Spare part planning for two demand streams
a decision support tool

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Spare Part Planning for Two Demand Streams: A Decision Support Tool

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Preface

As a concluding part of my Master Operations Management and Logistics at Eindhoven University of Technology, I will conduct my Master Thesis Project at the Maintenance Development (MD) department of NedTrain. The MD department is located at the headquarters of NedTrain in Utrecht (the Netherlands). The supervisors of my project are Simme Douwe Flapper (first supervisor, TU/e), Joachim Arts (second supervisor, TU/e), Willem van Jaarsveld (third supervisor, TU/e), Bob Huisman (NedTrain) and Wouter Fleuren (NedTrain).

This project was not possible if it were not for a couple of people that assisted me while I was doing this research. These people deserve some extra attention in this section. First of all, I would like to thank my first supervisor, Simme Douwe Flapper, for all his guidance throughout my entire Master Thesis Project. His feedback on my work was always very extensive and clear. All our meetings were centered around improving my research in a constructive way. Next, I would like to express my great gratitude for Wouter Fleuren. His expertise and enthusiasm made it possible to make a lot of progress in a short period of time. Our weekly meetings on Monday were not only very useful, but also a good moment to talk about our weekends. I also want to thank Bob Huisman, especially for the first few weeks in which he helped me settle in at NedTrain. Then, I want to thank my second supervisor, Joachim Arts, for helping me with the formulation of my mathematical model and for the meetings at the end of my project.

Last but not least, some other people I should not forget and want to thank: Thomas van Haperen for introducing me to Bob Huisman and arranging an interview, Koen Dekkers for devoting a couple of Friday mornings to my research and for helping me find the data I needed, Joost Florie for letting me participate in the 'simulation game', and all the other people at NedTrain, friends, and family that helped me in any way, shape or form.

Max Konings

Abstract

This research focusses on the planning of spare parts at the maintenance depots (OBs) and the repair shop at NedTrain. The Supply Chain Operations (SCO) department is mainly responsible for this planning, which includes the allocation of spare parts to demand in the OB, requesting expedited repairs at the repair shop to regulate inventory levels, and the scheduling of projects to replace a specific spare part in a number of trains. Parts are replaced during projects to prevent breakdowns and happen every 2-6 years, depending on the part. These projects are mainly referred to as Long Cycle Maintenance (LCM) due to their longer recurring cycles. The maintenance with shorter recurring cycles is referred to as Short Cycle Maintenance (ShCM), which is performed about every 3 months. During the period a project (LCM) is active, demand for the respective spare part can also arise from ShCM. Demand that arises from ShCM is unplanned and is usually the result of a failed part. The demand streams for replacing a failed part and replacing a part preventively have different penalty cost. Trains with a failed part cannot leave the OB until the part is replaced, whereas preventive maintenance for trains can be delayed and trains are allowed to leave the OB.

A decision support tool is developed which considers both demand streams for a specific spare parts and helps the planners of SCO to make assignment and expediting decisions in their daily operations. The assignment decisions are based on the cost for not assigning a spare part to either of the two demand streams. The tool also supports the planners in making expediting decisions, based on the upcoming demand and the incoming repair orders. A new policy is introduced, which allows the rationing of inventory for unplanned demand, meaning that it cannot be used to satisfy planned demand. Rationing can be used to ensure enough on-hand inventory for unplanned demand until the arrival of spare parts from repair.

Management Summary

Introduction

The goal of this research was to improve the planning of spare parts for the two demand streams that arrive at the maintenance depots (OBs) of NedTrain: Short Cycle Maintenance (ShCM) and Long Cycle Maintenance (LCM). The management at NedTrain felt that the assignment of spare parts of both streams could be improved. If the backlog cost of both demand streams are compared, it is clear that there is a significant difference and that there should be an assignment priority. However, this underlying priority is currently not considered in practice. The planners at Supply Chain Operations (SCO), who are responsible for the assignment of spare parts in the OB, do not have access to clear demand forecasts. This means that they are not able to determine whether it might be smarter to save some of the on-hand inventory for demand of a higher priority. There was also improvement possible in the scheduling of the repair process. The repair shops in which NedTrain repairs the replaced spare parts allow for the expediting of repairs. These expediting decisions are currently made on average once a week and include forecasts based on intuition. To improve the planning of the assignment and repair process at NedTrain, a decision support tool was developed to guide the parties involved with making expediting and rationing decisions.

Model

A mathematical model was developed that incorporates both the assignment of spare parts to the two demand streams at the OB and the scheduling of repair orders at the repair shop. The assignment of spare parts in this model can be divided into two separate decisions: assigning on-hand inventory to either of the two demand streams based on their backlog cost and rationing on-hand inventory for expected upcoming ShCM demand. This rationing policy was implemented because of the significantly higher backlog cost of ShCM compared to that of LCM. When delaying a project maintenance operation (LCM) means that the next time the train will return to the OB to perform its maintenance will be after the project end date, the total backlog cost for LCM increases. Penalty costs are used to punish project maintenance for every day it is performed too late (after the project end date). This can lead to the backlog cost of LCM becoming higher than that of ShCM and thus a switch in assignment priority and no more rationing of on-hand inventory for ShCM.

