

# Increasing Land-Monitoring equipment availability by improving the inventory policy in Fugro's workshop



Student: Jesse de Heus

Student number: s2781433

Study: Industrial engineering and management

University: University of Twente

First university supervisor: Dennis Prak

Second university supervisor: Martijn Koot

Company: Fugro

Company supervisor: Dennis Haidar and Vincent Schuurmans

# Preface

Dear Reader,

I am pleased to present to you my bachelor Thesis 'Increasing monitoring equipment availability by improving the inventory policy in Fugro's workshop' which is the result of the 6 months of research I performed at the Fugro's Land-Monitoring department in Leidschendam.

Firstly, I would like to express my gratitude to my company supervisors Dennis Haidar and Vincent Schuurmans for their efforts in supporting me whilst doing this research. They were always available to answer the questions I had during this research. I would also like to thank Fugro for giving me the opportunity to carry out this bachelor assignment. During the last 6 months I have learned a lot about the company itself and the field of work in general.

Furthermore, I would like to thank my first supervisor, Dennis Prak, for his open attitude, valuable advice, commitment and extensive feedback on how the study could best be structured. I could always get in touch with Dennis at short notice if I had any questions, whether we had an appointment or not. Finally, I want to thank Martijn Koot for taking a critical look to this study, but still managed to bring his criticism in a positive way.

I hope you enjoy reading this thesis.

Jesse de Heus

Enschede, August 23, 2024

# Management summary

This research was conducted at the Fugro Land-Monitoring department in Leidschendam, Netherlands. This department currently has a problem with the availability of inspected Land-Monitoring equipment, which is too low. The inspection of the Land-Monitoring equipment happens in Fugro's Land-Monitoring workshop. In this workshop an inspect-to-order policy is being used, a policy where the inspection of equipment takes place after the order is received. To increase this availability options for a inspect-to-stock policy were explored, in which equipment is inspected and stocked before the order is received, until the base stock level is reached, which is the maximum inventory level. The base stock level is determined by the fraction of equipment you want to be able to deliver directly from inspected stock without delay of calibration and inspection. The reason for the current inspect-to-order policy is that the order is inspected/calibrated as recently as possible and is therefore more reliable. On the other hand changing its policy towards a inspect-to-stock policy would reduce inconsistency in the workload in the workshop and increase the availability of equipment. To analyse the options of different base stock levels, the main research question for this thesis is:

*'How can the availability of Land-Monitoring equipment in the workshop of Fugro increase by using a base stock level?'*

After interviewing the staff in the department, it was found that there are 5 main equipment groups: loggers, ellitracks, vibration sensors, standpipe sensors (ellitrack excluded) and pore pressure sensors. In addition, there are many small equipment groups, but because of their small size these groups are outside the scope of this study. In the case of the Land-Monitoring equipment at Fugro, the workshop rents out the equipment to the project teams. The demand for this equipment, the rental period and inspection lead time are all stochastic.

For this thesis interviews were conducted to describe the current situation, then background information on production-inventory systems and common used inventory control policies were gathered from literature. Subsequently, a tool in VBA, excel macros, was created for calculating the base stock levels. For simplifications of this tool a standard base stock inventory system is used, in which the assumption have to be made that demand and lead time are normally distributed. The lead time is based on the amount of equipment to be inspected in combination with the processing times obtained from the interviews. In this tool, all the equipment inspected during this lead time is replenished to the stock at once.

To then evaluate the quality of the tool, the actual demand distribution was determined in the software 'EasyFit'. Next, experiment were performed in a simulation model that was built which considers the working hours it takes to replenish the base stock level and uses the correct demand distribution for the equipment found in 'EasyFit'. In the simulation, the base stock levels are input values and the KPIs are the average fill rate of all monitoring equipment groups. To find the required base stock levels, it is assumed that the inflow of uninspected Land-Monitoring equipment is exactly enough to restore the reserve stock.

The approximation of the minimum required base stock levels for a fill rate of 0.99 that were gathered when running the simulation model 20 times over a period of 10 years are depicted in Table 1 below.

Table 1: Approximation of the minimal required base stock level of inspected equipment to reach a fill rate of 0.99

| Equipment                              | Approximated required reserve stock of inspected equipment |
|--|--|
| Loggers                                | 29   |
| Ellitrack                              | 140  |
| Vibration sensors                      | 16   |
| Standpipe sensors (ellitrack excluded) | 34   |
| Pore pressure sensor                   | 12   |

Based on this study, the recommendations for Fugro's Land-Monitoring department are as follows:

- Use the results for the base stock level of inspected equipment as an indication to approximate your desired fill rate until the base stock level is recalculated with more data.
- Use the tool to recalculate the required base stock level when more data is available, because there are now only 54 weeks of data on equipment orders available. More data will increase the reliability of the results.
- Create an incentive for project managers to send the equipment back immediately when it is no longer being used on the project by charging equipment rental depending on the period they take it from the workshop instead of the period they use it on the project. This increases the probability that there will be a sufficient quantity of uninspected stock present in the workshop to supplement the inspected stock.

# Contents

|   |    |
|---|----|
| Preface .....   | 2  |
| Management summary.....   | 3  |
| List of Figures .....   | 7  |
| List of definitions.....  | 8  |
| Acronyms .....  | 8  |
| 1 Introduction .....  | 9  |
| 1.1 Fugro .....   | 9  |
| 1.2 Identification of main problem .....                              | 9  |
| 1.3 Problem cluster & core problem .....                              | 10 |
| 1.4 Norm and reality .....  | 11 |
| 1.5 Research design .....   | 12 |
| 1.5.1 Problem solving approach.....                                   | 12 |
| 1.5.2 Scope.....  | 16 |
| 1.5.3 Deliverables.....   | 16 |
| 1.6 Chapter Conclusion .....  | 16 |
| 2 Current situation .....   | 17 |
| 2.1 Purpose of the workshop .....                                     | 17 |
| 2.2 Current procedure.....  | 18 |
| 2.3 Function and inspection/calibration of the equipment groups ..... | 18 |
| 2.4 Input values model.....   | 19 |
| 2.4.1 service time per calibration/inspection .....                   | 19 |
| 2.4.2 Possible delays in service time due to errors .....             | 20 |
| 2.4.3 Demand distribution per equipment group.....                    | 21 |
| 2.4.4 lead time and orders per week .....                             | 22 |
| 2.5 Bottlenecks.....  | 23 |
| 2.5.1 Spotmaster database .....                                       | 23 |
| 2.5.2 Workload fluctuation .....                                      | 23 |
| 2.5.3 Stock shortage at the workshop .....                            | 24 |
| 2.6 Chapter conclusion.....   | 25 |
| 3 Literature review .....   | 26 |
| 3.1 Background inventory control policies.....                        | 26 |
| 3.2 Inventory control policies.....                                   | 26 |
| 3.3 Production inventory system .....                                 | 27 |
| 3.4 Chapter conclusion.....   | 28 |

|   |    |
|---|----|
| 4 Solution design.....                                      | 29 |
| 4.1 Classification workshop inventory system .....          | 29 |
| 4.2 Inventory control policy .....                          | 29 |
| 4.2.1 Review policy.....                                    | 29 |
| 4.2.2 Mathematical model.....                               | 30 |
| 4.2.3 Tool creation.....                                    | 31 |
| 4.2.4 Mathematical model assumptions.....                   | 31 |
| 4.3 simulation model .....                                  | 32 |
| 4.3.1 Model description .....                               | 32 |
| 4.3.2 Differences between tool and simulation model.....    | 33 |
| 4.3.3 Simulation model assumptions and simplifications..... | 34 |
| 4.3.4 Applications of the simulation model .....            | 34 |
| 4.4 Chapter conclusion.....                                 | 35 |
| 5. Results .....  | 36 |
| 5.1 Base stock levels tool .....                            | 36 |
| 5.2 Simulation optimisation .....                           | 37 |
| 5.3 Differences between tool and simulation results .....   | 38 |
| 5.4 Tool validation .....                                   | 40 |
| 5.4 Conclusion.....   | 43 |
| 6. Conclusion.....  | 44 |
| 6.1 Conclusion.....   | 44 |
| 6.2 Recommendations .....                                   | 45 |
| 6.3 Limitations and further research .....                  | 45 |
| References.....   | 47 |
| Appendix .....  | 49 |
| Appendix 1: .....   | 49 |
| Appendix 2: .....   | 52 |
| Appendix 2A.....  | 52 |
| Appendix 2B:.....   | 54 |
| Appendix 2C.....  | 55 |
| Appendix 3:.....  | 57 |

# List of Figures

|  |           |
|--|-----------|
| Figure 1: Problem Cluster.....   | 11        |
| Figure 2: research design .....  | 15        |
| <i>Figure 3: Number of units of equipment used at Fugro's Land-Monitoring projects based on 200 weeks of data .....</i>  | <i>17</i> |
| Figure 4: current workshop process.....  | 18        |
| Figure 5: distribution of the number of equipment units ordered per week based on 54 weeks of data .....   | 21        |
| Figure 6: Land-Monitoring equipment orders per week based on 54 weeks of data from Spotmaster .....  | 24        |
| Figure 7: total Land-Monitoring equipment orders 5 main groups over a period of 54 weeks.....  | 24        |
| Figure 8: overview Siemens' Technomatix Plant Simulation model .....   | 32        |
| Figure 9: Base stock level per fill rate per equipment group according to the tool described in Section 4.2 .....  | 36        |
| Figure 10: fill rate per base stock level, derived from simulation model with geometric distributed demand .....   | 37        |
| Figure 11: deviation between the results of the tool, the simulation with normal distributed demand and the simulation with geometric distributed demand ..... | 39        |
| Figure 12: deviation rate of the base stock level in the tool from the base stock level in the simulation per fill rate.....                                   | 40        |
| Figure 13: Fill rate comparison between tool and simulation model .....  | 41        |
| Figure 14: Filling deviation rate between simulation model and tool relative to the tool .....   | 42        |

# List of definitions

Important equipment groups = these are the 5 monitoring equipment groups with the highest demand. This study only focusses on these 5 groups.

Land-Monitoring equipment = equipment that is used by Fugro to monitor the ground

Calibration = the test performed to check whether the Land-Monitoring equipment still measures within the correct margins.

Workshop = the place where the Land-Monitoring equipment is inspected and calibrated

Spotmaster = Fugro's database for the Land-Monitoring department

Deviation rate = the percentual deviation which a measured value diverges from the expected value.

Inspect to order = a policy in which the inspection of equipment finds place after the equipment order has been placed.

Inspect to stock = A policy in which inspected equipment is placed in stock and the inspection finds place before the equipment order has been placed.

Base stock level = the order up to level to which stock is replenished after every review period.

Review period = a period after which the status of the inventory level is assessed.

full enumeration = a simulation optimisation technique where the results are found, because every possible solution is simulated.

standard base stock inventory system = an inventory system where products are replenished via orders from an external supplier of the product. In this inventory system products are returned to stock simultaneously.

Production inventory system = an inventory system where products are slowly re-stocked through production.

## Acronyms

OUL = Order up to level

SS = Safety stock

VBA = Visual Basic for Applications

KPI = Key Performance Indicator

MTO = Make-to-Order

MTS = Make-to-stock



# 1 Introduction

In this chapter, the introduction of this study, a short description is given on the practices of the company Fugro and the process in the workshop in Section 1.1. Next, the problem Fugro encounters regarding the availability of Land-Monitoring equipment is presented in Section 1.2 and 1.3. Then, the norm and reality are established in Section 1.4. Finally, in Section 1.5, the sub-questions are discussed and the deliverables are established. The chapter is Summarized in Section 1.6.

## 1.1 Fugro

This bachelor thesis is about the company Fugro, which was established in 1962. The name Fugro is an abbreviation of the Dutch words “Funderingstechnologie & grondmechanica”. In 1970 Fugro opened its first office abroad. Now, it is the largest geo data company in the world. The objective of their work is to create a map of the soil, which enables construction companies to monitor the subsidence when a new building is placed on it. In other words Fugro searches for the Geo data which is necessary to build or maintain buildings and infrastructure. The geo data is turned into practical advice for a more efficient design in construction. Through their geo data, the precise composition of the surface and subsurface is mapped and how the environment could affect this. By doing this, Fugro can help its clients to design the project in the most appropriate way. (Fugro, 2023)

In this research we will focus on the Land-Monitoring department. The Land-Monitoring department measures the ground to obtain data where other departments are more concerned with using this obtained data to draw conclusions. This ensures that the Land-Monitoring department is able to measure the soil properly. The equipment which is used for the Monitoring projects must be inspected periodically to ensure that it still measures in the correct values, which is done through calibration. The calibration and inspection process of all Fugro’s Land-Monitoring equipment takes place in the workshop located in Leidschendam at Fugro's headquarters.

## 1.2 Identification of main problem

In the process of the workshop there are a number of problems. In the current inspection process, equipment is inspected after an order is received. This regularly causes postponed projects and long lead times for equipment orders since projects send the equipment orders short before the start of the project and the workshop is not able to inspect equipment at short notice. It might also be the case that uninspected equipment is out of stock in the workshop preventing the workshop from fulfilling an order. Currently, there is no equipment immediately available when an equipment order is received, since the equipment is inspected after an order is received. Inspection and calibration of equipment is important, because equipment that has not recently been inspected or calibrated may break down while being used on a project. According to Fugro this happens about 3 times per week for all Land-Monitoring projects. At that point, an entire project is likely to be put on hold until a replacement part arrives on site or until that part has been repaired. This comes at a high cost, an average of 800 euros per day of project downtime according to Fugro’s employees.

## 1.3 Problem cluster & core problem

This thesis will attempt to solve the problem of the inadequate availability of inspected Land-Monitoring equipment that can be used at short notice. This is the main problem. The cause of this main problem, is that the number of Land-Monitoring equipment ordered in a week exceeds the working hours capacity of the workshop, because the time needed to inspect the equipment is larger than the available working hours.

The order exceeds capacity for two reasons. Firstly, the amount of work per employee in weeks with a peak demand is excessive due to a shortage of workshop personnel, however in a week with average demand only 51.6% of the available working hours are used. The other reason is the high workload fluctuations throughout the weeks, which is a consequence of the fact that the workshop personnel do not work in advance, but has an inspect-to-order policy. Three factors contribute to the lack of advance work: the first is the tendency of the project planners to order the equipment at short notice, the second reason for this policy is that there is not enough uninspected equipment on stock to inspect before orders are received, when the equipment in the workshop is out of stock the equipment should first return from a project, before it can be inspected. Currently the equipment is not returned to the workshop as soon as possible after the period of use, this is due to the fact that the projects do not have to pay rent for the period they own the equipment, but the projects only have to pay for the period the equipment is used, this is a potential core problem.

The third reason for having an inspect-to-order policy in the workshop is that equipment is inspected after the orders are received, which is the current policy. Currently it is unknown how much equipment should be inspected-to-stock to achieve a desired fill rate, because no inventory control policy exists. This cannot be determined, because the required base stock levels in order to achieve a desired fill rate are unknown, which is the chosen core problem of this thesis.

Another cause for the lack of an inventory control policy is that in order to optimize the policy we need data about the equipment arriving in the workshop and the number of equipment units lost or sold on a project per week. These are currently not processed, because that costs too much time and the benefits are unknown. Due to the lack of data, assumptions have been made to deal with this. Figure 1 depicts an overview of this root cause analysis described above.

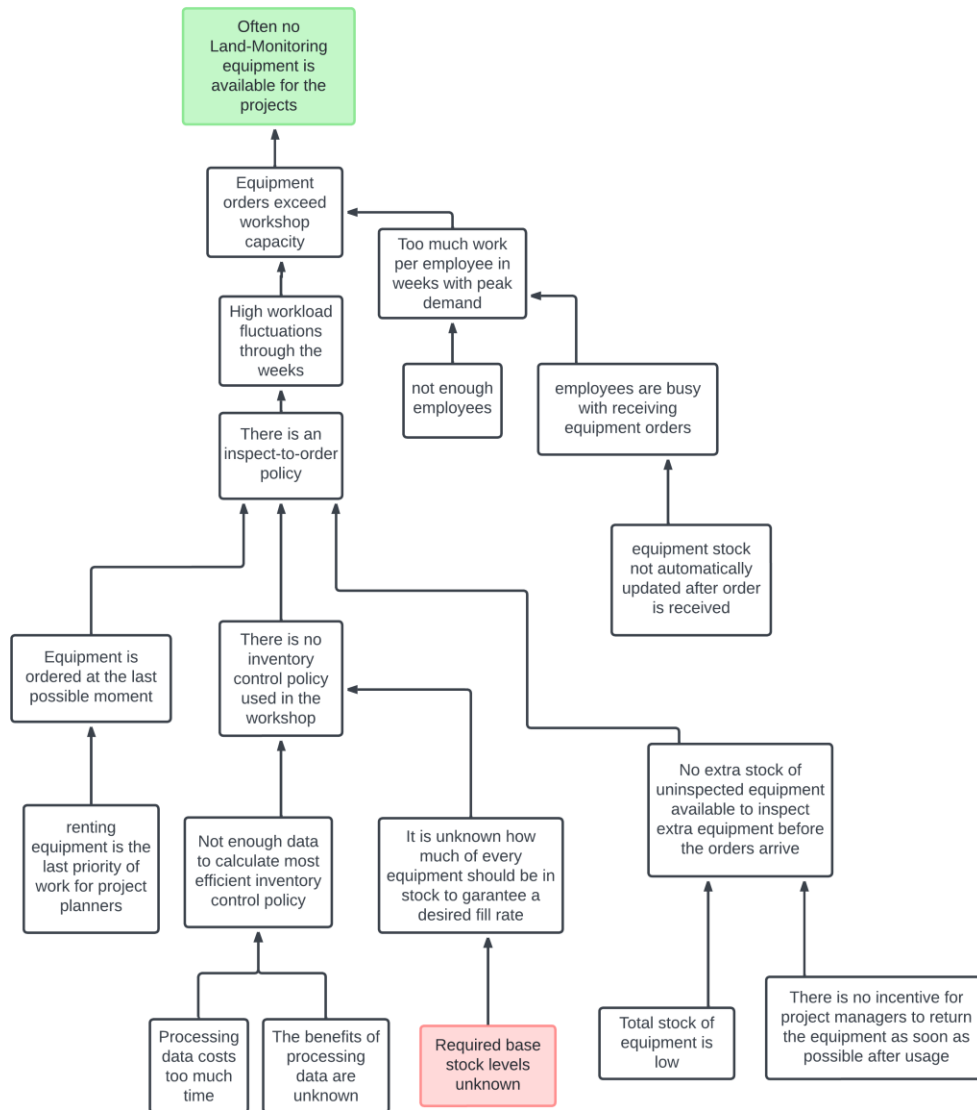


Figure 1: Problem Cluster

Main problem  
Core problem

## 1.4 Norm and reality

The research question of this thesis: *How can the availability of Land-Monitoring equipment in Fugro's workshop be increased by using a base-stock level?*

This research question is used to solve the main problem. To do this the main problem is transferred into an action problem, a situation where the reality deviates from the norm (Heerkens et al., 2017). Therefore, the KPI has to be decided. In this research question the KPI is: the availability of the Land-Monitoring equipment which is directly available after it has been ordered, because the equipment has already been inspected and calibrated. To set the target value for this, it is first important to measure the current value of this KPI. As the equipment currently being inspected after an order comes in, the current value of this KPI is 0%. This is a problem, since projects often order equipment at short notice. Therefore it is important that some of the equipment has already been inspected, otherwise there will not be enough time to inspect all ordered equipment before the start

of the project and projects will be postponed or cancelled because of this, which costs the company a lot of money. To make sure that a large part of the equipment already has been inspected before an order arrives an inventory control policy should be implied. That increases the availability of Land-Monitoring equipment orders which can be fulfilled from inspected stock. Hence the objective of this thesis is to find an inventory control policy that increases the availability of Land-Monitoring equipment that can be delivered directly from stock. To conclude the action problem of this research is defined as: *How can the direct availability of Land-Monitoring equipment in Fugro's workshop be increased from 0% to 99% by using a base-stock level?*

## **1.5 Research design**

In this section the research design which helps us to solve the core problem is described. In Section 1.5.1 we discuss the problem solving approach with regard to the research questions used to answer this research. For clarification, this problem solving approach is depicted in Figure 2 at the end of this section. In Section 1.5.2 the scope of this research is determined. In Section 1.5.3 the deliverables of this thesis are stated.

