Master Degree Project

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EXPLORING DYNAMIC COMPLEXITY IN THE SYMBIOSIS OF OPERATIONS AND MAINTENANCE FUNCTIONS

A Simulation-Based Optimisation Study

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Abstract

Maintenance, the process of preserving the condition of the equipment and performance in a production facility, stands for a considerable large cost in the budget of manufacturing organisations and is strongly affected by short-term philosophy. Therefore, both the long-term and short-term consequences of maintenance strategies need to be examined and analysed. The aim with this research is to investigate the dynamic complexity between the requirements from operations on the performance of maintenance, to illustrate the challenge of trading long-term and short-term requirements and benefits. These aspects have been studied through system dynamics (SD) modelling, simulation-based optimisation (SBO) and multi-objective optimisation (MOO). In order to illustrate the analysed problems, a state-of-the-art literature review has been created and two different scenarios have been evaluated. The scenarios are to investigate both the effects of more or less planned maintenance and the implication of a stock-and-flow structure for hiring and retirements of maintenance resources. A conceptual base model, created in previous research, has been applied and developed in order to meet the objectives.

From the performed experiments, it can be confirmed that with the use of SD simulation trends and consequences over longer periods of time are truly visualised. In the first scenario, the results indicate that a short-term maintenance management strategy is unprofitable over time. The simulation also reveals that improvement strategies and proactive work can revolutionise capability and profit over time, even if these strategies initially generate a higher cost. In the second scenario, where the effects of a major retirement are visualised, the results confirm that the company needs to act proactively in order to avoid great financial losses. Employee and average skill losses cause long-term negative effects on the capability and availability. The optimisation that has been performed, with the hiring rate as the main variable and the objectives of maximising availability, minimising the direct cost and minimising the indirect cost, has generated feasible solutions on the Pareto front.

In conclusion, the results from the experiments identify the behaviours and causal relationships in a maintenance system in symbiosis with operations. With the long-term goal of generating less reactive workload on the maintenance function, there are many benefits to obtain. The charted delays and causal relationships in the system indicate multi-level consequences, where a management approach should benefit financially from emphasising the importance of acting proactively and directing resources to improvement strategy work.

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List of Abbreviations

CBM	Condition-based maintenance
CM	Corrective maintenance
DES	Discrete-event simulation
DOE	Design-of-experiments
MOO	Multi-objective optimisation
MTTR	Mean time to repair
MTTF	Mean time to failure
MTBF	Mean time between failures
MWT	Mean waiting time
MDT	Mean down time
NSGA-II	Non-dominated sorting genetic algorithm
OEE	Overall equipment efficiency
PM	Preventive maintenance
RCA	Root cause analysis
SBO	Simulation-based optimisation
SD	System dynamics
SLA	Service level agreement
SOO	Single-objective optimisation
TPM	Total productive maintenance

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1 Introduction

In order to achieve a deeper understanding for the problem area, the research background is described in the introductory chapter. The aim, objectives, research area and delimitations are also presented. Also, the content and structure of the report are summarised and described.

1.1 Research Motivation and Background

Maintenance, the process of preserving the condition of the equipment and performance in a production facility, stands for a considerable large cost in the budget of manufacturing organisations. The maintenance process is strongly affected by short-term philosophy because of the high pressure on equipment utilisation that rises from global competition. Recent developments in the automation field, along with the increasing complexity of equipment and production systems, have increased the capitalisation in manufacturing firms (Garg & Deshmukh, 2006). This has led to more unplanned breakdowns, which causes more prevalent consequences across the plant. Short-term focused maintenance processes, where reactive maintenance is taking the greatest part, potentially leads to disturbance in the supply chain and thereby causes performance variations (Geary et al., 2006). With the implementation of proactive maintenance policies, however, the performance variations can be drastically reduced and the maintenance actions can instead contribute to an improved production performance (Alsyouf, 2009).

The goal of maintenance should include the development of production performance through proactive maintenance (Levitt, 2011). This means that by systematically reducing the need for maintenance interventions, through improvements that extend the maintenance intervals, the actual need for maintenance actions is reduced. When less maintenance is needed, less reactive repairs and less preventive repairs are performed, which enables more preventive actions which do not require downtime. Apart from the direct result in the form of increased production time, this also enables increased condition monitoring capacities, better knowledge generating processes and better continuous improvement processes.

However, the efforts that lead to more proactive maintenance must be well prioritised and assigned strategically. According to Blann (1997), maintenance needs to develop into a strategic tool with the aim to increase profitability and reduce quality defects. This requires a great skill of the organisation in determining which activities that actually maximise the value of maintenance in a strategic way. It is also a challenge for the organisation to correctly value the improvement actions, which should be traded into economic return. It is clear that the complexity of managing maintenance with a long-term philosophy knows no bounds.

During the last decade, simulation has been used as a tool to illustrate and optimise the costs that maintenance generates (Sharma et al., 2011). However, in order to discover and analyse the consequences of maintenance strategies both in the short term and in the long term, a feedback approach is needed. System Dynamics (SD) is a simulation-based methodology which enables analysis of the modelled systems by providing “what if”-scenarios to examine different strategies. SD simulation models enable feedback loops, which in turn enable the analysis of how multiple capabilities affect performance (Warren, 2005). With the use of SD, a hypothesis of the studied system can be developed and evaluated and is in this case an efficient tool in studying reactive and proactive maintenance behaviour (Linnéusson, 2018).

Although SD provides understanding of the studied system, another method is needed as a complement to trace different solutions and compare them against each other on different criteria. The method that is used for this purpose is simulation-based optimisation (SBO). Extended with the concept of multi-objective optimisation (MOO), not only one solution is sought, but several optimal solutions on the Pareto-front (Nguyen et al., 2014). The application of these methods in combination with SD is, however, very limited (Aslam, 2013). In fact, there are only a limited number of MOO studies that examines maintenance at all (Alrabghi & Tiwari, 2015). When optimising SD models, single-objective optimisation (SOO) is the method that is most commonly used (Jones, 2014). However, since SOO cannot handle several conflicting objectives, it is unsuitable for seeking solutions to managing long-term maintenance in a profit-making organisation. Conclusively, the development of the performance of maintenance processes is potentially beneficially supported by an SBO approach, which integrates MOO with SD in order to represent long-term solutions with several conflicting conditions (Linnéusson, 2018).

1.2 Research Aim and Objectives

The overall aim with this research is to investigate the dynamic complexity between the requirements from operations on the availability performance created by maintenance, to illustrate the challenge of trading long-term and short-term requirements and benefits. These aspects can be studied through SD modelling, where simulation of long-term and short-term consequences from different policies between the two functions is possible. This aim will be reached by applying an SD base model created in previous research by Linnéusson et al (2018) and adapting it to contain the required structures or functions in order to illustrate the analysed problems. Hence, the theme of the research is to adapt and evaluate new problem scenarios based on industrial real world problems, through "what if"-analyses and the application of MOO.

The described aim is accomplished by the following objectives:

- State-of-the-art literature review within the fields of SD applications in maintenance, as well as maintenance studies applying other simulation-based methods and MOO

- The evaluation and analysis of two different scenarios, where the research should investigate:

    1. The effects of more or less planned maintenance on long term and short term with regards to the availability performance to operations

    2. The implication of a more detailed stock-and-flow structure for hiring and retirements of maintenance resources and how the hiring rate can be optimally governed during the given conditions

1.3 Method

In this subsection, the different methods that are needed in order to fulfil the aim and objectives are presented. This includes both the research method and experimental method.

1.3.1 Research Method

The research approach is to apply a systems thinking philosophy to address the dynamic complexity problems in maintenance described above, by the use of a feedback-oriented and long-term focused procedure. It is therefore suitable to apply SD integrated with MOO. The research methods that will be used in this research are a literature review and experiments, where the datasets derived from the simulation model and optimisation runs are processed and analysed in order to draw conclusions. The literature review aims at identifying the scientific problems that exist within the specific area and also where there is a research gap. The most promising theories in this new area will be pointed out, which will identify a set of concepts that constitutes the foundation for this research. The literature in the this novel field is limited; however, the literature survey in in this research needs to focus on simulation-based applications in maintenance as well as any maintenance studies in which MOO has been applied.

1.3.2 Experimental Method

The aim of this research will be reached by the further development and extension of an SD base model, which has been created in previous research by Linnéusson et al. (2018). The model will be extended and adapted in order to address the different scenarios described above.

The model adaptions required to analyse the different scenarios are to:

- Modify constants in order to address S1
- Include a hiring and retirement structure in order to address S2
- Integrate the SD model with an MOO platform in order to support S2

The SD modelling will be performed in the software Vensim PLE. This software is a visual tool for systems modelling, in which conceptualisation, simulation, analysis, optimisation and documentation of dynamic systems can be performed. In this system, simulation models are built upon causal loops and stock and flow-diagrams. Interrelationships of the system are created by connecting words with arrows and are thereafter recorded as causal connections. The information that these relationships create is used by the Equation Editor in the software, in which the entities and equations or amounts are entered for each parameter. The model can be analysed throughout the building process, by the visualisation of the interrelationships and causal loops, but also through simulation runs of the complete model where the behaviour of the model can be thoroughly explored (Vensim User's Guide, 2007). The default distributions in the base model that are used in this research are based on experience and knowledge from different maintenance functions in the car manufacturing industry; the base model is validated through the publication thereof. The additional data needed in order to complete the model adaptions will be collected from published documents, such as previous research and literature.

When data from different simulation runs can be derived from the Vensim model, the software ModeFrontier will be used for the optimisation part. It is a Java-based application, where input and output variables are easily defined. A workflow is constructed by the connection of object nodes, which are drawn on a canvas and connected to each other by links. In order to execute the MOO, an algorithm is chosen in modeFrontier which generates a set of input variables for the Vensim model to evaluate. A Vensim interface application in modeFrontier, developed by Aslam (2013), loads the Vensim model, transfers the input values and settings to the Vensim model, evaluates the simulation and sends the information back to modeFrontier. The Vensim interface then runs the model in modeFrontier and retrieves the results, calculates the mean, maximum, minimum and standard deviation values for each variable and sends the values to the output text file. The optimisation in modeFrontier uses nine different nodes. The algorithm that is used in the optimisation is the commonly used, fast non-dominated sorting algorithm NSGA-II. When the optimisation in modeFrontier is completed, the input, output and optimisation objective results are stored and ready for analysis (Aslam, 2013). The Pareto front results that are generated by the optimisation will be discussed with respect to diversity and convergence in order to evaluate the optimisation that has been performed.

1.4 Delimitations

The delimitations that this research is confined to include all aspects and areas that are not included in the objectives. The results of the experiments have to be evaluated with regards to these delimitations, in order to draw correct conclusions. The major delimitation of this research project is the non-identified parameters in the SD model. These imaginary parameters have not been included in the model, but might exist in the real world and therefore would have affected the results of the experiment if the same experiment had been conducted in a real-world system. This is a common trouble when modelling in SD. However, this delimitation has been taken into consideration; the parameters that have been included in the model are the ones that are considered to affect the different relationships and key parameters with significant importance for the end results. In the research from where the base model is derived, discrete-event simulation has been used in order to create a hybrid model that can answer to different aspects of the research questions in that particular research. This project will, however, not perform any discrete-event simulation and the final conclusions will therefore be drawn upon the SD model and the results of the simulation and optimisation runs.

1.5 Content and Structure

After the introduction, where the problem description, aims and objectives are described, the chapter with the frame of references follows. In this chapter, research of the relevant areas is presented, which will constitute the basis for the following modelling choices and conclusions. The knowledge basis provided in this chapter is further extended and verified by the literature review presented in the next chapter. The frame of references and literature review are subsequently followed by the experimental part. Here, the methods and procedures that are used in order to fulfil the aim of the research are presented. The results of the experiments are presented and analysed in the following chapter, which also includes discussion about the results. In the chapter "Conclusions and Future Work", what the research has achieved is presented and the results of the experiments are feed-backed to the aim and objectives. The suggested future work is also included in this chapter. After the final chapter is a list of references.

2 Frame of References

In order to explain relevant theories in the field and to firmly establish the conclusions that are drawn from the results of the experiments of this study, literature in the relevant areas has been studied. The areas that have been studied are maintenance and operations, SD, SBO and MOO.

2.1 Maintenance and Operations

The performance of maintenance and the performance of operations are closely related, since sufficient maintenance performance enables the required performance of operations. One cannot exist without the other. In this subsection, the most prominent aspects of maintenance performance in symbiosis with operations have been covered.

2.1.1 Preventive and Corrective Maintenance

The performance of operations creates a need for maintenance actions. This need has to be balanced with the achievements from maintenance; an increased need calls for an increase in maintenance actions. These actions can be of two different natures: preventive or corrective. A maintenance action is called preventive maintenance (PM) if the action is performed before a fault occurs with the aim of preventing future errors; simultaneously, an action is called reactive maintenance, or corrective maintenance (CM), if the action is performed after the fault has occurred and thus aims at correcting the occurred error in the fastest way possible (Kouedeu et al., 2011). Both of these different maintenance actions are needed to some extent in every operating system. In a utopic production system, naturally, CM would not be needed. In a realistic scenario, there has to be resources available to perform CM in case of unexpected machine failures. However, one strong factor which definitely can reduce CM in a system is a well-established system for PM. PM is usually pre-determined maintenance activities, where the method of performing PM is based on the failure behaviour of the specific component. PM is usually performed at a fixed interval based on number of produced units, calendar time or processing time. Additionally, there is condition-based maintenance (CBM), which is a form of PM that is performed based on the condition of the equipment that is supposed to be maintained (Pintelon & Gelders, 1992).

The result of applying different number of preventive and corrective maintenance actions can be seen in figure 1. The red line represents the cost for reactive maintenance, the green line represents the cost for preventive maintenance and the blue line represents the total maintenance cost. It can be seen that with a low number of machine failures, there is no need for reactive actions. When this is compensated with too many preventive actions, the total cost increases (Smith & Hawkins, 2004). The same thing applies to the reversed scenario when there are many machine failures; when a high number of reactive actions are required, there is no temporal room for preventive actions. The lowest total cost can be achieved in the optimum point, where an intelligent maintenance policy is applied. This is where the cost for PM and CM is equal. An intelligent maintenance policy reduces the long-term maintenance costs as well as the number of machine failures.

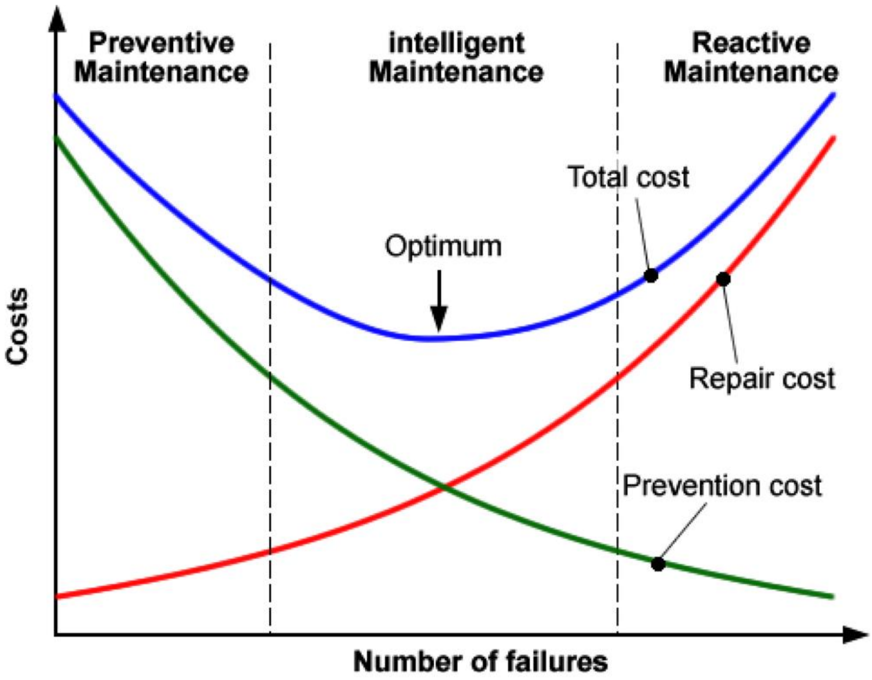


Figure 1. Graph of the total maintenance cost under different scenarios. Source: Tchakoua (2014).

However, applying different maintenance actions in a real-world system is not as straightforward as in theory. The aim of scheduling maintenance actions and resources is to perform as little maintenance as possible with the best output on operations (Scholl et al., 2012). Practically, this means that the goal of maintenance strategies is to find the most efficient maintenance action for each machine or system as well as finding the optimal PM interval for each machine and component. Since the PM interval can be based on a variety of different things, it is hard to determine what the PM interval for a specific machine or component should be based on. The PM interval should be determined on the basis of analyses of the specific system. Unfortunately, this is sometimes determined on the basis of habit, simplicity or lack of resources, which is why the PM in a manufacturing organisation may not be as efficient as it could have been. This, naturally, affects the performance of operations. Yet, even if the PM frequency is based on analyses and failure history of the studied system the intended PM and the actual result will differ, due to the margin of error. The maintenance actions that are applied will not always be accurate or decrease the number of unexpected events. Additionally, the same kind of components may need different maintenance activities scheduled differently, depending on where in the production system the component is produced. It is clear that there are many factors involved when an overall maintenance strategy should be developed. Therefore, it is necessary to develop and implement the optimal maintenance interval for each component and keep that interval continuously updated.

2.1.2 Availability Performance and Maintenance Terminology

The term “availability” is an important parameter in the field of maintenance. It is the traditional measurement for maintenance performance and is defined as the degree to which an equipment or system is in an operable state, or the ratio of the total time an equipment or system is capable of being used (Ljungberg, 2000). Availability can be expressed with some central maintenance measurements, according to the equation visualised in equation 1.

$$Availability = \frac{MTTF}{(MTTF + MTTR + MWT)} \quad \text{Eq. 1}$$

The measurements that define availability could be, for example, the measurements included in equation 1. These measurements are mean time to failure (MTTF), mean time to repair (MTTR) and mean waiting time (MWT) (Hagberg & Henriksson, 2010). According to this definition, MTTF is the time between one failure and the next, while MTTR is the time that is required to repair an equipment and MWT is the time that it takes for maintenance resources to appear with the right tools, documentation and material at the failed equipment. These relationships can be seen in figure 2. In some cases, the term mean time between failures (MTBF) is also used instead of MTTF. MTTR is also sometimes considered to be equal to mean down time (MDT), however, this indicates that there is no waiting time (MWT) and the combination of MTTR and MWT is therefore considered to be a better visualisation of the down time (Hagberg & Henriksson, 2010).

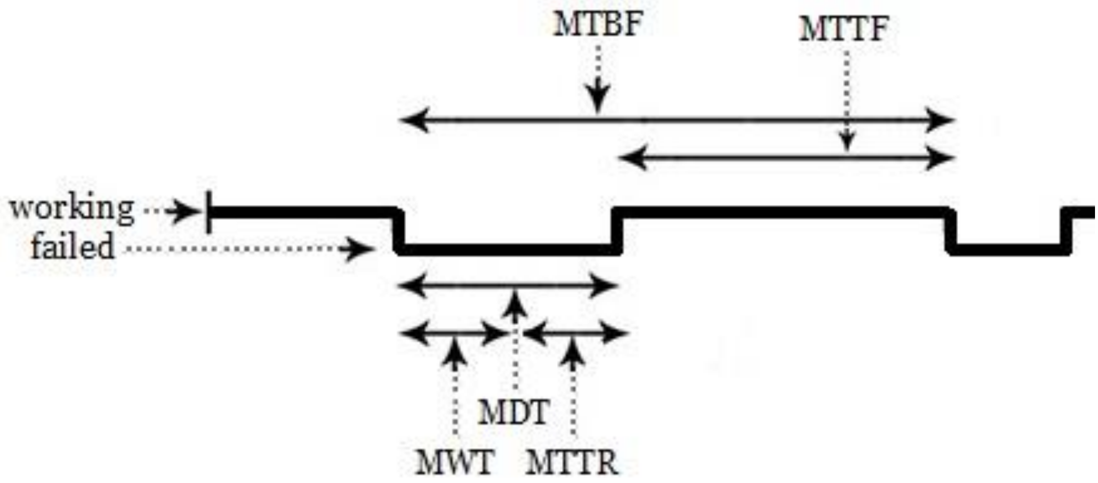


Figure 2. Measurements of availability. Based on Hagberg & Henriksson (2010).

Availability performance shows how maintenance actions contribute to improved measurements, such as supportability, maintainability and reliability (Hagberg & Henriksson, 2010). Supportability improves though decreased MWT. This is achieved by more and higher skilled workers, re-prioritising of resources to the most critical equipment, increased spare part coverage and more available tools and documentation. Maintainability is measured by MTTR and improves though increased failure detecting capacity and more standardised solutions. Reliability improves by increased MTTF, which is achieved by improved equipment, increased capacity of the resources, improved PM and decreased disruptive sensitivity. The improvement of these parameters enables an improved service level and operations performance on both short term and long term.

Availability performance measurements are also applied to a certain procedure for commitment between maintenance and operations called service level agreement (SLA). In this process, the requirements between the two parts are specified; these requirements are often concerning quality, availability and other responsibilities (Hagberg & Henriksson, 2010). The SLA optimally controls the prioritisation of maintenance resources, which is based on the maintenance need from operations and the present maintenance budget. It is typically defined according to MTTF, MTTR or MTBF, where the agreement states which party is responsible for throughput, fault reporting or fee paying. Counter-claims from maintenance on operations could also be included in the SLA. The availability performance measurements are usually used in this context to follow up the work that has been performed and also to constitute the basis for decisions about improvement of the work.

Another measurement that considers availability performance is overall equipment effectiveness (OEE). This is the standard for measuring manufacturing productivity. OEE is measured in percentage of quality, performance and availability (Hagberg & Henriksson, 2010). Thus, the OEE measurement enables a significantly more complete measurement of equipment performance than when only availability is considered (Ljungberg, 2000). Within the OEE metric, different kinds of losses are assigned to six different categories: equipment failure, setup and adjustments, idling and minor stops, reduced speed and delayed processing time, process defects and reduced yield (Dal et al., 2000). These kinds of losses are the most common causes of equipment-based productivity loss. Equipment failure and setup and adjustments are availability losses, while idling and minor stops and reduced speed are performance losses and process defects and reduced yield are quality losses. Some kinds of losses might cause other types of losses as well. By identifying the losses that occurs in the system and measure OEE correctly, important insights can be gained on how to systematically improve the manufacturing process with support from maintenance (Dal et al., 2000).