The other main component in this model is the decision to expedite repair orders that are currently in the repair shop. The repair shop allows the expediting of repairs for most parts. Expediting a repair means that the repair will be finished earlier than when it would be repaired according to its normal repair schedule. Because the expediting of repair orders involves the allocation of more resources to the repair or changing its priority level, it is more expensive than a normal repair. The model takes the expediting cost for repairs, the unavailability cost for trains that are not in operation, and the cost for delaying the maintenance of trains in consideration when determining the best expediting level for every period.

Conclusion

The model described above was used to develop a decision support tool which can be used in the daily operations at NedTrain. This decision support tool was developed in MS EXCEL for two important reasons. First, all computers at NedTrain are equipped with the MS Office package by default, including MS EXCEL. This means that no extra software packages have to be installed in order to open the tool. The second reason is that the planners at SCO, the main end-users, already use MS EXCEL in their daily operations. They understand how to find data in these files and how different cells or sheets are linked.

To evaluate the performance of the decision support tool and all the implemented policies, a case study of a project for a toilet module of the ICM train series was conducted. For the case study, we considered the six following policies:

1. Include both the expediting and rationing algorithm (complete decision support tool)
2. Only include the expediting algorithm
3. Only include the rationing algorithm
4. Exclude both the expediting and rationing algorithm
5. Expedite maximum number of spare parts in every period and exclude rationing
6. Only include an expediting policy that simulates current practice

The first 3 policies test the different functionalities of the tool and deliver their separate and combined results. The fourth policy simulates the situation where all parts are repaired according to the normal repair lead time and no rationing is used. To study the maximum effect that the expediting of repairs can have, we expedite the maximum number of parts every period in policy five. With the sixth policy, we approximate the current practice at NedTrain.

The KPI's used in this case study include the different cost components over the project duration and the service levels for ShCM and LCM. These service levels are calculated by dividing the sum of the number of parts allocated to the respective demand stream by the sum of the daily demands in the OB of that same demand stream. Figure 0.1 shows the KPI's for every policy.

The total cost over this project appears to be the lowest if we include both proposed algorithms (policy 1). Only including the expediting algorithm (policy 2) leads to total cost which is just 1% higher than policy 1 with almost identical service levels. We conclude from this that the expediting algorithm is already quite good to handle demand fluctuations for the demand pattern of the toilet module on its own. When we compare the policy without any of the algorithms included (policy 4) and the policy with only the rationing algorithm included (policy 3), we see that rationing for ShCM leads to lower total cost by sustaining high service levels for ShCM at the expense of the service levels of LCM. This shows that also the rationing algorithm adds value by making use of the difference in backlog cost for the two demand streams.

We wanted to show the difference between our proposed expediting algorithm and just expediting the maximum number of parts every period in policy 5. According to the results, our proposed expediting algorithm delivers about the same service levels as the maximum expediting policy at significantly lower expediting cost. This does not mean that our algorithm will never expedite the maximum number of parts in a given interval, but rather tells that it considers all costs in the model in making its decisions.

To determine the practical value of our model including both the proposed algorithms, we have to compare it to the simulation of current practice at NedTrain (policy 6). Current practice performs average if we consider all policies, but does have about 9% higher total cost than our proposed mathematical model, which includes both policies. Although policy 6 has very low expediting cost in respect to policy 1, it overcompensates this with high cost for the unavailability of trains, delaying of maintenance operations, and performing project maintenance after the project end date.

The case study we conducted showed very positive results of our proposed policies. The use of the decision support tool that was developed with the mathematical model created in this research, lead to a cost reduction of 9% compared to current practice. We advise NedTrain to implement this decision support tool in their future projects, by following the implementation plan provided in this research. We also advise SCO and NCB to use the simulation functionalities of the tool at the start of a new project to make lead-time and other agreements.