### **1.5.1 Problem solving approach**

In this Section the problem solving approach, which is used to answer the main research question systematically, is described. This approach divides the thesis into 5 stages to come up with a conclusion for the main research question. First, the current situation is defined. Next, the existing theories about inventory policies are explored in a literature study. Then, the inventory control policy for increasing the equipment availability is designed by creating a tool and a simulation model. Subsequently, the results of this tool and the simulation model are discussed. Finally, the conclusion of this thesis is given. These 5 stages represent the Chapters 2 to 6 of this thesis.

Furthermore, this section is used to elaborate on the approach of working through the chapters, with the sub-questions and explanations of their significance for the problem solving approach of this thesis.

#### **Chapter 2: Current situation**

In this chapter, the current procedure for inspecting the equipment is analysed. The use of the equipment and the current planning procedure are described. The current problems within the process and their cause is examined. Besides that, an overview of the available data is given that is used later in this research as input values for the tool of Chapter 4. This chapter is divided into 5 sub-questions:

*2.1 What is the purpose of Fugro's Land-Monitoring workshop?*

*2.2 What is the current procedure for inspecting/calibrating the equipment in the workshop?*

*2.3 What is the function of the different equipment groups?*

*2.4 What are the current values for the processing times for the different equipment groups, the probabilities of delay, the demand distribution and the total lead time in Fugro's workshop?*

*2.5 What are the bottlenecks in the current procedure which cause long lead times and low availability of Land-Monitoring equipment?*

The information about the current procedure of the workshop is conducted by interviews. This gives us a clear overview on the process. The processing time per unit of equipment for the different equipment groups and the bottlenecks of the current procedure are conducted by partially observing in the workshop and partially interviewing the workshop employees. This information is necessary to decide what the weekly capacity of the workshop is. This information is used in the solution design. The information about the bottlenecks of the current process are known it will be easier to come up with solutions.

### **Chapter 3: literature review**

In this chapter is searched for already existing literature about the topic, which is relevant to this study and can help us solving Fugro's problems by means of validated models. A systematic literature review is done to find suitable sources for the research question. This Literature review is divided into 2 sub-questions:

*3.1 What are common used inventory control policies that are relevant for Fugro's availability problem?*

*3.2 How can safety inventory be optimized for production-inventory system?"*

First, the characteristics for inventory control policies are explained. Then different benefits and disadvantages are explained by referring to other studies. The description of the different inventory control policy will be used to choose the inventory control policy that suits Fugro's inventory problem, this inventory control policy is used in the solution design of Chapter 4.

To answer the second sub-question of this chapter, the importance of safety stock in an inspect-to-order policy is explained. To then use the literature review to discover how other researchers have handled a production inventory system.

### **Chapter 4: solution design**

This chapter is about the solution design of the problem. In this section a tool is created after which a simulation model is designed to be compared with the tool. The safety stock will be the experimental factor in the solution design. The Chapter is divided into 2 sub-questions:

*4.1 How can a tool be designed which calculates the required base stock level for different fill rates that is effective for the inventory system in the workshop of Fugro?*

*4.2 How can a simulation model be designed which simulates the inventory model for different base stock levels?*

The chapter starts with a description of formulas for the best fitting inventory control policy that are used to create a tool with the programming tool VBA. Subsequently a simulation model is designed by using the information from the current procedure. This simulation model is used in Chapter 5 to optimize the results from the tool and then to validate the tool. If the tool is validated, Fugro can use this tool to estimate the required base stock levels in the future instead of having to use the complex simulation model.

### **Chapter 5: results**

In the tool some assumptions are done which could influence the reliability. To improve the findings of this research, a simulation optimisation with full enumeration is used. To evaluate the influence of each of the assumptions on the reliability of the tool. Then, the validation of the tool is examined

using a maximum allowable deviation rate of 5%. In order to do this, the chapter is divided into 4 sub-questions:

*5.1 What are the required base stock levels to achieve a desired fill rate for the main groups of Land-Monitoring equipment according to the tool?*

*5.2 What are the required base stock levels to achieve a desired fill rate for the main groups of Land-Monitoring equipment according to the simulation model?*

*5.3 How are the results of the tool and the simulation model effected by the differences between these two models?*

*5.4 Can the tool be validated using a maximum allowable deviation rate for fill rates of 5%?*

### **Chapter 6: conclusion**

In the conclusion the results of the solution are evaluated. Here we check if the norm, the desired fill rate, is reached. On this basis the recommendations for the company Fugro are made. In these recommendations we advise the company on how to implement the solution. Finally, there is elaborated on the limitations of this research and the further research that could improve the accuracy of the recommendations.

An overview of the research design is depicted in Figure 2 on the next page.

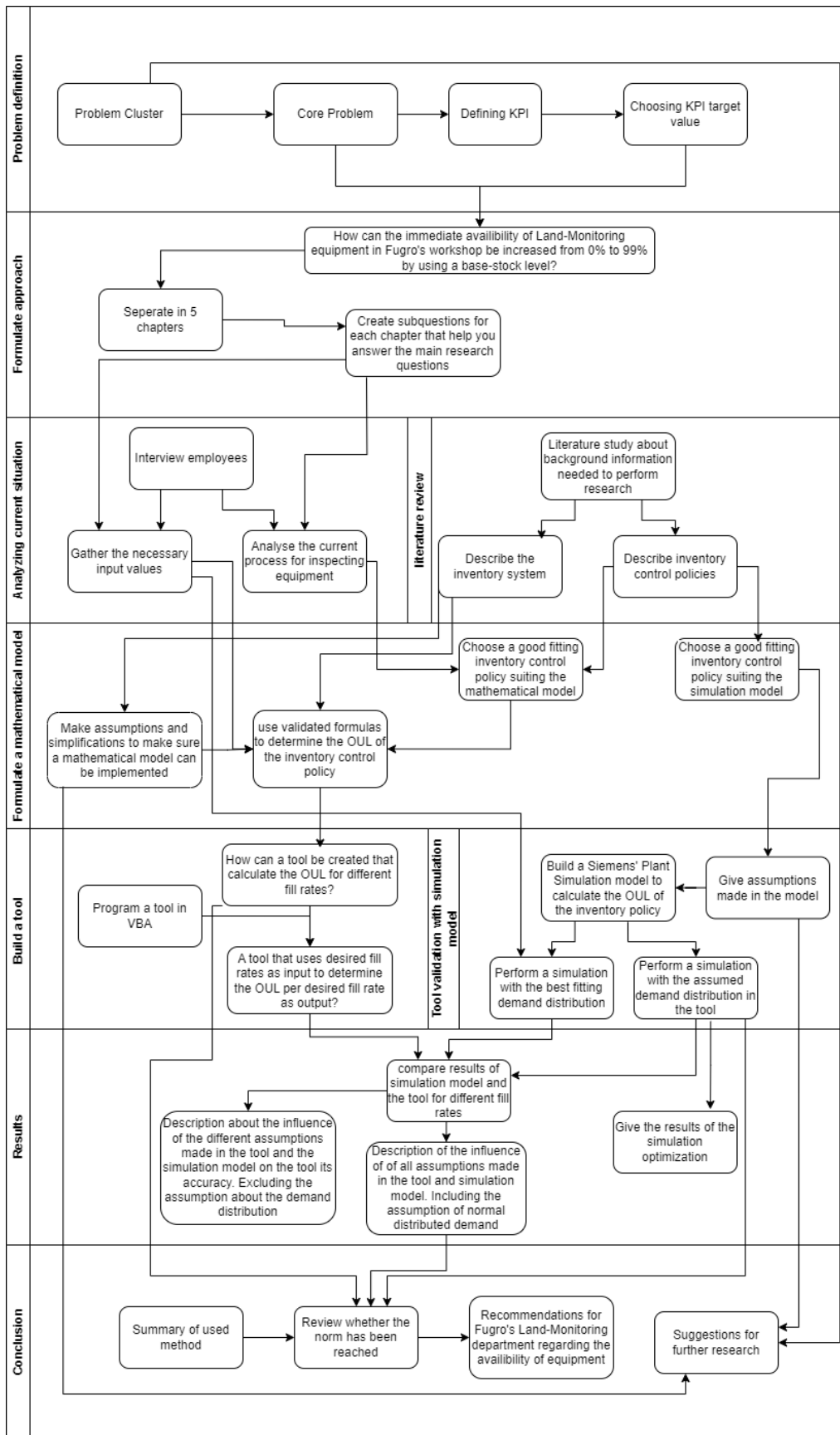


Figure 2: research design

## 1.5.2 Scope

The workshop rents out 56 different equipment groups to the Land-Monitoring projects. The workshop staff spend 40% of their time inspecting and calibrating the five largest groups of equipment. In this thesis we will focus on these five main groups. Which are loggers, ellitracks, vibration sensors, standpipe sensors and pore pressure sensors. For these groups we focus on the direct availability of inspected and calibrated equipment assuming that the total stock of equipment in circulation is sufficiently large.

## 1.5.3 Deliverables

The deliverables of this bachelor are a tool designed to estimate the required base stock level of inspected equipment in the workshop. For the design of this tool, VBA and Excel have been used. Besides that a simulation model is made in Siemens' Plant Simulation which optimizes the results from the tool, to then evaluate the accuracy of this tool.

## 1.6 Chapter Conclusion

In this chapter we introduced the company, the Land-Monitoring department which is investigated in this thesis and the problem it is currently experiencing in the workshop of the Land-Monitoring department. We analysed this problem by creating a problem cluster where we found that the core problem is that the base stock levels to reach a desired fill rate are unknown. This core problem have to be solved in order to solve the action problem, which is *"How can the direct availability of Land-Monitoring equipment in Fugro's workshop be increased from 0% to 99% by using a base-stock level?"*. Chapter 2 describes the current process and provides data about the current situation, which is used in Chapter 4 to solve the core problem.



## 2 Current situation

In this chapter the current situation regarding the calibration and inspection of Fugro’s Land-Monitoring workshop is analysed. The information gathered from this chapter is used as input for the mathematical model. This chapter is divided into 4 sections. In Section 2.1 the task of the workshop is discussed. In Section 2.2 the current procedure of the calibration and inspection of the equipment are explained. Section 2.3 elaborates on the function of the equipment groups discussed in this thesis. In Section 2.4 the required input values such as, the processing times for the different equipment groups, the probabilities of delay, the demand distribution and the total lead time are given. In Section 2.5 the bottlenecks regarding the availability of the equipment are analysed. Finally, in Section 2.6 the chapter is concluded.

### 2.1 Purpose of the workshop

To ensure that Fugro's Land-Monitoring department can carry out its soil investigations, Land-Monitoring equipment is needed. The number Land-Monitoring equipment units used on projects by Fugro fluctuates from week to week. Figure 3 depicts the number of units of Land-Monitoring equipment used per equipment group per week for all Land-Monitoring projects added together and The current capacity or amount of material in circulation of all 5 groups separately is given in Table 2.1.

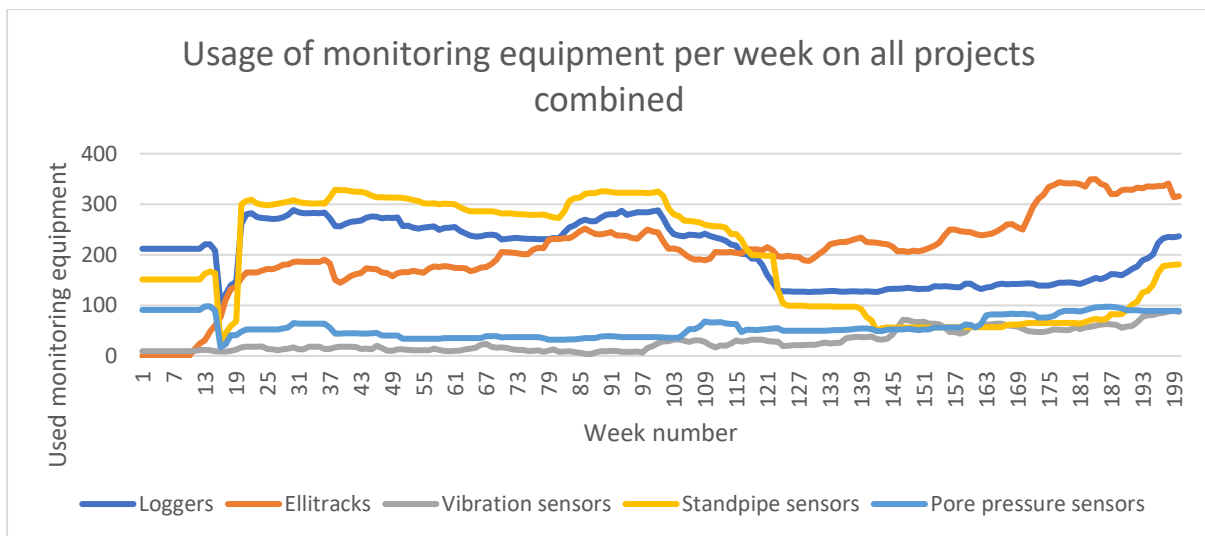


Figure 3: Number of units of equipment used at Fugro's Land-Monitoring projects based on 200 weeks of data

Table 2.1 total amount of equipment in circulation

| Equipment group                         | Number of units of equipment in circulation |
|---|---|
| Loggers                                 | 480   |
| Ellitracks                              | 707   |
| Vibration sensors                       | 125   |
| Standpipe sensors (Ellitracks excluded) | 589   |
| Pore pressure sensors                   | 343   |

When a project needs new equipment to use on the project it must be ordered at the workshop. The number of ordered equipment is different from the number of used equipment, since equipment which is already used the previous week does not have to be ordered again. It is ordered at the beginning of the period of use. The equipment ordered by projects must first be inspected or calibrated. This is done in the workshop. Of the 5 equipment groups discussed in this thesis 3 groups should be inspected. These equipment groups are loggers, ellitracks and vibration sensors. The reason that these equipment groups need to be inspected is that when the equipment is returned from the previous project it may not be working properly. The inspection of the equipment is to check that it is working properly. There are also 2 groups that needs to be calibrated. These are pore pressure sensors and standpipe sensors (excluding ellitracks). Calibration involves checking that the equipment is still measuring within the correct margins.

## 2.2 Current procedure

In this section a simplified process that the equipment goes through is described. When equipment is returned to the workshop, the workshop employees start cleaning the equipment. Then, the standpipe sensors and pore pressure sensors are calibrated if the employees have the time to do so and a first inspection is performed on the loggers, the vibration sensors and the ellitracks if equipment does not work it is repaired or send back to the supplier. Subsequently, all the equipment is put on stock. When the equipment is ordered it is recalibrated/inspected for the second time, this time different aspects are inspected. Next, the employee report its findings from calibration and inspection in the database "Spotmaster". Finally, the workshop employee notifies the project team that the equipment is ready to pick up. The project team keeps the equipment till the end of the project, after which it is returned to the workshop. Figure 4 depicts an overview of the current process described above.

Equipment orders may come in scattered throughout the week, but as projects often require several pieces of equipment and a project orders all its required equipment at once, most of the demand comes in one week at a time. In weeks with high demand, it is even more likely that a large proportion of the orders come in at the same time, since high demand is often caused by 1 specific large project starting that week.

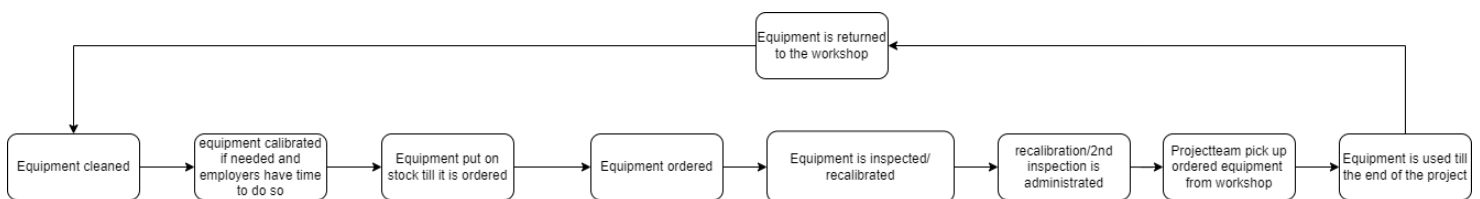


Figure 4: current workshop process

## 2.3 Function and inspection/calibration of the equipment groups

This section elaborates on the function of the 5 equipment groups involved in this study. The first equipment group to be discussed are the loggers. Loggers are used to send the information from the sensor to the office where they use the data. All sensors need loggers, except ellitracks. The inspection of loggers is divided into two stages: the first is when the logger arrives in the workshop, and the second is just before the equipment is send to the project

Secondly, the standpipe sensors (ellitacks excluded) are discussed. These standpipe sensors are used to measure the groundwater level. When arriving in the workshop the sensors are calibrated. After calibration the sensors are put into storage until they are sent to another project. In addition to the normal standpipe sensors, we also discuss a special type of standpipe sensor - the ellitrack - in this thesis. Ellitracks are also used to measure groundwater levels. The difference between ellitracks and other standpipe sensors is that the ellitrack is like a standpipe sensor and a logger in one. When arriving in the workshop the ellitracks are put into storage with batteries in them, so that they will keep working. As a result, the ellitracks do not need to be calibrated, but they can simply be inspected the moment an ellitrack is ordered by a project. Since the battery is left in the ellitrack, it is easy to check when an order comes in whether the ellitrack shows a groundwater level deviation from 0 meter in the time it was placed into storage in the workshop or not. If that is the case the ellitrack is no longer usable and another ellitrack should be sent to the project, the old ellitrack will be disposed.

Next, the pore pressure sensors are discussed. As well as the standpipe sensor, the pore pressure sensors are only calibrated when they arrive in the workshop. This sensor measures the pressure of the ground water.

Lastly, the functioning and service time of the vibration sensors are described. These sensors are calibrated at the supplier's, but inspected in the workshop when they come back from the project, and before they are sent to a project.

## **2.4 Input values model**

This section is used to get an overview of the different input values needed for the Mathematical model build in chapter 4. In Section 2.4.1 the service time per inspection/calibration of the equipment groups is given. In Section 2.4.2 we address possible delays in service time due to faulty equipment, non reparable equipment and errors in the calibration process. In Section 2.4.3 the distribution of the orders per equipment group are derived. Then, in Section 2.4.4 it is shown how the lead time for equipment orders is determined.

### **2.4.1 service time per calibration/inspection**

This section elaborates on the servicetimes for the different steps in the inspection and calibration process on the equipment groups discussed in Section 2.3. These service times are gathered by interviews with the workshop staff and are rough estimations. Besides the inspection or calibration of the equipment every piece of equipment needs 5 minutes of administration after each calibration or inspection and 5 minutes of cleaning time per unit of equipment are used after the arrival of the equipment. An overview of the average service times for the different steps in the workshop per unit of equipment is depicted in Table 2.2.