2.1.3 Hiring and Retirement of Maintenance Resources

The employment lifecycle, a human resources model that identifies different stages of the employment process, can be used to identify the different employment stages and connect those stages with the level of skill among the employees (Jacoby, 2015). The lifecycle and learning process of the employees are most efficiently represented with three different skill levels: low-skilled workers, medium-skilled workers and high-skilled workers (Production Systems Analysis & Optimisation using FACTS Analyser Professional, 2017). This could be translated into different stages at the learning curve, which can be seen in figure 3. When the learning process has just started, the time for a worker to produce one unit is usually high, but decreases over time as the knowledge and experience increases (Albrecht et al., 2005). A low-skilled worker represents a worker with reduced knowledge and experience. In the recruitment process, the people which seem best suited for the employment according to different criteria should be chosen (Jacoby, 2015). The new employee should then be introduced to the work that is supposed to be done. At this stage, the employee starts the learning process by taking part of documentation and knowledge from a mentor that is experienced in the field.

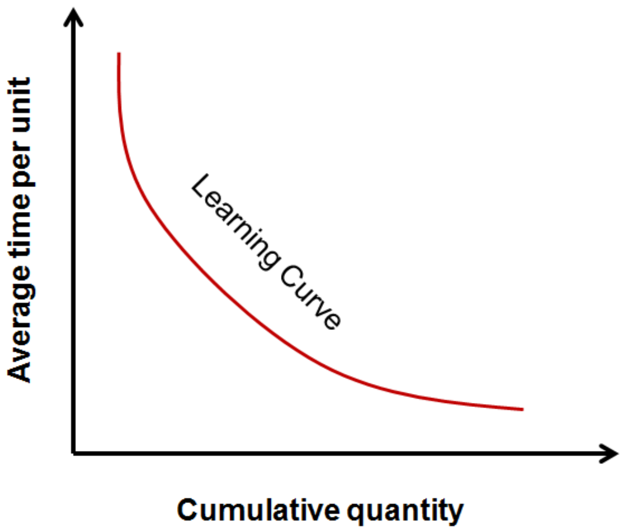


Figure 3. The learning curve. Source: http://community.plm.automation.siemens.com

The medium-skilled worker represents the worker that has spent some time on the position and is comfortable with the work. The learning curve of the worker is at this point considered to be levelled out (Jaber, 2011). This process can be speeded up by the setting of objectives and goals, developed in conjunction with personality profile assessments and identified training needs. Employees in this stage represent semi-skilled workers that have less training than skilled labour but more training, knowledge and experience than unskilled labour. When the employee is considered almost fully developed in the work that is supposed to be performed, the worker is considered to be a high-skilled worker (Jaber, 2011). This worker could, however, be close to retirement. In the final stage of the employment lifecycle, the employee leaves the company. This requires another cycle of recruitment, if the company still has the same work load and performance demands.

Generally, large retirement resignations are facing many companies today. This can be applied to maintenance organisations as well. There is a contemporary challenge of how to ensure that knowledge in the maintenance function remains and that maintenance resources perform the maintenance work with the required quality. Major retirement, which causes a large employee turnover, might affect maintenance performance by variation in work performance and longer MTTR and MWT. This might result in shorter MTTF, which naturally affects operations output negatively. In order to address these potential issues before they occur, more low-skilled workers should be employed while the high-skilled workers are still present. Experienced consultants could also be used for this purpose.

The integration of a hiring and retirement structure to an SD model could be done with the use of a co-flow structure. It has been pointed out by Sterman (2000) that SD models could improve by capturing the characteristics of the stocks, which is the purpose of a co-flow structure. It is a parallel structure that can be used in order to account for the characteristics of the items or components in a stock and flow structure (Hu & Keller, 2009). The generic co-flow structure can be seen in figure 4, which has been developed by Sterman (2000). The flow of the attributes mirrors the flow of the fundamental stock. For every unit that adds to the “stock”, an associated attribute is added to “total attribute”; when the number of units in the “stock” decreases, a corresponding decrease occurs in the “total attribute”.

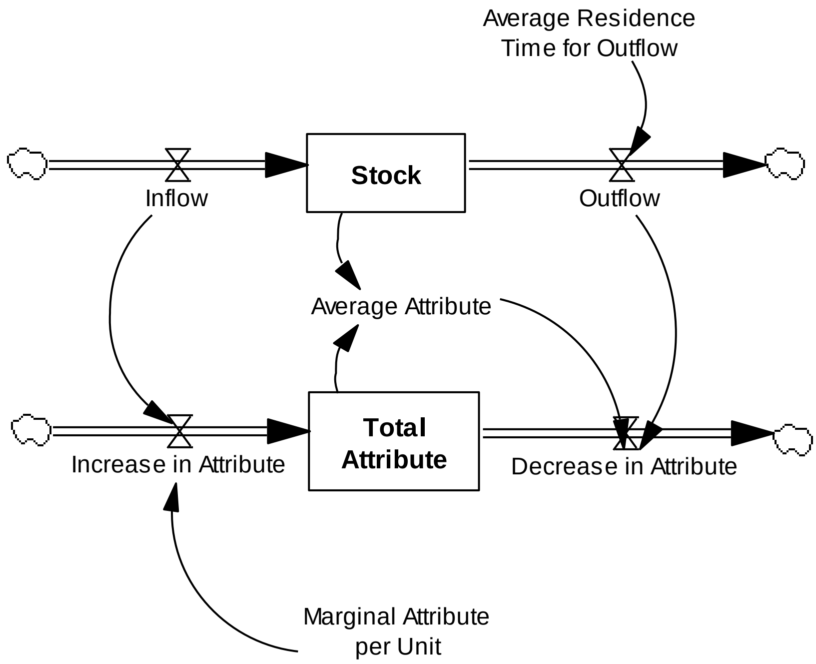


Figure 4. General co-flow structure. Source: Sterman (2000).

2.2 System Dynamics

System dynamics (SD) is using a systems thinking approach in order to understand the dynamic behaviour of a system in a simulation model. It is an approach that quantifies data that is otherwise considered to be of qualitative nature and builds the model on information feedback and delays. SD modelling transforms the information flow in a system into structures in the model; different equations create the relationships between the variables in the structure. This enables analysis of the information feedback. With the use of SD modelling, the behaviour of a system can be investigated as well as the system’s response to different changes on both short term and long term. New kinds of behaviours, that are unidentified in the present but may occur in the future, can be discovered through analysis of an SD model (Bhushi & Javalagi, 2004). The aim of modelling with SD is to identify and analyse root causes by quantifying the behaviour of the system, as well as enabling experiments on different scenarios (Sterman, 2000, Morecroft, 2007).

2.2.1 System Dynamics Philosophy

Within SD philosophy, or system thinking, the three concepts of dynamic complexity, feedback structures and mental models are central (Senge, 1990). In order to truly understand a system, analysis of the system must penetrate the patterns and trends and identify the underlying structures and mental models (Senge, 1990). The major pillars of SD is to think of the bigger picture, balance short-term and long-term perspectives, recognise the dynamic, complex and interdependent nature of systems, take into account both measurable and nonmeasurable factors and reflect on the fact that people in a system are part of the system in which they function. Some of the laws of system behaviour, according to Senge (1990), are that the problems of today come from yesterday's solutions, that behaviour grows better before it grows worse and that cause and effect are not closely related in time and space.

Since reality is far from as simplified as it sometimes seems in simulation models, issues about affecting parameters that have not yet been identified often occur. However, by the use of SD, the dynamic complexity of reality can be captured. SD is therefore suitable for the visualisation and analysis of dynamic systems; it is especially suitable when there are many affecting parameters, delays and complex feedback structures, such as in maintenance systems. Reasons to why dynamic complexity arise in systems are, according to Sterman (2000), because systems are dynamic, tightly coupled, governed by feedback, non-linear, history-dependent, self-organising, adaptive, counter-intuitive, policy resistant and characterised by trade-offs. Another construct that is in the core of SD is the concept of feedback loops. The most common thinking pattern among people is linear, not circular, which is a potential problem as linear thinking leaves feedback loops unrealised. In fact, feedback loops are the underlying structure of every changing event and its causal factors and thus controls everything that changes over time. In reality, a course of events seldom occurs linearly. Instead, a problem initiates an action, which generates a result that eventually causes future problems, possibilities and actions thereof. Reality is a complex of circular feedback loops. Every change and action occurs within this circular network. By the realisation of this structure, complex SD models of very complex systems can be successfully developed.

The third major pillar within system thinking is the mental models of people. All decisions that are made have the foundation in the decision-makers' metal models. Mental models are simply assumptions, thinking patterns and simplifications in people's minds that are used in order to interpret, categorise and understand the environment. These models contain enormous amounts of information and perceptions of the reality; every mental model is unique. Those characteristics make mental models hard to measure (Senge, 1990). According to Checkland (1981), it is not the problems themselves that are the complex issue, but the way the problem-owners perceive the problem. This arises as a challenge to any system due to the fact that mental models cannot be changed until willingness to change occurs. Since the mental models guide people's decisions and actions, SD aims at creating a communication between the simulation model and the mental models that affect the system though decision-making. The mental models are often fairly accurate about the details of a system, but are completely unreliable in perceiving what behaviour the available information might result in. An SD model uses the information stored in the mental models and identifies the dynamic consequences, thus solving the unreliability problem (Forrester, 2009).

2.2.2 Basic Structure of a System Dynamics Model

Forrester (1968) presents the basic structure for representing a system in an SD model in four different hierarchies: the closed boundary, the feedback loop, levels and rates and finally the policy substructure in systems, which contains four components: goal, observed conditions, discrepancy between goal and observed condition and desired action (see figure 5). The closed boundary is a philosophical view, based on feedback thinking. The core thought within this philosophy is that what crosses the boundary only has a minor effect on the behaviour of the system. The boundary strictly depends on the problem that is modelled and thus, the elements that affect the problem are included. The second hierarchy, the feedback loop, is the basic structure in the system. Levels and rates are the two different variable types that are used in an SD model. A level defines the current condition by containing the information that constitutes the inputs or outputs in a rate equation. The first component of the policy sub-structure, the goal, is the desired state of a level and the observed condition is the apparent state of that level. The SD system pays attention to the discrepancy, or the difference, between the goal and the observed condition, which affects the desired action. Hence, the action that is taken can compensate for the identified difference.

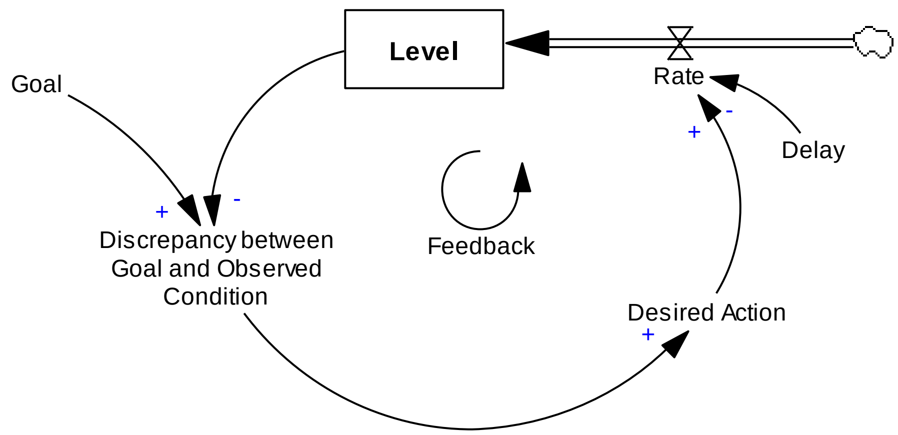


Figure 5. Basic SD model with levels, rates, auxiliaries and constants. Source: Linnéusson (2018).

There are three central building blocks within SD modelling: stocks, flows and feedbacks. These are built by combinations of levels and rates, which enables an almost infinite variety of ways to represent a system. In this case, "stock" and "level" refers to the same building block, which is also applicable to "flow" and "rate". Levels are ruled by the rates that are connected to them (see figure 5), where several in- and out flows are possible. The rates, on the other hand, are either controlled by another rate or an equation. The rate equation is comprised of either auxiliaries, constants or both. There can also be stand-alone input parameters, which are considered to be constants in the system that are unaffected by the other variables. The cloud symbol at one end of the rate arrow (see figure 5) represents a model boundary, which can include another level inside. The feedback loops in the model visualises the adjustment of a value towards the desired or actual value (Campuzano & Mula, 2011).

2.2.3 The System Dynamics Modelling Process

When an SD model is created, it needs to be translated from the mental models of the system. This is a process of several stages. The first step is problem articulation, where the boundary is selected (Sterman, 2000). When the problem is understood and articulated, a hypothesis should be created that is supposed to be evaluated in the modelled system. At this stage, relevant literature should be studied as well as the real-world situation. An SD model should be built upon all available information, including the mental models in the system. This means that the analysis of the studied system is not confined to data that has been numerically recorded (Forrester, 2009). After the data has been collected, the simulation model is built in order to execute the experiments and test the hypothesis. The model that is built should include the initial conditions, behavioural relationships, parameter estimation and decision rules that are part of the studied system (Sterman, 2000). It has to be logically consistent, with clearly defined variables, unambiguous equations and the same units of measure on both sides of each equation (Forrester, 2009). Then, the model should be thoroughly tested in order to determine the validity of the model. The behaviour that is firstly generated by the model might be impossible; in this case, the model needs to be refined (Forrester, 2009). The model should generate plausible results that correspond to its purpose (Sterman, 2000). However, when the model is refined, surprising behaviour of the system are often not model errors, but instead something that occurs in real life that has not been realised yet (Forrester, 2009). At the final stage, the different policies should be exhaustively tested and thoroughly evaluated in the environment that has been created.

2.2.4 Simulation Model Validation

The validation of a model is an important process in simulation modelling that aims at building confidence on how well a model corresponds to a significant system. Forrester (1961) argues that validation of an SD model is hard, since there is a lack of validation procedures within this area. However, the model validation for any simulation model should be judged by how well it suits its defined purpose. The general purpose for industrial simulation models is to visualise the system behaviour and constitute the basis for analyses, thus aiding with the improvement of the industrial system. One perception of model validation is that confidence only can be reached by numerical or quantitative justification. This does not seem reasonable, since the largest part of the human knowledge is qualitative, not quantitative. However, even if the data is of qualitative nature, all variables and parameters of the system need to be considered both individually and in correspondence to the system that they are part of (Forrester, 1961). Hence, the ultimate test is the comparison of the results of the simulation model to what occurs in a real-world system. This is, however, not always possible. In the early phases of simulation modelling, only some degree of confidence can be established (Forrester, 1961).

The first concern of model validation should be if there are significant objectives that the modelling process should fulfil. The objectives must relate to behaviours or scenarios that have a significant impact on the studied system and thus the organisation that the system lies within; otherwise, an accurate model has no value. The approximate extent of the improvements that hopefully follows also has to be defined. A model can be considered valid according to how well the model represents the decision-making details and the total behaviour of the system. When this has been considered, the first test is to evaluate if the behaviour of the model is not obviously implausible. Serious defects will, however, usually expose themselves through model failure (Forrester, 1961). A general framework has been proposed by Barlas (1996) in order to identify different validation criteria. According to this analysis, there are three main categories of validation tests that should be executed: direct structure tests, structure-oriented behaviour and behaviour pattern tests. Conclusively, if the model does not fail, is considered to be relevant to its purpose and can aid in the decision-making processes, validation of the model is supported.

2.2.5 System Dynamics Modelling Issues

Even if SD modelling has many advantages compared to other simulation methods, naturally, there are some disadvantages and problem areas as well. Wolstenholme (1997) states that the issues with SD modelling include abstract parameters, soft variables, detail escalation and model ownership. Difficulty can also arise when the model shall be implemented, for which there is limited support (Richmond, 1994, Forrester, 1994). There is also a possibility that there are some pedagogical issues when the theory and methodology of SD are explained, which could be a reason to why the usage rate of the method is considerably low in decision-making processes (Warren, 2005). Moreover, since an SD model contains few building blocks, it is easy to over-simplify the system that is supposed to be represented. This perceived simplicity potentially leads to false analyses and decisions thereof. However, the low number of levels of building blocks also enables accessible methodology explanation as well as endless system complexity if the modelling process is followed correctly and the modelling is thoroughly performed. Sterman (2000) points out that one of the main difficulties within SD modelling is the formalisation of the equations that defines the interaction between the parameters of the model. Another complex matter is whether or not all elements of a system that actually causes effect on the key parameters have been identified and included in the model. In both of these cases, there is no procedure for judging the validity. Hence, the quality and applicability of the model depends on the experience, creativity and modelling skill of the modeller (Sterman, 2000).

2.3 Simulation-Based Optimisation

Simulation-based optimisation (SBO) is the process of optimising a system according to certain objectives from input variables gained from simulation analysis (Carson & Maria, 1997). When a system has been mathematically and visually modelled, simulation runs generate data that can explain the behaviour of the system. The goal of these kinds of experiments is to evaluate the effect that different values of the input variables has on the studied system. In order to find the optimal value for these input variables within minimum time and computation, optimisation can be used (Carson & Maria, 1997). The optimisation process starts with the input parameters and constraints from the simulation model, which are processed by an optimisation algorithm. A set of values for the decision parameters are generated by the algorithm, which is used by the simulation model as input variables. When the input parameters to the simulation model have been received, a simulation run is performed. The output parameters that are generated from the simulation run are returned to the optimisation application, which runs the algorithm again with the aim to generate a new set of decision variables. This is an iterative process, which is continued until a certain, pre-determined criterion is fulfilled (Syberfeldt, 2009). When the optimisation process is stopped, several optimal solutions will be obtained according to the objectives of the optimisation.

2.4 Multi-Objective Optimisation

The most common optimisation approach when optimising in SD is single-objective optimisation (SOO) which considers only one objective function. However, with the use of multi-objective optimisation (MOO), several conflicting objectives can be evaluated. This optimisation results in several optimal solutions that constitute the Pareto front (Nguyen et al., 2014). One solution is said to dominate another if the solution is not worse than the other, with respect to all objectives, in combination with the fact that the solution is also considered to be better than the other one in at least one of the objectives (Deb, 2001). In figure 6, which represents optimisation results from a two-objective optimisation where both objectives are supposed to be minimised, the Pareto front represents the red line in the graph. The utopia point can be seen in (0, 0). All solutions that are dominated by the Pareto front solutions lies in the feasible region that satisfies both objectives and the given constraints.

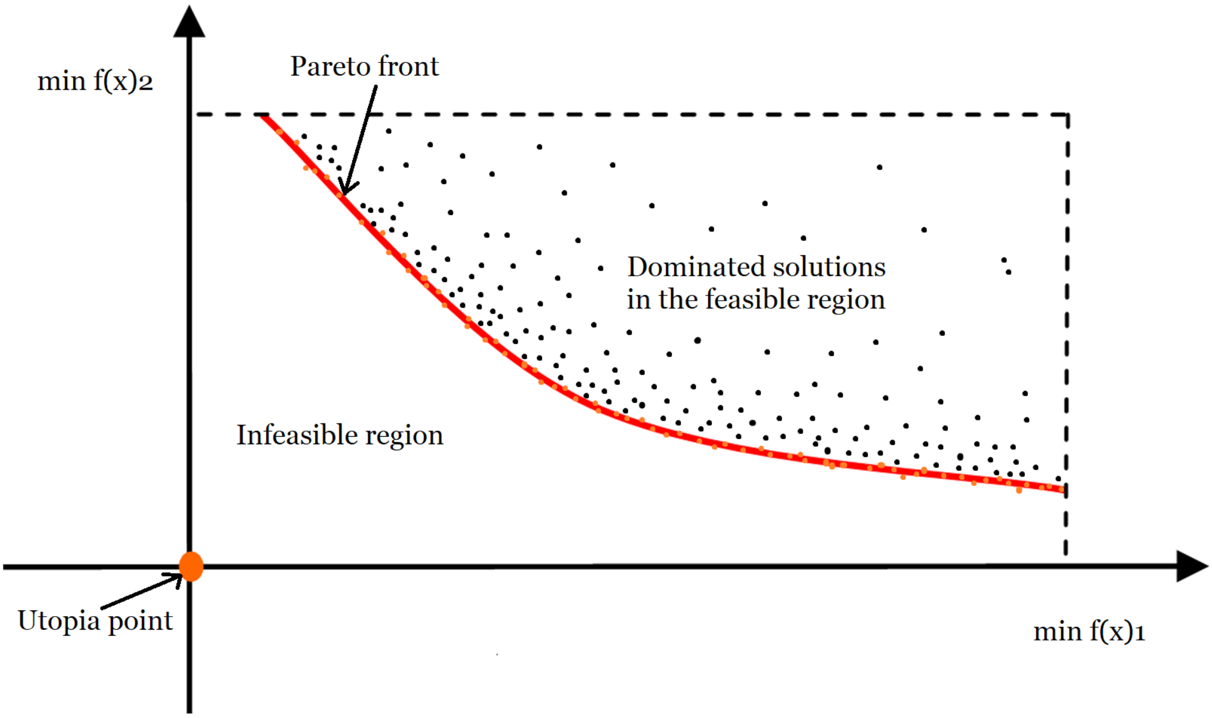


Figure 6. Pareto-front solutions. Based on Deb (2001).

Even if the application of MOO to simulation models developed in SD software is not common yet, there are many applications of MOO in discrete-event simulation (DES) models. There are also many maintenance optimisation problems that have been solved with MOO and DES. However, the process of SBO indicates that MOO can be performed within any simulation method, which enables the application of MOO in SD models. The MOO process follows the procedure of performing SBO (see chapter 2.3 for further details), where the optimisation and the simulation part are separated. There are many optimisation algorithms that can be used for this purpose. However, one of the most commonly used algorithms, developed by Deb et al. (2002), is the Fast Elitist Non-Dominated Sorting Genetic Algorithm (NSGA-II). This algorithm is one of the most popular population-based metaheuristic algorithms, due to its ability to generate solutions that constitute good approximations of the Pareto-optimal front.

3 Literature Review

Previous research in field that deals with maintenance problems expressed with simulation models, SBO and/or MOO has been studied and analysed in order to confirm the experimental design in this research as well as to strengthen the conclusions that will be drawn upon the results of the experiments. The thorough review of the existing literature in the research that has been performed identifies the research problem that this study is concerned with, as well as the research gap which this research project aims to fill.

3.1 Maintenance Performance and System Dynamics

The previous research in the field that connects maintenance and SD is limited. However, the research that has been made evaluates maintenance strategies, behaviour and performance on operations with regards to cost, availability and sometimes also reliability. In some cases, the research only aims at identifying and analysing the cause-and-effect relationships between maintenance and operations. One study in the aviation area, which has been conducted by Fang and Zhaodong (2015), aims at applying SD in order to analyse the causal factors for cost generation within the maintenance area. A stock and flow model is created, which is adjusted over time in order to determine a profitable maintenance strategy. The model successfully calculates the effect of failure rate and PM rate on maintenance cost. These results provide a thorough decision support for the management upon what maintenance strategy to apply; the results also verify the practicality of using SD for analysing maintenance dynamics.