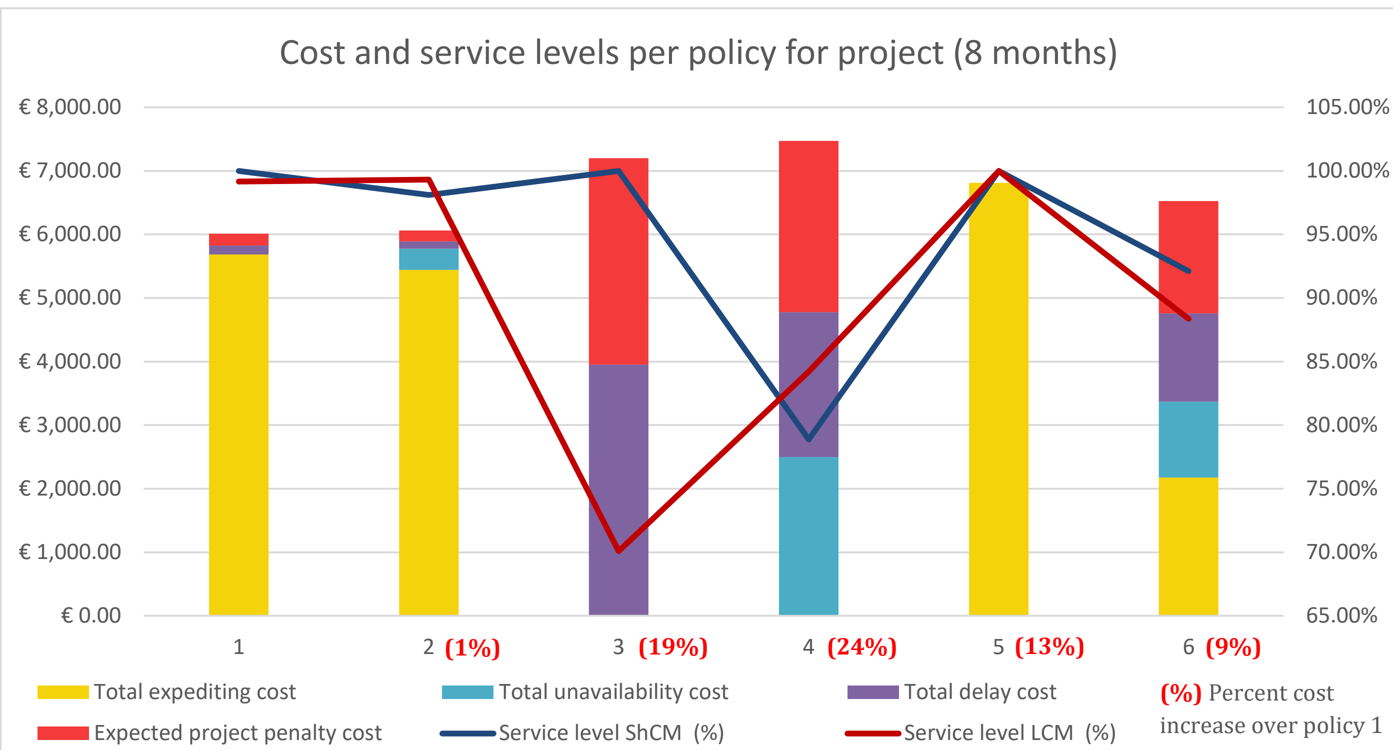

Figure 0.1: Costs and service levels for the case study project March '16 – October '16 (8 months)

Table of Contents

List of Figures

List of Tables

Introduction

NedTrain wants to improve the process of assigning spare parts to the two demand streams that arrive in their Maintenance Depots (OBs). These two demand streams can be either of the type Short Cycle Maintenance (ShCM) or Long Cycle Maintenance (LCM). The penalty cost for not assigning a spare part to a demand is different for both demand streams. Supply Chain Operations (SCO), responsible for the planning of these parts, indicated the need for a decision support tool to help their planners to determine to which maintenance operation a specific spare part needs to be assigned and how to plan the repairs of replaced spare parts. In this research, the effects of using expedited repairs and the option to withhold inventory will be analyzed with respect to the total cost. These total costs consist of the penalty cost for not timely performing either ShCM or LCM and the cost related to repairing parts at the repair shop.

Chapter 1 provides a brief company description of NedTrain and its internal departments. The problem statement is presented, followed by a more in-depth description of NedTrain's supply chain and the relation this research has with existing literature. In chapter 2, the design of the research is set out and includes the research questions and the scope of this research. The mathematical model that was developed in this research is presented in chapter 3. First, a description of all variables and equations is introduced. Then, the assumptions, the mathematical equations, and the two algorithms for this model are presented. An explanation of the functionalities of the decision support tool and an implementation plan for this tool are given in chapter 4. Chapter 5 contains a case study of one spare part under different policies, to evaluate and validate the decision support tool. In chapter 6, answers to the main research questions are formulated, accompanied with a discussion concerning the limitations of this research and suggestions for future research.

1. Background

1.1 Company Description

NedTrain is responsible for all maintenance operations for the fleet of the Dutch Railways (NS). NS is the primary passenger railway operator in the Netherlands and provides rail services on the Dutch main rail network. Formerly, these maintenance operations were performed directly by NS, but after a new European Union Directive in the 1990s, there needed to be a formal separation into two companies. After this separation, NedTrain remained a full subsidiary company to NS Group. The goal of NedTrain is to ensure safety and cleanliness for all 1.2 million daily train passengers on the way to their destination.

1.1.1 Facilities

NedTrain currently has 30 facilities to conduct their maintenance activities, strategically located on the railway network throughout the Netherlands. The locations can be divided into one of the following categories, each with its own specific set of activities:

- **Service Company (SB)**: overnight storage facilities where trains undergo small maintenance (every 2 or 12 days) and cleaning activities;
- **Maintenance Depot (OB)**: facilities in which larger maintenance operations like Short Cycle Maintenance (every 3 months) and Long Cycle Maintenance (every 2-6 years) are performed;
- **Components Company (NCB)**: revision workshop in which replaced parts are revised;
- **Refurbishment and Overhaul Workshop (R&O)**: overhaul facility where complete trains are revised or modernized

This research focusses on the demand that arrives in the maintenance depots and the revision of part. Currently, NedTrain has 4 depots, situated in Onnen, Leidschendam, Watergraafsmeer and Maastricht. The NCB is centrally located within the Netherlands in Tilburg. NedTrain also uses external repair shops for some parts. These repair shops are included in this research.

1.1.2 Departments

The four main business units of NedTrain are Business Development, Maintenance & Service, Fleet Services and Refurbishment & Overhaul. This research was conducted under the supervision of the Maintenance Development group, part of the Maintenance Management department, all belonging to the Fleet Services business unit. The end user of the model developed in this research will be the Supply Chain Operations (SCO) department. SCO is divided into a logistics department and a purchasing department. The logistics department is responsible for supplying the OBs with ready-for-use (RFU) parts. They do this by controlling NedTrain's closed-loop supply chain for repairable spare parts and the supply of consumables (items that are discarded after replacement). This closed-loop supply chain at NedTrain is explained in section 1.3.

1.2 Problem Statement

In the introduction of this proposal, the problem was already briefly discussed. In this section we will specify the problem statement and explain how the situation is currently handled.