Table 2.2: service time per inspection/calibration per unit of equipment

| equipment type                         | Arrival in workshop after it is used on project |                        |                |                               | Departure from workshop to project |   |                                 |
|--|---|------------------------|----------------|-------------------------------|------------------------------------|---|---------------------------------|
|  | Cleaning  | Inspection/calibration | administration | Total processing time arrival | Inspection                         | administration                          | Total processing time departure |
| Loggers                                | 5 minutes                                       | 20 minutes             | 5 minutes      | 30 minutes                    | 15 minutes                         | 5 minutes                               | 20 minutes                      |
| Ellitrack                              | 5 minutes                                       | 10 minutes             | 0 minutes      | 15 minutes                    | 10 minutes                         | 5 minutes                               | 15 minutes                      |
| Vibration sensor                       | 5 minutes                                       | 20 minutes             | 0 minutes      | 25 minutes                    | 20 minutes                         | 5 minutes                               | 25 minutes                      |
| Standpipe sensors (Ellitrack excluded) | 5 minutes                                       | 10 minutes             | 5 minutes      | 20 minutes                    | 0 minutes                          | 5 minutes (which include recalibration) | 5 minutes                       |
| Pore pressure sensor                   | 5 minutes                                       | 12 minutes             | 5 minutes      | 22 minutes                    | 0 minutes                          | 5 minutes (which include recalibration) | 5 minutes                       |

## 2.4.2 Possible delays in service time due to errors

It could be the case that there are additional steps which need to be taken for inspection and calibration of the equipment, which increase the required service time per unit of equipment. The additional steps that may be required, which impact the service time per unit of equipment, are outlined below:

- Equipment may have to be recalibrated because the first calibration did not succeed.
- During the equipment inspection, it may transpire that the equipment is faulty and must be repaired.
- The faulty equipment cannot be repaired, so new equipment should be inspected/calibrated.

In case of equipment being faulty, the inspection time is doubled. The recalibration costs the same time as the first calibration. An overview of these probabilities per equipment group is depicted in Table 2.3. These probabilities are analogous to the service times per inspection/calibration gathered by an interview with the staff of the workshop and are rough estimations.

Table 2.3: Probabilities of recalibration, faulty equipment and non-reparable equipment.

| Equipment type       | 2 calibration | Faulty | Equipment is faulty and non-reparable |
|----------------------|---------------|--------|---------------------------------------|
| Logger               | 0             | 0.25   | 0.125                                 |
| Ellitrack            | 0             | 0.4    | 0.4                                   |
| Vibration sensor     | 0             | 0.1    | 0.1                                   |
| standpipe sensor     | 0,2           | 0      | 0,05                                  |
| Pore pressure sensor | 0,2           | 0      | 0,05                                  |

### 2.4.3 Demand distribution per equipment group

Since the quantity of equipment ordered influences how much time the workshop staff spends processing these orders, this section is used to find a theoretical distribution of the equipment orders per week. The distribution of equipment ordered per week per equipment group is depicted in Figure 5. In contrast to the number of equipment used on project, there are only 54 weeks of data available on the number of ordered equipment.

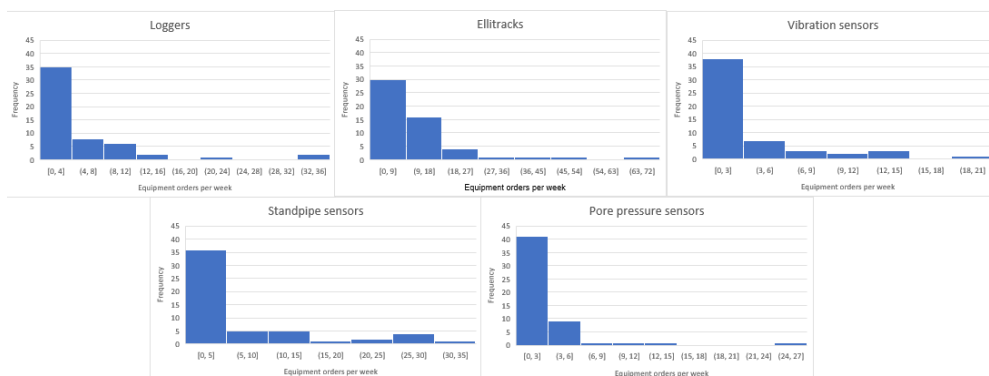


Figure 5: distribution of the number of equipment units ordered per week based on 54 weeks of data

The distribution of the weekly equipment orders in Figure 5 is used to visualise the distribution that the equipment orders follow. To find out which of the theoretical distributions best fits this data on the number of equipment orders per week over 54 weeks, the software EasyFit is used to do a goodness of fit test for 24 different theoretical distributions. These distributions with their values for the test statistics are depicted in Appendix 1A. In EasyFit, the continuous theoretical distributions are tested with 3 different goodness of fit tests, the chi-square test, the Kolmogorov-Smirnov test and the Anderson-Darling test. The discrete distributions are only tested with the Kolmogorov-Smirnov test and the Anderson-Darling test. To compare these theoretical distribution we used the Anderson-Darling test, because this is the most recent and therefore we expect it to be the most accurate method for fitting distributions. The Anderson and Darling test was created in 1952 to try to improve the chi square test and the Kolmogorov-Smirnov test by using a weight factor, which increases the weight at the extremities of the distribution (Liu, 2022).

For all the equipment groups the theoretical distribution closest to the dataset is the geometric distribution with parameter p. Table 2.4 depicts the equipment groups with the corresponding p values.

Table 2.4: p values of the geometric distributed orders per week for main equipment groups

| Equipment group                       | p       |
|---------------------------------------|---------|
| Logger                                | 0,16564 |
| Ellitrack                             | 0,08194 |
| Vibration sensor                      | 0,25116 |
| Standpipe sensor (ellitrack excluded) | 0,12766 |
| Pore pressure sensor                  | 0,31395 |

## 2.4.4 lead time and orders per week

In this section the mean lead time of the inspection/calibrations of the orders per week and its standard deviation are determined, which are necessary to calculate the required safety inventory of inspected equipment in Chapter 4. Furthermore, the mean and standard deviation of the equipment orders per week is determined in this section, which are also used as input values in Chapter 4.

The mean and standard deviation of the lead time are established by using the data of 54 weeks of equipment orders and the service time per equipment. This service times consider the values from Table 2.3, the probabilities that: calibration needs to be redone, equipment is faulty and equipment is not repairable, thus a new equipment piece should be inspected. From this data, a total workload in hours per week is calculated.

Since a total of 40 hours per week is available for the inspection and calibration of all the 5 main equipment groups involved in this study combined, all the inspection and calibration time of the amount of equipment ordered in a week of all these groups is added together. Then, the required working hours for inspection and calibration of the ordered equipment is divided by 40 hours, since that is the number of available working hours for all these equipment groups combined. From this the replenishment lead time for each of these 54 weeks is calculated. By using descriptive statistics in excel, the mean lead time and standard deviation of replenishment of inspected equipment are derived. The lead time for the replenishment of inspected equipment for a specific week can be derived by Equation 1 in which we assume that all equipment is ordered at the same time.

$$L_t = \left( \sum_{i=1}^5 \left( (1 + f_i * h_i) / (1 - r_i * n_{it}) + ((1 + c_i * k_i) / (1 - r_i * n_{it})) / 40 \right) \right) \quad (1)$$

Where:

$L_t$  = Lead time in week t

$f_i$  = the probability that equipment i is faulty.

$c_i$  (2nd calibration) = the probability equipment i needs a second calibration.

$r_i$  = Probability that equipment i is not repairable

$h_i$  = hours of outgoing service needed per equipment i

$k_i$  = hours of incoming service needed per equipment i

$n_{it}$  = the demand for equipment i at week t

The required input values to calculate an inventory policy, which improves the direct availability of the equipment are depicted in Table 2.5 and Table 2.6. These required input values are the mean and the standard deviation of the number of units of ordered equipment per week, the minimal replenishment quantity and the mean and the standard deviation of the replenishment lead time in weeks. The mean number of units of ordered equipment per week and its standard deviation is analogous to the replenishment lead time gathered by using descriptive statistics in Excel.

Table 2.5: the mean and standard deviation in equipment orders per week for the different equipment groups.

| Equipment group           | Loggers | Ellitracks | Vibration sensors | Standpipe sensors | Pore pressure sensors |
|---------------------------|---------|------------|-------------------|-------------------|-----------------------|
| Mean demand               | 5,037   | 11,204     | 2,981             | 6,834             | 2,185                 |
| Standard deviation demand | 7,483   | 12,356     | 4,619             | 9,464             | 4,331                 |

Table 2.6: Mean lead time replenishment in weeks, standard deviation in lead time replenishment of inspected equipment in weeks and minimal quantity of replenishment in units.

|                             |              |
|-----------------------------|--------------|
| Mean lead time              | 0,5155 weeks |
| Standard deviation Leadtime | 0,3458 weeks |
| Quantity replenishment      | 1 unit       |

## 2.5 Bottlenecks

In this section the bottlenecks of the current equipment availability are discussed. We will first analyse the bottlenecks in the Spotmaster database in Section 2.5.1. Then, the workload capacity bottleneck is evaluated in Section 2.5.2. Finally, the shortage of stock is analysed 2.5.3.

### 2.5.1 Spotmaster database

When generating a quote, it is important that stock is visible to a project team. This is currently not the case, meaning that those responsible for preparing a project have to make phone calls to the workshop to find out if the equipment is available, instead of making an order in the system where stock can be adjusted automatically. Answering the phone calls is a time-consuming activity for the workshop.

In addition, purchased equipment is immediately added to the stock in the database without considering the lead time of the delivery. This causes the available stock of Land-Monitoring equipment to be overestimated, which reduces the availability of the equipment.

### 2.5.2 Workload fluctuation

At the moment, all kinds of different Land-Monitoring equipment requests come in to the workshop shortly before the start of the project. According to a workshop employee the reason for this is that the equipment requests are the last priority for those responsible for preparing a project. Once the project employees and contracts are set, the equipment is requested. So, most of the inspection of equipment is for rush requests. In addition, the demand for equipment varies significantly from week

to week. This causes fluctuating workload in the workshop, because it is difficult to work ahead when equipment requests only arrive at the last possible moment. This increase in workload fluctuations decreases the availability of the equipment, because the workshop can only inspect/calibrate up to a certain amount of equipment per week. Figure 6 depicts the demand for equipment per week and the fluctuations in workload. Figure 7 clarifies the equipment ordered per week per equipment group.

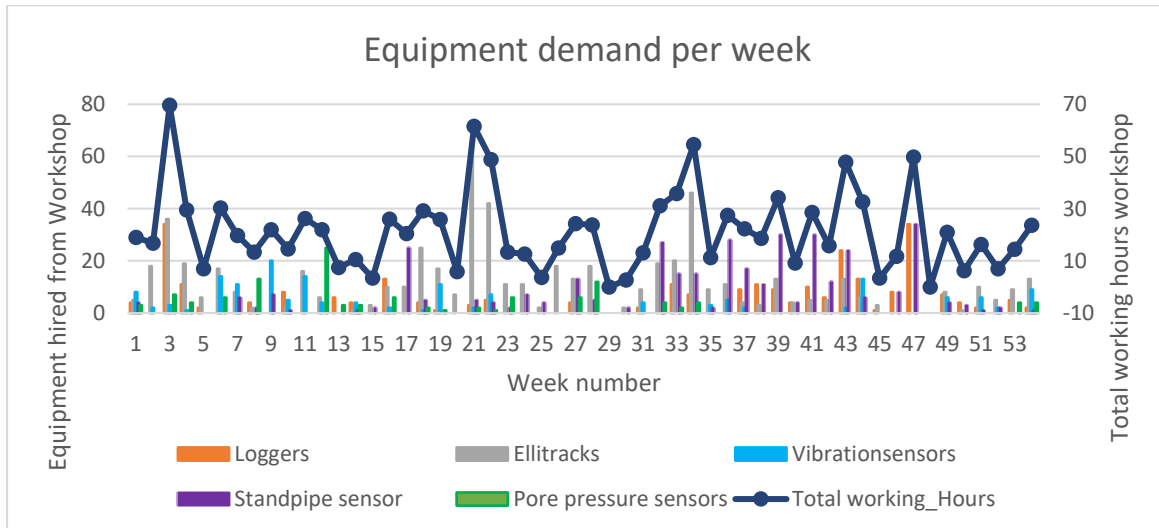


Figure 6: Land-Monitoring equipment orders per week based on 54 weeks of data from Spotmaster

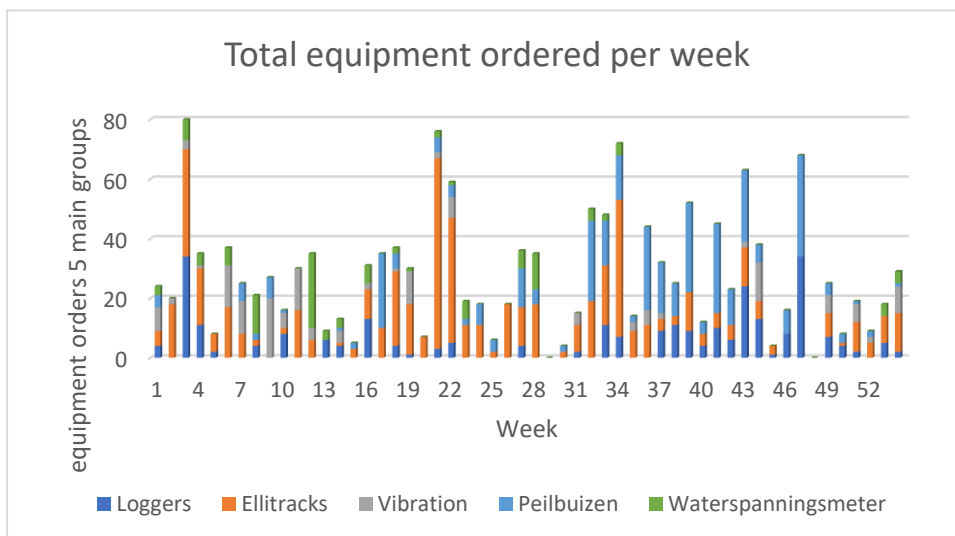


Figure 7: total Land-Monitoring equipment orders 5 main groups over a period of 54 weeks

### 2.5.3 Stock shortage at the workshop

Due to a frequent shortage of uninspected equipment coming back from the projects, it is difficult to maintain a reserve stock to increase the availability of Land-Monitoring equipment. This problem is partially caused by the fact that the project teams do not have to pay to rent the equipment if it is not used on the project, instead of projects having to pay for the time the equipment is owned. Because of this, when the equipment is no longer necessary, the project employees just store it in their car as a spare part, simply because there is no incentive to return the equipment on time. For



the workshop, however, lending out materials while not being used does incur a cost. Therefore, in order to still be able to provide equipment, Fugro's total inventory must increase. This involves investment costs.

## 2.6 Chapter conclusion

In Chapter 2, the research question 'What is the current procedure of Fugro's Land-Monitoring Workshop?' is answered. To answer this research question, the subject has been divided into 4 parts, which all contribute to exploring opportunities to increase the availability of Land-Monitoring equipment:

*Purpose of the workshop* – defines the function of the workshop and establishes the main equipment groups that are investigated in this thesis. In addition, this section depicts the amount of Land-Monitoring equipment used by these groups over time and the total land monitoring equipment in circulation.

*Current procedure* – explains the process the equipment goes through from the moment it enters the workshop. This information can be used when defining the replenishment lead time and building the simulation, as there is now a clear overview of the steps to be taken.

*Equipment groups* – elaborates on the function of the equipment groups and the processing time to be considered when an order from a particular equipment group arrives. Finally, this Section shows the number of units of equipment ordered per week, which can be used as input value for Chapter 4.

*Bottlenecks* – Defines the problems in the current situation. The bottlenecks for the immediate availability of Fugro's Land-Monitoring equipment are:

- The extra unnecessary work of handling orders, because the inventory data is not visible for project preparers, because the inventory data is not automatically updated after equipment is ordered or equipment is returned from the project.
- The high workload fluctuation due to a inspect-to-order policy and the short notice on which orders are made.
- The shortage of uninspected equipment, which is returned from projects, due to the fact that projects do not have an incentive to return equipment as soon as possible after the period of use, because the projects only pay for the period of use, not for the period they own the equipment.

These bottlenecks are used to identify possible solutions for the main research question of this thesis.

To conclude, this chapter is used to give an overview of the current situation, providing us with information about the input values for the simulation and finally defining the problems that the department is experiencing. In Chapter 3 a Literature Review is conducted to fill in the knowledge gaps and find a solution for these problems. Then, the processing times and orders per week depicted in Section 2.3 are used as input values for the tool and the simulation model in Chapter 4.

# 3 Literature review

In this chapter we perform a literature study about the application of safety stocks to minimize the backorders in the workshop of Fugro's Land-Monitoring department. In this chapter we try to answer two sub-questions, which are: "What is an appropriate inventory control policy for Fugro's Land-Monitoring workshop?" and "How can safety inventory be optimized for production-inventory system?"

To answer the first sub question. In Section 3.1 the importance of an inventory control policy is described and background information is given. To then elaborate in Section 3.2 on continuous and periodic review policies for inventory systems in which ordered stock arrives all at the same time. In order to then answer the second sub-question of this chapter. Section 3.3 describes inventory systems where stock is gradually replenished by means of production and probabilistic demand.

## 3.1 Background inventory control policies

Inventory control policies are used in supply chain management and help determining inventory levels and manage fill rates. The three main problems that are resolved in a replenishment control system are according to (Silver, 2016):

1. The time interval between assessments of the inventory status.
2. The timing on which replenishment orders should be placed, the reorder point.
3. The quantity of the replenishment.

According to Maulaya, (2019) inventory management is used to make a trade-off between 3 aspects. Firstly ordering cost, which include administrative cost to place an order and transporting cost. Secondly holding cost, the cost of carrying an product in inventory for a specified period of time, is an important aspect. Thirdly, the shortage cost, which is the cost of not being able to satisfy customer demand in time.

According to Tayfur et al., (1989) quantity of the replenishment depends on what happens with orders which are not fulfilled from on hand inventory. These can either be lost in the system, which is called a lost sales system or the sales can be backordered. In case of backordering stock can be negative and backorders are satisfied directly after new stock arrives.

## 3.2 Inventory control policies

The time between assessment of inventory status is a trade-off between time it takes to check the inventory and on the other hand the longer the interval between assessment, the higher the variations in demand could be. It could also be the case that demand is always known, which we call a continuous review policy.

A continuous review policy ( $s,S$ ) is an inventory policy where the stock is directly ordered after the inventory level drops below  $s$ , the reorderpoint, and the quantity of stock ordered is exactly enough to reach level  $S$ , the OUL. A continuous review policy is beneficial when demand fluctuates a lot and is unpredictable, because it allows for a more flexible response to unexpected demand (Pejman, 2024). A base-stock policy is a special case of a continuous review policy, which is used by Maulaya et al., (2019). Where the reorder point is  $S-1$  and  $S$  is the base stock level, the desired stock level. In

other words, at the moment demand is satisfied, a new order is placed immediately so that the inventory level is equal to the base-stock level. The main advantage of continuous review policy in comparison to periodic review policies is that less safety stock is required to achieve the same fill rate, because there is no more safety stock required over the period between stock assessments.