There are some examples of studies where the evaluation of different maintenance strategies successfully have been modelled and simulated with SD. One study that evaluates different maintenance strategies with the use of SD modelling and simulation is conducted by Chumai (2009). This is a case study of both the current and possible future maintenance strategies for a Thailand plant, compared with benchmarking plants in the US. The study aims at illustrating that a proper maintenance strategy can reduce cost and increase availability. A generic plant maintenance system is modelled with an SD approach, covering various plant types. The plant uptime and maintenance cost are used as output parameters. Compared to the benchmarks, the levels of reactive maintenance actions were similar at the studied plants; however, this was not the case for the levels of preventive maintenance actions at fixed intervals and the levels of condition-based maintenance actions. The results of the simulation runs suggest that traditional PM levels should be reduced and condition-based maintenance should instead be increased in order to generate lower maintenance cost and higher availability. Similarly, in a master level thesis, Kothari (2004) evaluates maintenance policies and PM interval through SD in order to achieve lower system degradation and higher availability. The results from the simulation indicate that there is an optimal preventive maintenance interval for the model, which is built with limited preventive maintenance capacity. The results also verify that more frequent PM is needed when the load factors increase.

Böhm et al. (2008) also conducted a maintenance strategy study, where the aim was to identify efficient maintenance strategies in traffic systems by SD simulation. Various different maintenance strategies were evaluated: corrective, preventive, pre-determined, condition-based, etc. In this study, the difficulty of finding efficient maintenance strategies was observed, since each maintenance strategy has different options of cost, impact on the equipment, duration, process period, etc. Therefore, cause-and-effect chains between these parameters were identified and modelled with SD. The models enable the comparison of the efficiency of various maintenance strategies and also the combination of activities that leads to an overall efficient strategy. The most efficient strategies with regards to cost were identified through optimisation. With this model, the current maintenance strategy of a system could be evaluated and a future improved strategy could be composed.

It has also been shown that SD can be used for other maintenance strategy purposes. In his paper, Thun (2004) discusses the use of TPM (total productive maintenance) as an approach for improving maintenance systems. TPM is a maintenance strategy for achieving improvements through the focus on the processes, machines, employees and equipment that adds value to the end customer and thus generates profit to the company. The aim of TPM is to keep all equipment in top condition in order to avoid delays and breakdowns. According to this study, however, TPM is seldom successfully implemented. The aim of this study was to present reasons for the failure of TPM and changes that can be made in order to success with the implementation of the strategy. In order to reach an understanding of why the implementation of TPM often fails, the dynamics of maintenance were modelled with SD before it was analysed and discussed. Simulation runs of the model revealed the changes that needed to be made in order to success with the implementation; the results also showed that the performance of the TPM system can be worse in the beginning, but improves over time. Thus, this study shows the long-term and short-term benefits and requirements a maintenance strategy can have on the overall system.

Baliwangi et al. (2007) have explored and identified the behaviour of components and maintenance systems under different maintenance policies. The aim with the study was thus to generate maintenance policy options to the management, where the impact of the implementation of those policies has been predicted on the basis of an SD simulation model. With the use of SD modelling, the behaviour of each integrated system and its components could be studied. By analysing these behaviours, the effect of different operations and maintenance policies with regards to system reliability, operational cost and maintenance cost could be identified. For each of the studied policies, the SD model has simulated failure rate, time to perform a maintenance action, decision of whether or not a maintenance action should be carried out, degree of how well the maintenance action has been performed, effect of each component after maintenance has been performed as well as both operational and maintenance cost. A case study is presented in the paper, in which the simulation model is applied. The study indicates that the behaviour of a maintenance system depends on the system components' characteristics. This study certainly shows that maintenance and operational activity in symbiosis with each other contribute to the overall performance of the system; it also shows that these dynamics can be modelled with the use of SD. Thus, the simulation model presented by Baliwangi et al. can constitute as a basis for decisions for the management.

An article by Khorshidi et al. (2015) deals with the subject of modelling reliability-centred maintenance with the use of SD. Reliability-centred maintenance aims at deciding the level of corrective and preventive maintenance with regards to cost in order to improve the reliability of the system. The model presented in the study was built of a causal loop diagram, to represent the causal relationships between the elements in the system, and a stock and flow structure to simulate the entire system. Different maintenance strategies, with different levels of corrective and preventive maintenance, have been applied to this model and evaluated with regards to availability and cost. The results of the study indicate that increased levels of improvement actions increases availability but impose higher cost. By this analysis, two conflicting objectives in maintenance systems have been identified. To solve this, an optimisation viewpoint was useful. Another study also examines maintenance systems from a reliability angle with the use of SD modelling. According to Basirat et al. (2013), the reliability is an essential performance indicator in order to assess the capability of a maintenance system. In the study, the authors have modelled and analysed a maintenance system through SD with the aim of achieving control and reliability evaluation. Series of stock and flow diagrams were integrated in the model, which allowed a higher level of reliability. The results of the simulation runs with the proposed methods show that better decision making should be possible under different conditions. The study also indicates that analysing maintenance systems through SD could provide new thinking to the management.

There are also some recent studies by Linnéusson et al. (2015, 2016, 2017 & 2018) that aim at modelling and simulating maintenance behaviour and performance through SD. In the first study, Linnéusson et al. (2015) proposed a systems thinking modelling concept that visualises the interdependencies that maintenance has with financial parameters, operations and customer behaviour. This paper aims at acknowledging the effects that maintenance has on operations on both long term and short term and the financial consequences thereof, mainly to point out the directions of the future work in the field. It also includes an example of a model of a machine strategy problem that connects the physical assets and actions with the financial aspect. Linnéusson et al. states that the usage of systems thinking modelling when dealing with maintenance issues enables learning from consequences of strategies and policies in the studied system, thus enabling evaluation of future scenarios that supports decision-making.

In the second study by Linnéusson et al. (2016), the research focus has deepened into justifying investments in preventive maintenance work with the use of SD. The paper by Linnéusson et al. (2018), published in *International Journal of Production Economics*, is partly passed on the paper from 2016. Here, Linnéusson et al. studied the effectiveness of using SD as a tool to visualise cause-and-effect relationships and interdependencies within and without the maintenance function. A model was presented in the study that quantifies the dynamic factors of maintenance performance, which constitute the basis for a systems analysis on the consequences from different maintenance strategies. The model was constructed with parts from previous research in maintenance and SD modelling and theory. From the two experiments that have been executed in the model from 2016, an analysis of how different strategies of reactive and preventive maintenance behave in symbiosis with each other over time can be made. The results from the experiment in the paper from 2018 show both short-term and long-term consequences from different strategies and also dynamics in the system that has not been identified in previous literature.

In another paper by Linnéusson et al. (2017), an analysis is presented in order to justify the study of maintenance with a system behaviour perspective. Once again, Linnéusson et al. points out that managing maintenance is an act of balancing the short-term economic requirements with the long-term strategic thinking. An SD maintenance performance model was combined with MOO and insights from the investigation of the Pareto-front solutions can be drawn by visualising the performance of the key parameters. Thus, this paper confirms that the use of MOO for the output of an SD maintenance performance model is effective. In fact, the authors state that there is no return to the single use of SD when system behaviour is explored. The authors also confirm that the correct interpretation of the Pareto-front solutions strongly rely on the understanding of the dynamic relationships, non-linearity and delays in the model, thus strengthening the research method that has been chosen in this research project.

3.2 Maintenance Performance and Optimisation

In contrary to the literature about studying maintenance in an SD environment, there are many studies that cover maintenance and SBO and maintenance and MOO. In some cases, these two topics are also combined. In their paper Oyarbide-Zubillaga et al. (2008) do exactly this; the article focuses both on modelling and optimising preventive maintenance in a manufacturing environment. The objective of the optimisation was to determine the optimal frequency for preventive maintenance, with regards to the criteria of cost and profit. SD was not used for the modelling part, but instead the modelling technique of DES was utilised. In this paper, the suitability of using multi-objective evolutionary algorithms when dealing with multi-objective problems within maintenance management was proven to generate satisfying results. Another study that combines discrete event simulation with optimisation is a study by Cao et al. (2013). The optimal maintenance policies were sought from the costs and availability of the system, which were estimated by DES and the Optimal Budget Computing Allocation algorithm. The study shows that the OCBA algorithm is efficient in identifying the optimal maintenance policies, while simultaneously improving the simulation efficiency.

A study that uses DES for maintenance modelling is presented in an article by Scholl et al. (2012). One key application area where discrete event simulation can be used is planning and scheduling of extended maintenance activities, according to the authors. In this study, a simulation model was built with the aim of evaluating the effects of maintenance activities in a long-term perspective. A simulation-based, multi-stage approach for scheduling of maintenance activities was presented in the paper. However, when the long term effects are supposed to be evaluated, DES is probably not the most suitable simulation method; the technique cannot be used to properly visualise general trends and effects in a long-term perspective. A study that uses DES for modelling of field maintenance is a study by Alabdulkarim et al. (2011). DES is good at representing stochastic systems, which was taken advantage of in this study where field maintenance was counted as one of those stochastic systems with conflicting demands. However, this study also points out the research gap in the literature regarding maintenance and simulation.

Another paper that combines maintenance performance modelling and optimisation is a paper by Seif et al. (2017). Here, Seif et al. (2017) discuss the problem of how to financially defend the capture of machine time from operations to perform preventive maintenance in order to prevent machine failure. To address this problem, the authors presented a permutation flow shop scheduling problem with multiple maintenance requirements. This was modelled as a mixed-integer linear program with conflicting objectives, thus requiring MOO. The first objective in the study was to minimise the total maintenance cost and the second objective was to minimise the total tardiness by sequencing the maintenance activities. The computational results verify the efficiency of the solution methodology proposed in the paper.

Seif et al. (2017) also points out that a genetic algorithm can become ineffective for solving real-world problems if it does not consider the unique structure of the problem. Here, it seems like a dynamic understanding of the system is required in order to achieve results that can confirm solutions that can be effective in a real-world scenario. A visualisation of the system and its complex relationships might have been helpful in the conclusion-making, which the study in this paper seems to lack. Similarly, in a study by Savsar (2008), a discrete mathematical model was used, integrated with an iterative simulation procedure. In this study, the author pointed out that both corrective and preventive maintenance can cause significant production losses. One of the solutions to this, according to the author, is the implementation of intermediate buffers in the production line. Savsar (2008) also argues that productivity and reliability calculations for this kind of problem are complex and closed form solutions are not considered possible when the model is extended with preventive and corrective maintenance. Here, this study indicates that other tools could be more successfully used in order to address these complex issues.

In a paper by Christer et al. (1998), the authors developed a delay-time model, with the aim to model and optimise preventive maintenance in a delay-time process. This was applied in a case study, where the values of the delay-time process were estimated from maintenance failure records. Based upon the model, an inspection model was added in order to better describe the relationship that exists between the interval of the preventive maintenance and the total downtime. The study by Wen-yuan & Wang (2006) further uses and develops this model. The aim with the study was to optimise the preventive maintenance interval, with a model that is fitted to the estimated number of defects. This number was identified when PM had been performed and the number of failures had been recorded. An optimal inspection interval for preventive maintenance was identified in the study, which was based upon the estimated parameters in the model. Even though delay time was considered in the two proposed models, the dynamic view of the studied systems is lacking and therefore also the generalisability.

There are many articles that discuss the subject of optimisation of maintenance functions and performance. In an article, Rezg et al. (2003) proposes an integrated method for performing preventive maintenance and inventory control in a production line consisting of multiple machines with no intermediate buffers is proposed. The authors have modelled the production line in order to simulate the behaviour under different maintenance and control strategies. Simulation and genetic algorithms were combined into a methodology, which, according to the study, performs well compared to the analytical solutions. An article by Khatab et al. (2014) also deals with the subject of optimisation of preventive maintenance. The production system that is supposed to be maintained is subject to stochastic degradation; thus, the model proposed in the article takes both corrective and preventive maintenance into account. In this model, both of the different maintenance types were considered to be imperfect, which in this case means that the execution of these actions brought the system to a state that lied somewhere between the best scenario and the worst scenario. The objective of the optimisation was to maximise the average availability of the system by finding the optimal number of preventive maintenance actions as well as the optimal reliability threshold. Another take on the subject is a study proposed by Ayed et al. (2012), which partly deals with the subject of finding a preventive maintenance policy that reduces the machine degradation and simultaneously minimises the total cost in a randomly failing manufacturing system. However, these studies lack the long-term view of how the preventive maintenance actions might affect the availability over time and also what other factors that might have a substantial effect on performance indices.

In a study, Moghaddam et al. (2010) proposes a new MOO model which aims at determining the optimal preventive maintenance frequency in a multi-component system. The planning horizon in this model was divided into periods, in which maintenance, replacement, or "do nothing" must be planned for each component. The objectives for the optimisation were to establish an action plan for each component, while minimising the total cost and maximise the overall system reliability. The authors notified the complexity of MOO in the maintenance area in the article and therefore used two metaheuristic solutions to solve the problem. Nonetheless, Pareto-optimal solutions that satisfied both objectives could be obtained after the completed optimisation. The study in the article proposed by Das Adhikary et al. (2015) also successfully uses MOO for scheduling of preventive maintenance actions. The objectives in this study were to maximise availability, while minimising the total maintenance cost. The objective functions were then optimised with the use of a multi-objective genetic algorithm. The model has then been applied in a case study, which shows the results that the profit at a plant can be increased when the two objectives are met. However, it is hardly only the obvious parameters that actually affect maintenance cost and availability; in a real-system implementation, other factors also have to be taken into consideration. This shows the need of a modelling tool that can handle the dynamic complexity of maintenance systems.

Some maintenance optimisation has also been performed on single-machine cases. In the article by Liao et al. (2016), an optimisation model of preventive maintenance and production scheduling were proposed. The objectives of this optimisation were to minimise the total completion time as well as the total maintenance cost, which were met by the consideration of the deteriorating effect and similarity-dependent setup times. Liao et al. (2016) also suggested a hybrid maintenance planning strategy, based upon the proposed optimisation model. In this strategy, preventive maintenance actions were performed on the basis of failure rate threshold. To ensure that minimum repair was performed, the age of the machine were taken into consideration in order to better predict the rate of unexpected failure. A genetic algorithm was used to perform the optimisation. Computational results from the study show that the model could meet the objectives successfully. However, even if the models proposed in the study generate satisfying results, there are many additional factors that would affect the performance indices in a real-world system. The impact of the cause-and-effect relationships that exist in every system is not identified in these kinds of studies, which is why long-term benefits in a real-world system would be hard to ensure if a model of a single-machine maintenance optimisation is implemented.

Marsequerra et al. (2002) also proposes a study that aims at optimising maintenance. In this study, a condition-based maintenance policy was implemented in a continuously monitored multi-component system; the decisions of maintaining this system were dynamically based on the observed condition of it. The optimal degradation level, beyond which preventive maintenance could be performed, was determined by a genetic algorithm where the objectives were, as in many other maintenance optimisation studies, to maximise profit and availability. However, the evolution of the degradation of the system was based on Monte Carlo simulation, which models some degree of dynamics in the degradation process as well as account for the limitations in the number of available maintenance workers. The study shows that the approach of combining genetic algorithms and Monte Carlo simulation is efficient in the search for the most optimal solutions. In this study, some dynamic complexity of the problem is acknowledged and modelled through the Monte Carlo simulation, an approach which seems to be rare in this field. Most studies of maintenance and SBO cannot properly evaluate "what if"-scenarios, due to the lack of dynamics in the modelled systems. However, the fact that the Monte Carlo simulation generated satisfying results in this complex of problems as well indicates that this is a method that needs to be further evaluated when modelling and optimising maintenance problems. The results of this study also show the importance of including dynamic complexity in the process of modelling and optimisation.

In a system which uses small batch sizes and hence has much variability, the job shop schedule has to be responsive to changes in the production plan. This applies to the preventive maintenance models as well, which, in turn, has to be responsive to changes in the job shop schedule. These required dynamics in a preventive maintenance model was addressed in the study by Zhou et al. (2012). In the model proposed in the study, the optimal maintenance practice for this dynamic system was determined by the maximisation of the cumulative opportunistic maintenance cost savings. A numerical example showed that the model tackles the addressed problem better than the other commonly used models. Even if this article only addresses the problem of scheduling preventive maintenance, dynamics is taken into consideration when the model is created. The study shows that there is a need for models that can handle dynamic maintenance problems.

3.3 Summary of the Literature Review

In this section, the literature review has been summarised. In total, 28 different papers on the subjects of simulation and/or optimisation applications of maintenance issues have been reviewed. Table 1 summarises the content of each article in five sections: **article** describes the reference, **research scope** presents the aim and main field of the article, **simulation modelling technique** shows the simulation approach that has been used if simulation modelling has been applied, **optimisation technique** shows the algorithm that has been used for the optimisation if optimisation has been applied and lastly **optimisation objective(s)** presents the objectives of the optimisation if optimisation has been applied. For the articles where a certain section is inapplicable, that specific section is marked with **NA*.

Table 1. Summary of the literature review.

Article	Research scope	Simulation modelling technique	Optimisation technique	Optimisation objective(s)
Alabdulkarim et al. (2011)	Maintenance systems modelling	DES	**NA*	**NA*
Ayed et al. (2012)	PM and maintenance strategies optimisation	**NA*	Unspecified algorithm	Min: Total cost
Baliwangi et al. (2007)	Maintenance strategies modelling	SD	**NA*	**NA*
Basirat et al. (2013)	Maintenance reliability modelling	SD	**NA*	**NA*

Böhm et al. (2008)	Maintenance strategies modelling and optimisation	SD	Optimisation feature in the software AnyLogic	Min: Maintenance cost
Cao et al. (2013)	Maintenance policies modelling and optimisation	DES	Optimal Budget Computing Allocation Algorithm	Min: Maintenance cost Max: Availability
Christer et al. (1998)	PM modelling and optimisation	*NA	Unspecified algorithm	Min: PM interval Min: Total unit downtime
Chumai (2009)	Maintenance performance modelling	SD	*NA	*NA
Das Adhikary et al. (2015)	PM optimisation	*NA	Genetic algorithm	Max: Availability Min: Maintenance cost
Fang & Zhaodong (2015)	Maintenance strategies modelling	SD	*NA	*NA
Khatab et al. (2014)	PM optimisation	*NA	Unspecified algorithm	Max: System reliability Min: PM actions Max: Availability
Khorshidi et al. (2015)	Maintenance strategies modelling	SD	*NA	*NA
Kothari (2004)	Maintenance strategies modelling	SD	*NA	*NA
Liao et al. (2016)	PM and maintenance scheduling optimisation	*NA	Genetic algorithm	Min: Total completion time Min: Total cost
Linnéusson et al. (2015)	Maintenance performance modelling	SD	*NA	*NA
Linnéusson et al. (2016)	Maintenance performance modelling	SD	*NA	*NA
Linnéusson et al. (2017)	Maintenance strategies modelling and optimisation	SD	NSGA-II	Max: Availability Min: Maintenance cost Min: Consequential maintenance cost
Linnéusson et al. (2018)	Maintenance performance modelling	SD	*NA	*NA
Marsequerra et al. (2002)	Maintenance strategies modelling and optimisation	Monte Carlo simulation	Genetic algorithm	Max: Profit Max: Availability
Moghaddam et al. (2010)	PM and maintenance scheduling optimisation	*NA	Generational genetic algorithm & simulated annealing	Min: PM interval Min: Total cost Max: System reliability
Oyarbide-Zubillaga et al. (2008)	PM modelling and optimisation	DES	Genetic algorithm	Min: PM frequency Max: Profit

Rezg et al. (2003)	PM modelling and optimisation	Simulation software	Genetic algorithm	Min: PM interval Min: Stock levels
Savsar (2008)	Maintenance strategies modelling	Discrete mathematical model integrated into an iterative simulation procedure	*NA	*NA
Scholl et al. (2012)	Maintenance scheduling modelling	DES	*NA	*NA
Seif et al. (2017)	PM optimisation	*NA	Genetic algorithm	Min: Maintenance cost Min: Tardiness
Thun (2004)	Maintenance performance modelling	SD	*NA	*NA
Wen-yuan & Wang (2006)	PM modelling and optimisation	*NA	Unspecified algorithm	Min: PM interval Min: Total unit downtime
Zhou et al. (2012)	PM optimisation	*NA	Unspecified algorithm	Max: Maintenance cost savings

3.3.1 Research Scopes

The different research scopes that have been adopted in the different articles are summarised in figure 7. However, many of the included papers deal with multiple subjects and some subjects can be hard to distinguish from another; for example, articles that models and optimises PM often handles maintenance scheduling problems and optimisation of maintenance strategies as well. That having been said, figure 7 shows that PM optimisation and maintenance strategies are the most common research scopes of the ones that have been covered in this literature review, while a smaller amount of papers covers maintenance scheduling and maintenance performance. In fact, most articles deals with maintenance performance in one way or another, but the articles that have been considered to mainly cover maintenance performance are papers that do not have any other main scope.

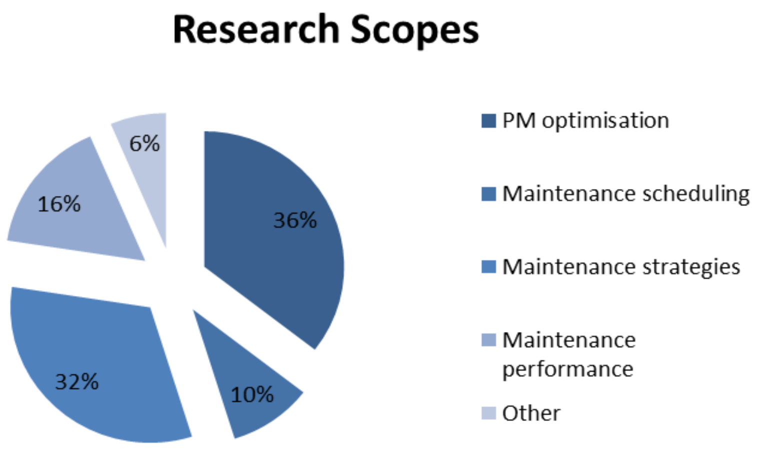


Figure 7. Diagram of the different research scopes.

3.3.2 Simulation Modelling Techniques

The different simulation modelling techniques that have been covered in this literature review are mainly SD and DES, even if some other simulation modelling techniques occur as well. 19 of the 28 covered papers (67.9 %) uses simulation modelling and these papers have been represented in figure 8. Figure 8 shows that SD is the most frequently used simulation modelling technique, with over 60 % of the reviewed articles that involves simulation. However, these numbers do not represent the percentage of the available papers that deal with SD in combination maintenance and DES in combination with maintenance. Since this research aims at using SD to model and optimise maintenance problems, all of the found maintenance SD papers with relevant scopes for this study have been covered in this literature review. Due to the chosen search techniques, there might be other available articles within the area as well. DES is excluded from the empirical part of this research; only some important maintenance DES papers are therefore included.