The 4 maintenance depots (OBs) perform the larger, periodic maintenance operations for the fleet that NedTrain maintains. All trains have to visit the OB approximately 4 times per year for their Short Cycle Maintenance (ShCM). The exact arrival at the OB depends on the planning made by the NSR (Nederlandse Spoorwegen Reizigers) department of NS (Dutch Railways). They aim to get trains to the OB for ShCM without making too many detours. In practice this means that trains can arrive a couple of days before or after their 3-month maintenance cycle. ShCM is also called regular maintenance because of its recurring scheduling. Because most trains in the fleet are not fully equipped with sensors to monitor parts on a continuous basis, some parts of the train need to be manually checked by the maintenance workers while the train is in the OB for ShCM. These checks are condition based, meaning the maintenance workers look whether a part is currently in a predetermined condition or state related to upcoming failures. If a part fails one of these checks, or is even completely defect, it needs replacement. The state in which the spare part is currently in, is stochastically distributed. So, most spare parts needed during these maintenance operations are not known beforehand.

This is different for trains that come in for Long Cycle Maintenance (LCM), also referred to as project maintenance. These projects are planned well ahead of time and take place once every 2-6 years, depending on the part. All the parts needed are known before these maintenance operations take place. These projects are given a starting date and an ending date within which they need to be executed. Every time a train visits an OB for ShCM during this period, maintenance workers will try to perform a planned project if the required parts and enough resources are available at that time. It could also be decided that the train leaves without performing the project maintenance and that they will try it again during its next visit to the OB.

The Supply Chain Operations (SCO) department is responsible for both the planning of these projects and the supply of spare parts to the 4 OBs. The management of SCO focusses on the long term planning of the different projects by setting the duration of the project and the weekly targets of trains that need to undergo project maintenance. The planners of the SCO department are more focused on the day-to-day planning of all maintenance operations in the OB. They are responsible for the allocation of spare parts in the OBs inventory to the demand that arises from ShCM and LCM. Currently, this assignment happens in a first-come, first-served way. Maintenance workers in the OB will tell the planners which parts they need and if these parts are on stock, the planners will assign these to the maintenance operations. When the demand for this part is larger than the current inventory level, not all maintenance operations can be executed. Not having an item on stock for a maintenance operation results in cost for not being able to perform that replacement (penalty cost). These penalty costs are different for ShCM and LCM due to the different effects a backlog has on the respective maintenance. As explained before, LCM can be delayed when not enough resources are available. When parts are needed for ShCM, it means that maintenance workers found a defect part in a train. When this part is considered critical for the functioning or safety of the train, this train cannot leave the OB before it gets replaced. Trains will be unavailable for the transport of passengers and daily costs for unavailability of the train are incurred, based on the passenger capacity. These unavailability costs are significantly higher than the cost of delaying maintenance.

The SCO managers feel that the way the assignment of parts takes place at the moment is not optimal and that there is room for improvement. Currently, the SCO planners and maintenance workers will only take the cost for delaying maintenance and unavailability of trains in consideration if there is a maintenance operation of a higher priority at that moment inside the OB. Because the difference in penalty cost between ShCM and LCM can be significant, the management would like the planners of SCO to look at a longer time horizon when assigning parts. This includes upcoming demand and spare parts returning from repairs. The decision to expedite of repairs is currently solely based on intuition. The management indicates the need for a decision support tool which can help SCO to make these decisions and improve the planning of spare parts for the two demand streams.

1.3 Closed-loop Supply Chain

This research focusses on a specific part of NedTrain's supply chain that can be characterized as a closed-loop supply chain. The logistics department of SCO, the party that addressed the problem, controls this closed-loop supply chain. This section explains the supply chain of NedTrain as a whole and specifies the parts relevant for this research.

The life cycle for spare parts (series of stages through which the part passes during the span of it being used in operation) in NedTrain's supply chain either starts at the procurement of the part or its revision. A part's cycle ends after a part is replaced due to its condition or a failure. A brief overview of NedTrain's supply chain can be seen in Figure 2.1. Within a closed-loop supply chain, the life cycle of a product is followed throughout this supply chain and the aim is to recover most value every cycle. In the next two sections, the demand and supply for spare parts in this supply chain are discussed.

1.3.1 Spare Part Demand

For present maintenance operations, NedTrain uses around 60,000 different types of spare parts. The use of a closed-loop supply chain with revision capabilities is only possible for repairable spare parts within the categories:

- **Rotables**: "items that constitute a sufficiently large subsystem of the original equipment to warrant a separate usage based maintenance strategy" (Arts, 2013). For rotables at NedTrain, a maximum inter overhaul time (MIOT) is set, which is the maximum amount of time/usage stipulated in their maintenance program before they need to be overhauled.
- **Repairables**: items that go to a repair shop after they have been replaced. These items are replaced according to a usage based or a condition-based maintenance policy. After they return from the repair shop, they will return to inventory and can be used for replacement.

We will refer to a part in either of the two categories as a repairable spare part. In this research, we focus on repairable parts that are used for Short Cycle Maintenance (ShCM) and Long Cycle

Maintenance (LCM). These two demand streams arrive both in the OBs but have different cycle lengths. Rolling stock arrives approximately every 3 months for ShCM and every 2-6 years for LCM. For LCM, replacement of a specific part is certain and thus the demand for it is known; whereas replacement of a part during ShCM depends, for most parts, on its condition and thus its demand is stochastic. This condition is a well recognizable and measurable state of the spare part that is closely associated with an upcoming failure. According to SCO, there are currently about 300 repairable spare parts that are used in both LCM and ShCM. Most of these parts are replaced within a single OB that is specialized in the replacement of this part and has the proper equipment and knowledge to do so.

