance aims to increase operational efficiency and reduce costs, the effect of the framework on these KPIs was simulated and compared in a FMCG case study. This case study was done using a cooling compressor system in a beverage production facility of Heineken UK. It was found that, even if more failures are predicted than necessary, the intelligent planning of maintenance by this framework leads to a decrease of indirect costs. When a fully accurate prediction of the remaining useful life is used, this prescriptive maintenance system can also increase a systems operational efficiency and reduce maintenance costs next to the decrease of indirect costs. Therefore it is considered

that the proposed framework improves maintenance planning by means of prescriptive maintenance. It can be concluded that the influence on overall production time was largest, which led to the decrease of the indirect costs of lost production. This could, for this specific system, be attributed to the fact that maintenance was planned in such way that simultaneous maintenance, and therefore system downtime, was prevented.

Although the case study showed promising results, room for improvements has been found. Firstly, the quality of the predictive algorithm proved to be essential to the functioning of the model. Testing this framework with a high quality prediction is therefore a recommendation for future research. An important factor that should be considered is the trade-off between accuracy and earliness of prediction. Furthermore, testing the framework with a more complicated system in the FMCG industry will show if this system is indeed scalable enough for the desired application. Before this framework can be implemented in an industrial setting, the proper infrastructure has to be in place. This includes a well structured data collection system, a software platform where the framework is placed and a clear human-machine interface. When these enablers are in place, the use of this framework could lead to improved efficiency, reduced costs and increased production time.

Acknowledgements

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References

The references can be found in the bibliography before this appendix.