In a periodic review policy the inventory is brought back to predetermined levels at the beginning of every period (Arda et al., 2004). The benefit of a periodic review policy over a continuous review policy is that the system is simpler. Whereas with continuous review policy there had to be continuous checks on whether there was still enough stock, this now happens only once in the period (Zhang et al., 2016). There are two possible policies for periodic reviews, (R, s, S) policy and (R, S) policy. In an (R, s, S) system the inventory is assessed once in the predetermined time interval. If the inventory level is larger than s, the reorder point, no order is placed. However, if the inventory level is smaller than s. An order is placed, the order quantity is determined by subtracting the on hand inventory from the OUL, so that the inventory level S, the OUL, is reached. In a (R, S) policy, after every replenishment cycle, the inventory is increased to level S independently of the current inventory level (Permatasari et al., 2017). The (R, S) policy is also called the base-stock replenishment policy. Boute et al, (2007) have used this (R, S) policy to analyse the base stock levels taking into account demand variability and lead time variability. As is described in the standard base-stock replenishment policy of this research, the base stock level is determined by the expected demand during the review period plus the stochastic replenishment time and the safety stock which is used as an buffer for the variance in demand and lead time.

### **3.3 Production inventory system**

In this section background information about production inventory systems is given. Production-inventory systems are combining production processes with inventory management. The advantage of production inventory systems in comparison to normal inventory systems is the ability to buffer against uncertainties in production which is the lead time. Production inventory systems are more complex, because there have to be dealt with capacity constraints (Silver et al., 2016).

Gregory et al. (1983) highlight the importance of differentiating between make-to-stock (MTS) and make-to-order (MTO) production strategies in inventory planning. In a MTS production system, the quantity of production is based on forecasted demand, indicating an intention to directly satisfy customer demand. As production occurs prior to the receipt of an order, it is essential to implement a safety stock to accommodate potential variability in demand and lead time. In contrast, a make-to-order (MTO) production system involves the manufacture of the product subsequent to the receipt of the order. Thus, in a MTO system, a safety stock is unnecessary. However, certain raw materials may require a safety stock.

To describe a production-inventory system Baek & Moon, (2015) used an queuing model wherein the lead time is contingent upon the demand. Moreover, the lead time is contingent to the on hand inventory level. For high demand, the lead time is longer due to the increased probability of the supplier running out of stock. In such a case, new stock is produced, in response to stock-outs. The proportion of stock produced after a stock-out event is higher for higher demand, which further increases the queue for products and thus the lead time becomes larger. In accordance with Little's Law, as used by Sanajian and Balcioglu (2008), the number of orders within the system is equivalent to the arrival rate of orders multiplied by the average waiting time. In this study, the rate of order arrivals is known. The average waiting time of an order is calculated in order to ascertain the average number of orders in the system that have yet to be fulfilled. Similarly, Altioek and Shiue (2000) used a

queuing model to describe a production-inventory system, wherein a multi-product model was utilised. In this research, the demand for disparate product categories is assumed to be independent of one another. The steady state is then calculated to ascertain the average inventory. Based on these outcomes, lead times and base stock levels can be determined.

Since it is difficult to use a simple formula to calculate these queuing models to minimise the total cost of inventory. Usually algorithms are build to do so. As is done by Zoysa & Rupasinghe, (2017) who build a Genetic Algorithm in order to optimize the safety stock under various constraints which were implemented in the algorithm. In this algorithm different variables can be optimized simultaneously. Furthermore this Genetic algorithm is able to adjust safety stock levels or reorder points based on changing demand patterns.

Since it is difficult to build a formula which calculates the performance metrics Karaman & Altiok, (2007) used a simulation model to validate the findings of the analytical model by comparing the performance metrics from the model to the results generated by the discrete-event simulation model. This simulation also validates the assumptions that have been made in the analytical model.

### **3.4 Chapter conclusion**

This chapter has been used to provide us with knowledge that we need in for the coming chapters of this thesis. In the first two sections of this chapter the research question: “What is an appropriate inventory control policy for Fugro’s Land-Monitoring workshop?” is answered. In the first section we describe the aspects of an inventory control policy: the review period, the reorder point and the order quantity. Then, in Section 3.2 common used inventory control policies are given, where the difference between periodic review policies and continuous review policies are described. Continuous review policies need a lower safety stock than periodic review policies. But periodic review policies are more simple as described by Boute et al. (2007). In Chapter 4 the best fitting research policy for Fugro’s workshop is chosen. Section 3.3 answers the second research question: “How can safety inventory be optimized for production-inventory system?” In this section the importance of safety inventory in production-inventory systems is described. Where MTO and MTS inventory systems are distinguished by (Gregory et al., 1983). For MTS inventory systems, safety stock is required. In contrast to MTO, where no safety stock is required, since the production starts after the order is received. This literature about the MTO and MTS can be mentioned as the inspect to order policy currently used at Fugro’s workshop where safety stock is unnecessary and the inspect to stock policy, which is our proposed solution for the equipment availability problem of Fugro’s workshop. This supports the statement that Fugro’s equipment availability problem should be solved using base-stock levels.

In the remainder of Section 3.3 models for production-inventory systems are described. Baek & Moon, (2015) created a model in which the lead time is contingent upon the demand, to do so a queuing model is used in their research. Altiok and Shiue (2000) described a queuing model in which multi product was handled by the same machines. This is comparable with Fugro’s workshop. But where the machines are mentioned as the multi product manufacturing systems in the research of Altiok and Shiue. In the case of Fugro’s workshop the staff is the multi product manufacturer. Also, Sanajian and Balcioglu (2008) used a queuing model to describe an inventory-production system. However to solve these queuing models a lot of complex algorithms should be used as in done in Zoysa & Rupasinghe, (2017). To validate the assumptions of analytical models a discrete event simulation can be used, as is done in Karaman & Altiok, (2007).

# 4 Solution design

In this chapter, the safety stock of the different types of Land-Monitoring equipment are calculated. To do this the chapter is divided into 3 parts. In section 4.1 a classification of the inventory system is given by using the literature found in Chapter 3. In Section 4.2 the design of the tool is defined. Then, in Section 4.3 the design of the simulation model is described. Finally, the chapter is summarized in Section 4.4

## 4.1 Classification workshop inventory system

In our solution a inspect to stock policy is proposed. For this policy we need safety stock as stated in the research of Gregory et al. (1983), discussed in Chapter 3. Since the production time in this inventory system is proportional to the demand during that period, because all the demand have to be inspected and the inspection time is assumed to be deterministic. The inventory system of Fugro's workshop can best be classified as a production-inventory system. Where the demand is the number of orders placed in a week. Orders arrive largely at the same time during the week. The number of orders placed per week is a non-negative variable. In this inventory system backorders are allowed, which means that the on hand stock can be negative and the delivery of the order is postponed. Backorders are fulfilled as soon as possible directly after inspection.

## 4.2 Inventory control policy

In this section a model is created which gives Fugro an indication of the required reserve stock to fulfill demand. In Section 4.2.1 the inventory review policy is chosen. After which the mathematical model used to calculate the base-stock level is shown in Section 4.2.2. Then, the creation of a tool which uses the model from section 4.2.2 to determine the safety stock is described in Section 4.2.3. Finally, we evaluate the simplifications and assumptions made in this model 4.2.4. For the calculations in this section, the input values are derived from the Spotmaster database about equipment requests during a period of 54 weeks are used.

### 4.2.1 Review policy

In this chapter an analytical model is created, which determines a base-stock replenishment policy with periodic review ( $R, S$ ). The reason this inventory review policy is chosen is because the equipment orders in a week often occur at the same time. Namely, when a major project begins. As a result, there is usually no time between orders that are place in the same week to inspect equipment to get back to base-stock level. So, the inventory can be refilled only after all the orders of that week has been placed and demand which could be fulfilled from on hand inventory is satisfied. This is the reason we choose a policy of periodic review to model the situation. In this periodic review policy the stock is assessed at the end of each period  $R$ . The inspection of new equipment is initiated at that moment and continues until the base stock level  $S$  is reached. The period during which this happens is called the inspection period. At the end of the inspection period, all the equipment which is inspected during this period is replenished to inventory simultaneously. In our model,  $R$ , the review period, has a value of 1 week since the data about the equipment demand is also given per week. Choosing a smaller review period would make the calculation unreliable, since we would have to divide that week's demand into parts, while we do not know whether the demand of that week

came into the workshop all at once or spread out over that week. The one week review period chosen does not pose a problem for the maximum capacity of the workshop. In fact, there is no capacity limit to the amount of equipment that can be stored in the workshop, because the workshop is large enough and the pieces of equipment are small. In addition, there is enough equipment in circulation to increase the base stock so that the stock of inspected equipment only needs to be checked once a week.

## 4.2.2 Mathematical model

In this section a model is build which calculates the required value of  $S$ , the base-stock level. To find the base stock level, the safety stock, the expected demand per review interval, and the anticipated demand for the lead time of a replenishment order, which is the average amount of time the inspection period takes, should be known. Now, a formula for calculating the base-stock level from the safety stock and the expected demand during a review period plus replenishment interval is presented. Subsequently, a formula for approximating the safety stock per intended fill rate is given assuming normally distributed demand.

Table 4.1 depicts the variables which are used for the formulas that are introduced within this section. This table gives an overview of the variables.

Table 4.1: overview of variables

| Variables  | Explanation of the variable   | value  |
|------------|---|--|
| $S_i$      | The required base stock level of equipment $i$  | Still needs to be calculated with the models in this section |
| $E(T_p)$   | The expected number of periods it takes for a replenishment to arrive, in other words the expected lead time of a replenishment order     | weeks  |
| R          | The number of weeks of a review period  | 1 week   |
| $E(D_i)$   | The expected demand for equipment $i$ during a week   | Depicted in Table 2.5 (recall section 2.4.4)                 |
| $SS_i$     | The minimal required safety stock to achieve a desired fill rate. The safety stock is used as a buffer to fulfill fluctuations in demand. | Still needs to be calculated with the models in this section |
| $z$        | safety factor   | Still needs to be calculated with the models in this section |
| $s_L$      | the standard deviation in lead time   | 0,3458 weeks (recall Section 2.4.4)                          |
| L          | average lead time   | 0,5155 weeks (recall Section 2.4.4)                          |
| $\sigma_D$ | standard deviation in demand  | Depicted in Table 2.5 (recall section 2.4.4)                 |
| $\sigma_L$ | the standard deviation of demand during lead time   | Still needs to be calculated with the models in this section |
| fr         | The desired fill rate   | -(is the experimental factor in this model)                  |
| Q          | The minimal replenishment quantity  | 1 unit of equipment  |

In Equation 2,  $S_i$ , base stock level of equipment  $i$ , covers the expected demand during replenishment interval plus lead time and the safety stock. Safety stock is used for unexpected fluctuations in demand. The larger  $S_i$  the higher the availability of equipment  $i$ . According to Boute et al., (2007) the formula for  $S_i$  is:

$$S_i = (E(T_p) + R) * E(D_i) + SS_i \quad (2)$$

According to Chopra & Meindl when the orders are normally distributed and backorders are allowed, the required safety stock for a desired fill rate can be found by using Equation 3, 4 and 5.

$$\sigma_L = \sqrt{E(D_i)^2 * s_L^2 + L * \sigma_D^2} \quad (3)$$

$$z = \phi\left(\frac{Q(1-fr)}{\sigma_L}\right)^{-1} \quad (4)$$

$$SS_i = z * \sigma_L \quad (5)$$

When combining Equation 2 to 4, Equation 6 can be created, which is used to calculate the base stock level for equipment  $i$ . From Equation 6 a tool is designed in VBA.

$$S_i = \phi\left(\frac{Q(1-fr)}{\sqrt{E(D_i)^2 * s_L^2 + L * \sigma_D^2}}\right)^{-1} * \sqrt{D^2 * s_L^2 + L * \sigma_D^2} + (E(T_p) + R) * E(D_i) \quad (6)$$

### 4.2.3 Tool creation

Based on Equation 6, the tool calculates the approximated required base stock levels for the fill rates 0.8, 0.805, ..., 0.995. The trade-off for choosing a higher base stock level is that although the fill rate of the equipment will be increased it may be the case that if the inspection/calibration of equipment is outdated it have to be redone, which is a waste of working hours. Because of this trade-off, we want to depict the required base stock levels of different fill rates in this tool.

There is a small inaccuracy in the tool. For finding the safety factor, this tool uses the Standard Normal Loss Function table. Since the values for the standard normal loss function in the table are rounded to 4 decimals, some  $G(z)$  values are the same. When this occurs, in order to facilitate this research, the tool employs the lowest safety factor.

### 4.2.4 Mathematical model assumptions

In order to utilise this model a number of assumptions have to be made.

- we assume the demand of the different groups of Land-Monitoring equipment to be independent of each other.
- for simplification of this model we assume that the lead time and the demand are normally distributed and follow an identical independent distribution through the weeks. To test the correctness of this assumption, a goodness of fittest for the normal distribution have been performed. The results of this goodness of fittest are depicted in appendix 2C.
- To simplify this model we assume that the lead time follows a normal distribution and is independent of the demand during that period.
- We assume a total 40 working hours per week are spent on the 5 groups of this research.
- The service times per calibration/inspection are as denoted in Table 2.2 and assumed to be deterministic

- the probabilities of mistakes in the calibration process, faulty equipment and non reparable equipment are as stated in Table 2.3.
- Finally, it should be noted that the results from the tool can have a slight deviation from the model, due to the manner in which the tool selects the safety factors from the Standard Normal Loss function table (recall Section 4.2.3).

## 4.3 simulation model

Because of the simplifications and assumptions used in the formula, the mathematical model is tested on its accuracy with a simulation model where the correct demand distribution and lead time distribution can be implemented, since the demand distribution used in the model, the normal distribution, can be rejected with a least a 98% confidence interval for all the equipment groups. In the simulation model there is also time reserved for pairing the equipment to the project. In this section the simulation model is discussed. In Section 4.3.1 a short description of the model is given. Then, in Section 4.3.2 the differences between the simulation model and the tool are summed up. Subsequently, in Section 4.3.3 the assumptions and simplifications made in the simulation are reflected. In Section 4.3.4 there is elaborated on the applications of the model.

### 4.3.1 Model description

In this section a description is given of the simulation model which is simulated in Siemens' Technomatix Plant Simulation. The model is depicted in Figure 8.

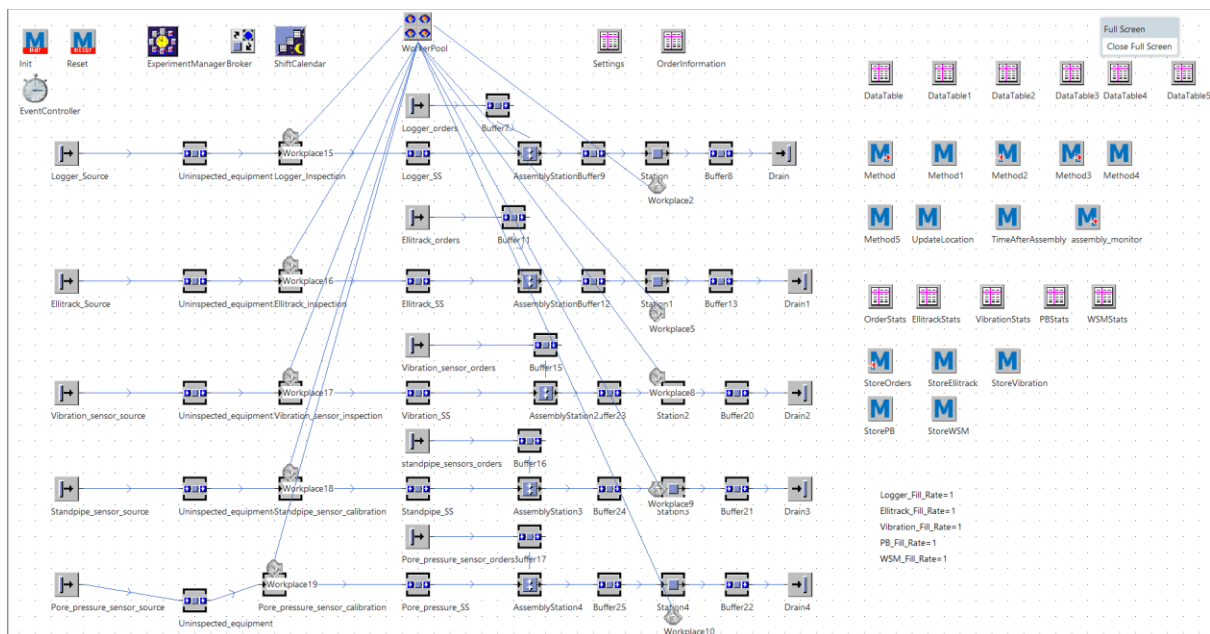


Figure 8: overview Siemens' Technomatix Plant Simulation model

In the simulation model the equipment of the different equipment groups arrive at the respective sources and are then queued in a waiting room for uninspected equipment. After which it is cleaned, calibrated, inspected and administered as soon as an employee is present. To then be placed on stock with a capacity of the base-stock level. When orders come in at the beginning of the week, they are satisfied from stock. If the demand exceeds inspected inventory, the residual demand is met



by inspecting extra equipment directly after the order. After the orders are placed and equipment is on stock, an employer pairs the equipment to the project. The sources of the respective equipment groups deliver an infinite amount of uninspected equipment since the capacity constraint of the equipment which is in circulation is not in the scope of this research. With the same reason, the capacities of the waiting rooms for uninspected equipment are infinite. The processing times of the subsequent inspections and calibrations are based on Table 2.2 (recall Section 2.4.1) and take into account the delay probabilities of Table 2.3 (recall Section 2.4.2). The arrival and departure inspections are merged, so these inspections are carried out in a single operation, one after the other. The base-stock levels are the capacity of the waiting rooms in which the inspected/calibrated equipment units are placed. This capacity is used as the experimental factor in this research. Then, the model is simulated for all different experiments of the defined in the experiment manager of Siemens' Plant Simulation. As stated above for the inspection/calibration of the equipment and the pairing of the equipment to the project a workshop employee is required. In total there are three workshop employees, who all work 40 hours per week. 2 of them spend 40% of their time on the 5 most important equipment groups and 1 of them spends only 20% of the time on these equipment groups, which is the manager, because he has other obligations. So, this simulation considers that at maximum 40 hours per week are spend on handling these 5 groups.

The KPI which is measured in the simulation model is the fill rate which can be determined by equation 7.

$$\text{Fill rate} = \frac{\text{demand which can be satisfied directly from stock}}{\text{total demand}} \quad (7)$$

In this fill rate it is measured what fraction of the equipment is filled from base stock level and can directly be paired to the projects instead of that the fraction of orders where there have to be waited till the equipment is calibrated/inspected. The demand which is directly satisfied from stock is determined by the processing time of the depicted assembly stations in Figure 8. When this processing time is zero the order is directly satisfied from stock. These information is saved in the 'stats' tables depicted on the right side of Figure 8. Then, the mean fill rate per equipment group is calculated in the respective 'Store' methods, also depicted on the right side of Figure 8. The codes of these method for one of the equipment groups is depicted in Appendix 3.

### 4.3.2 Differences between tool and simulation model

The simulation model is slightly different from the tool. In this section these differences are summed up.