1.3.2 Spare Part Supply

In each of the OBs, there is a local stock point for spare parts. In the case of no local stock available in the OB, it can be supplied by the LLC central warehouse located in Tilburg. The central warehouse, on its turn, is supplied by either the internal repair shop (NCB), the external repair shop or external suppliers, as can be seen in Figure 2.1.

If a repairable part is replaced during a maintenance operation, it is transferred to the SCO central warehouse. From there, it is transferred to the closely located NCB, where they decide to perform the revision internally or at an external repair shop. When overhauling a part, the terms revision and repair are used to denote different states of a part when it arrives. Revision is used for degraded parts and repair for parts that have completely broken down. Because there is no clear line between both and the fact is not significant for our problem, these two terms will be used interchangeably.

Some parts are exclusively repaired at external suppliers and have a longer expected repair lead time on average. SCO gives orders to both the repair operations executed at both the NCB and the external suppliers. For most parts, the repair shops have the possibility to expedite a repair order. Expedited orders will be revised faster than regular orders and thus will be earlier available for the OBs. The cost for an expedited repair is higher than the cost for a 'normal' repair due to the allocation of more resources to the repair process or due to the change in repair priority level in respect to other spare part types. When the failed part is revised and RFU, it is transferred back to the central warehouse, from where they are assigned and transported to the different OBs.

1.4 Literature Review

In this section, some important parts of the literature review (Konings, 2016), that was conducted as part of this research, are presented. After this extensive review, there were no existing models or frameworks found which could be directly applied to this research. However, some ideas and concepts from various articles were used in the development of our mathematical model. These concepts were combined to construct the final model of this research. The table in *Appendix C* presents an overview of all articles in the review and also shows the existing gap in literature, as none of the articles covers all the different aspects of this research.

1.4.1 Inventory Rationing

Our research differentiates the two demand streams, ShCM and LCM, which arrive in the OB. Because there are different costs related to these demand streams, NedTrain treats these differently. Multiple demand streams, for a specific product, with each a different set of characteristics are most commonly referred to as customer classes. These customer classes can be prioritized by either the shortage cost or the different service levels. Problems in literature concerning different types of demand differentiation often find better results when inventory rationing is introduced. An inventory rationing policy introduces the possibility to deny the assignment of inventory on-hand to a demand arrival, if this can improve the (expected) total revenue or total cost in the long run. This policy requires that the shortage cost for the respective customer classes are different. Inventory rationing can have a positive effect on the total cost if it is used to reserve some inventory for the arrival of customer classes with higher shortage cost. The more significant the difference in shortage cost is, the more effect rationing will have (Dekker, Klein & Rooij, 1998). Because shortage cost for ShCM are notably higher than those for LCM, due to the cost of unavailability of trains, this technique can be useful in this research. Different methods of inventory rationing are found in literature. Most of these methods include the use of dynamic programming to analyze the long-term effects of these rationing decisions, but some contributions to this subject propose simpler, heuristics. One of the first heuristic to tackle the complexity and computing times of dynamic programming was presented by Topkis (1968). He studied a discrete-time periodic review system with zero lead time and showed that the optimal inventory rationing policy was a dynamic threshold policy. In the following years, the threshold policy was broadly covered in literature.

Dekker, Klein & Rooij (1998) studied different machines used in a large petrochemical plant. Potential breakdowns of these machines resulted in different losses to the firm due to equipment criticality. Some equipment in the plant was quite critical for continuous operations, while other were almost redundant. “Equipment criticality is defined here as sustaining production in a safe and efficient way” (Dekker et al, 1998). This is comparable to the two demand streams at NedTrain, where spare part shortage for ShCM can lead to unavailability of trains and shortage for LCM only to cost for delaying. Dekker, Klein & Rooij (1998) also consider two customer classes, critical and non-critical, and propose a rationing policy that reserves some of the stock for the critical demand (S_c). The order-up-to level is formulated as $S_c + S$. When the stock on-hand drops to the level S_c, all remaining stock is reserved for critical demand and non-critical demand results in backorders. In numerical examples, results for scenarios with and without the use of stock reserved for critical demand are compared. It shows that for smaller values of the ratio between penalty cost for non-critical and critical demand, the total average cost are the same for these scenario’s and for larger ratio’s, the rationing policy leads to a lower average cost.

Liu et al. (2015) also studied the rationing problem for inventories. They considered a multi-class dynamic inventory system with $K(\geq 2)$ customer classes. “As the penalty cost of different classes are different, it is natural to backlog some lower priority classes with lower penalty cost to reserve stock for future demands from higher priority classes” (Liu et al. 2015). Their dynamic threshold policy indicates the on-hand inventory above which demand for a certain demand class is satisfied at a specific point in time. If the on-hand inventory at that time is smaller than or equal to this value, the demand is backordered. At the end of the period, the system reorders the inventory with zero lead time and the outstanding backorders are fulfilled. The objective of the model is the minimization of the sum of the penalty cost for backordering demand and the holding cost for on-hand inventory.