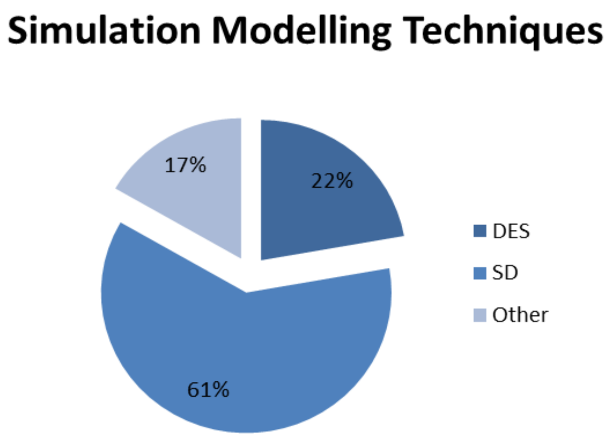


Figure 8. Diagram of the different simulation modelling techniques.

3.3.3 Optimisation Techniques

The different optimisation techniques that have been used in the articles that aim at optimising different aspects of maintenance problems have been summarised in figure 9. 15 of the 28 covered papers (53.6 %) uses optimisation and those papers are represented in figure 9. In many cases, the algorithm that has been used for the optimisation is unnamed in the article. These algorithms have been labelled "unspecified". However, the diagram shows that the genetic algorithm is the most commonly used for solving maintenance issues, being used in 53 % of the optimisation articles.

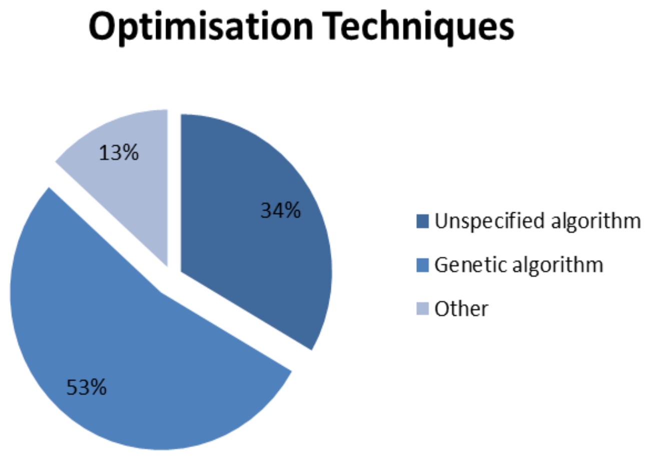


Figure 9. Diagram of the different optimisation techniques.

3.3.4 Optimisation Objectives

The optimisation objectives from the optimisation runs that have been conducted in the articles that aim at optimising maintenance issues have been summarised in figure 10. Of the 15 articles that uses optimisation, only two are single-objective while the rest are multi-objective (86.7 %). The diagram reveals, not surprisingly, that the PM interval is the most common objective. Since the research scope summary showed that most articles deal with PM from different angles, this has to be mirrored in the optimisation objectives. Minimising maintenance cost, minimising the total cost and maximising availability are also commonly used objectives. Table 1 also shows that most of the studied articles whose research scope is some kind of optimisation have multiple objectives.

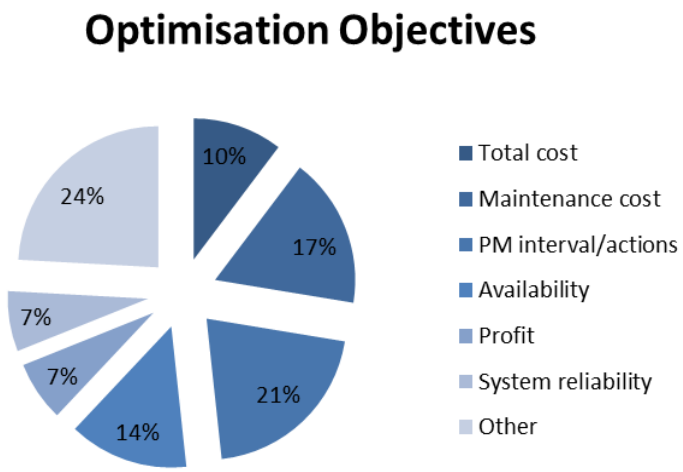


Figure 10. Diagram of the different optimisation objectives.

3.4 Analysis of the Literature Review

An analysis of the articles that has been reviewed has been performed. This literature review aims at identifying the scientific problems that exist within the specific area and also where there is a research gap. The most promising theories in this new area are pointed out, which identifies a set of concepts that constitutes the foundation for this research. Since the field of maintenance modelled with SD is novel and the literature therefore is limited, the literature review has been extended to include maintenance in combination with SBO and/or MOO. The search words that has been used to find the articles in the literature review are "maintenance + optimisation", "maintenance + system dynamics", "maintenance + simulation", "maintenance + multi-objective", "maintenance + discrete event" and "maintenance + performance". The searches have been performed at Google, Google Scholar, DiVA Portal, Scopus, Science Direct, IEEE Xplore and Tayor & Francis Online. The articles that have been covered are published papers in journals or at conferences, although some are theses on doctoral and master level, and hence the methods and results are considered to be valid and trustworthy.

In conclusion, it is clear that different complex maintenance issues can be successfully expressed with simulation models and optimised with MOO. The articles that deal with the subject of maintenance and MOO often tackle the problem of scheduling preventive maintenance or evaluating various maintenance policies under different circumstances. Most papers narrow the research to different scheduling or policy problems; few papers that deal with maintenance issues from an SD perspective focus mainly on how maintenance performance affects production performance. Here, a research gap is identified for a holistic view of maintenance performance in symbiosis with operations.

In the maintenance studies where SD is applied, the complexity and dynamics of the maintenance system is revealed. Therefore, several conflicting objectives are identified in these studies. This finding shows that optimisation is needed in order to solve maintenance problems in SD. The objectives for the MOO are most commonly to minimise the maintenance cost, the total cost, or to maximise the profit, while simultaneously maximising the availability or minimising the PM interval. The studies in the reviewed articles show that genetic algorithms perform well with these objectives and can therefore be considered to be suitable for optimising maintenance performance. This conclusion confirms the choice of using the genetic algorithm NSGA-II in this research.

Some articles that deal with the subject of maintenance and SBO use DES as the modelling method. When this method is used in order to simulate different maintenance functions and the interaction with operations, it is generally hard to achieve complete generalisability. In addition, DES software cannot handle data of qualitative character and therefore softer aspects, such as the effect of people's mind-sets, are missed out. For every model that has been simulated in software that cannot handle dynamic complexity, the delays, feedback structure, cause-and-effect relationships and long-term perspective are not addressed and therefore their effects on the system remain hidden. There is a strong need for charting and identifying these effects, both on short term and long term, which is where SD might step in. In the articles that discuss the subject of maintenance from an SD perspective, the promising results confirm that this is a new research area that needs to be further explored. There are many "what if"-scenarios regarding maintenance performance in symbiosis with operations that needs to be evaluated with a dynamic and long-term perspective, including the scenarios in the objectives of this research project. It can be concluded that the application of SD for maintenance problems addresses and identifies the dynamic complexity that most state-of-the-art maintenance and simulation studies lack.

4 Empirics

In this chapter, the empirics of this research are presented. First, the base model is described in detail and its behaviour and underlying structure are analysed. Then, the design of the different experiments is presented for the two different scenarios that have been evaluated.

4.1 The Base Model

The base model that has been used for the following experiments has been developed by Linnéusson (2018) and carefully described in the paper by Linnéusson et al (2018). The model represents the strategic development of maintenance, where the aim of creating the model was to generate general, representative behaviours of maintenance in symbiosis with operations. Since the model structure is built with the purpose of moving towards generalisability, the evaluation of a specific case requires extensions and adaptions. The Vensim simulation modelling software has been used in order to create the model. Figure 11 illustrates an interpretation of the policy structure diagram of the model. In this overview of the model, only the balancing loops are visible and the growth mechanisms are therefore excluded. One assumption that has been made is that every equipment failure reduces production performance, which may not be the case in a real-world scenario. The benefits of different maintenance strategies, where there is proactive work involved, may therefore be even larger when the maintenance actions can be performed outside of production hours.

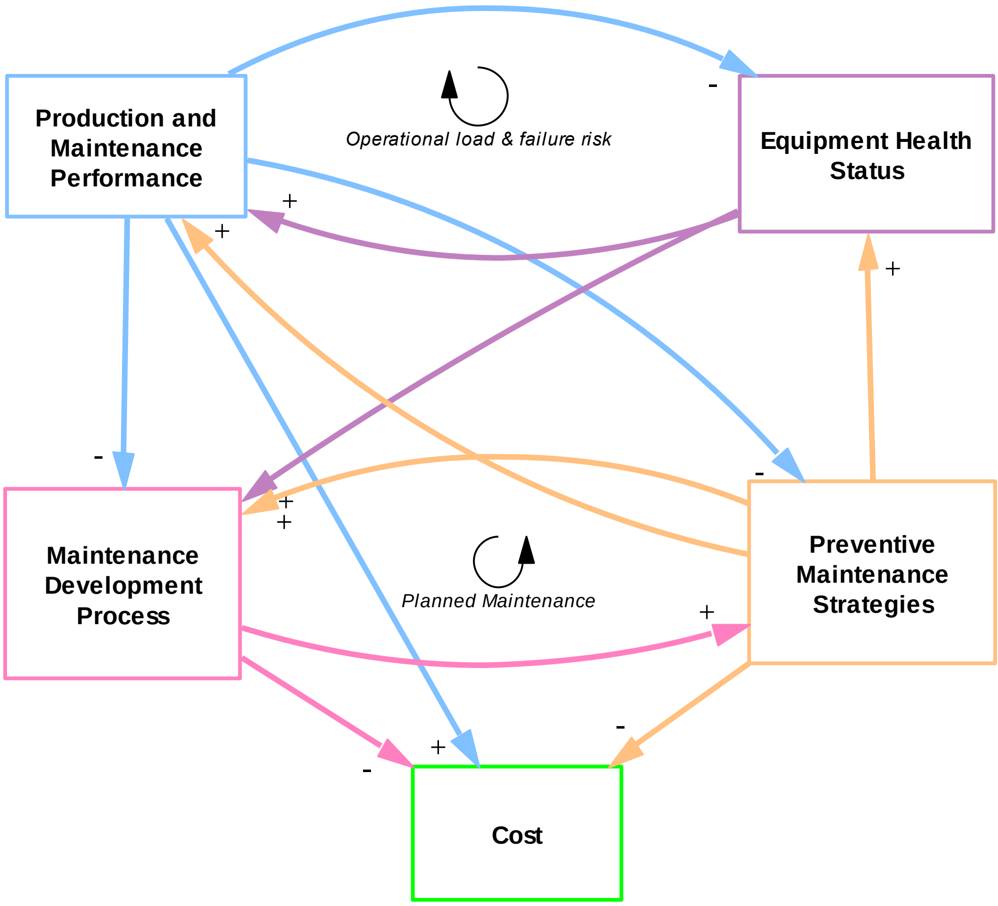


Figure 11. Policy structure diagram of the base model. Based on Linnéusson et al. (2018).

The different parts in the policy structure diagram in figure 11 above, which are production and maintenance, equipment health, preventive maintenance, maintenance development and cost, are described in more detail below.

4.1.1 Production and Maintenance

In this section of the model, the availability is defined, as well as staffing and the performed scheduled and unscheduled maintenance actions. An interpreted simplified overview of the structure can be seen in figure 12. The availability is calculated as a consequence of the reliability of the equipment, which in this case is the equipment in full functionality divided by the number of equipment. Equipment are utilised as units that flow between the stocks. The variable *equipment in full functionality* and the *breakdown rate* moves the equipment to *unscheduled maintenance*, where it waits for an *unscheduled repair*. Similarly, the *takedown rate* moves the equipment to *scheduled maintenance*, where it waits for a *scheduled repair*. After a repair has been completed, the equipment is once again counted as *equipment in full functionality*. The *takedown rate* depends on the *applied maintenance methodology in preventive maintenance*, *planning and scheduling of preventive maintenance* as well as on the level of accessible equipment. This is based on the variable *pressure to produce*, where lower values of *availability* limits the proactive actions. The effectiveness of the scheduled and unscheduled repairs varies, since the mean down time (MDT) for unscheduled repairs are longer than for the unscheduled repairs.

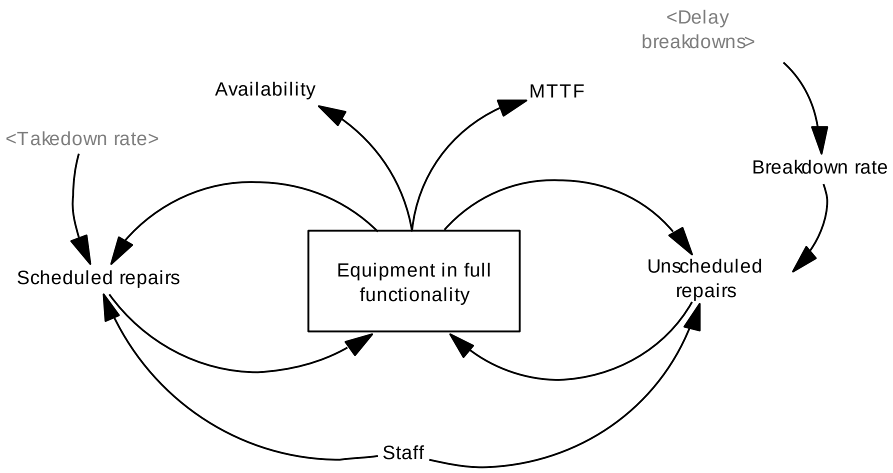


Figure 12. Simplified overview of the production and maintenance section of the base model. Based on Linnéusson et al. (2018).

4.1.2 Equipment Health Status

This section defines the structure responsible for equipment health, which defines the aggregated equipment reliability, or the risk of failure, in the system. An interpreted simplified overview of the structure can be seen in figure 13. In this part of the system, defects are treated as units, which are generated by production and eliminated through repairs. Increased production performance inevitably leads to increased load of the equipment, which generates more defects. The defects that occur in the stock *equipment health* are eliminated with repairs, where each repair is proportional to the number of defects in order to generate more efficient repairs when the health status is poor.

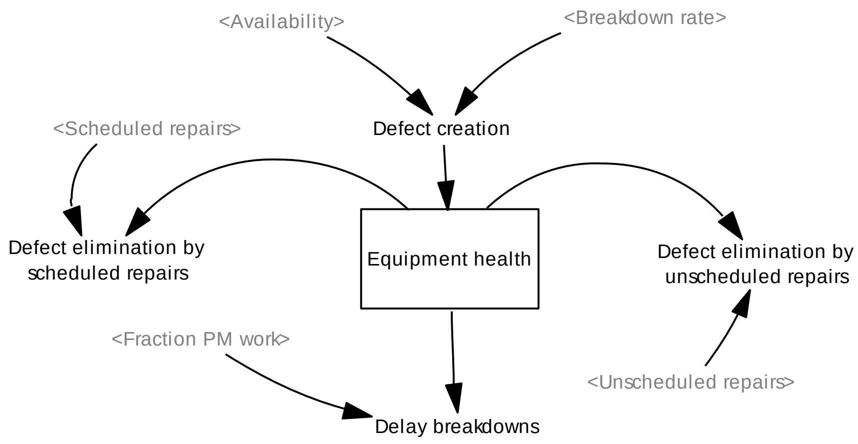


Figure 13. Simplified overview of the equipment health status section of the base model. Based on Linnéusson (2018).

4.1.3 Preventive Maintenance Strategies

The structure that manages preventive maintenance performance defines the takedown rate for the planned repairs. An interpreted simplified overview of the structure can be seen in figure 14. This model section utilises PM work orders as units and uses this in order to regulate the work order flow. There are three different types of PM work orders in the model: PM using fixed intervals, PM using CBM inspection plans and PM using CBM sensors. The actual *takedown rate* is decided on the basis of the level of the methodology that is being used; different values of scheduling capabilities, work order stock and pressure to produce regulate the *takedown rate* as these parameters are prioritised over maintenance actions.

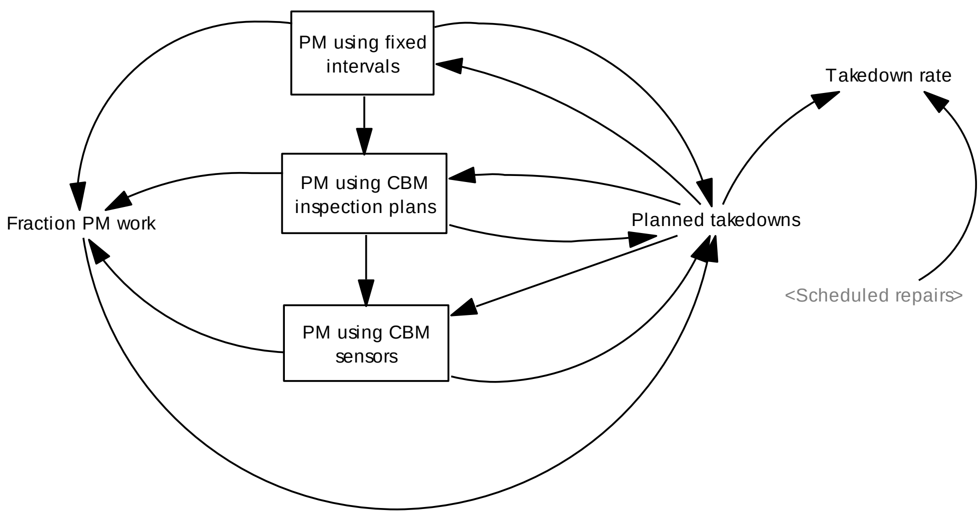


Figure 14. Simplified overview of the preventive maintenance strategies section of the base model. Based on Linnéusson et al. (2018).

4.1.4 Maintenance Development Process

The structure that represents the development process details the level of maintenance improvement for each simulation run. An interpreted simplified overview of the structure can be seen in figure 15. Information from breakdown reports flow through this structure and constitutes the foundation for the possibility of performing root cause analysis (RCA). RCA aims at improving reliability by learning from failures. Thus, this structure defines the pace of the maintenance development process on the basis of resources, delays, work progress, work pressure and different policies. However, the number of maintenance engineers decides if any improvement should take place; without engineers, no breakdown reports are created and thus no RCA can be performed.

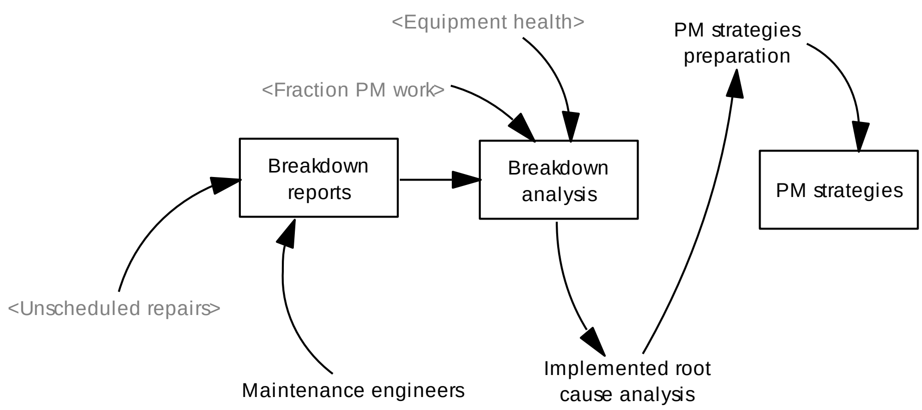


Figure 15. Simplified overview of the maintenance development process section of the base model. Based on Linnéusson (2018).

4.1.5 Cost

The structure that defines the cost section of the base model can be seen in an interpreted simplified overview in figure 16. This section calculates both the direct maintenance cost as well as the consequential maintenance cost. These two variables are summarised in the maintenance total cost, which in combination with the availability decides if the company experiences profit or loss. The direct and indirect costs are generated by cost from breakdowns, resources, spare parts and lost contribution margin due to eventual lost production time. These factors are also affected by the levels of planned and unplanned maintenance work.

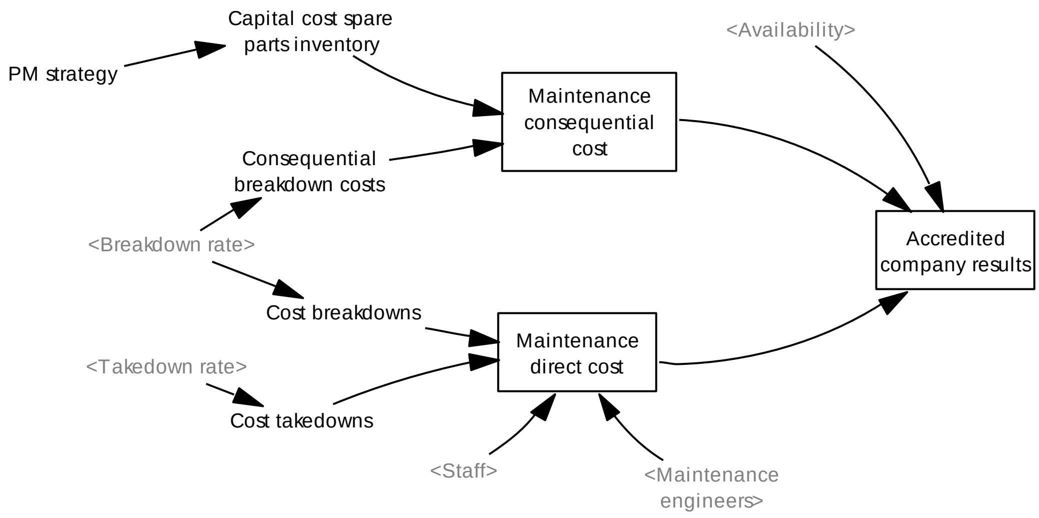


Figure 16. Simplified overview of the cost section of the base model. Based on Linnéusson (2018).