- In the mathematical model, we assumed that the inventory is assessed at the end of every week and from that point on the stock is increased to base-stock level again. In this simulation model we assume that all the demand arrives at the beginning of the week and the inspected equipment gradually comes back into stock during that week. So, the review policy for the simulation could best be described as a base-stock level policy with continuous review instead of periodic review. In the simulation model, however, demand arrives at the beginning of the week. Nevertheless, using a periodic review policy for the tool have been a good method for an estimation of the base stock level, as the equipment orders in the tool were spread over the week.
- In addition in the simulation model the time for pairing the equipment to the project is considered, which is not done in the tool, because the pairing of the equipment to the project is a task that is executed after the order has been placed and thus cannot be taken

into account in the used tool, since the lead time is the period it takes to put equipment in inventory and not the time it takes to handle an order.

- In the simulation the lead time depends on the number of orders. Since an employer must be present to perform each task in the simulation model and the employees have a maximum of 40 available working hours per week in total. When there are more equipment orders the total lead time increases, because the inspection period is longer as Baek & Moon, (2015) have showed in their research. In contrast, the tool employs a standard base stock model where the inspection period and thus the lead time is independent of the demand.
- The tool uses fill rates as input values and gives base stock levels as output values. While the simulation model uses base stock levels as their input values and provide fill rates as their output values.
- Finally, different demand distributions can be applied in the simulation, which is important since Appendix 2A and 2C has shown that the normal distribution used in the tool is not the best fitting demand distribution and can be rejected with at least a 98% confidence interval (recall introduction Section 4.3)

### **4.3.3 Simulation model assumptions and simplifications**

Just as in the model from Section 4.2 assumptions are made in this simulation model.

- As described in Section 4.3.1, for simplicity of this research it is assumed enough uninspected equipment arrives to refill the base stock level.
- We assume that the demand for equipment follows exactly the theoretical distribution determined from “EasyFit”.
- Besides that, as in Section 4.2.5, we assume that 40 working hours per week are spent on the 5 groups of this research and the service times and probabilities of faulty equipment and non-reparable equipment corresponds with Table 2.2 and 2.3.

### **4.3.4 Applications of the simulation model**

In this section the applications of the simulation model is discussed. First, a simulation optimization is used to improve the quality of the findings of this research. Then, the simulation model is used to verify the results of the tool per fill rate.

For the simulation optimisation, full enumeration is used with the experiment manager in Siemens’ Plant Simulation. After the simulation optimisation have been performed, the base stock levels resulting from the tool are compared to the output of the simulation. These results are then used to validate the tool, since there are some differences between the tool and the simulation model as described in Section 4.3.2. The validation of the tool is split into two simulation performances. To distinguish the influence of the demand distribution on the reliability of the tool from the influence of the other differences between the simulation model and the tool, the simulation is first performed under normal distributed demand, because that is the demand distribution assumed in the tool. Then, the simulation is performed under the resulted demand distribution from Section 2.4.3, which is the geometric distribution with the p-values depicted in Table 2.4 (recall Section 2.4.3). After this simulations are performed, the precision of the tool can be demonstrated to confirm the validity of the model.

## 4.4 Chapter conclusion

In this chapter, the solution design is described. In the first section, the characteristics of the inventory system of the workshop are determined. In Section 4.2 the inventory policy is chosen. The base-stock replenishment policy with periodic review  $(R, S)$ , after which the value  $R$  is chosen and the formulas from Section 4.2.2 are used to create the design of a tool which can calculate the value of the base stock level for different desired fill rates. Finally, the assumptions and simplifications of the tool are summed up.

The third section describes a simulation model that could provide a more accurate estimate of the required base stock level since fewer simplifications and assumption have to be made in this model. For example, the best-fitting theoretical demand distribution can be implemented in the simulation model and lead time is dependent on demand. Whereas the formula used in the tool assumes a normal demand distribution and the lead time was independent of demand in the tool. For the simulation model a continuous review policy is used.

From the tool used, the minimum required base stock levels can be shown as a result in chapter 5. The simulation model described in this chapter is used in Chapter 5 to initially do a simulation optimisation through full enumeration and then to compare the results from the tool with the results of the simulation so that the tool can be validated and it can be described how the assumptions and simplifications made when designing the tool affect the accuracy of the tool.

.

# 5. Results

In this chapter different insights into the results of the mathematical model are given. The accuracy of the mathematical model is reflected in ‘Siemens’ Technomatix Plant Simulation’ where theoretical distributions for the equipment demand are used. The theoretical distributions for demand are based on the actual demand of 54 weeks. In Siemens’ Plant Simulation different scenarios are analyzed.

This chapter is divided into 5 parts. In Section 5.1 the results of the mathematical formula are given for different fill rates. In Section 5.2 the results of the simulation optimization using full enumeration are given. In Section 5.3 the difference between the results of the simulation model and results of is analysed. In section 5.4 the tool is validated, in which the influence of the assumptions made in the tool are examined by using a deviation rate to assess the validity of the tool. In Section 5.5 the chapter is summarized with its most important conclusions.

## 5.1 Base stock levels tool

In this section an overview of the results, the base stock levels per fill rate per equipment group, from the tool designed in Section 4.2 are given. Figure 9 depicts the required base stock level per desired fill rate according to the tool. These results are based on the input values from Table 4.1 (recall Section 4.2.2)

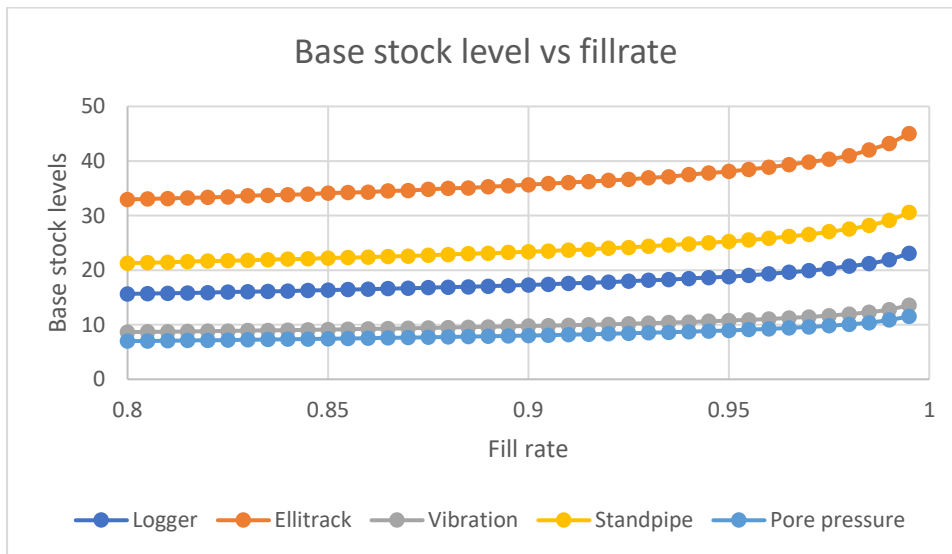


Figure 9: Base stock level per fill rate per equipment group according to the tool described in Section 4.2

As shown in Figure 9, the fill rate increases as we increase the base stock level. The increase in fill rate per unit of base stock level added becomes smaller as the fill rates increase. It is also the case that for equipment groups with a high standard deviation in demand the difference of the fill rate per unit added to the base stock level is smaller than for equipment groups with a lower standard deviation in demand. For choosing the base stock level a trade-off should be made between a higher fill rate and a higher probability that equipment inspections/calibrations are outdated.

To reach a fill rate of 0.99, the required base stock levels calculated with the tool from Chapter 4 are given in the Table 5.2.

Table 5.2: required base stock level 0.99 fill rate

| Equipmentgroup                          | Base stock level |
|---|------------------|
| Loggers                                 | 22               |
| Ellitracks                              | 44               |
| Vibration sensors                       | 13               |
| Standpipe sensors (ellitracks excluded) | 30               |
| Pore pressure sensors                   | 11               |

## 5.2 Simulation optimisation

In this Section a simulation optimisation is used to improve the quality of the findings regarding the base stock levels. The reason for the quality increase is that less assumptions have been made in the simulation and the simulation model is designed as an production-inventory system. While the tool is build as an standard base stock inventory system. Besides that in the simulation model the time for pairing equipment to projects and the geometric demand distributions can be taken into account as discussed in Section 4.3.2. The output of the simulation model is under geometric distributed demand is depicted in Figure 10.

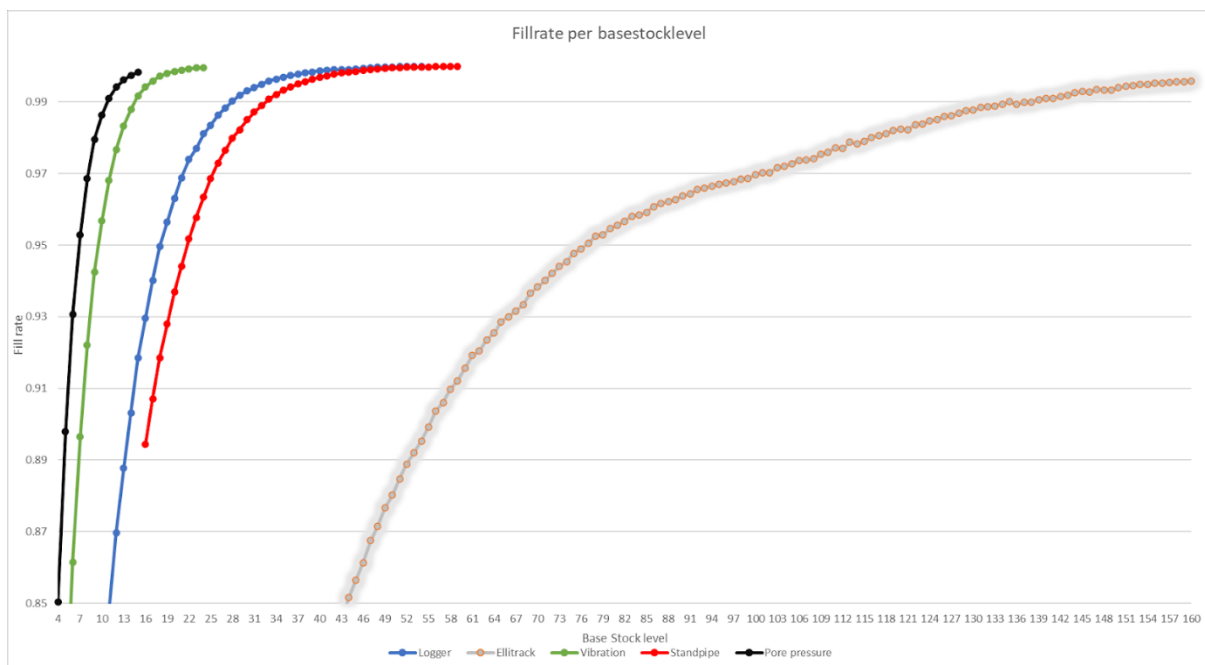


Figure 10: fill rate per base stock level, derived from simulation model with geometric distributed demand

Figure 10 depicts the average fill rates per base stock level over 20 observations with a run length of 10 years per observation. In this figure it is analysed how the fill rate will increase as we

incrementally increase the base stock level. Assuming these averages, Table 5.4 depicts indications of the base stock levels required to achieve a fill rate of 0.99

Table 5.4: Estimation of the required base stock level for a fill rate of 0.99 resulting from full enumeration in the simulation model

| Equipment group                         | Base stock level |
|---|------------------|
| Loggers                                 | 29               |
| Ellitracks                              | 140              |
| Vibration sensors                       | 16               |
| Standpipe sensors (ellitracks excluded) | 34               |
| Pore pressure sensors                   | 12               |

When the base stock levels per fill rate resulting from the formula are compared to the simulation results. There are some differences, for example the base stock level resulting from this simulation is 140 and the tool estimated a required base stock level of 44 for the same fill rate. The differences between the results of the simulation model and the results of the tool are discussed in Section 5.3.

### 5.3 Differences between tool and simulation results

The mathematical model used in Section 4.2 might be usable to get an indication of the required base stock level for a desired fill rate in a short period of time. However, as shown in the previous sections of this chapter there is a difference between the results of the simulation model and the results of the tool. Because of that this section is used to explain these differences in the results and analyse the influence these assumptions had on the results of the tool.

Since we want to be able to see how each of these changes between the simulation and the tool affect the accuracy of the tool, we analyzed the deviation in required base stock levels using 2 simulation models. The first simulation has normally distributed demand, so that we can look at the effect of:

- the simplification of independency between lead time and demand
- the difference in review
- the lack of time reserved for pairing equipment to the project in the tool

Before we implement the best fitting theoretical demand distribution in the simulation model, which is used in the second simulation. Figure 11 depicts the results for the required base stock levels for the tool, the simulation with normal distributed demand and the simulation with geometric distributed demand.

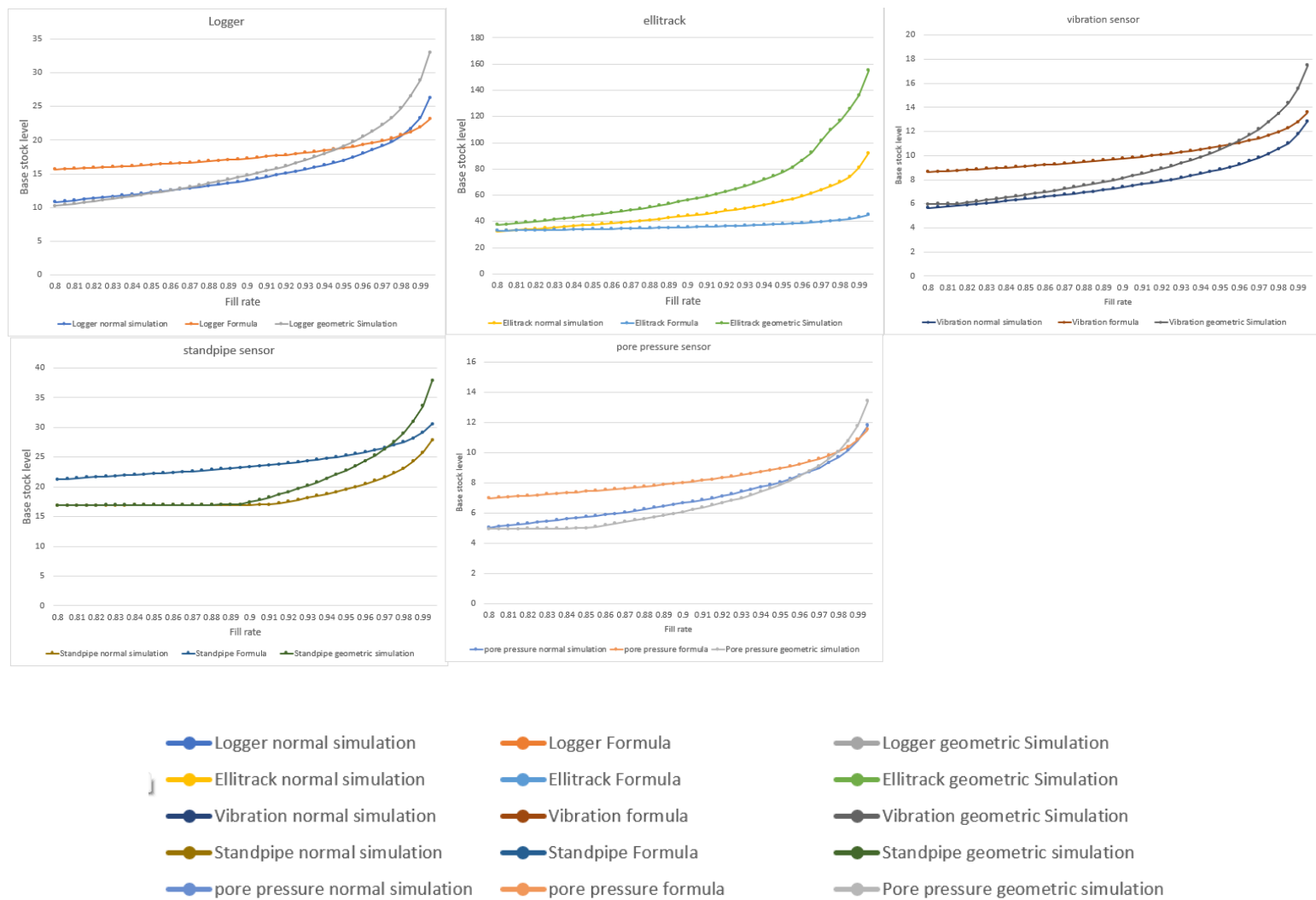


Figure 11: deviation between the results of the tool, the simulation with normal distributed demand and the simulation with geometric distributed demand

Figure 11 shows some difference between the formula used in the tool and the results from the simulations. We can see that the tool always slightly overestimates the required base stock level compared to the simulations, except for ellitracks and for high fill rates. In those cases the tool actually underestimates the required base stock level in comparison to the simulation results. The overestimation of the base stock level can be justified by the difference in control policy. In the tool, in addition to the calculated safety stock, there is always an additional stock of the expected demand during the review period plus the replenishment lead time. This additional stock is not considered in the simulation model.

The fact that in the case of the ellitracks, the simulations show a higher required base stock level than calculated by the tool can be explained by the fact that the tool does not take into account an increased lead time in case there are more orders and in the simulation model this increased lead time is considered. Since the ellitracks have the highest expected demand of all equipment groups and therefore the lead time for refilling the base stock level will be the largest. This will not always be possible within a week, since there are only 40 hours available for processing the 5 main groups, it is logical that the simulations here expect a higher required base stock level than expected in the formula. Similarly, when fill rates are higher, the simulations also expect the required base stock level to rise faster than calculated by the formula. After extremely high demand, the base stock level

cannot recover within a week due to the workshop capacity, just as in the case of high demand at ellitracks.

Furthermore, it became evident that for higher fill rates, the deviation between the simulation model and the tool is larger for the simulation with geometric distributed demand than for the simulation with normally distributed demand. This can be justified by the fact that a geometric distribution exhibits greater values at its extremities compared to a normal distribution.