1.4.2 Expediting Procedures

When the on-hand inventory of a spare part at one of the OBs or at the central warehouse gets too low to satisfy the expected demand, SCO can make some calls to the repair shop to expedite outstanding repair orders. The repair shops are able to reduce the remaining repair lead times by devoting more resources and/or prioritizing the repair of that specific part. These resources can include engineers, tools and equipment. For most repairables the number of parts in NedTrain's closed-loop supply chain is constant. So, reducing repair lead times is a useful way to control the stock levels. What should be noted is that due to the devotion of more resources and altering the planning, expediting outstanding repair orders is more expensive than following the regular repair schedule. A trade-off between the cost for the expediting policy and the downtime cost should always be made. In literature, these expediting repair policies are covered under the umbrella of expediting procedures. Expediting procedures include all policies used to reduce the current (remaining) lead time of a product until it arrives in stock. These policies do not only concern repair lead times but also manufacturing and shipping lead times.

Expediting Repairs
In his research at NedTrain, Arts et al. (2013, 2016) considered the joint problem of finding the best turn-around stock and expediting policy for repairables. He proposed an expediting policy that depends on the number of outstanding items in regular repair $X_i(t)$ and the state of the exogenous Markov process $Y(t)$, which are both observed by the decision maker. A Markov modulated demand is assumed, which includes the dependence on the state of modulating chain of demand $Y(t)$. This is modelled in continuous time and with an infinite planning horizon $[0, \infty)$. In his policy, Arts (2013) assumes the expedited lead time to be deterministic and the regular lead time as being a convolution of the expedited lead time and several exponential phases, as can be seen in Figure 1.1.

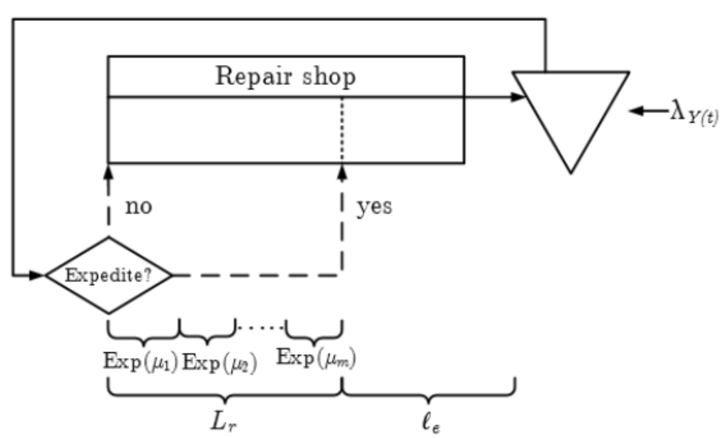

Figure 1.1: Repairable item inventory system with the possibility to expedite repair (Arts, 2013)

They also assume that parts can always be repaired (no condemnation) and that defective parts are immediately sent to the repair shop in an $(S-1, S)$ replenishment policy. The research concludes that when demand fluctuates slowly, the performance of the system can be written as a weighted sum of the performance of systems facing stationary Poisson demand. This expediting policy seems to fit the fluctuating demand in our situation, but the decision to expedite the repair of an item is triggered by a replacement. This means that there is no option to speed up the repair process for parts that are currently in regular repair and no parts are replaced, which, according to Koen Dekkers of SCO, is the option SCO uses most frequently.

Louit et al. (2010) present a dynamic control system for an adjustable single server repair facility that closer resembles the current practice at NedTrain. In this single server repair facility, the repair rate can be expedited or slowed down, with higher repair cost for faster rates. Louit et al. (2010) suggest that repair facilities can expedite the repair rate by (1) the use of flexible labor, (2) subcontracting, or (3) proactive use of overtime. The selection of the repair rate depends on the number of units in operational condition. The objective is the minimization of the expected cost per unit time for the inventory system in the long run. This cost per unit consists of: capital cost for the complete inventory, operational holding cost for on-hand inventory, shortage cost, and repair cost. An industrial case study shows that the use of the optimal control policy for the rate of component repair outperforms a policy with a constant repair rate. Although this model includes the possibility to expedite outstanding repair orders, it cannot do this for separate repair orders or parts. When the expediting repair rate is initiated, it applies to all parts that are currently in repair.

Expediting Outstanding Orders

The research on expediting outstanding repairs is still limited and, to our knowledge, the expediting of repairs for separate orders or parts has not yet been covered. However, in literature concerning emergency shipments for stock items, a small stream exists that considers outstanding orders. One of the first models to include the expediting of outstanding orders was proposed by Allen & D'Esopo (1968). They model an (s,Q) policy with a third operational parameter E called the expediting level. The deterministic regular lead time is defined as L and the deterministic emergency lead time as R, with $R < L$. Whenever the inventory on hand drops to the expediting level, an outstanding order will be delivered after a period R from that moment. When defining X as the reorder point and Y_t as the number of demands occurring between zero and t, the expected 'effective' lead time can be calculated as follows:

$$\mathbb{E}(Z) = L - \int_0^{L-R} \mathbb{P}(Y_t \leq X - E)dt$$

The interval between 0 and $L-R$ for expediting an order is taken because expediting after $L-R$ periods after it was sent to repair would be illogical, as the order will arrive later than L. Using this expression for the expected lead time for this policy, expressions for the expected inventory, expected shortage rate, and the expected total cost can be determined. The model uses initial order cost and unit cost of an item and adds additional unit cost per item expedited and order cost per order expedited. This model assumes that the cost per item expedited is constant and does not decrease as its time outstanding gets closer to L. In the repair shop at NedTrain, the cost of expediting parts decreases over the time they spent in repair. This is due to the fact that the progress of the repair increases over time, and increased repair progress implies fewer resources needed for expediting.