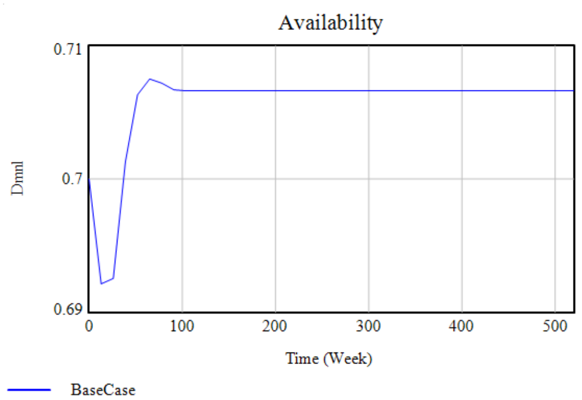
4.1.6 Base Case

The reference frame that constitutes the basic settings and starting position for the forthcoming experiments has been summarised in the base case. It uses the CBM methodology, where the foundation is the settings from the experiment run in previous research called CBMi_50%_4w (Linnéusson et al., 2018, p. 162) which uses the preventive maintenance strategy with CBM inspection plans. These settings have been chosen on the basis of the stable results in studies in previous research. The explicit settings can be seen in table 2. The number of resources for the scheduled and unscheduled repairs is fixed in the original paper; in the following experiments, the initial number of resources varies but the distribution of the resources remains the same. No maintenance engineers have been included in the base case, which means that no breakdown reports are created and thus no improvement of the maintenance strategy can be done. The parameters that have been chosen to evaluate the following experiments with are availability, MTTF, scheduled and unscheduled repairs, maintenance direct and consequential cost as well as the accredited company results. The simulation horizon has been set to ten years (or 520 weeks, as week is the unit of time that has been chosen for these simulation runs).

Table 2. Settings for the base case experiment run.

Run	Re-sources Sched-uled Repair	Re-sources Unsched-sched-uled Re-pair	Goal Frac-tion CBM over PM	Initial level of PMfi	Fraction PMfi from RCA	Fraction CBMi from RCA	Inspec spec-tion Inter-val	Fixed Inter-ter-val	Maintenance Engi gi-neers
Base Case	0.1*21	0.9*21	50 %	50 %	50 %	50 %	4 w	52 w	0

According to the result graphs from the simulation run of the base case, which can be seen in figure 17 – 23, the model reaches equilibrium after a little less than two years. The availability is stable from the very beginning; during the first two years of the simulation, the availability varies from 69.2 % to 70.8 %, before stabilising at 70.7 %. The MTTF follows the same pattern and stabilises at 10.8 weeks. According to figure 19, the amount of scheduled maintenance stabilises at 4.3 equipment per week, while the amount of unscheduled maintenance stabilises at 32.6 equipment per week. The total number of defects, which measures the equipment health, stabilises at 8614 defects. The cost of maintenance is approximately 142 000 dollars per week in the equilibrium state, while the consequential cost of maintenance is approximately 352 000 in the same state. This results in an accredited company result that starts at zero in week one and increases linearly to more than two million dollars after ten years.



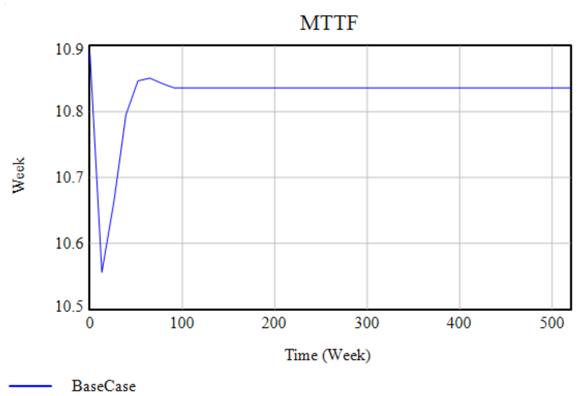


Figure 17 and 18. Graphs of the availability and MTTF of the base case.

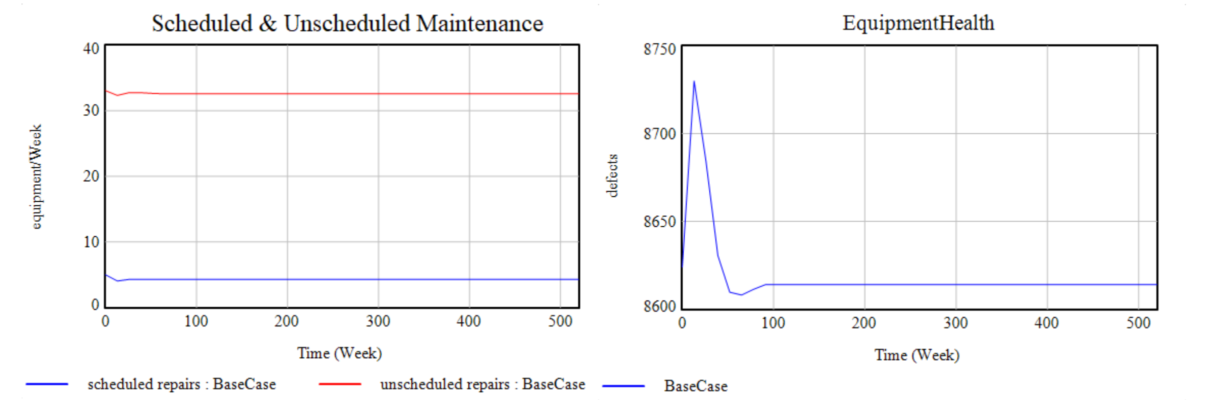


Figure 19 and 20. Graphs of the scheduled and unscheduled maintenance as well as the equipment health of the base case.

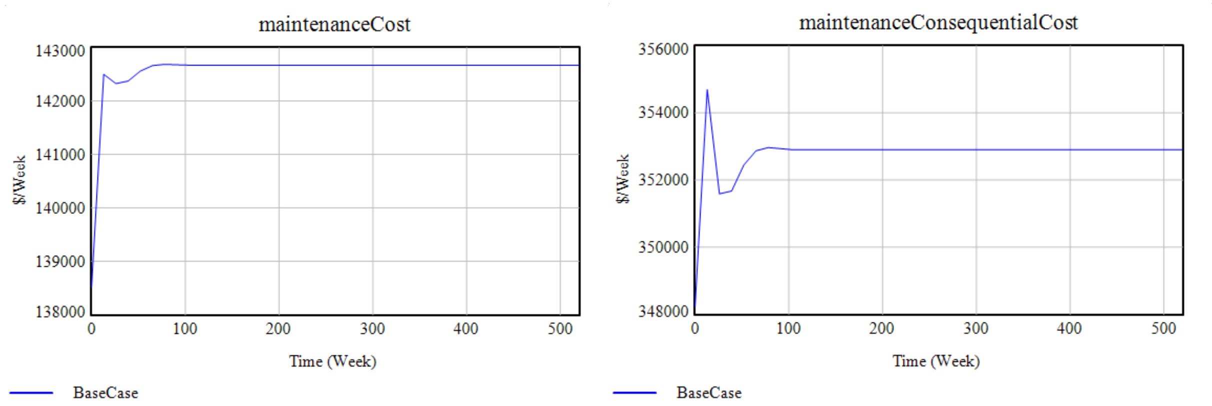


Figure 21 and 22. Graphs of the maintenance cost and the consequential maintenance cost of the base case.

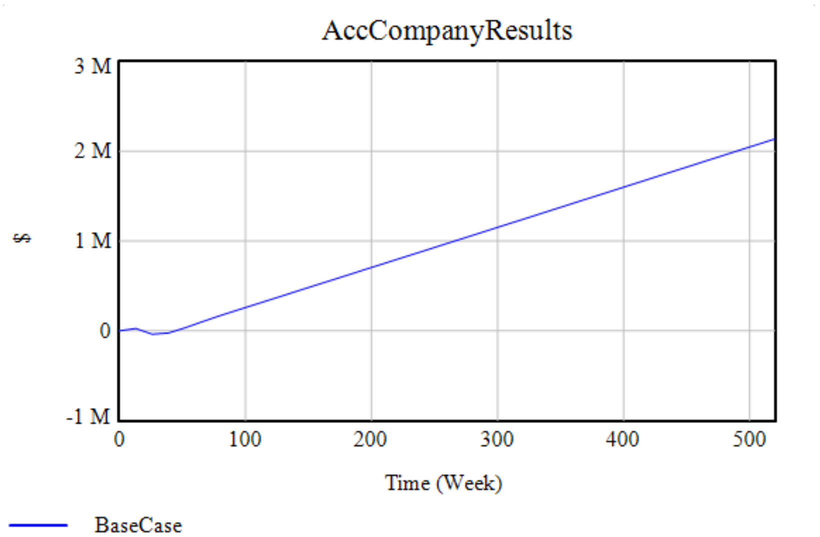


Figure 23. Graph of the accredited company results of the base case.

4.2 Experiments

This chapter describes the approach of the experiments that has been conducted. The methods that have been chosen in order to address the objectives of this research project have been chosen on the basis of the frame of references and the literature review. The choice of methods is the application of SD simulation in the software Vensim PLE as well as MOO with the use of Vensim in combination with the software modeFronter. The experiments that have been performed can be feed backed to the different scenarios, whose evaluation has generated answers to the aim and objectives.

4.2.1 Scenario 1

In the first scenario, the effects of more or less planned maintenance should be evaluated. This has been done with the use of different levels of scheduled and unscheduled maintenance. The effects thereof have been evaluated according to availability, MTTF, equipment health, cost and profit. The behaviour over time has then been compared to the base case scenario. In order to evaluate the effects of less planned maintenance on long term, an experiment has been conducted where the system experiences drastically less planned maintenance during two years. This shock occurs after two years of the simulation, when the model just has stabilised. The values that have been modified in order to create this shock are the inspection interval as well as the fixed interval for planned repairs. These parameters can be used to regulate the amount of planned maintenance that occurs in the system. In the base case, these intervals have values of four respective 52 weeks. Previous research shows that a shorter interval for the planned inspections does not generate further positive results, which is why this has been considered the shortest interval for the inspections. Concerning the fixed interval for the planned repairs, both shorter and longer intervals can be used. In the base case, these parameters have a constant value, but in the experiment their values need to change over time. This is regulated by STEP functions, according to equations 2-5.

$$fixedInterval = 52 + StepFunctionFixedInt \qquad \text{Eq. 2}$$

$$inspectionInterval = StepFunctionInspInt \qquad \text{Eq. 3}$$

$$StepFunctionFixedInt = STEP\big((4*52), 104\big) + STEP\big((-4*52), 208\big) \qquad \text{Eq. 4}$$

$$StepFunctionInspInt = 12 + STEP(10, 104) + STEP(-10, 208) + STEP(-8{,}260) \qquad \text{Eq. 5}$$

These equations generate planned repairs and planned inspections that vary over time according to the graphs in figure 24 and 25. The interval for the planned repairs increases from 52 weeks to 261 weeks after two years of simulation, before returning to 52 weeks after additionally two years. This indicates that the level of planned maintenance is drastically reduced during the two years that the shock occurs in the system. The inspection interval follows almost the same pattern, but starts at 12 weeks instead of the four week scenario in the base case. After two years, the value increases to 22 weeks before dropping to 12 weeks again. However, after another year, the interval is further reduced to four weeks.

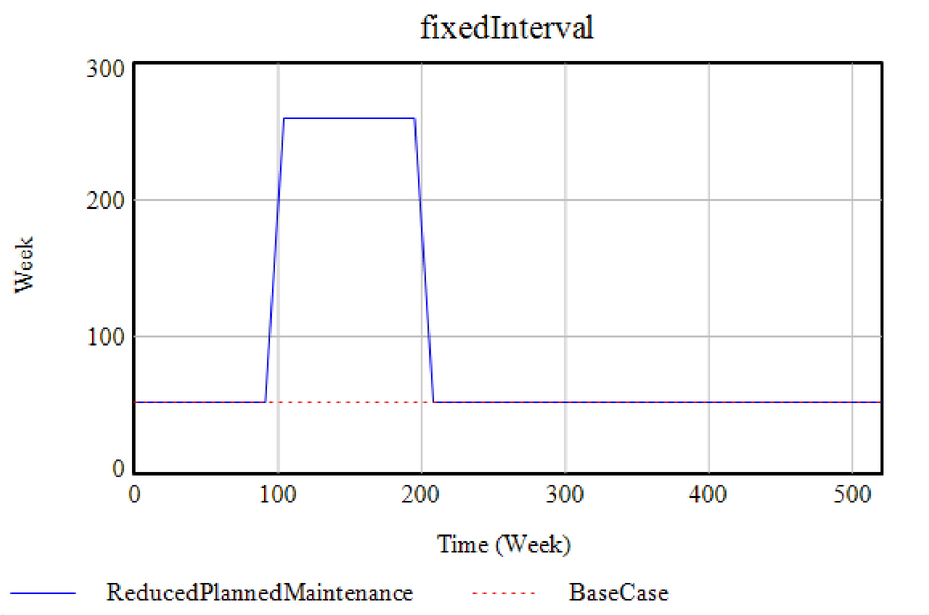


Figure 24. Graph of the fixed interval with reduced planned maintenance in scenario 1.

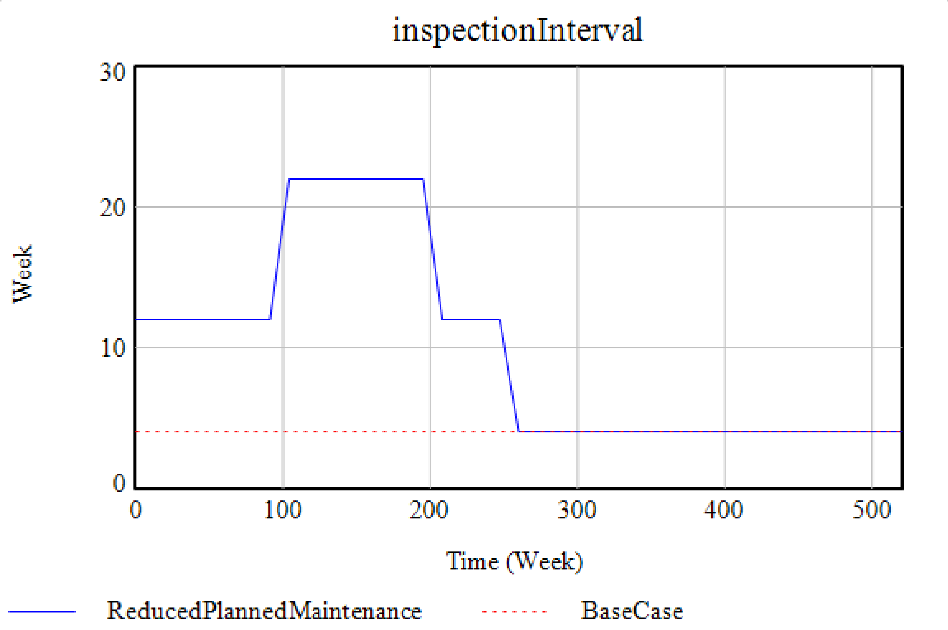


Figure 25. Graph of the inspection interval with reduced planned maintenance in scenario 1.

Another thing that has been taken into consideration in the second part of this experiment is the use of maintenance engineers, who enables the creation of breakdown reports and thus enables improvement in the system. In both the base case and the first scenario with reduced maintenance, the number of maintenance engineers is set to zero. However, it is an interesting aspect to evaluate if the system recovers more quickly after the two-year shock when there are processes that aims at improving and optimising maintenance actions. When the level of preventive actions in a system is as drastically reduced as in this experiment, it is reasonable to presume that the improvement work during this period decreases as well. In order to cut the cost generated by maintenance, a common short-term solution is to reduce all preventive actions; this also includes improvement engineers. Thus, the equation that includes or excludes maintenance engineers also uses a STEP function, which can be seen in equation 6 – 7 and figure 26. The simulation starts with three maintenance engineers, which are cut during the two-year reduction of preventive actions. Subsequently, one engineer is reintroduced during one year before the number is increased to three again.

$$numberMaintenanceEngineers = 3 + StepFunctionNoMaintenanceEngineers$$ Eq. 6

$$StepFunctionNoMaintenanceEngineers = STEP(-3, 104) + STEP(1, 208) + STEP(2, 260)$$ Eq. 7

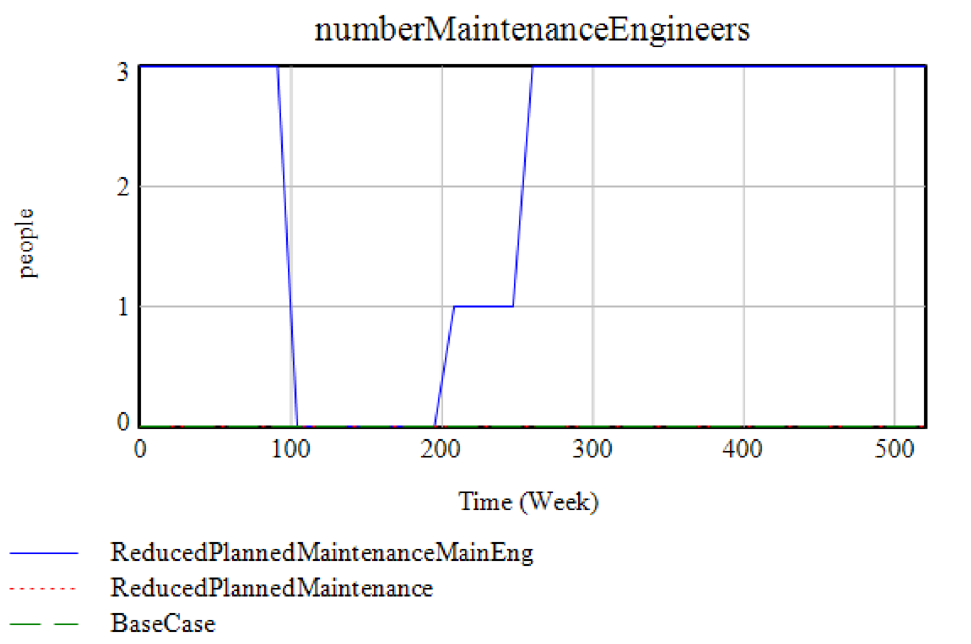


Figure 26. Graph of the number of maintenance engineers with reduced planned maintenance in scenario 1.

4.2.2 Scenario 2

This scenario is edified by the addition of another dynamic structure to the base model, which increases the complexity of the system. The structure that has been included is a hiring and retirement structure, which has been built on the basis of a co-flow structure (Hu & Keller, 2009). The structure can be seen in figure 27. There are two flows, where one handles the number of employees and the other one handles the skill level of the employees. In the first flow, the employees are the stock; the skills are the stock in the other flow. The output variables that are integrated with the base model are *net staff change* and *skill*. The staff that is considered in this case is only the repair personnel, not the maintenance engineers.

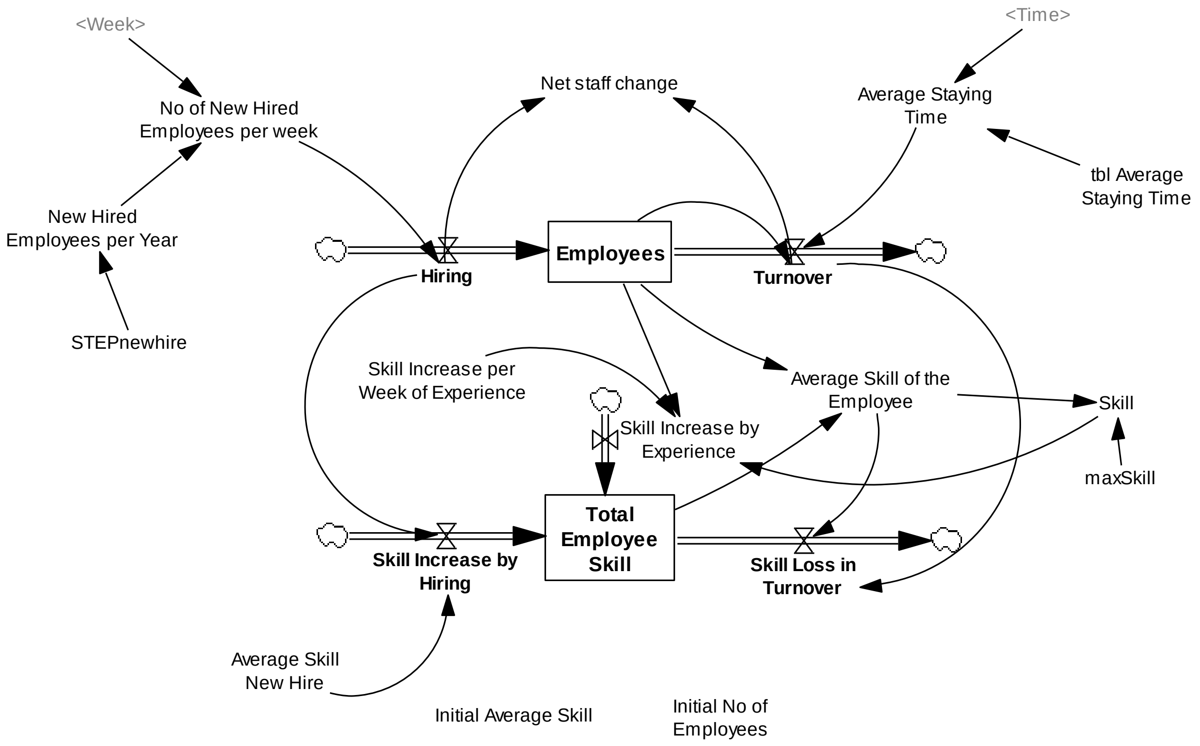


Figure 27. Structure of the hiring and retirement model in scenario 2. Based on Sterman (2000).

The input variables in this structure are *new hired employees per year, initial number of employees, average staying time, skill increase per week of experience, initial average skill* and *average skill new hire*. These variables are also constants. The initial number of employees is, according to the base case, 21 persons. In order to reach equilibrium in the model, some base case settings have been identified. Initially, 2.1 persons per year are hired. The average staying time is initially ten years, the initial average skill 0.85 and the *average skill new hire* is 0.7. The skill level values represent the skill level of each employee. When an employee is hired, the skill level is 0.7. This represents a low skilled worker. Over time, the new hired employee gains experience and counts as fully trained after approximately 2.88 years with *skill increase per week of hiring* adding 0.002 for every week of experience. When the person has reached the maximum skill level, which is represented with the value 1, no more skills can be added to that person.