To get a better idea of the deviation of the required base stock level calculated by the tool from the results obtained from the simulation with the geometrically distributed demand, the deviation rate for base stock levels has been calculated in Equation 8 and this percentage deviation is shown per fill rate in Figure 12.

$$\text{Base stock deviation rate (\%)} = \frac{|S_T - S_{SM}|}{S_{SM}} * 100 \quad [8]$$

Where:

$S_T$  = the base stock level calculated in the tool

$S_{SM}$  = the base stock level resulting from the simulation model

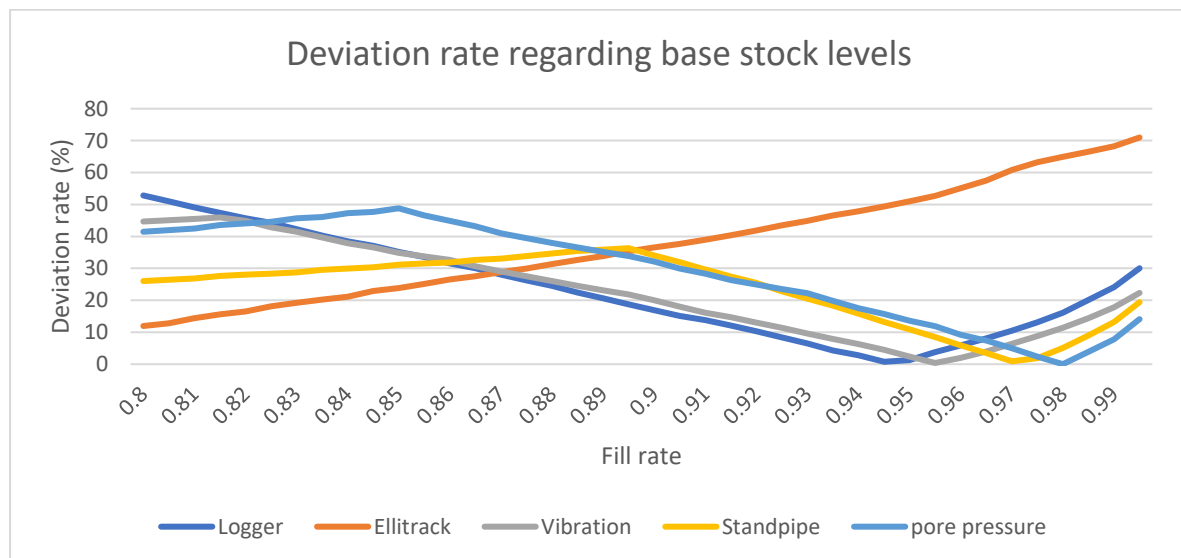


Figure 12: deviation rate of the base stock level in the tool from the base stock level in the simulation per fill rate

## 5.4 Tool validation

The tool described in Section 4.2 might be usable for Fugro to get an indication of the required base stock level for a desired fill rate in a short period of time, without having to run a simulation which is more complex. However, since a number of assumptions had to be made when creating the tool as described in Section 4.2.4, we would like to test whether this tool gives the right indications by comparing the fill rates resulting from the tool to the fill rates resulting from the simulation model designed in Section 4.3. Since Section 5.3 shows us that the deviation between the results of the tool and the results of the simulation depends on the fill rate to which the results are applied. In this section we are also considering different fill rates to assess the validity of the tool.

Figure 13 depicts the compared fill rates, the fill rates calculated in the tool and the fill rates resulting from the simulation model with the actual demand distribution. In this figure a reference line have been placed. This line is used to visualise the perfect fill rate estimation. When the fill rate of an



equipment group is on the reference line, the tool calculates exactly the same base stock level for that equipment group as resulted from the simulation model. When the simulation results show a lower fill rate than calculated in the tool for the same base stock level, the point is depicted on the right side of the reference line. When the calculated fill rate from the tool is lower than the fill rate resulting from the simulation, the point is depicted on the left side of the reference line.

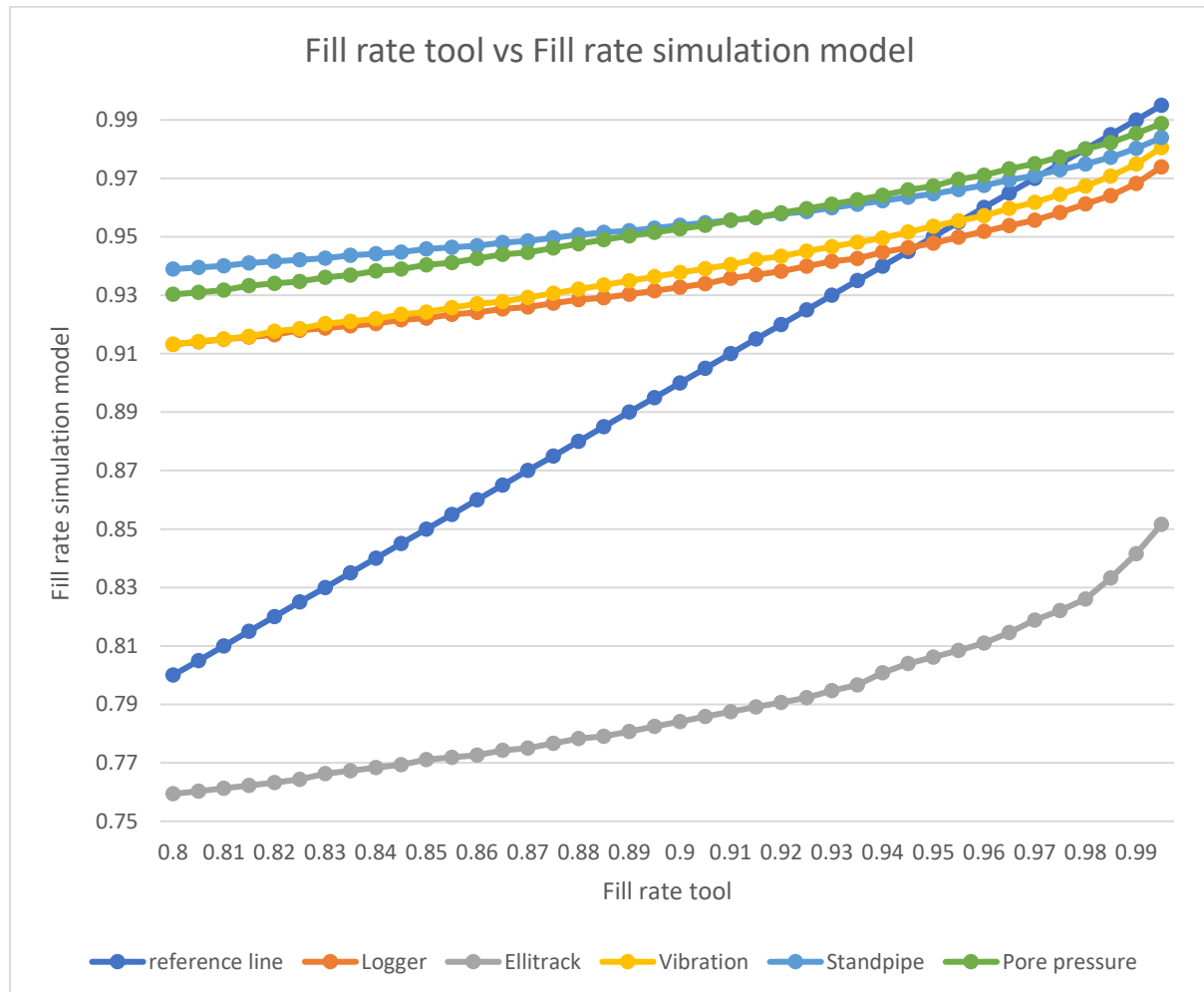


Figure 13: Fill rate comparison between tool and simulation model

In Figure 13 we indeed see as can also be derived from Figure 11 (recall Section 5.3) that for the ellitracks the calculated fill rates from the tool are lower than resulted from the simulation and for the other equipment groups of this study the tool calculates lower fill rates unless the desired fill rate calculated in the tool is high. In that case, the tool calculation results are depicted at the right side of the blue line, which means that the calculation of the tool expect the fill rate to be higher than it in reality is.

The fill rates between which each of the equipment groups, except for the ellitracks, crosses the reference line are depicted in Table 5.3.

Table 5.3 Crossing points of the reference line in Figure 13

| Equipment group       | Fill rate                                 |
|-----------------------|---|
| Loggers               | 0.945-0.95                                |
| Vibration sensors     | 0.955-0.96                                |
| Stand pipe sensors    | 0.97-0.975                                |
| Pore pressure sensors | Reference line is crossed at exactly 0.98 |

To validate this tool we want to know the deviation rate between the fill rate of the tool and the fill rate of the simulation model. This deviation rate depicts the percentage deviation between the fill rates resulting from the simulation and the fill rates of the tool relative to the fill rate calculated in the tool. In this study we call this deviation rate, the ‘filling deviation rate’, which is calculated in Equation 9.

$$\text{Filling deviation rate (\%)} = \frac{|fr_T - fr_{SM}|}{fr_{SM}} * 100 \quad [9]$$

Where:

$fr_T$  = the fill rate calculated in the tool

$fr_{SM}$  = the fill rate resulting from the simulation model

In Figure 14 the filling deviation rates for the fill rates between 0.8 and 0.995 have been depicted.

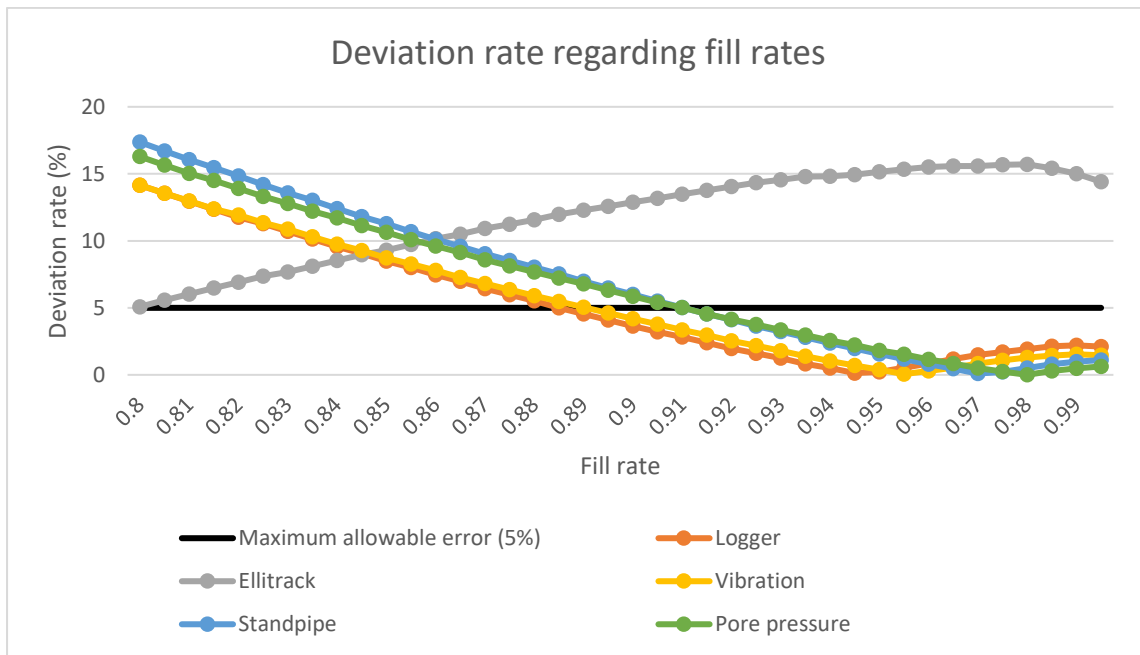


Figure 14: Filling deviation rate between simulation model and tool relative to the tool

In Figure 14 it is shown that the tool is not reliable for ellitracks, because for all the depicted fill rates, the ‘filling deviation rate’ exceeds the maximum allowable error of 5%. In case of the other equipment groups. The validity of the tool depends on the fill rate.

Table 5.4 depicts for which fill rates the tool we created in this study can be validated.

Table 5.4: fill rates for which the tool can be validated using a maximum allowable error of 5%

| Equipment groups      | Fill rate between which the tool can be validated using the 5% maximum allowable error. |
|-----------------------|---|
| Loggers               | >0.885  |
| Ellitracks            | Not validated   |
| Vibration sensors     | >0.895  |
| Standpipe sensors     | >0.915  |
| Pore pressure sensors | >0.915  |

Since the goal of this research is to achieve a fill rate of 0.99, Table 5.5 depicts the ‘filling deviation rate’ for the equipment groups for a 0.99 fill rate.

Table 5.5 ‘filling deviation rate’ in percentages per equipment group for a 0.99 fill rate based on results from the tool

| Equipment groups      | ‘filling deviation rate’ in (%) |
|-----------------------|---------------------------------|
| Loggers               | 2.2%                            |
| Ellitracks            | 15%                             |
| Vibration sensors     | 1.5%                            |
| Standpipe sensors     | 1%                              |
| Pore pressure sensors | 0.5%                            |

## 5.4 Conclusion

To conclude, in Section 5.1 the base stock levels calculated in the tool for a fill rate of 0.99 are depicted in Table 5.1 and subsequently the results of the simulation optimization for this fill rate are depicted in Table 5.2. When the tool from Chapter 4 is compared to the simulation model in Section 5.3 it turned out that the tool overestimated the required base stock level for the lower fill rates and underestimates the required base stock levels for the higher fill rates, except for ellitracks where the required base stock levels calculated in the tool are continuously lower than the required base stock levels resulting from the simulation for the fill rates involved in the tool. In Section 5.4 the validity of the tool is assessed by using a maximum allowable deviation rate for fill rates of 5%. It became evident that the tool is validated for the fill rates above 0.915 for all equipment groups involved in this study, except for ellitracks. The tool could not be validated for the use of ellitracks in any of the fill rates tested. The results of this chapter are used for the findings discussed in the management summary and the conclusion of this thesis.

# 6. Conclusion

Through this thesis a mathematical model was made to improve the estimation on fill rates per base stock level. Later in this research the accuracy of this model was tested by means of a simulation model. The input used in the mathematical model and the simulation was derived from Chapter 2, the current situation. The theory from the Literature review in Chapter 3 supported the mathematical model. Using the results of the model and the simulation, recommendations are made, taking into account the limitations of this study.

In this chapter the main research question is answered:

*How can the availability of Land-Monitoring equipment in Fugro's workshop be increased by using a base-stock level?*

In Section 6.1 the used method is summarized and the conclusion of this thesis is given. In Section 6.2 the recommendations for the company are made. Section 6.3 shows the limitations of the current study and discusses possible fields for further investigation.

## 6.1 Conclusion

In Section 1.3 the problem was analysed by a problem cluster. Then, in Section 1.5 the sub questions were given which were used to find the answer to the main research question. The input values for the model were addressed in the current situation. In Chapter 3 about the literature review, some background information of the inventory system was given. Chapter 4 provided us with a mathematical model which can be used to calculate the base stock level per fill rate under some assumptions and simplifications. Later in that chapter a simulation model was made which estimates the fill rate for experiments with base stock levels under different assumptions and simplifications.

In the results of the simulation model, we found that if we assume that the equipment returned from projects is large enough, the fill rates could increase to 0.99 without increasing working hours, by bringing forward the inspection period from after the equipment order to before the equipment order. A reserve stock of inspected equipment should be introduced to reach a 99% fill rate. This reserve stock would be: 29 loggers, 140 ellitracks, 16 vibration sensors 34 standpipe sensors (excluded ellitracks) and 12 pore pressure sensors.

Lastly, since a simulation model is complex, the tool can be used by Fugro to estimate the required base stock levels for different fill rates. But before this can be used, the fill rates of the results of the tool were compared to the resulting fill rate of the simulation model to validate the tool. For the validation a maximum allowable deviation rate of 5% is respected. It was found that the tool could be validated for all equipment groups with a fill rate higher than 0.915, except for the ellitracks. For all the measured fill rates for the ellitracks, the deviation rate in fill rate of the simulation model relative to the fill rate of the tool was above 5%. For example, in the case of a fill rate of 0.99, the measured deviation rate was 15%.

## 6.2 Recommendations

Because the current results are based on 54 weeks of data, the service times are assumed to be deterministic and we assume that enough uninspected equipment arrives in the workshop to refill the base stock levels. It can be questioned whether the results are reliable. Since it became evident that a lot of equipment was still stored on projects, although it was not being used on these projects anymore, which decreased the level of uninspected stock in the workshop and could decrease the ability to perform the inspect-to-stock policy. That can consequently lead to a reduction in the availability of equipment for new projects.

Because of this insights the following recommendations are made:

- Use the results for the base stock level of inspected equipment as an indication to approximate your desired fill rate until the base stock level is recalculated with more data.
- Use the tool to recalculate the required base stock level when more data is available, because there are now only 54 weeks of data on equipment orders available. More data will increase the reliability of the results.
- Create an incentive for project managers to send the equipment back immediately when it is no longer being used on the project by charging equipment rental depending on the period they take it from the workshop instead of the period they use it on the project. This increases the probability that there will be a sufficient quantity of uninspected stock present in the workshop to supplement the inspected stock.

## 6.3 Limitations and further research

This study has some limitations, so there are some improvements for further research. In this section the limitations of the study and the possibilities for further research are investigated.

The software programme that keeps track of the stock was revamped a year ago, which has meant that only 1 year of stock data is available. Because of this, it is impossible to get a clear picture of how much uninspected stock is returned from the projects per week. This is because rental periods are regularly longer than one year. A lot of equipment that was rented out more than a year ago is still being returned and is therefore not included in the system. Besides that, measuring the calibration time and finding the right distribution for it could lead to an improvement of the results. In addition it would help if the possibilities of faulty equipment were known.

Furthermore, the trend of the equipment demand has not been taken into account in this study. It is assumed that there is no trend or seasonal demand. For further investigation it would improve the quality of the results if the trends of equipment demand were taken into account.

In addition, in order to keep enough equipment in circulation, it might be interesting for further research to study what the ideal reorder point for buying new equipment from the supplier would be, in order to keep the total stock at the desired level, considering the delivery times and the average number of equipment units that are lost or sold on the project.

For further research it may be interesting to model the inventory system as a queuing model, to implement the dependency between demand and lead time in the mathematical model already. However, then the tool that would be more complex. So, companies looking for a simplified way to optimise their production inventory system can use my research to similarly design a tool that estimates the base stock levels required to achieve specific fill rates.

Finally, one of the limitations of this study is that no research was done on prioritising the inspection of different equipment groups according to the inspected stock present in the workshop at the time. In order to do this in a follow-up study, the waiting time in the simulation could be measured. Based on this, costs could then be linked to these waiting times. Finally, the service time per piece of equipment can be used to see how working time can best be allocated to save as much waiting time costs as possible.