Chiang (2010) considers a continuous review system where lead-time consists of two components: manufacturing lead-time and delivery lead-time. The manufacturing lead-time is the time needed for the supplier to manufacture the quantity ordered which includes the set-up time, job processing time and waiting time. In this paper, the manufacturing lead-time is assumed constant. The delivery lead-time can take on two different deterministic values corresponding respectively to the regular and fast transportation modes. Order expediting can occur due to the use of the faster transportation mode. The policy proposed by Chiang (2010) can be considered as an extension of the (s,Q) model. In addition to the variables s and Q, this policy introduces the expedite-up-to level R. Part of an order is expedited if inventory falls below R at the end of the manufacturing lead-time, the remaining part is delivered via a regular shipment mode. This practice is referred to as order splitting and can be seen in Figure 1.2. The amount expedited is equal to the difference between the inventory and the level of R. The lead-time L consists of the manufacturing lead-time M and the delivery lead-time N. The delivery lead-time N refers to the regular supply mode and can be shortened to G $(i.e., G < N)$ if a fast supply mode is used. The decision to expedite (part of) an outstanding order is taken at the end of M. This shows some similarities with the practice at NedTrain. Expediting decisions at NedTrain are most commonly made during the time the order is in repair and usually involve a part of the outstanding orders and not all. Also, the part M in this policy, where expediting is not yet possible, can be related to the transport and waiting time that is included in the repair lead-time at NedTrain. Computational results that this policy could be useful in situations with high service levels, large demand variability, small extra cost for expediting, or long manufacturing lead-times.

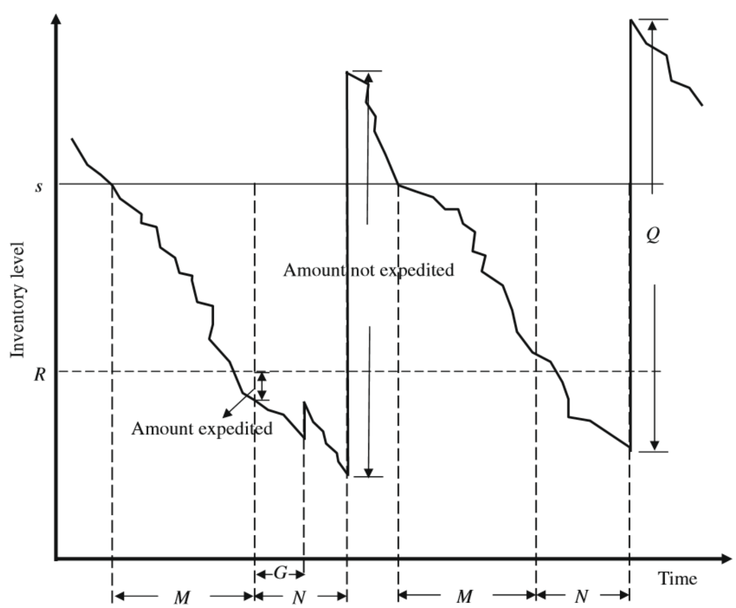

Figure 1.2: An order expediting control policy by Chiang (2010)

2. Research Design

2.1 Research Formulation

Constructing a mathematical model requires the formulation of an objective and which decisions can be made. All were formulated after discussions with the management of SCO, NCB and Maintenance Development. These conversations were aimed at determining the respective interests and the ways the current situation can be improved.

2.1.1 Research Objective

This section aims at defining a clear objective for this research with the interests of NedTrain in mind. Because NedTrain is a subsidiary company of NS, and most of its operations are commissioned by NS, maximizing revenue is not one of its objectives. It is important, however, that the cost related to all maintenance activities are kept as low as possible. While keeping these costs low, NedTrain also has to consider several (1) regulatory, (2) safety, (3) availability and (4) time objectives.

For this specific problem within NedTrain, the objective will be a simplified version of reality for mathematical and modeling purposes, and only concern the cost. Because availability and time objectives also play a major role in the planning of spare parts, we will punish the (expected) exceeding of these targets with penalty cost. In this research, unavailability is related to trains that were expected to be in operation but are still in the OB waiting for a maintenance operation. Performing all project maintenance operations within the given project interval can be seen as a time objective. The objective function of the model will be the minimization of the total cost related to the assignment and repair of spare parts. These total costs consist of the penalty cost for not performing either ShCM or LCM, the cost related to repairing parts at the NCB or at an external repair shop, and the cost for project maintenance which is performed outside the project interval.

2.1.2 Research Decisions

To realize the objective of this research, we need to introduce decisions that have an effect on this objective. Discussion with the management and engineers within NedTrain led to a list of possible variables that can be introduced into this research and represent decisions that can actually be made within the company. Because of their unknown effects on the total cost, these decision variables can offer new insights for the management of NedTrain.

- **Assignment:** the decision to which of the two demand streams a spare part in inventory should be assigned. Also, the decision whether a spare part should be assigned to either of the demand streams at all.
- **Expedited repair:** if a spare part is out-of-stock or expected to go out-of-stock, SCO has the option to expedite the repair of parts in the repair shop. The expediting of repairs is possible when the part is already in repair.