The employee stock-and-flow structure depends on the following variables, according to equation 8 – 11.

$$Employees = INTEG(Hiring - Turnover, Initial\ No\ of\ Employees)$$ Eq. 8

$$Net\ staff\ change = Hiring - Turnover$$ Eq. 9

$$Hiring = No\ of\ New\ Hired\ Employees\ per\ week$$ Eq. 10

$$Turnover = \frac{Employees}{Average\ Staying\ Time}$$
Eq. 11

The skill stock-and-flow structure is calculated likewise, according to equations 12 – 14.

$$Total\ Employee\ Skill = INTEG(Skill\ Increase\ by\ Experience + Skill\ Increase\ by\ Hiring - Skill\ Loss\ in\ Turnover, (Initial\ No\ of\ Employees * Initial\ Average\ Skill))$$
Eq. 12

$$Skill\ Increase\ by\ Hiring = Hiring * Average\ Skill\ New\ Hire$$
Eq. 13

$$Skill\ Loss\ in\ Turnover = Turnover * Average\ Skill\ of\ the\ Employee$$
Eq. 14

The *skill increase by experience* variable, which can be seen in equation 15, adds 0.002 skills per employee per week, unless *skill* is 1; when the employees are fully trained, no further skill increase is possible.

$$Skill\ Increase\ by\ Experience = Employees * Skill\ Increase\ per\ Week\ of\ Experience * (1 - Skill)$$
Eq. 15

The variable *average skill of the employee* represents the average skill level of the staff, which varies between 0.7 and 1. The average skill level is calculated according to equation 16.

$$Average\ Skill\ of\ the\ Employee = IF\ THEN\ ELSE((\left(\frac{Total\ Employee\ Skill}{Employees}\right) \geq 1, 1, IF\ THEN\ ELSE((\left(\frac{Total\ Employee\ Skill}{Employees}\right) \leq 0.7, 0.7, \left(\frac{Total\ Employee\ Skill}{Employees}\right)))$$
Eq. 16

The parameter *skill* has been created for the purpose of incorporating the skill level of the employees to different parameters in the maintenance base model. According to equation 17, the *average skill of the employee* is divided by *maxSkill*, which is 1 in this scenario. In order to generate matching units, the *skill* parameter is dimensionless.

$$Skill = \frac{Average\ Skill\ of\ the\ Employee}{maxSkill}$$
Eq. 17

This hiring and retirement structure interacts with the base model at several different places. The varying number of employees affects the resources for scheduled and unscheduled repairs with the flow *staff change*, which just equals the variable *net staff change* (see figure 28). Depending on the pace of hiring and turnover, the net staff change generates a positive or negative value that represents if the total number of employees are increasing or decreasing. This change is integrated to the stock of the resources for unscheduled repairs.

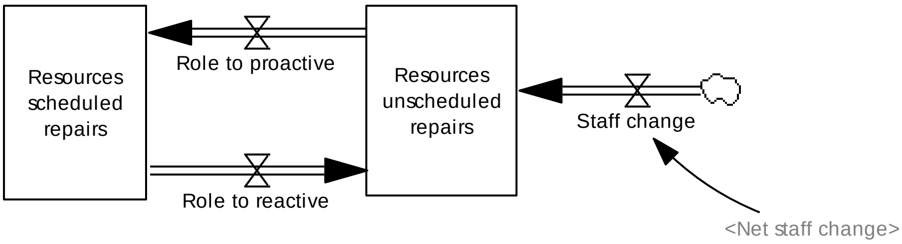


Figure 28. Implementation of the hiring and retirement structure to the base model in scenario 2. Based on Linnéusson et al. (2018).

When the value of the *average skill of the employee* is close to 1, the maintenance functions in the base model remain unaffected. However, when this value decreases, it affects the variables *quality of inspections* as well as *defect elimination per repair*. Other variables that are connected to skill level in the model are *analytic capabilities* and *useful info in reports*. These variables control the fraction of available data for root cause analysis. Analytic capabilities of the staff are capabilities of applying root cause analysis, understanding statistics and choosing appropriate methods. However, since there is no maintenance engineers included in this scenario, no breakdown reports or root cause analyses can be made. Even if the *analytic capabilities* and *useful info in reports* are affected by skill level, these parameters do not affect the model in this scenario. Thus, *quality of inspections* and *defect elimination per repair* are the only parameters that are integrated with the skill level. In the base case, the *quality of inspections* and *max fixed defects per repair* parameters are constants with values of 1 respective 8.The *quality of inspections* variable determines the staff's ability to identify defective equipment. The value 1 implies that the inspection has been completed and that a number of defects per week are found. When the value decreases below 1, few or no defects are found during inspections. The same concept applies to the variable *max fixed defects per repair*. With a lower skill level of the total staff, the quality of the performed inspections is affected negatively and the number of defects a person can fix during one repair is reduced. The new calculations for *quality of inspections* and *defect elimination per repair* can be seen in equation 18 – 19, where a staff skill level below 1 reduces the quality of inspections as well as the number of defects that are eliminated with each repair.

$$Quality\ of\ Inspections = 1 * Skill \qquad \text{Eq. 18}$$

$$Defect\ Elimination\ per\ Repair = MAX(max\ fixed\ defects\ per\ repair * Skill * fractionEquipmentHealthOverPossibleDefects\ , 1) \qquad \text{Eq. 19}$$

In this completed hiring and retirement structure, integrated with the maintenance base model, two different experiments have been conducted. These experiments result in three simulation runs, which generate different values for the average staying time as well as the number of new hired employees per year. As in the base case, the time unit is weeks and the simulation horizon is ten years. The first simulation run “ConstantStayingTime” serves as a steady state simulation run, where the average staying time has a constant value of ten years. The model is in equilibrium with these settings. In the second simulation run, “Decreasing-StayingTime”, the average staying time decreases from ten years to five years during a five-year period. This is supposed to illustrate that major retirement are facing the company within these five years. In the third simulation run, “DecreasingStayingTimeHireSTEP”, the hiring number is increased by additionally two employees per year after five years, which exemplifies a strategy that the management might apply when it is obvious that major retirement is approaching. The different values for the average staying time and the number of new hired employees per week can be seen in the graphs in figure 29 and 30.

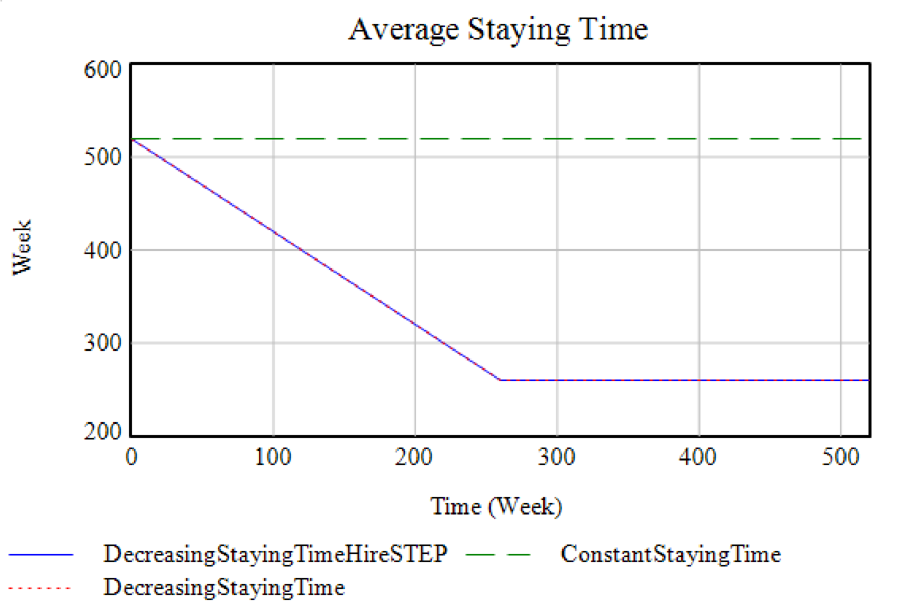


Figure 29. Average staying time for the simulation runs in scenario 2.

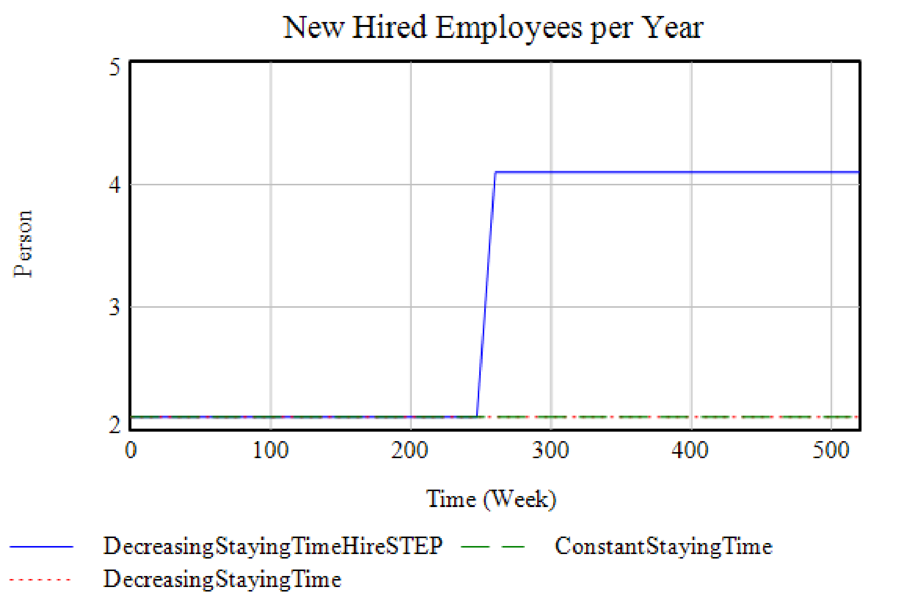


Figure 30. Number of new hired employees per week for the simulation runs in scenario 2.

4.2.3 Optimisation

In order to find the optimal hiring rate in scenario 2, which generates high levels of availability and low cost, optimisation is needed. The optimisation runs are based on the optimisations by Linnéusson (2018), with some adjustments to the scenario that is being evaluated in this research. In order to achieve profitable solutions the turnover margin is increased to 740 000 at 100 % availability; in the base case, this value was 600 000. Remaining settings are the same as in the base case, except for the fact that maintenance engineers are included. The objectives for the optimisation are, however, the same. This optimisation is considered to be multi-objective, since there are three conflicting objectives. The objectives are to maximise availability, minimise maintenance cost and minimise maintenance consequential cost. Since it is the optimal hiring rate with regards to cost and availability that is supposed to be evaluated, different values of the variable *new hired employees per year* has been tested in the optimisation with an input range of 0 – 20 in 0.1 step increments. These small steps of the hiring rate generates a more accurate outcome. The optimisation is evaluated in three different experiments: firstly, a base case where the number of employees is constant (21 persons), secondly, an experiment where the average staying time is constant (ten years) and thirdly, an experiment where the average staying time is decreasing (ten years to five years, see figure 29). All of these experiments have an initial value of 21 persons, but in the two latter experiments this value varies over time. The solutions in the optimisation run that are considered feasible are those who generate a positive outcome of the accumulated profit. The optimisation is run with the algorithm NSGA-II with 3000 initial iterations.

5 Results and Analysis

In this chapter, the results of the experiments and optimisation are presented and analysed. This includes the evaluation of the two scenarios presented in the previous chapter. Discussions of the results for the different scenarios and the optimisation are also presented.

5.1 Scenario 1

The output graphs from the experiment run of the first scenario can be seen in figure 31 – 37. The key parameters that constitute the foundation for the results analysis are availability, MTTF, scheduled repairs, maintenance's direct and consequential cost as well as the accredited company results. Apart from the steady state simulation run, the two other simulation runs both include a drastic reduction of the planned repairs during two years, occurring after two years of simulation time. In the simulation run "ReducedPlannedMaintenance", which is represented by a red solid line in the result graphs below, no maintenance engineers are used. This means that no breakdown reports can be created and therefore no improvement of the system can be made. In the other simulation run "ReducedPlannedMaintenance-MainEng", represented by a blue solid line in the result graphs, three engineers are used from the beginning, cut during the shock years and reintroduced at the same time as the planned repairs are increased again.

It is obvious that the system is severely affected by the drastic reduction of the planned repairs. The availability decreases from 70 % to almost 60 % during the shock period (see figure 31); it also takes a year before the availability has recovered and returned to its original value. When maintenance engineers are used, the availability follows the same pattern, even though it recovers slightly more quickly. In this case, it takes longer time before the availability has stabilised; this is, however, due to the fact that the availability increases to approximately 95 % after a few years of improvement work. The MTTF follows almost exactly the same pattern as the availability (see figure 32).

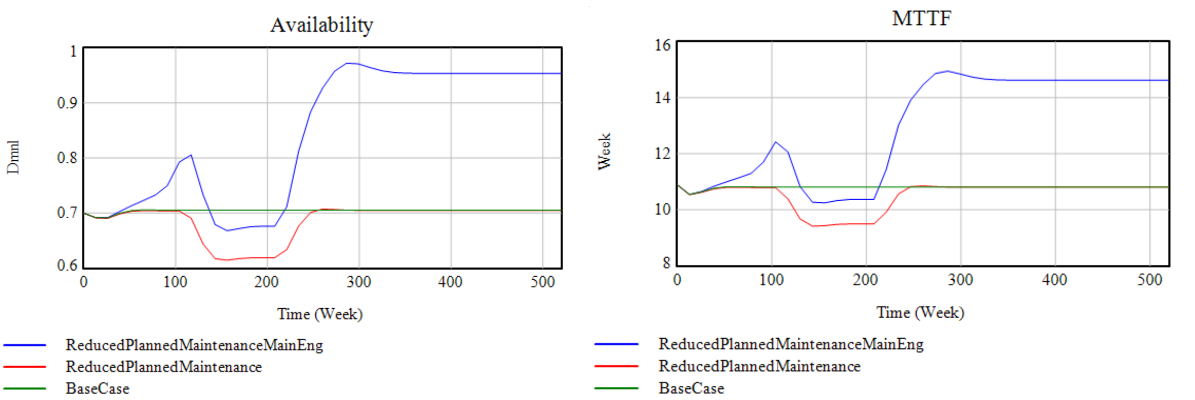


Figure 31 and 32. Graphs of the availability and MTTF of the experiment with reduced number of planned repairs in scenario 1.

The graph of the scheduled repairs (see figure 33) confirms that the scheduled repairs really are reduced during this period of time and the other reactions in the system are results thereof. It is also evident that the use of maintenance engineers and a proactive strategy drastically increases the number of scheduled repairs when the shock has ended. The equipment health suffers during this period, according to figure 34. The defects are heavily increased in both cases.

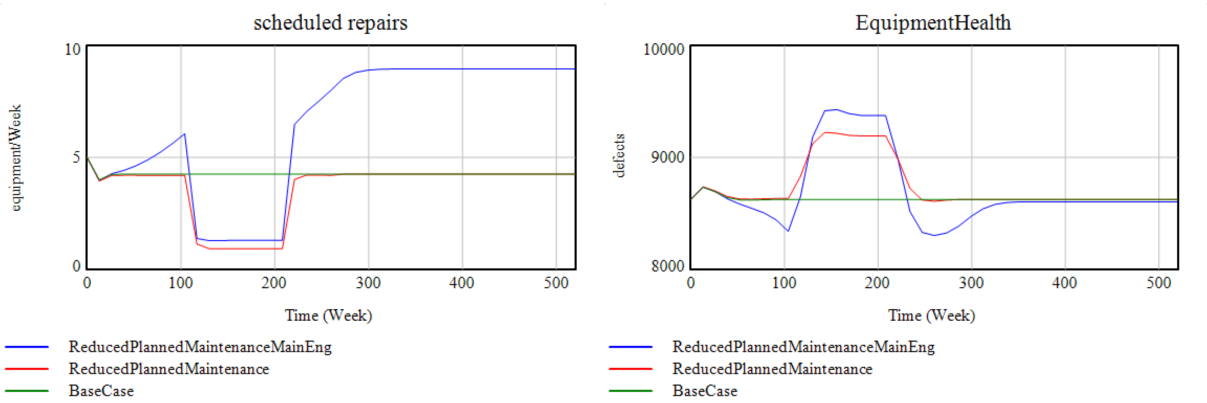


Figure 33 & 34. Graphs of the scheduled repairs and equipment health of the experiment with reduced number of planned repairs in scenario 1.

The different cost measurements can easily result in misguidance. Regarding the direct cost that maintenance generates (see figure 35), it seems as the reduction of proactive actions also reduces the cost. The improvement work, as well as the cost for additionally three employees, also visualises adversely in this graph with a cost increase of 10 000 $ per week. However, the consequential cost of maintenance shows otherwise. This cost increases at the beginning of the shock, before reducing when the proactive actions are reintroduced. The consequential cost also subsequently stabilises at a lower cost than in the base case (see figure 36), not higher as in the direct cost.

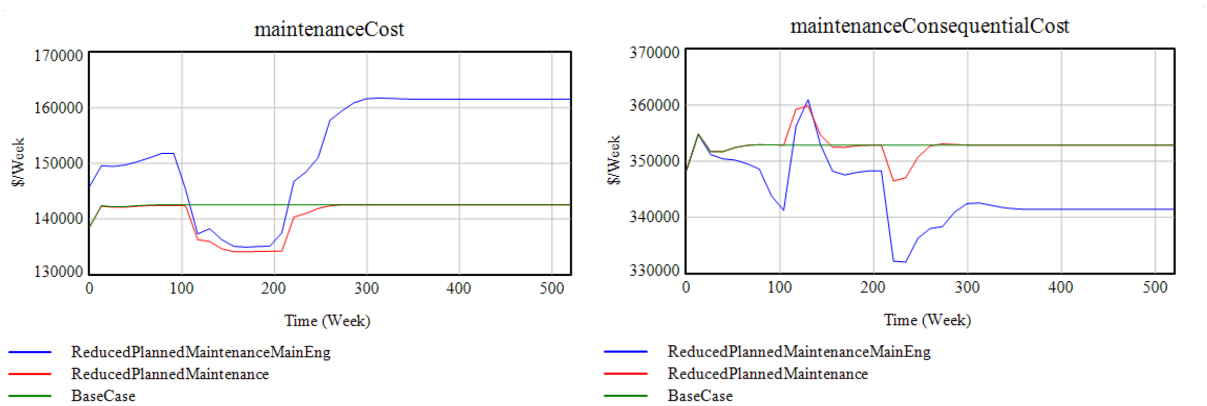


Figure 35 & 36. Graphs of maintenance's direct and consequential costs of the experiment with reduced number of planned repairs in scenario 1.

All of this is summarised in figure 37, which shows the accredited company results for the different scenarios. Where the base case generates a small but stable profit for the company, the policy with strategic improvement work generates a relatively large income: more than 25 million $ six years after the two-year reduction of proactive actions has ended. It is also clear that, even though the direct cost of maintenance decreases temporarily, the company still runs at a severe loss six years after the reintroduction of proactive processes. The trend that visualises in the graph in figure 37 suggests that if the proactive actions had been cut for a longer period of time, the company would suffer a loss of 10 million $ after no longer than three years after the start of the simulation run.

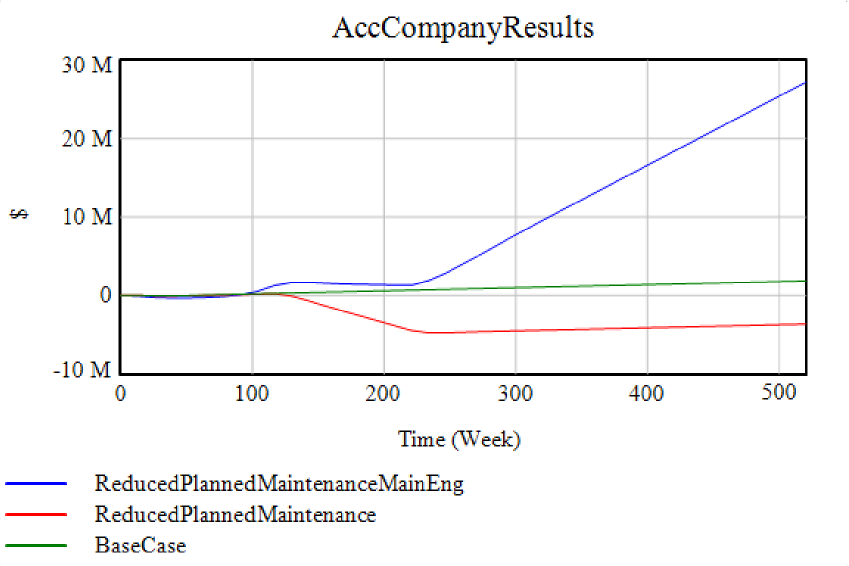


Figure 37. Graph of the accredited company results of the experiment with reduced number of planned repairs in scenario 1.

5.1.1 Discussion of the Scenario 1 Results

Delays and inertia in the system are truly exposed in this experiment, since it is evident that the system needs almost a year to recover from the shock. In the scenario where maintenance engineers are used in order to enable improvements, it takes almost three years for the system to reach a new equilibrium after the shock has ended. However, the simulation results show that with the use of a proactive strategy, the capabilities of the system increases drastically as the number of breakdowns decreases. This strategy is clearly profitable, even though more people are hired and more scheduled repairs are performed. The results of the simulation also reveal that when the direct costs of maintenance are cut with the aim of achieving a short-term financial solution, the consequential costs of maintenance in the form of increased amounts of defects and breakdowns simultaneously increases; thus, there is no long-term profit to be made with such a strategy.

5.2 Scenario 2

The output graphs from the experiment run of the second scenario can be seen in figure 38 – 43. The three different simulation runs result in different numbers of the total staff, which varies over time. In the simulation run where the average staying time is constant (ten years), the model is in a steady state; thus, the sum of the staff is constant. As figure 38 indicates, however, a decreasing staying time will reduce the workforce with eight persons in a ten-year period when two people are hired per year. In the third experiment, when additionally two people are hired after five years, the total workforce slowly increases but has not yet reached its initial value of 21 persons after another five years.

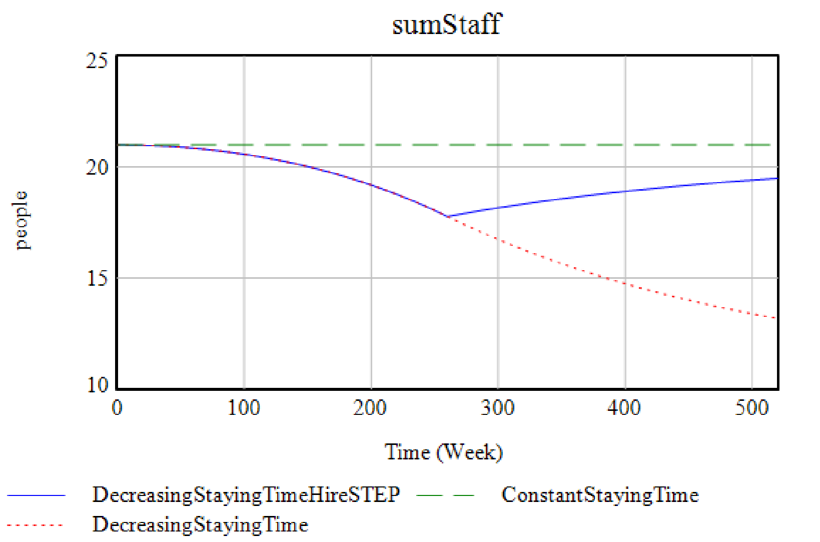


Figure 38. Graph of the sum of the staff for the different simulation runs in scenario 2.