# References

- Altiok, T., & Shiue, G. A. (2000). Pull-type manufacturing systems with multiple product types. *IIE Transactions*, 32(2), 115-124. <https://link.springer.com/article/10.1023/A:1007654113063>
- Baek, J. W., & Moon, S. K. (2015). A production–inventory system with a Markovian service queue and lost sales. *Journal of the Korean Statistical Society*, 45(1), 14–24. <https://doi.org/10.1016/j.jkss.2015.05.002>
- Boute, R. N., Disney, S. M., Lambrecht, M. R., & Van Houdt, B. (2007). An integrated production and inventory model to dampen upstream demand variability in the supply chain. *European Journal Of Operational Research*, 178(1), 121–142. <https://doi.org/10.1016/j.ejor.2006.01.023>
- Cassandras, C. G., & Panayiotou, C. (2004). *Inventory Control for Supply Chains with Service Level Constraints: A Synergy between Large Deviations and Perturbation Analysis*. Center for Information and Systems Engineering, Boston University, en Department of Electrical and Computer Engineering, University of Cyprus. <https://link.springer.com/article/10.1023/B:ANOR.0000012283.36012.e8>
- Fugro. (2023). Our history and timeline | Fugro. <https://www.fugro.com/about-us/history>
- Gregory, G., S. A. Klesniks, and J. A. Piper. 1983. Batch production decisions and the small firm. *Journal of the Operational Research Society* 34(6), 469–477. [Batch Production Decisions and the Small Firm on JSTOR](#)
- Heerkens, H., Van Winden, A., Tjoitink, J.W. (2017). Solving managerial problems systematically. *Noordhof Uitgevers*. <https://ut.on.worldcat.org/search/detail/979417116?lang=en&queryString=Solving%20managerial%20problems>
- Karaman, A., & Altiok, T. (2007). A multi-echelon supply chain model. *European Journal of Operational Research*, 193(1), 222-237. <https://doi.org/10.1016/j.ejor.2007.10.018>
- Liu, C. (2022). Powerful omnibus tests of goodness-of-fit. <https://doi.org/10.48550/arxiv.2209.08050>
- Maulaya, A., Ridwan, A., & Santoso, B. (2019). Spare Part Inventory Policy Planning based on FRMIC (Fuzzy-Rule-based approach for Multi-Criteria Inventory Classification) using Base-Stock Policy Method (S-1, S). Atlantis Press. <https://doi.org/10.2991/icoemis-19.2019.36>
- Pejman, S., Seifbarghy, M., & Pishva, D. (2024). A location-inventory-pricing model for a three-level supply chain distribution network. *RAIRO - Operations Research*, 58(3), 2075–2106. <https://doi.org/10.1051/ro/2024057>
- Permatasari, P. M., Ridwan, A. Y., & Santosa, B. (2017). Inventory policy determination for raw materials in ILY Pharmaceutical using periodic review (R, s, S) and periodic review (R, S) method to minimize total inventory cost. *MATEC Web Of Conferences*, 135, 00056. <https://doi.org/10.1051/mateconf/201713500056>
- Silver, E. A., Pyke, D. F., & Thomas, D. J. (2016). *Inventory and Production Management in Supply Chains*. CRC Press. <https://doi.org/10.1201/9781315374406>
- Tayfur, Altiok, T., & Melamed, B. (1989). (R, r) Production/inventory System. *Operations Research*, 37(2). <https://pubsonline.informs.org/doi/abs/10.1287/opre.37.2.266?journalCode=opre>

Zhang, Z., & Unnikrishnan, A. (2016). A coordinated location-inventory problem in closed-loop supply chain. *Transportation Research Part B Methodological*, 89, 127–148.  
<https://doi.org/10.1016/j.trb.2016.04.006>

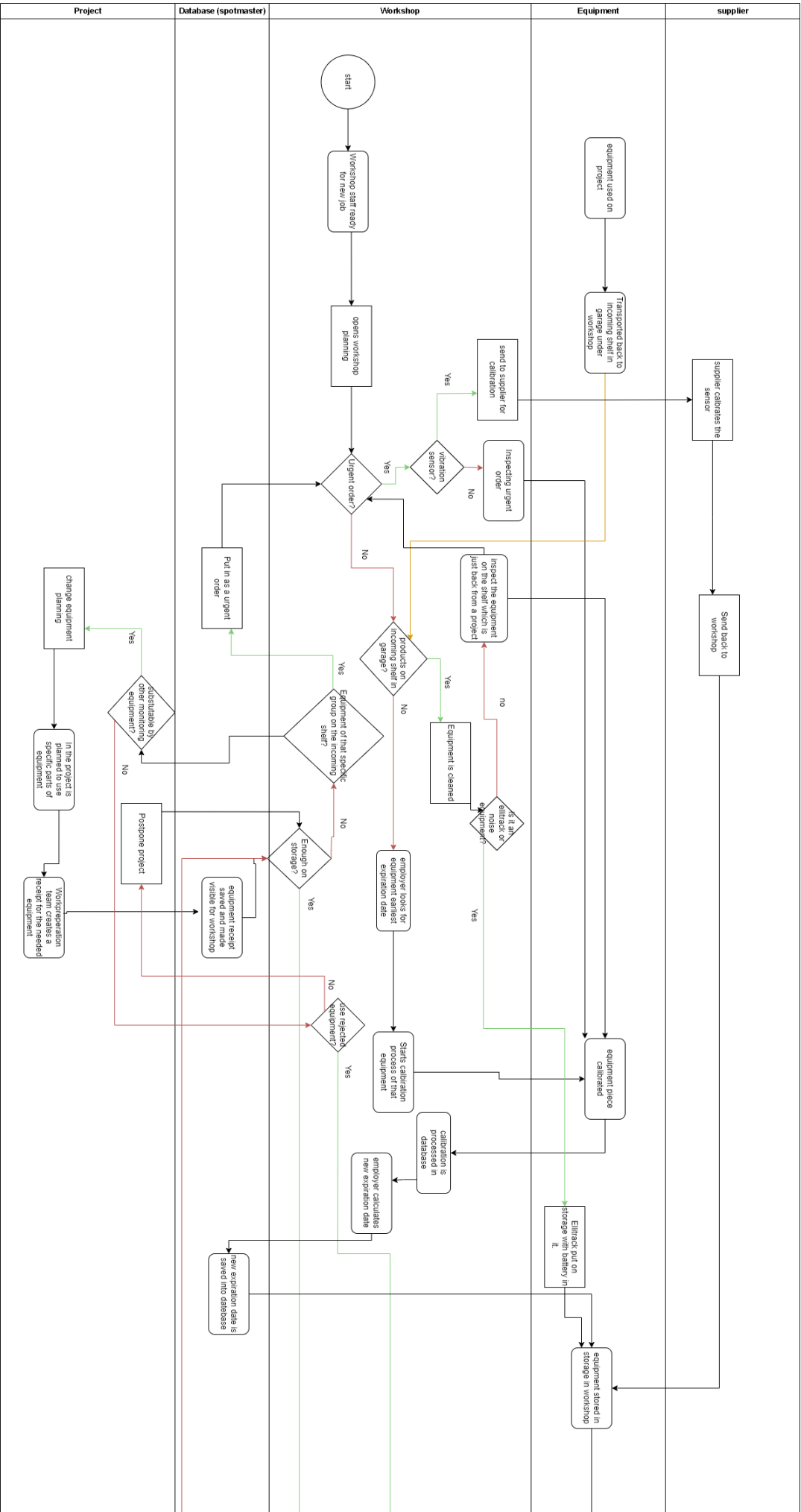
Zoysa, D. C. D. Z. D. L. and Rupasinghe, T. (2017). An analytical modelling approach to optimize safety stock of winery supply chains (wsc). World Conference on Supply Chain Management, 30-38.  
<https://doi.org/10.17501/wcosm.2017.2103>

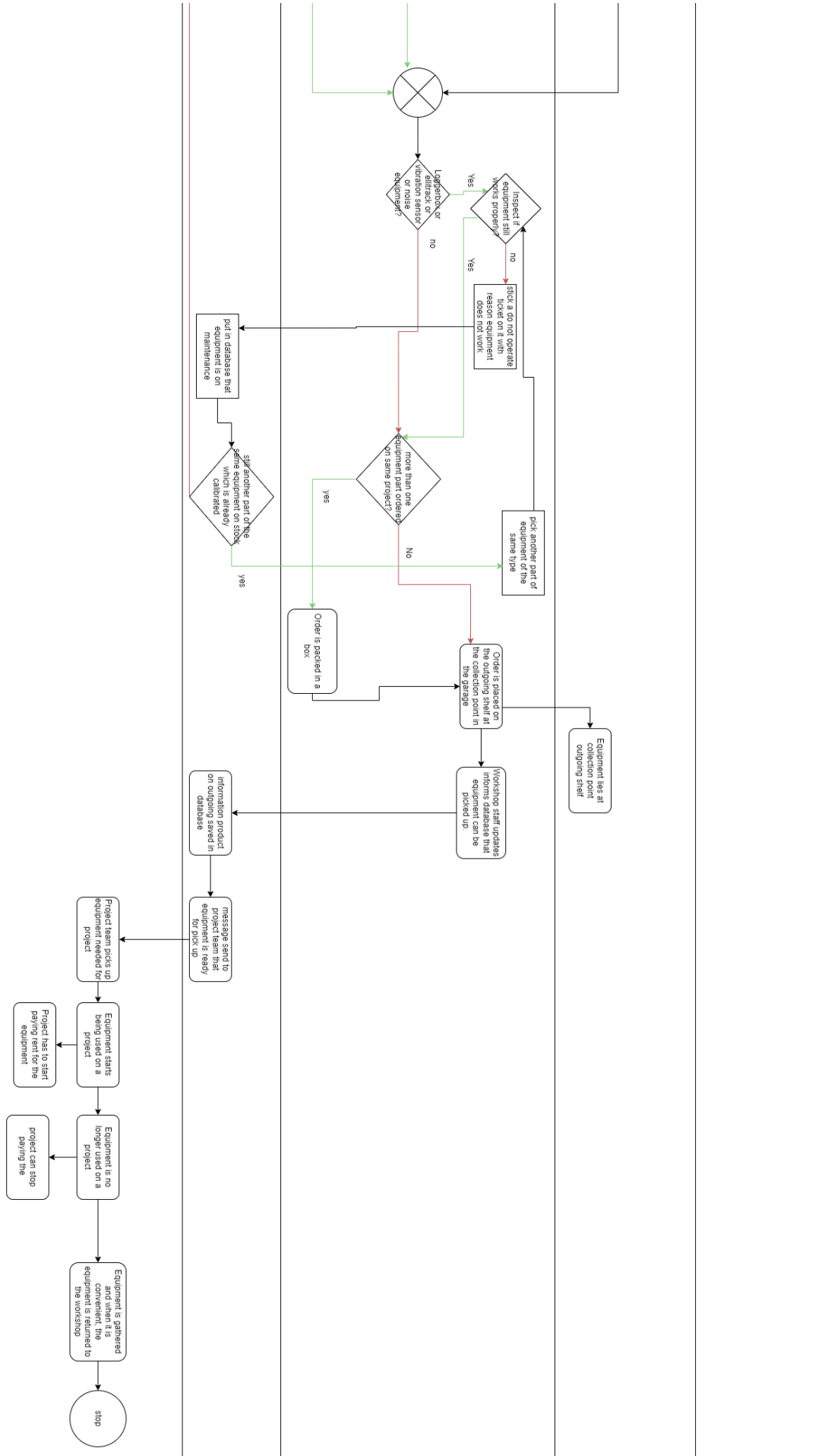


# Appendix

## Appendix 1:

This appendix gives an extensive overview of the current process in Fugro's Land-Monitoring workshop. In the current process, when a workshop employee is idle, then the workshop employee checks whether there are any orders for equipment that have not yet been inspected. If this is not the case, an employee will clean, inspect or calibrate equipment that has recently returned from a project. When this is also done, time is spent on calibrating large batches of pore pressure sensors or standpipe sensors (ellitracks excluded) that have not been calibrated for a long time. The calibrations and inspections are then administered in the database and the equipment is shipped to the project. If there is an order, but there is no uninspected equipment of that group in stock and no substitutable equipment available, the workshop employer notifies the project and the project is postponed or continues using uninspected unreliable equipment. An overview of the process is depicted in a figure on the Page 50 and 51.





## Appendix 2:

This appendix depicts the results of the distribution fitting in the software Easyfit. In appendix 2A, the best fitting theoretical distributed demand is depicted by using the Anderson Darling test. In Appendix 2B, the confidence interval of the best fitting theoretical distributed demand is depicted. Appendix 2C depicts the confidence interval of the normal distribution.

### Appendix 2A

Loggers:

| #  | Distribution     | Kolmogorov Smirnov |      | Anderson Darling |      | Chi-Squared |      |
|----|------------------|--------------------|------|------------------|------|-------------|------|
|    |                  | Statistic          | Rank | Statistic        | Rank | Statistic   | Rank |
| 10 | Normal           | 0,25044            | 1    | 4,9854           | 1    | 7,5372      | 1    |
| 5  | Exponential (2P) | 0,38889            | 3    | 258,88           | 13   | 21,995      | 2    |
| 4  | Exponential      | 0,38889            | 5    | 7,0489           | 3    | 21,995      | 3    |
| 6  | Gamma            | 0,38889            | 6    | 5,3373           | 2    | 24,535      | 4    |
| 12 | Weibull          | 0,38889            | 8    | 7,6687           | 4    | 26,903      | 5    |
| 7  | Gamma            | 0,38889            | 7    | 30,729           | 11   | 44,668      | 6    |
| 13 | Weibull          | 0,38889            | 9    | 28,251           | 8    | 44,754      | 7    |
| 9  | Lognormal        | 0,40588            | 11   | 29,857           | 10   | 44,868      | 8    |
| 8  | Lognormal        | 0,40588            | 10   | 29,856           | 9    | 44,868      | 9    |
| 3  | Chi-Squared      | 0,4197             | 12   | 26,879           | 7    | 46,815      | 10   |
| 2  | Chi-Squared      | 0,38889            | 4    | 13,554           | 5    | 51,333      | 11   |
| 1  | Beta             | 0,44894            | 13   | 109,3            | 12   | N/A         |      |
| 11 | Uniform          | 0,30569            | 2    | 15,897           | 6    | N/A         |      |
| 14 | Erlang           | No fit             |      |                  |      |             |      |
| 15 | Erlang (3P)      | No fit             |      |                  |      |             |      |
| 16 | Triangular       | No fit             |      |                  |      |             |      |

| # | Distribution   | Kolmogorov Smirnov    |      | Anderson Darling |      |
|---|----------------|-----------------------|------|------------------|------|
|   |                | Statistic             | Rank | Statistic        | Rank |
| 2 | Geometric      | 0,22324               | 1    | 2,4436           | 1    |
| 1 | D. Uniform     | 0,32                  | 2    | 15,281           | 2    |
| 3 | Poisson        | 0,38673               | 3    | 40,003           | 3    |
| 4 | Bernoulli      | No fit (data max > 1) |      |                  |      |
| 5 | Binomial       | No fit                |      |                  |      |
| 6 | Hypergeometric | No fit                |      |                  |      |
| 7 | Logarithmic    | No fit (data min < 1) |      |                  |      |
| 8 | Neg. Binomial  | No fit                |      |                  |      |

Best fit = geometric distribution

Ellitracks:

Goodness of Fit - Summary

| #  | Distribution     | Kolmogorov Smirnov |      | Anderson Darling |      | Chi-Squared |      |
|----|------------------|--------------------|------|------------------|------|-------------|------|
|    |                  | Statistic          | Rank | Statistic        | Rank | Statistic   | Rank |
| 6  | Gamma            | 0,11111            | 3    | 8,4692           | 3    | 4,9183      | 1    |
| 5  | Exponential (2P) | 0,11111            | 1    | 20,957           | 11   | 5,4518      | 2    |
| 4  | Exponential      | 0,11111            | 2    | 8,2713           | 2    | 5,4518      | 3    |
| 10 | Normal           | 0,18294            | 8    | 3,3527           | 1    | 5,4705      | 4    |
| 7  | Gamma            | 0,13376            | 5    | 10,238           | 5    | 6,9887      | 5    |
| 14 | Weibull          | 0,11846            | 4    | 9,8              | 4    | 6,9908      | 6    |
| 9  | Lognormal        | 0,15935            | 7    | 10,658           | 7    | 8,6169      | 7    |
| 8  | Lognormal        | 0,15934            | 6    | 10,658           | 6    | 8,617       | 8    |
| 13 | Weibull          | 0,20219            | 9    | 11,995           | 8    | 22,613      | 9    |
| 3  | Chi-Squared      | 0,24207            | 11   | 21,265           | 12   | 25,5        | 10   |
| 11 | Triangular       | 0,39337            | 13   | 37,675           | 14   | 37,385      | 11   |
| 2  | Chi-Squared      | 0,32006            | 12   | 31,116           | 13   | 39,0        | 12   |
| 1  | Beta             | 0,43818            | 14   | 13,164           | 9    | 71,561      | 13   |
| 12 | Uniform          | 0,23823            | 10   | 18,257           | 10   | N/A         |      |
| 15 | Erlang           | No fit             |      |                  |      |             |      |
| 16 | Erlang (3P)      | No fit             |      |                  |      |             |      |

| # | Distribution   | Kolmogorov Smirnov    |      | Anderson Darling |      |
|---|----------------|-----------------------|------|------------------|------|
|   |                | Statistic             | Rank | Statistic        | Rank |
| 2 | Geometric      | 0,08647               | 1    | 0,61075          | 1    |
| 1 | D. Uniform     | 0,25581               | 2    | 17,998           | 2    |
| 3 | Poisson        | 0,37382               | 3    | 45,193           | 3    |
| 4 | Bernoulli      | No fit (data max > 1) |      |                  |      |
| 5 | Binomial       | No fit                |      |                  |      |
| 6 | Hypergeometric | No fit                |      |                  |      |
| 7 | Logarithmic    | No fit (data min < 1) |      |                  |      |
| 8 | Neg. Binomial  | No fit                |      |                  |      |

Best fit = geometric distribution

Vibration sensors:

| #  | Distribution     | Kolmogorov Smirnov |      | Anderson Darling |      | Chi-Squared |      |
|----|------------------|--------------------|------|------------------|------|-------------|------|
|    |                  | Statistic          | Rank | Statistic        | Rank | Statistic   | Rank |
| 10 | Normal           | 0,25044            | 1    | 4,9854           | 1    | 7,5372      | 1    |
| 5  | Exponential (2P) | 0,38889            | 3    | 258,88           | 13   | 21,995      | 2    |
| 4  | Exponential      | 0,38889            | 5    | 7,0489           | 3    | 21,995      | 3    |
| 6  | Gamma            | 0,38889            | 6    | 5,3373           | 2    | 24,535      | 4    |
| 12 | Weibull          | 0,38889            | 8    | 7,6687           | 4    | 26,903      | 5    |
| 7  | Gamma            | 0,38889            | 7    | 30,729           | 11   | 44,668      | 6    |
| 13 | Weibull          | 0,38889            | 9    | 28,251           | 8    | 44,754      | 7    |
| 9  | Lognormal        | 0,40588            | 11   | 29,857           | 10   | 44,868      | 8    |
| 8  | Lognormal        | 0,40588            | 10   | 29,856           | 9    | 44,868      | 9    |
| 3  | Chi-Squared      | 0,4197             | 12   | 26,879           | 7    | 46,815      | 10   |
| 2  | Chi-Squared      | 0,38889            | 4    | 13,554           | 5    | 51,333      | 11   |
| 1  | Beta             | 0,44894            | 13   | 109,3            | 12   | N/A         |      |
| 11 | Uniform          | 0,30569            | 2    | 15,897           | 6    | N/A         |      |
| 14 | Erlang           | No fit             |      |                  |      |             |      |
| 15 | Erlang (3P)      | No fit             |      |                  |      |             |      |
| 16 | Triangular       | No fit             |      |                  |      |             |      |

| # | Distribution   | Kolmogorov Smirnov    |      | Anderson Darling |      |
|---|----------------|-----------------------|------|------------------|------|
|   |                | Statistic             | Rank | Statistic        | Rank |
| 2 | Geometric      | 0,22324               | 1    | 2,4436           | 1    |
| 1 | D. Uniform     | 0,32                  | 2    | 15,281           | 2    |
| 3 | Poisson        | 0,38673               | 3    | 40,003           | 3    |
| 4 | Bernoulli      | No fit (data max > 1) |      |                  |      |
| 5 | Binomial       | No fit                |      |                  |      |
| 6 | Hypergeometric | No fit                |      |                  |      |
| 7 | Logarithmic    | No fit (data min < 1) |      |                  |      |
| 8 | Neg. Binomial  | No fit                |      |                  |      |