B

Cooling process

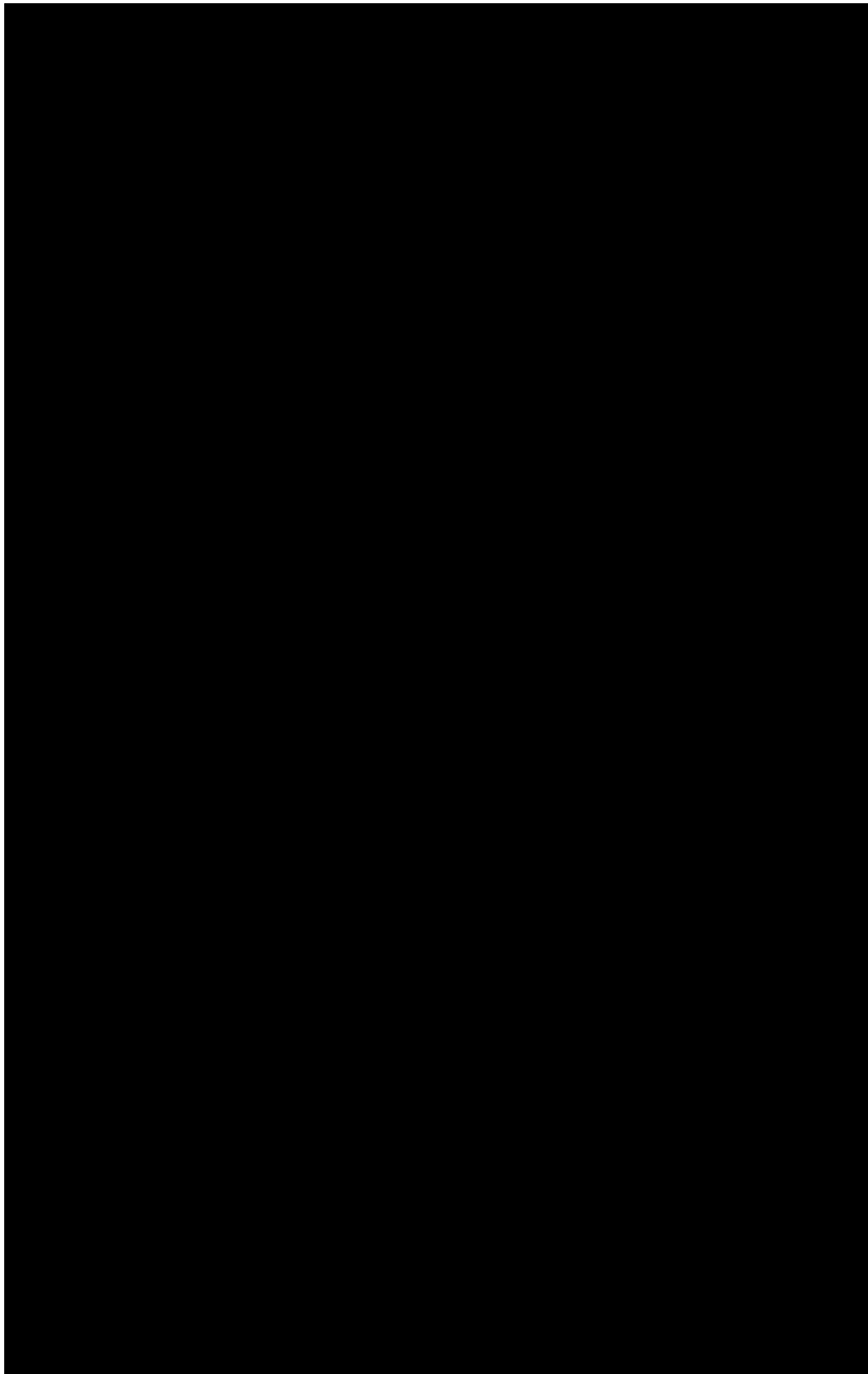


Figure B.1: P&ID of cooling system, Bulmers Cider Plant, Hereford UK

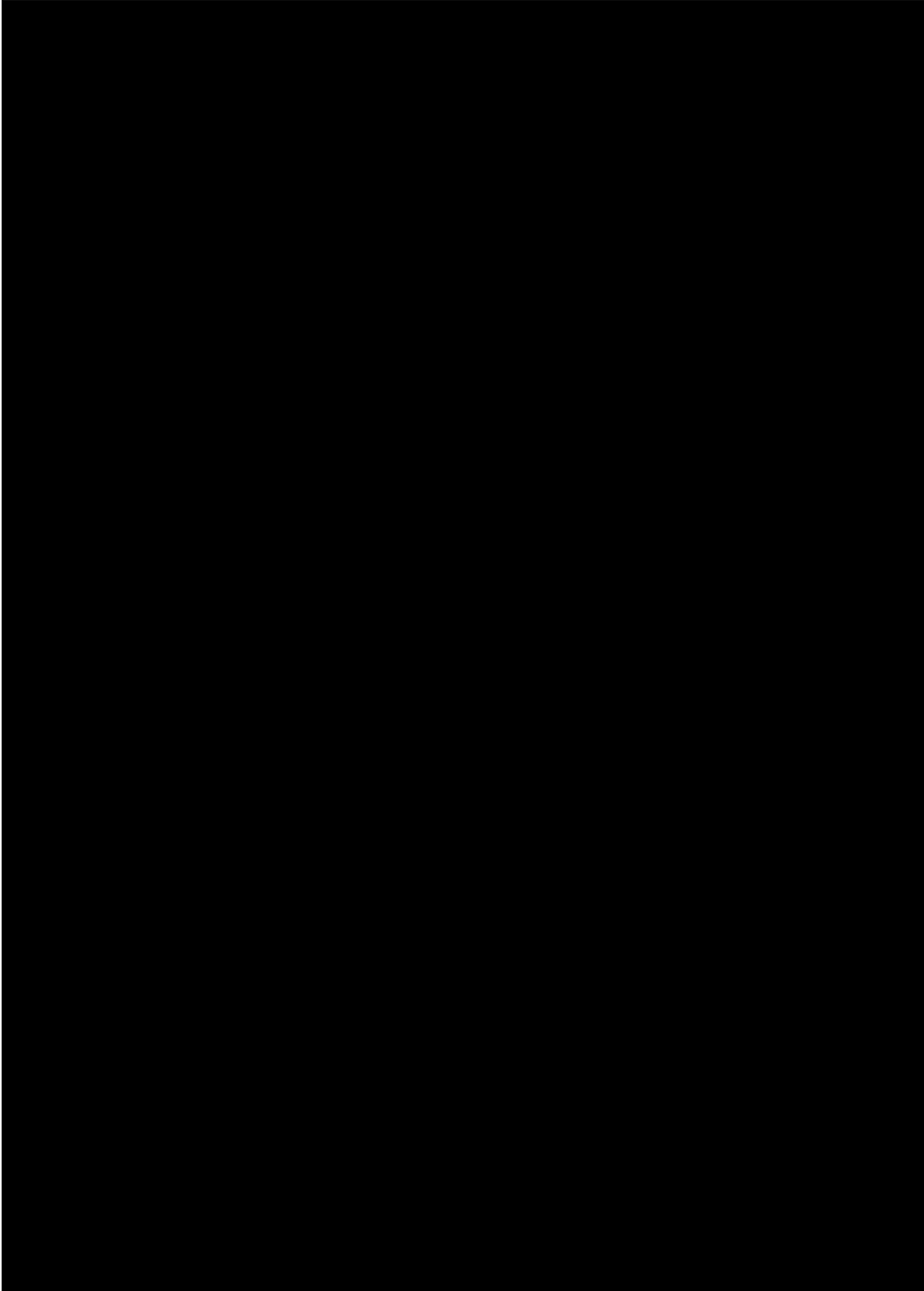


Figure B.2: P&ID of Grasso SP1 TB-5B compressor