The patterns that the sum of the staff follows in the three different simulation runs mirrors in the resources for the unscheduled repairs. During these experiments, the resources for the scheduled repairs remain two, since this is its minimum value. The resources for the unscheduled repairs, however, vary. From the results in the graphs in figure 39 and 40 it is evident that when there are few available resources to perform unscheduled repairs, less unscheduled repairs are performed. This affects the equipment health and availability negatively.

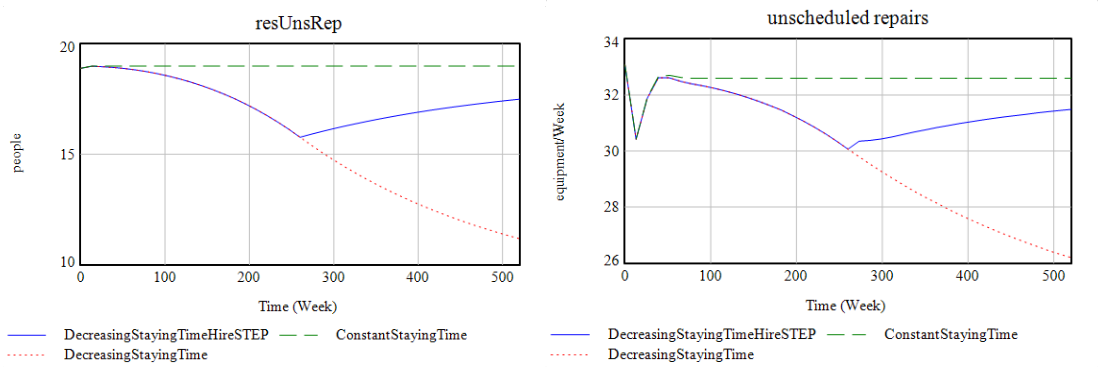


Figure 39 & 40. Graphs of the available resources for the unscheduled repairs and the executed unscheduled repairs for the different simulation runs in scenario 2.

The graph of the average skill of the employee can be seen in figure 41. While the *skill increase per week of experience* is 0.002, the average skill of the employee is in balance at its initial value of 0.85 when the average staying time is constant. The second simulation run shows that when the average staying time decreases, the average skill follows; also, as more people retire and the sum of the employees decreases, this too applies to the average skill level. In the third simulation run, however, the average skill decreases when the number of new hires almost doubles. Even if there are more employees than before, the skill level of the new hires is only 0.7 when they are introduced; this is why the total skill level of the staff decreases. This disturbance in the skill level balance is what the average skill graph of the "DecreasingStayingTimeHireSTEP" simulation run displays.

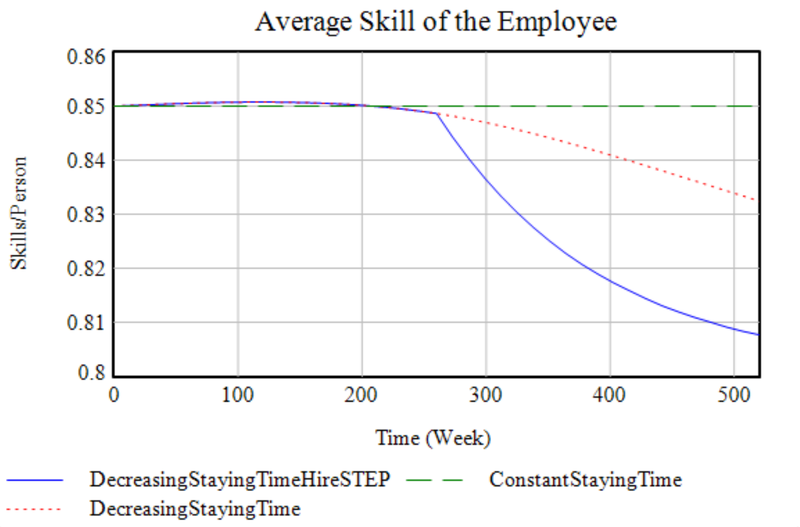


Figure 41. Graph of the average skill of the employee for the different simulation runs in scenario 2.

During the first five years of the simulation, the MTTF follows the same pattern for all of the experiment runs (see figure 42). When the hiring rate is constant, the MTTF stabilises at approximately 8.5 weeks after only a year. However, when the hiring rate is doubled after five years, the MTTF instead decreases. In this experiment, the number of equipment in full functionality has a decreasing trend while the breakdown rate simultaneously has an increasing trend compared to the other two experiments. This is the reason to why the MTTF decreases when the hiring rate is increased. This is an effect of the reduced value of the average skill of the employee, which a higher percentage of new hired employees generate.

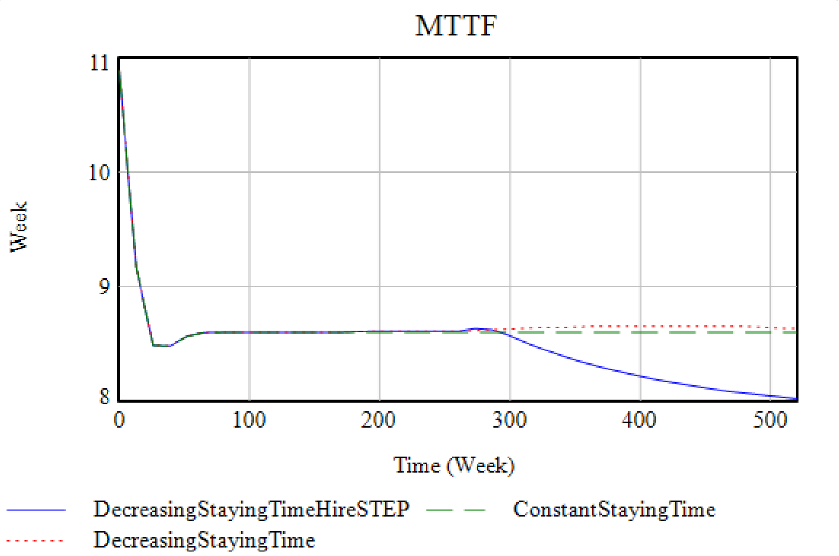


Figure 42. Graph of the MTTF for the different simulation runs in scenario 2.

The effect of the varying values of the average skill of the employee and the sum of the staff results in different values of the availability, which can be seen in figure 43. With a constant average staying time of ten years, the availability stabilises after approximately one year at 56 %. With a decreasing average staying time, however, the availability decreases to about 45 % after ten years. With four new hires per year instead of two, the availability decreases at a much slower pace. However, after ten years, the availability still has not reached its steady state value. It is clear that the system needs more employees with higher average skill level in order to work optimally and generate higher values of the availability.

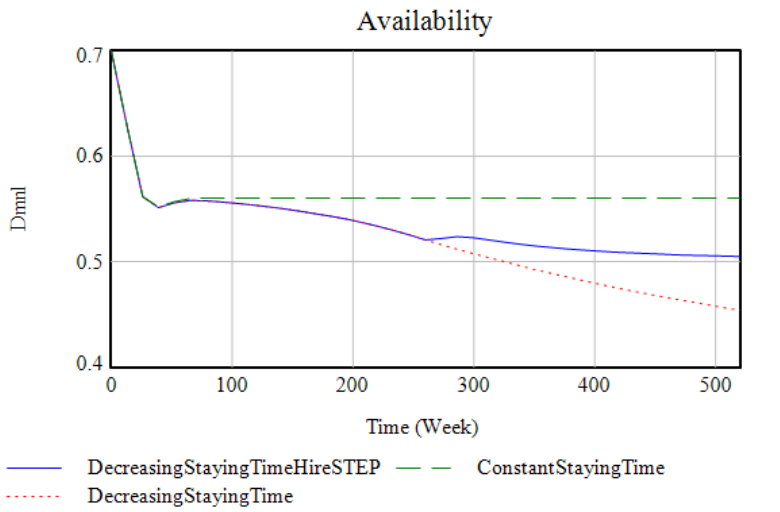


Figure 43. Graph of the availability for the different simulation runs in scenario 2.

5.2.1 Discussion of the Scenario 2 Results

Some result graphs can seem to show problematical results if they are not analysed correctly. One of those graphs is the behaviour of the *average skill of the employee* over time (see figure 41). There is a decrease in the skill level in the third simulation run, when the average staying time is decreasing and the hiring rate is doubled when the increasing retiring rate has started to decrease the total number of employees. This skill decrease is partly due to the fact that many new hired employees with lower skill levels decrease the total average skill; this is also because equation 16 is designed in a way that results in lower levels of the average skill if the skill levels remain unchanged, but the workforce is increased in number. This may lead to the false conclusion that the total skill level of the workforce is reduced only because the workforce is extended. However, since the total number of employees is taken into account in several different places in the maintenance base model, the benefit or disadvantage of the number of employees and their average skill level in combination with each other generate accurate end results.

When the results from these three simulation runs are summarised, it can be concluded that the lag and delays in the system result in a much slower pace than expected for the improvement actions to gain effect. Some reactions in the system only appear after a long period of time. Therefore, preventive actions cannot be enforced when the consequences have occurred without severe losses in the system. The importance of acting proactively cannot be emphasised enough. For example, with constant values of the number of hired people per year and the average staying time, the model reaches equilibrium quite fast. When these values vary, severe consequences occur in the system. When major retirement is facing a company, it is too late to increase the hiring pace when the workforce has already started to reduce. Even if more people are hired when problems related to reduced workforce starts to show, the number of employees cannot quickly be restored. The lag in the system generates delays that negatively affect the workforce, and thus also the skill level of the workforce, for many years. This, in turn, affects the whole maintenance performance, which generate higher costs and reduced profit for the company.

5.3 Optimisation

The results from the different optimisation runs are summarised in this subchapter and can be seen in figure 44 - 55. Three different experiments have been performed and the results thereof are visualised in graphs in these figures.

5.3.1 Experiment 1 – Base Case

First, the base case experiment was executed and evaluated in order to generate comparison material for the other two experiments. The evaluation procedure for the base case optimisation runs applied an initial 50 design-of-experiments (DOE) using 3000 evaluations. This led to 34 Pareto front solutions. These 34 solutions were then applied as the new DOE using 30 000 evaluations, which resulted in 277 Pareto front solutions for the base case. The reason to why so few solutions were generated is probably because a constant value of the total number of employees and no hiring rate create a very limited area for the model. The 2D scatter plot for the correlation between the availability and the accredited company result can be seen in figure 44. Here, the maintenance cost and the consequential maintenance cost are summarised on the x-axis into the accredited company results. Each value of the accredited company result has a corresponding value of the availability on the y-axis. The small number of solutions results in poor diversity and convergence to the Pareto optimal front. In this graph, it seems that high values of availability also create high profit values. However, disregarding the consequences from a reality which most certainly includes hiring and retirement dynamics may lead to a misjudgement of the potential profit. Figure 44 and 46 show these differences.

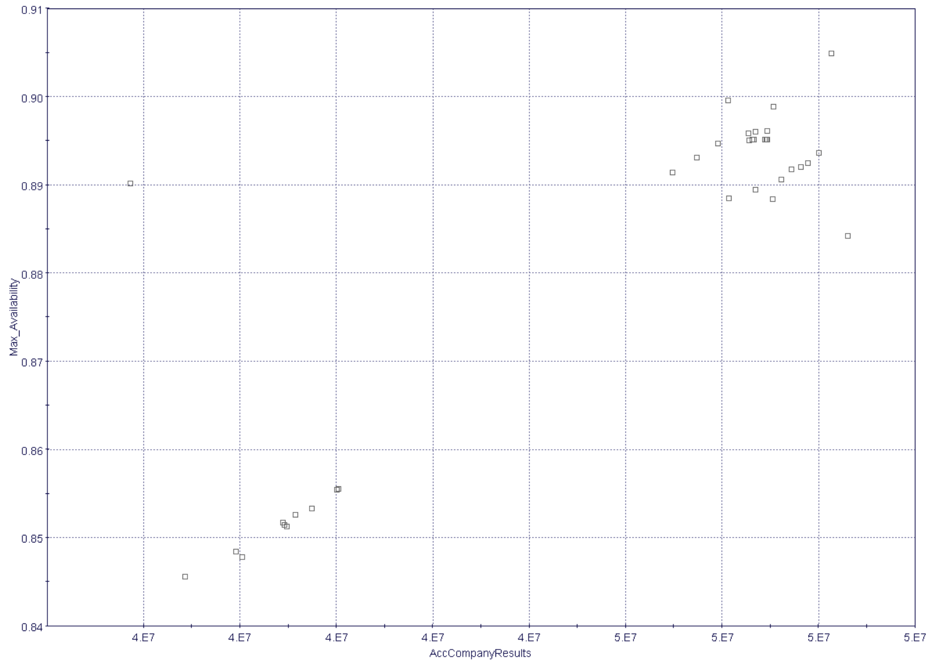


Figure 44. 2D scatter plot of the Pareto front for availability and accredited company results of the base case.

5.3.2 Experiment 2 – 10 years

For the second experiment with varying values of the hiring rate and a constant average staying time of ten years, 50 DOEs with 3000 evaluations led to 570 Pareto front solutions. These solutions were used in the next DOE of the remaining 30 000 solutions. This experiment generated Pareto front solutions on the three different objective parameters according to figure 45, where the convergence is better than in the first experiment but the poor diversity remains. This graph indicate that a high value of the availability generate both high direct costs and consequential costs. It also show that low direct costs result in high consequential costs and vice versa.

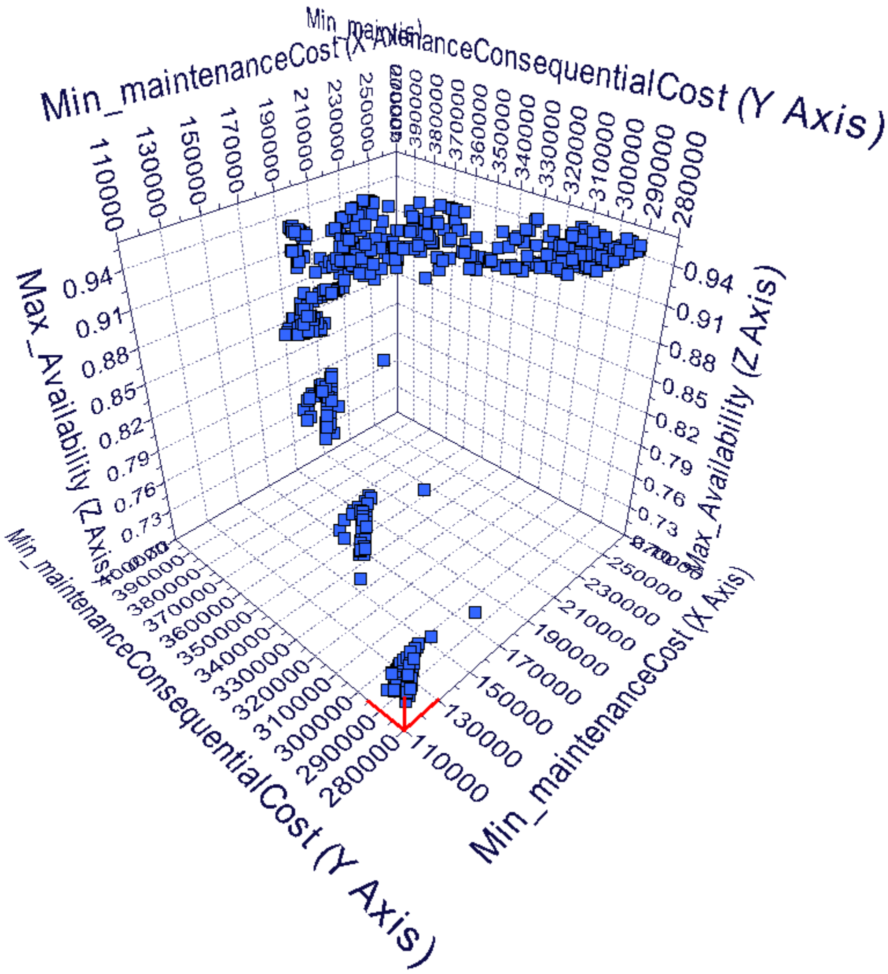


Figure 45. 3D graph of the objective parameters for the experiment with constant average staying time.

With varying values of the hiring rate, the best solutions with regards to availability and company results constitutes the Pareto front in the 2D scatter plot in figure 46. The results in this graph correspond better to reality than the results in the graph in figure 44. However, figure 46 indicates that solutions on the higher range of availability result in lower profit.

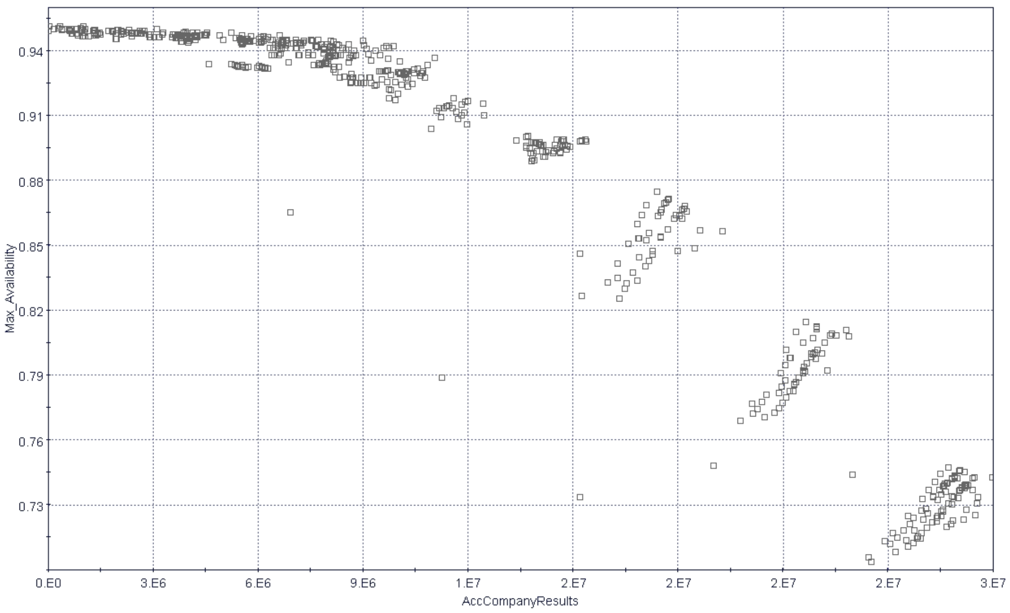


Figure 46. 2D scatter plot of the Pareto front for availability and accredited company results with constant average staying time.

Different values of the hiring rate result in different values of the availability and the accredited company results (see figure 47 – 48). These graphs indicate that a high hiring rate generate a higher value of the availability, but at the same time, a high hiring rate affect the company results negatively. The highest availability is achieved when the hiring rate is almost 13 people per year, while the most profitable company results are achieved when the hiring rate is close to zero.

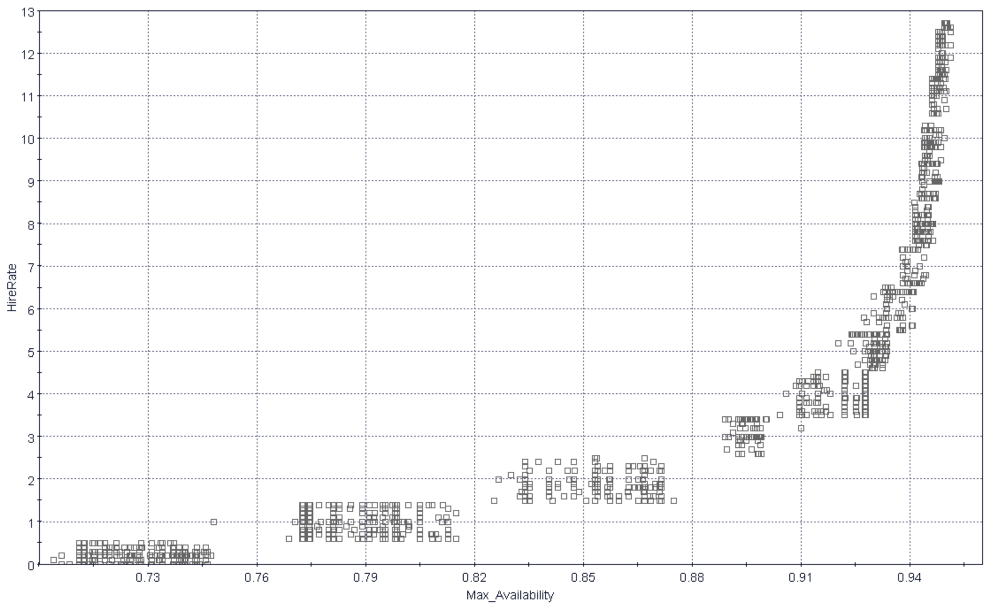


Figure 47. 2D scatter plot of the hiring rate in comparison with the availability with constant staying time.

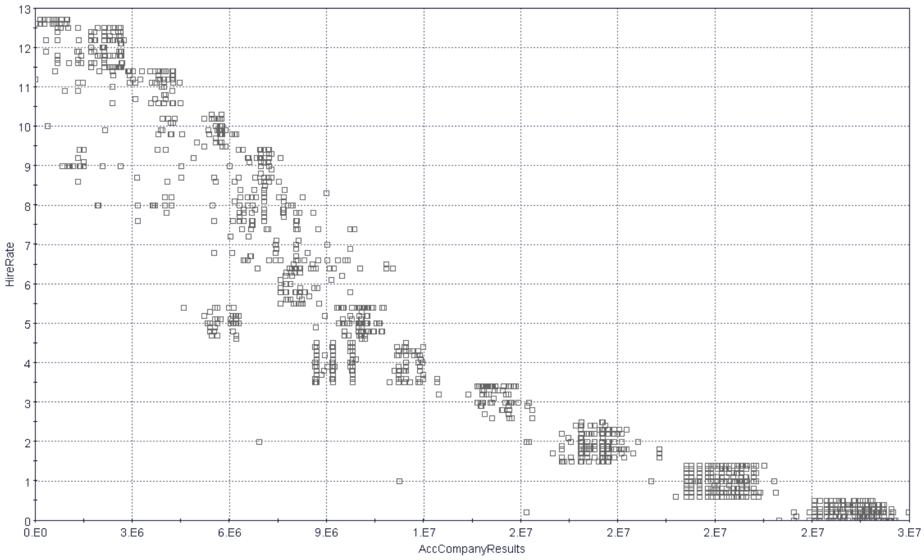


Figure 48. 2D scatter plot of the hiring rate in comparison with the accredited company results with constant staying time.