Best fit = geometric distribution

Standpipe sensor (ellitrack excluded):

| #  | Distribution     | Kolmogorov Smirnov |      | Anderson Darling |      | Chi-Squared |      |
|----|------------------|--------------------|------|------------------|------|-------------|------|
|    |                  | Statistic          | Rank | Statistic        | Rank | Statistic   | Rank |
| 10 | Normal           | 0,25044            | 1    | 4,9854           | 1    | 7,5372      | 1    |
| 5  | Exponential (2P) | 0,38889            | 3    | 258,88           | 13   | 21,995      | 2    |
| 4  | Exponential      | 0,38889            | 5    | 7,0489           | 3    | 21,995      | 3    |
| 6  | Gamma            | 0,38889            | 6    | 5,3373           | 2    | 24,535      | 4    |
| 12 | Weibull          | 0,38889            | 8    | 7,6687           | 4    | 26,903      | 5    |
| 7  | Gamma            | 0,38889            | 7    | 30,729           | 11   | 44,668      | 6    |
| 13 | Weibull          | 0,38889            | 9    | 28,251           | 8    | 44,754      | 7    |
| 9  | Lognormal        | 0,40588            | 11   | 29,857           | 10   | 44,868      | 8    |
| 8  | Lognormal        | 0,40588            | 10   | 29,856           | 9    | 44,868      | 9    |
| 3  | Chi-Squared      | 0,4197             | 12   | 26,879           | 7    | 46,815      | 10   |
| 2  | Chi-Squared      | 0,38889            | 4    | 13,554           | 5    | 51,333      | 11   |
| 1  | Beta             | 0,44894            | 13   | 109,3            | 12   | N/A         |      |
| 11 | Uniform          | 0,30569            | 2    | 15,897           | 6    | N/A         |      |
| 14 | Erlang           | No fit             |      |                  |      |             |      |
| 15 | Erlang (3P)      | No fit             |      |                  |      |             |      |
| 16 | Triangular       | No fit             |      |                  |      |             |      |

| # | Distribution   | Kolmogorov Smirnov    |      | Anderson Darling |      |
|---|----------------|-----------------------|------|------------------|------|
|   |                | Statistic             | Rank | Statistic        | Rank |
| 2 | Geometric      | 0,18716               | 1    | 2,8504           | 1    |
| 1 | D. Uniform     | 0,30303               | 2    | 28,033           | 2    |
| 3 | Poisson        | 0,46641               | 3    | 68,488           | 3    |
| 4 | Bernoulli      | No fit (data max > 1) |      |                  |      |
| 5 | Binomial       | No fit                |      |                  |      |
| 6 | Hypergeometric | No fit                |      |                  |      |
| 7 | Logarithmic    | No fit (data min < 1) |      |                  |      |
| 8 | Neg. Binomial  | No fit                |      |                  |      |

Best fit = geometric distribution

Pore pressure sensors:

| # | Distribution   | Kolmogorov Smirnov    |      | Anderson Darling |      |
|---|----------------|-----------------------|------|------------------|------|
|   |                | Statistic             | Rank | Statistic        | Rank |
| 2 | Geometric      | 0,22324               | 1    | 2,4436           | 1    |
| 1 | D. Uniform     | 0,32                  | 2    | 15,281           | 2    |
| 3 | Poisson        | 0,38673               | 3    | 40,003           | 3    |
| 4 | Bernoulli      | No fit (data max > 1) |      |                  |      |
| 5 | Binomial       | No fit                |      |                  |      |
| 6 | Hypergeometric | No fit                |      |                  |      |
| 7 | Logarithmic    | No fit (data min < 1) |      |                  |      |
| 8 | Neg. Binomial  | No fit                |      |                  |      |

Best fit = geometric distribution

## Appendix 2B:

### Loggers:

| Geometric [#2]     |         |         |         |         |         |  |
|--------------------|---------|---------|---------|---------|---------|--|
| Kolmogorov-Smirnov |         |         |         |         |         |  |
| Sample Size        | 54      |         |         |         |         |  |
| Statistic          | 0,22324 |         |         |         |         |  |
| P-Value            | 0,00761 |         |         |         |         |  |
| Rank               | 1       |         |         |         |         |  |
| $\alpha$           | 0,2     | 0,1     | 0,05    | 0,02    | 0,01    |  |
| Critical Value     | 0,14292 | 0,16332 | 0,18144 | 0,20289 | 0,21768 |  |
| Reject?            | Yes     | Yes     | Yes     | Yes     | Yes     |  |
| Anderson-Darling   |         |         |         |         |         |  |
| Sample Size        | 54      |         |         |         |         |  |
| Statistic          | 2,4436  |         |         |         |         |  |
| Rank               | 1       |         |         |         |         |  |
| $\alpha$           | 0,2     | 0,1     | 0,05    | 0,02    | 0,01    |  |
| Critical Value     | 1,3749  | 1,9286  | 2,5018  | 3,2892  | 3,9074  |  |
| Reject?            | Yes     | Yes     | No      | No      | No      |  |

### Ellitracks:

| Geometric [#2]     |         |         |         |         |         |  |
|--------------------|---------|---------|---------|---------|---------|--|
| Kolmogorov-Smirnov |         |         |         |         |         |  |
| Sample Size        | 54      |         |         |         |         |  |
| Statistic          | 0,08647 |         |         |         |         |  |
| P-Value            | 0,78199 |         |         |         |         |  |
| Rank               | 1       |         |         |         |         |  |
| $\alpha$           | 0,2     | 0,1     | 0,05    | 0,02    | 0,01    |  |
| Critical Value     | 0,14292 | 0,16332 | 0,18144 | 0,20289 | 0,21768 |  |
| Reject?            | No      | No      | No      | No      | No      |  |
| Anderson-Darling   |         |         |         |         |         |  |
| Sample Size        | 54      |         |         |         |         |  |
| Statistic          | 0,61075 |         |         |         |         |  |
| Rank               | 1       |         |         |         |         |  |
| $\alpha$           | 0,2     | 0,1     | 0,05    | 0,02    | 0,01    |  |
| Critical Value     | 1,3749  | 1,9286  | 2,5018  | 3,2892  | 3,9074  |  |
| Reject?            | No      | No      | No      | No      | No      |  |

### Vibration sensors:

| Geometric [#2]     |         |         |         |         |         |  |
|--------------------|---------|---------|---------|---------|---------|--|
| Kolmogorov-Smirnov |         |         |         |         |         |  |
| Sample Size        | 54      |         |         |         |         |  |
| Statistic          | 0,22324 |         |         |         |         |  |
| P-Value            | 0,00761 |         |         |         |         |  |
| Rank               | 1       |         |         |         |         |  |
| $\alpha$           | 0,2     | 0,1     | 0,05    | 0,02    | 0,01    |  |
| Critical Value     | 0,14292 | 0,16332 | 0,18144 | 0,20289 | 0,21768 |  |
| Reject?            | Yes     | Yes     | Yes     | Yes     | Yes     |  |
| Anderson-Darling   |         |         |         |         |         |  |
| Sample Size        | 54      |         |         |         |         |  |
| Statistic          | 2,4436  |         |         |         |         |  |
| Rank               | 1       |         |         |         |         |  |
| $\alpha$           | 0,2     | 0,1     | 0,05    | 0,02    | 0,01    |  |
| Critical Value     | 1,3749  | 1,9286  | 2,5018  | 3,2892  | 3,9074  |  |
| Reject?            | Yes     | Yes     | No      | No      | No      |  |

### Standpipe sensors (ellitrack excluded):

| Geometric [#2]     |         |         |         |         |         |  |
|--------------------|---------|---------|---------|---------|---------|--|
| Kolmogorov-Smirnov |         |         |         |         |         |  |
| Sample Size        | 54      |         |         |         |         |  |
| Statistic          | 0,18716 |         |         |         |         |  |
| P-Value            | 0,03957 |         |         |         |         |  |
| Rank               | 1       |         |         |         |         |  |
| $\alpha$           | 0,2     | 0,1     | 0,05    | 0,02    | 0,01    |  |
| Critical Value     | 0,14292 | 0,16332 | 0,18144 | 0,20289 | 0,21768 |  |
| Reject?            | Yes     | Yes     | Yes     | No      | No      |  |
| Anderson-Darling   |         |         |         |         |         |  |
| Sample Size        | 54      |         |         |         |         |  |
| Statistic          | 2,8504  |         |         |         |         |  |
| Rank               | 1       |         |         |         |         |  |
| $\alpha$           | 0,2     | 0,1     | 0,05    | 0,02    | 0,01    |  |
| Critical Value     | 1,3749  | 1,9286  | 2,5018  | 3,2892  | 3,9074  |  |
| Reject?            | Yes     | Yes     | Yes     | No      | No      |  |

### Pore pressure sensors:

| Geometric [#2]     |         |         |         |         |         |
|--------------------|---------|---------|---------|---------|---------|
| Kolmogorov-Smirnov |         |         |         |         |         |
| Sample Size        | 54      |         |         |         |         |
| Statistic          | 0,22324 |         |         |         |         |
| P-Value            | 0,00761 |         |         |         |         |
| Rank               | 1       |         |         |         |         |
| $\alpha$           | 0,2     | 0,1     | 0,05    | 0,02    | 0,01    |
| Critical Value     | 0,14292 | 0,16332 | 0,18144 | 0,20289 | 0,21768 |
| Reject?            | Yes     | Yes     | Yes     | Yes     | Yes     |
| Anderson-Darling   |         |         |         |         |         |
| Sample Size        | 54      |         |         |         |         |
| Statistic          | 2,4436  |         |         |         |         |
| Rank               | 1       |         |         |         |         |
| $\alpha$           | 0,2     | 0,1     | 0,05    | 0,02    | 0,01    |
| Critical Value     | 1,3749  | 1,9286  | 2,5018  | 3,2892  | 3,9074  |
| Reject?            | Yes     | Yes     | No      | No      | No      |

## Appendix 2C

Loggers: normal distribution can be rejected with a 99% confidence interval.

| Normal [#10]       |         |         |         |         |         |
|--------------------|---------|---------|---------|---------|---------|
| Kolmogorov-Smirnov |         |         |         |         |         |
| Sample Size        | 54      |         |         |         |         |
| Statistic          | 0,25044 |         |         |         |         |
| P-Value            | 0,0018  |         |         |         |         |
| Rank               | 1       |         |         |         |         |
| $\alpha$           | 0,2     | 0,1     | 0,05    | 0,02    | 0,01    |
| Critical Value     | 0,14292 | 0,16332 | 0,18144 | 0,20289 | 0,21768 |
| Reject?            | Yes     | Yes     | Yes     | Yes     | Yes     |
| Anderson-Darling   |         |         |         |         |         |
| Sample Size        | 54      |         |         |         |         |
| Statistic          | 4,9854  |         |         |         |         |
| Rank               | 1       |         |         |         |         |
| $\alpha$           | 0,2     | 0,1     | 0,05    | 0,02    | 0,01    |
| Critical Value     | 1,3749  | 1,9286  | 2,5018  | 3,2892  | 3,9074  |
| Reject?            | Yes     | Yes     | Yes     | Yes     | Yes     |
| Chi-Squared        |         |         |         |         |         |
| Deg. of freedom    | 3       |         |         |         |         |
| Statistic          | 7,5372  |         |         |         |         |
| P-Value            | 0,05661 |         |         |         |         |
| Rank               | 1       |         |         |         |         |
| $\alpha$           | 0,2     | 0,1     | 0,05    | 0,02    | 0,01    |
| Critical Value     | 4,6416  | 6,2514  | 7,8147  | 9,8374  | 11,345  |
| Reject?            | Yes     | Yes     | No      | No      | No      |

Ellitracks: normal distribution can be rejected with a 98% confidence interval.

| Normal [#10]       |         |         |         |         |         |
|--------------------|---------|---------|---------|---------|---------|
| Kolmogorov-Smirnov |         |         |         |         |         |
| Sample Size        | 54      |         |         |         |         |
| Statistic          | 0,18294 |         |         |         |         |
| P-Value            | 0,04704 |         |         |         |         |
| Rank               | 8       |         |         |         |         |
| $\alpha$           | 0,2     | 0,1     | 0,05    | 0,02    | 0,01    |
| Critical Value     | 0,14292 | 0,16332 | 0,18144 | 0,20289 | 0,21768 |
| Reject?            | Yes     | Yes     | Yes     | No      | No      |
| Anderson-Darling   |         |         |         |         |         |
| Sample Size        | 54      |         |         |         |         |
| Statistic          | 3,3527  |         |         |         |         |
| Rank               | 1       |         |         |         |         |
| $\alpha$           | 0,2     | 0,1     | 0,05    | 0,02    | 0,01    |
| Critical Value     | 1,3749  | 1,9286  | 2,5018  | 3,2892  | 3,9074  |
| Reject?            | Yes     | Yes     | Yes     | Yes     | No      |
| Chi-Squared        |         |         |         |         |         |
| Deg. of freedom    | 4       |         |         |         |         |
| Statistic          | 5,4705  |         |         |         |         |
| P-Value            | 0,24234 |         |         |         |         |
| Rank               | 4       |         |         |         |         |
| $\alpha$           | 0,2     | 0,1     | 0,05    | 0,02    | 0,01    |
| Critical Value     | 5,9886  | 7,7794  | 9,4877  | 11,668  | 13,277  |
| Reject?            | No      | No      | No      | No      | No      |

Vibration sensors: normal distribution can be rejected with a 99% confidence interval.

| Normal [#10]       |         |         |         |         |         |
|--------------------|---------|---------|---------|---------|---------|
| Kolmogorov-Smirnov |         |         |         |         |         |
| Sample Size        | 54      |         |         |         |         |
| Statistic          | 0,25044 |         |         |         |         |
| P-Value            | 0,0018  |         |         |         |         |
| Rank               | 1       |         |         |         |         |
| $\alpha$           | 0,2     | 0,1     | 0,05    | 0,02    | 0,01    |
| Critical Value     | 0,14292 | 0,16332 | 0,18144 | 0,20289 | 0,21768 |
| Reject?            | Yes     | Yes     | Yes     | Yes     | Yes     |
| Anderson-Darling   |         |         |         |         |         |
| Sample Size        | 54      |         |         |         |         |
| Statistic          | 4,9854  |         |         |         |         |
| Rank               | 1       |         |         |         |         |
| $\alpha$           | 0,2     | 0,1     | 0,05    | 0,02    | 0,01    |
| Critical Value     | 1,3749  | 1,9286  | 2,5018  | 3,2892  | 3,9074  |
| Reject?            | Yes     | Yes     | Yes     | Yes     | Yes     |
| Chi-Squared        |         |         |         |         |         |
| Deg. of freedom    | 3       |         |         |         |         |
| Statistic          | 7,5372  |         |         |         |         |
| P-Value            | 0,05661 |         |         |         |         |
| Rank               | 1       |         |         |         |         |
| $\alpha$           | 0,2     | 0,1     | 0,05    | 0,02    | 0,01    |
| Critical Value     | 4,6416  | 6,2514  | 7,8147  | 9,8374  | 11,345  |
| Reject?            | Yes     | Yes     | No      | No      | No      |

Standpipe sensors: normal distribution can be rejected with a 99% confidence interval.

| Normal [#10]       |         |         |         |         |         |
|--------------------|---------|---------|---------|---------|---------|
| Kolmogorov-Smirnov |         |         |         |         |         |
| Sample Size        | 54      |         |         |         |         |
| Statistic          | 0,25044 |         |         |         |         |
| P-Value            | 0,0018  |         |         |         |         |
| Rank               | 1       |         |         |         |         |
| $\alpha$           | 0,2     | 0,1     | 0,05    | 0,02    | 0,01    |
| Critical Value     | 0,14292 | 0,16332 | 0,18144 | 0,20289 | 0,21768 |
| Reject?            | Yes     | Yes     | Yes     | Yes     | Yes     |
| Anderson-Darling   |         |         |         |         |         |
| Sample Size        | 54      |         |         |         |         |
| Statistic          | 4,9854  |         |         |         |         |
| Rank               | 1       |         |         |         |         |
| $\alpha$           | 0,2     | 0,1     | 0,05    | 0,02    | 0,01    |
| Critical Value     | 1,3749  | 1,9286  | 2,5018  | 3,2892  | 3,9074  |
| Reject?            | Yes     | Yes     | Yes     | Yes     | Yes     |
| Chi-Squared        |         |         |         |         |         |
| Deg. of freedom    | 3       |         |         |         |         |
| Statistic          | 7,5372  |         |         |         |         |
| P-Value            | 0,05661 |         |         |         |         |
| Rank               | 1       |         |         |         |         |
| $\alpha$           | 0,2     | 0,1     | 0,05    | 0,02    | 0,01    |
| Critical Value     | 4,6416  | 6,2514  | 7,8147  | 9,8374  | 11,345  |
| Reject?            | Yes     | Yes     | No      | No      | No      |

Pore pressure sensors: normal distribution can be rejected with a 99% confidence interval.

| Normal [#10]       |           |         |         |         |         |
|--------------------|-----------|---------|---------|---------|---------|
| Kolmogorov-Smirnov |           |         |         |         |         |
| Sample Size        | 54        |         |         |         |         |
| Statistic          | 0,30694   |         |         |         |         |
| P-Value            | 5,1588E-5 |         |         |         |         |
| Rank               | 1         |         |         |         |         |
| $\alpha$           | 0,2       | 0,1     | 0,05    | 0,02    | 0,01    |
| Critical Value     | 0,14292   | 0,16332 | 0,18144 | 0,20289 | 0,21768 |
| Reject?            | Yes       | Yes     | Yes     | Yes     | Yes     |
| Anderson-Darling   |           |         |         |         |         |
| Sample Size        | 54        |         |         |         |         |
| Statistic          | 7,7245    |         |         |         |         |
| Rank               | 5         |         |         |         |         |
| $\alpha$           | 0,2       | 0,1     | 0,05    | 0,02    | 0,01    |
| Critical Value     | 1,3749    | 1,9286  | 2,5018  | 3,2892  | 3,9074  |
| Reject?            | Yes       | Yes     | Yes     | Yes     | Yes     |
| Chi-Squared        |           |         |         |         |         |
| Deg. of freedom    | 3         |         |         |         |         |
| Statistic          | 11,723    |         |         |         |         |
| P-Value            | 0,00839   |         |         |         |         |
| Rank               | 1         |         |         |         |         |
| $\alpha$           | 0,2       | 0,1     | 0,05    | 0,02    | 0,01    |
| Critical Value     | 4,6416    | 6,2514  | 7,8147  | 9,8374  | 11,345  |
| Reject?            | Yes       | Yes     | Yes     | Yes     | Yes     |



## Appendix 3:

Below, the method which measures the fraction of orders that is directly satisfied from stock is depicted. This specific method is used to calculate the fill rate of Ellitracks, but for the other equipment groups the fill rate is determined with a comparable method.

```
var TheDim:integer
var waiting:real
var i:integer

-- Store stats
TheDim:=OrderStats.yDim+1
--Orderinformation.copyRangeTo({1,@}..{3,@}, OrderStats, 1,TheDim)
--OrderStats["DepartureTime",TheDim]:=root.EventController.SimTime
--OrderStats["OrderLeadtime",TheDim]:= root.EventController.SimTime-OrderInformation["ArrivalTime",@]
--OrderStats["WaitingService", TheDim]:= OrderInformation["Time_Outgoing",@]-OrderInformation["Time_incoming",@]
OrderStats["Fill", TheDim]:= OrderInformation["Time_Assembled",@]-OrderInformation["ArrivalTime",@]
If root.EventController.SimTime > 90*24*3600
If OrderStats["Fill", TheDim] = 0
    Fill_Rate += 1
    OrderStats["Filling", TheDim] := 1
Else
    OrderStats["Filling", TheDim] := 0
end
end
Logger_Fill_Rate := OrderStats.meanValue({"Filling", *})
OrderInformation.CutRow(@)
@.move(Drain)
```

In this code the column 'Fill' in the table 'OrderStats' depicts the total time the order have been in the assemblystation. For orders where inspected/calibrated equipment have been on stock, this time is 0 seconds. To then calculate the fill rate, first all the equipment with a Fill time of 0 seconds get a value of 1 in the Column 'Filling' and the orders that have been in the assemblystation longer than 0 seconds, so the orders that are not directly satisfied from on hand inventory of inspect/calibrated equipment, get the value 0 in the 'Filling' column. Finally the average value of the column 'Filling' is calculated which results in the fill rate of that equipment group.