In order to combine the results from the scatter plots in one graph and thus reach better understanding of the results of the optimisation, parallel coordinate heat maps can be used. These graphs visualises the performance of the selected variables. In figure 49, the hiring rate is in focus, while the accredited company result is emphasised in figure 50. Each line in the graphs represents one solution, where the line visualises the value that each solution has assigned for the different variables. With the use of these graphs, distinguishing patterns for successful solutions can be identified. The red and orange lines in figure 49 represent the solutions that have the highest level of availability, approximately 95 %, and their values for the other specific variables are displayed. For instance, the highest levels of availability seem to also include a high hiring rate, low breakdown rate and high takedown rate, but only a small profit. In figure 50, the red and orange lines instead represent the solutions that are the most profitable. These solutions have low levels of availability, approximately 73 %, and a low hiring rate; they also have a low breakdown rate and a medium takedown rate. The only thing that the successful solutions from figure 49 and 50 seem to have in common is low levels of breakdown rate.

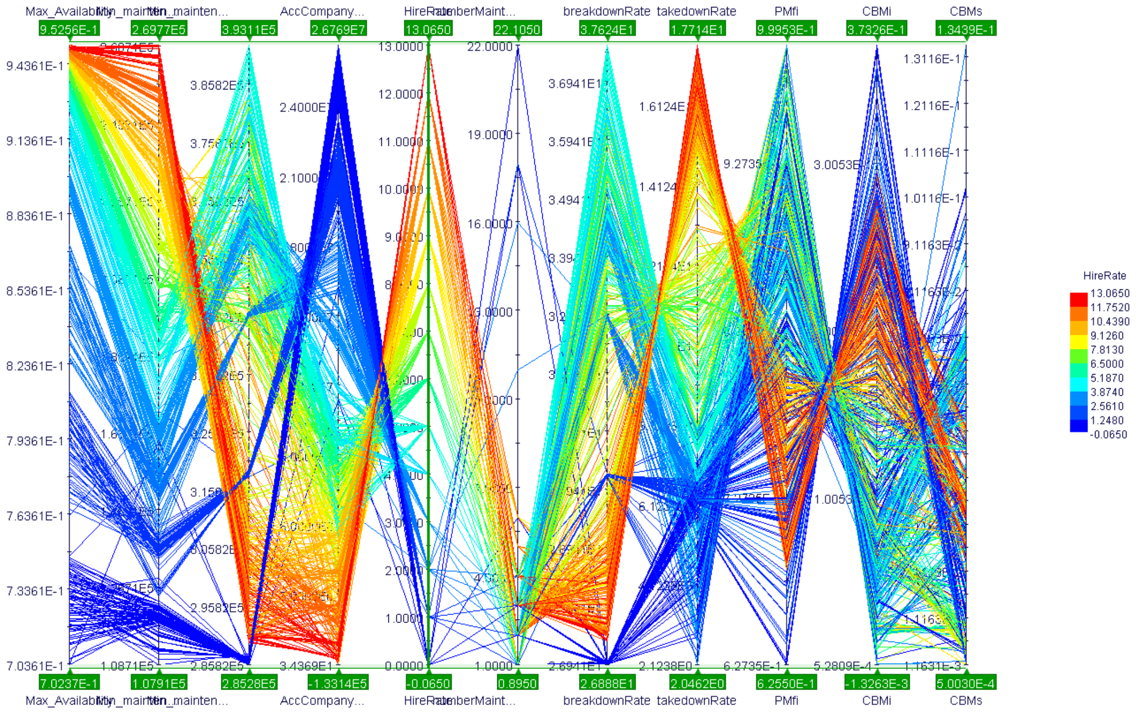


Figure 49. Parallel coordinate heat map of the hiring rate with constant staying time.

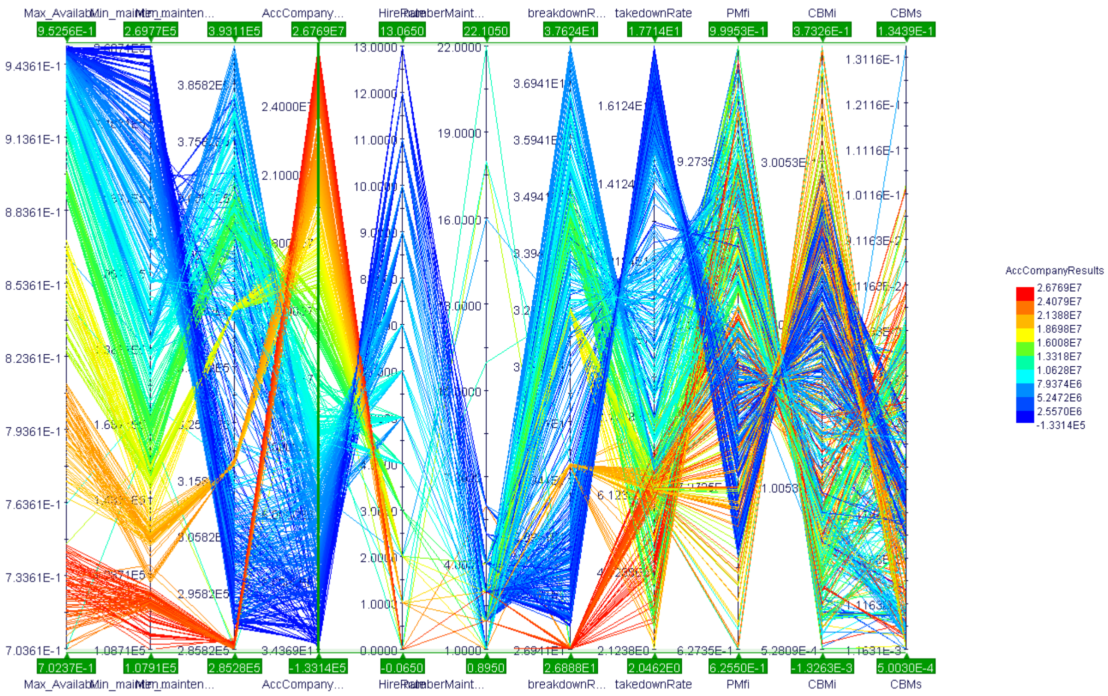


Figure 50. Parallel coordinate heat map of the accredited company results with constant staying time.

5.3.3 Experiment 3 – 10 years to 5 years

Also for the experiment when the average staying time is decreasing, 50 DOEs generated 3000 evaluations, which led to 853 Pareto front solutions. These were used in the next DOE of the remaining 30 000 solutions. The Pareto front solutions for this experiment generate values for the three different objective parameters according to figure 51. There is no dramatic change from the 3D graph of the objective values for the experiment with constant average staying time. This graph also shows that a high value of the availability generate both high direct costs and consequential costs as well as visualises the trend that low direct costs result in high consequential costs and vice versa.

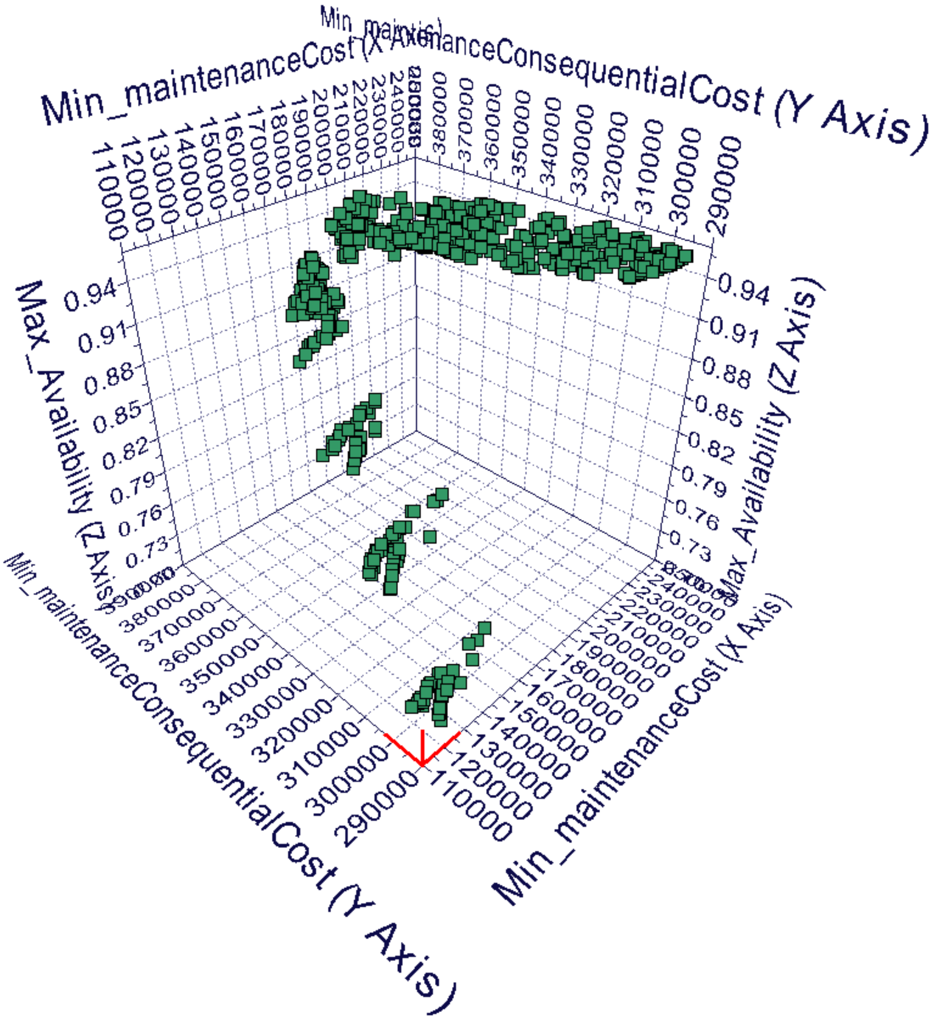


Figure 51. 3D graph of the objective parameters for the experiment with decreasing average staying time.

The solutions are pictured in 2D scatter plots of the hiring rate in comparison with the availability and the accredited company results, which can be seen in figure 52 and 53. Compared to the graphs for the constant average staying time optimisation, the solutions follow the same pattern. In order to achieve the same levels of availability and profit, however, additionally one person per year needs to be included in the hiring rate.

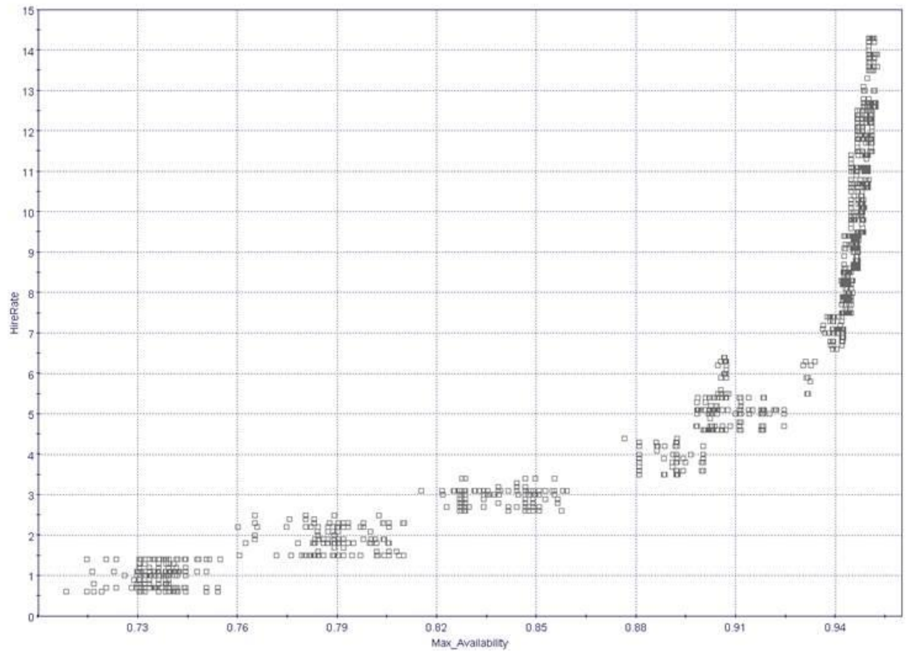


Figure 52. 2D scatter plot of the hiring rate in comparison with the availability with decreasing staying time.

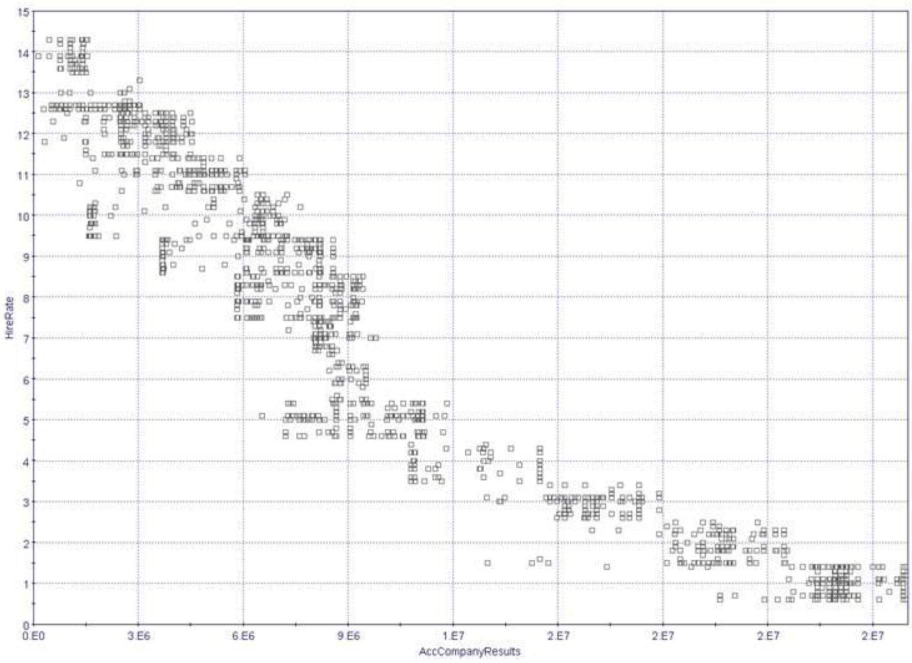


Figure 53. 2D scatter plot of the hiring rate in comparison with the accredited company results with decreasing staying time.

Also in the parallel heat coordinate maps for this optimisation run, the patterns are similar (see figure 54 and 55). These graphs also show that for the same results, a small increase in the hiring rate is required. This is logical, since in this simulation run the retiring rate is increased over time; in order to perform with as high availability and as low cost as possible, the total staff needs to be a certain number of people with a certain average skill level. When the retiring rate is increased, the hiring rate must respond in order to maintain the total number of employees.

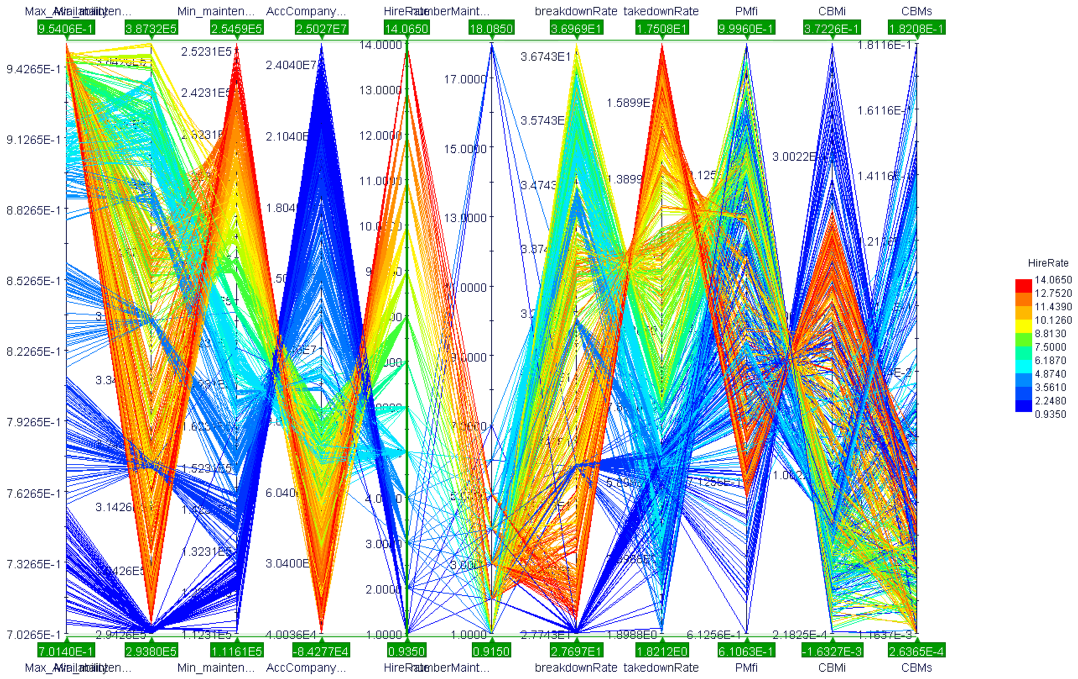


Figure 54. Parallel coordinate heat map for the hiring rate with decreasing staying time.

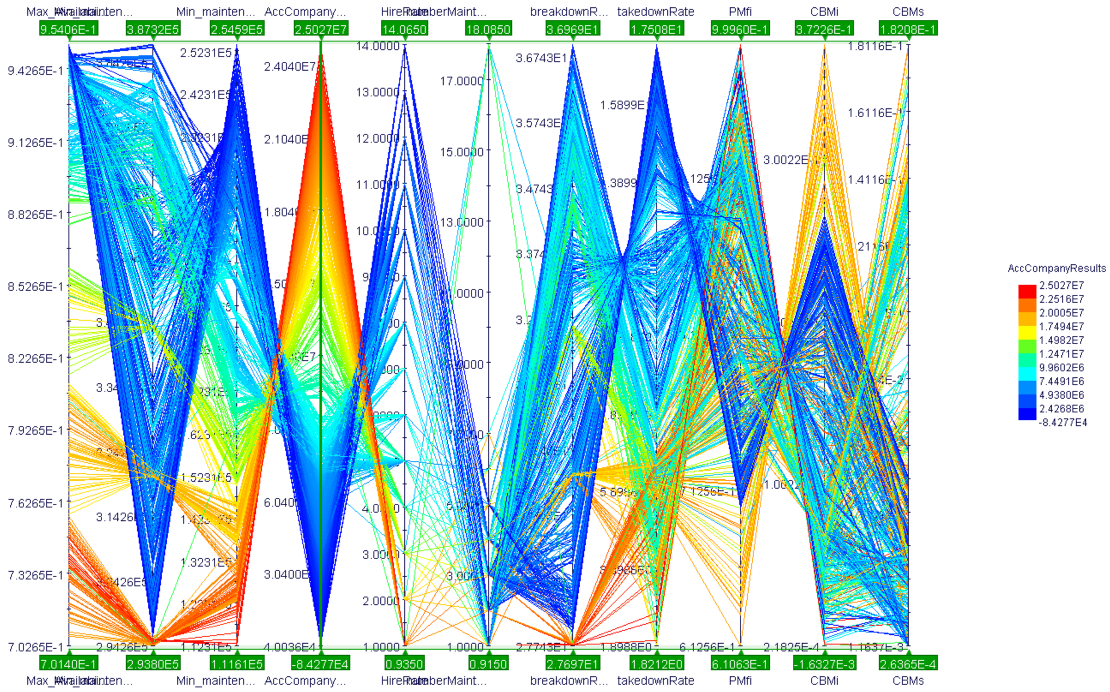


Figure 55. Parallel coordinate heat map for the accredited company results with decreasing staying time.

5.3.4 Discussion of the Optimisation Results

In the base case experiment run, where the number of employees was constant and no hiring rate was included, few Pareto front solutions were generated. The results of this experiment are dubious, since the results indicate that a high availability would generate high profit when the other experiments indicate the opposite. Therefore, this experiment is considered to be detached from reality; no real scenario has a constant number of employees and no hiring or retiring in ten years. Disregarding the consequences from these dynamic complexities may lead to a misjudgement of the potential profit. When the results of the other two optimisation runs are summarised, it can be concluded that a high hiring rate generate a high availability and a low hiring rate generate high profit. Thus, a high availability results in high costs, while high profit results in low availability. This correlation between the availability and the accredited company results is similar to the results with constant staying time (see figure 46). It can be concluded that high availability levels does not automatically generate much profit, due to all the costs and efforts that are required in order to achieve the high availability levels.

Another interpretation of the result that a high profit seems to be generated by low availability could be that the most successful solutions generate evenly distribution of hires during the simulation period. The same hiring frequency is probably not needed during the whole simulation period, especially not when the retiring rate varies over time. When the hiring rate is confined to the same yearly frequency over the whole period, it has to be high enough to cover up for the periods when more employees are required. This creates excess costs during the periods when the hiring rate is too high for the actual employee requirements. Since the retiring rate decreases over time in the second optimisation run, the hiring rate should have the ability to follow the same pattern and not be confined to a constant number during the whole simulation period.

6 Conclusions and Future Work

The aim with this research was to investigate the dynamic complexity between the performance of maintenance and the requirements from operations, including the evaluation of both long-term and short-term effects from different maintenance scenarios. The accomplishments of this research include the evaluation and analysis of two different scenarios, where the effects of more or less planned maintenance and the implication of a structure for hiring and retirements constitute the objectives. In line with the objectives, a state-of-the-art literature review has also been created, which identifies the research gap of evaluating the cause-and-effect relationships between maintenance and production performance that this research aim to fill. The results of the literature review verify the promising future for exploring maintenance issues with SD in combination with MOO.

The experimentation of the scenarios generated varying results. It can, however, be concluded that with the use of SD simulation, trends over longer periods of time are visualised. In the first scenario, the visualisations show that short-term maintenance management is not profitable over time. With lower levels of planned maintenance and proactive actions, the direct maintenance cost is decreased; this, however, result in a drastic increase in the consequential maintenance cost, which generates lower profit. The SD simulation runs also reveal that improvement strategies and proactive work can revolutionise capability and profit over time, even if these strategies initially generate a higher cost. In the second scenario, the dynamics of a hiring and retirement structure in a maintenance function have been evaluated. In the experiment where the effects of a major retirement are visualised, the results confirm that the company needs to act proactively in order to avoid great losses. The effect of employee losses affects the system negatively for many years, even if there is an increase in the hiring rate when the effects of major retirement have begun to appear in the system. Additionally, the decrease in average skill of the employee, which a large number of new hires generate, affects the quality of inspections and defect elimination per repair negatively. This generates decreases in capability and availability that take many years to restore. The optimisation that has been performed, with the hiring rate as the main variable, shows that a high hiring rate generate high availability; despite this, it is not a profitable strategy. It can be concluded that high availability levels do not generate any significant increase in profit, due to the costly efforts that are required to achieve these availability levels.

For future work, the effect of varying customer demand and stochastic production volume on the performance of maintenance needs to be confirmed. The optimisation of the hiring and retirement structure could be improved by including different levels of the hiring rate during different periods of the simulation in order to generate a more detailed result of how the hiring rate could optimally change over time with the given conditions of the average staying time. Ideally, the hiring and retirement structure would be applied to a real scenario and studied through a case study in order to further verify the results.

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