2.2 Research Questions

The mathematical model and the decision support tool must include some functionalities to improve the way the situation is currently handled:

1. The first functionality is including the possibility to keep a specific spare part in stock, even though there is demand for it. Withholding a part for a likely upcoming arrival of another maintenance type with higher penalty cost, could have a positive effect on the total cost. Implementing this function in the model requires the input of several parameters regarding the likeliness of arrivals and the time period to withhold.
2. The second functionality is to include an expediting repair policy in the model. Implementing this policy has to make it possible to expedite a repair order based on the actual demand and likely arrival of demand for that part.

After these two functionalities are implemented in the model, its performance (to-be) needs to be tested by performing a case study for NedTrain and comparing the results to the current situation (as-is). Then, a plan for the use and implementation within NedTrain should be defined. These goals for this research can be presented as the following five research questions:

1. *How does withholding spare parts for upcoming maintenance operations affect the total cost?*
2. *How can an expediting repair policy that considers expected demand arrivals be used to improve the assignment of spare parts?*
3. *How can the mathematical model be transformed into a decision support tool for SCO to help them with the assignment of spare parts?*
4. *How does this model function within the closed-loop supply chain of NedTrain compared to the as-is situation?*
5. *How can a decision support tool to compute the assignment of spare parts and give repair orders be implemented for further use?*

2.2.1 Underlying Research Questions

In order to answer the main research questions, underlying sub-questions are composed. The number in front of the sub-question indicates to which main research question it is related.

1a. *How are spare parts currently assigned to the two demand streams?*
1b. *What are the cost of not having an item on stock for both ShCM and LCM?*
1c. *What should the inventory level, lead time for outstanding repairs and the minimal expected value of an upcoming demand of a higher priority be in order to withhold a specific spare part?*
1d. *How long should a part be withheld for an upcoming demand of a higher priority?*

2a. *How can the expediting repair policy in the repair shop be modelled?*
2b. *At what expected demand arrival should a repair order be expedited?*
2c. *How does the new expedited repair policy perform compared to the current expediting policy?*

3a. *How can the as-is situation of the planning of spare parts be modeled?*
3b. *Which costs can be used to compare the as-is situation to the to-be situation?*

3b. *What is the difference in total annual cost between the as-is situation and the to-be situation?*

4a. *What requirements does SCO have for the decision support tool?*

5a. *How could NedTrain benefit from implementing the decision support tool?*
5b. *What actions does NedTrain need to undertake to implement the decision support tool and what are the cost bound to these actions?*

2.2.2 Research deliverables

Discussions with all parties involved at NedTrain (SCO, NCB, workers at OB) led to the following deliverables for this research:

1. Mathematical model that incorporates both the assignment of spare parts in the OB to the two demand streams, and the scheduling of repairs at the repair shop
2. Decision Support Tool that can be used by SCO in their daily operations
3. Case study to test the performance of the Decision Support Tool
4. Implementation, validation and verification of the tool
5. User manual for Decision Support Tool

2.3 Scope

The timeframe in which this research has to be conducted is limited. It will need to focus on the key aspects of the problem and leave other aspects out of scope. Following is a discussion per aspect whether or not it should be inside the scope of this research. An overview of the scope is outlined in red in Figure 2.1.

Capacity
The warehouse at the NCB, to keep defect spare parts before their revision, is considered large enough by the NCB management. To date, the capacity of the warehouse has never been reached. For the inventories in the central warehouse and at the OBs, also ample capacity is assumed. We will also leave the repair capacity in the repair shop out of scope because the actual repair capacity is determined by many factors like workers, tools, and machines being available. We feel that this will not lead to large problems because during an active project, the respective spare parts have an increased priority at the NCB and get more resources devoted to their repairs.

Single-item vs multi-item
A train has thousands of different repairable spare parts that can break down. A model that integrates the failure patterns and repairs of these parts would be able to estimate quite precisely how long a train has to stay in the OB and what the inventory of all these parts should be. However, modelling all these interdependencies is very complex because of each part's variance and the correlations between parts. This research will focus at a project for a single spare part at a time. This makes for easier control over the inventory and repairs of this part.

Spare parts demand
In many NedTrain facilities, demand for specific spare parts arises. This research will only focus at the demand streams for spare parts at the 4 maintenance depots (OBs). The two demand streams

that arrive at these facilities are ShCM and LCM. NedTrain uses the term Extra BinnenKomst (EBK) for unplanned and unscheduled maintenance operations that arrive in the OBs. These arrivals are trains that need immediate maintenance due to sudden failures or defects. SCO does not use these EBKs very often because they are really expensive. It is also very difficult to predict when an EBK is needed, so we will leave these out of the scope altogether.

Spare parts supply

The situation will be modelled as a closed-loop supply chain; only parts that return from revision and inventories of spare parts are seen as sources of spare part supplies. An assumption is made that all parts that go into repair can be revised into RFU parts. The procurement of new spare parts is left out of scope.

Lead times

The time between the replacement of a spare part at the OB and it returning back at the OB from repair is called the repair lead time. The repair lead time is made up out of the time a part is in stock and in the buffer at the repair shop, the repair time of this item and the time it takes to transport the item to the different facilities. The model will work with a single repair lead time, including all activities mentioned above. Before a project starts, NCB and SCO usually make agreements regarding the length of this lead time. During the projects, NCB generally proves to fulfil these agreements quite well. So, we will assume that this lead time is constant, to be able to plan the arrival of parts from repair.

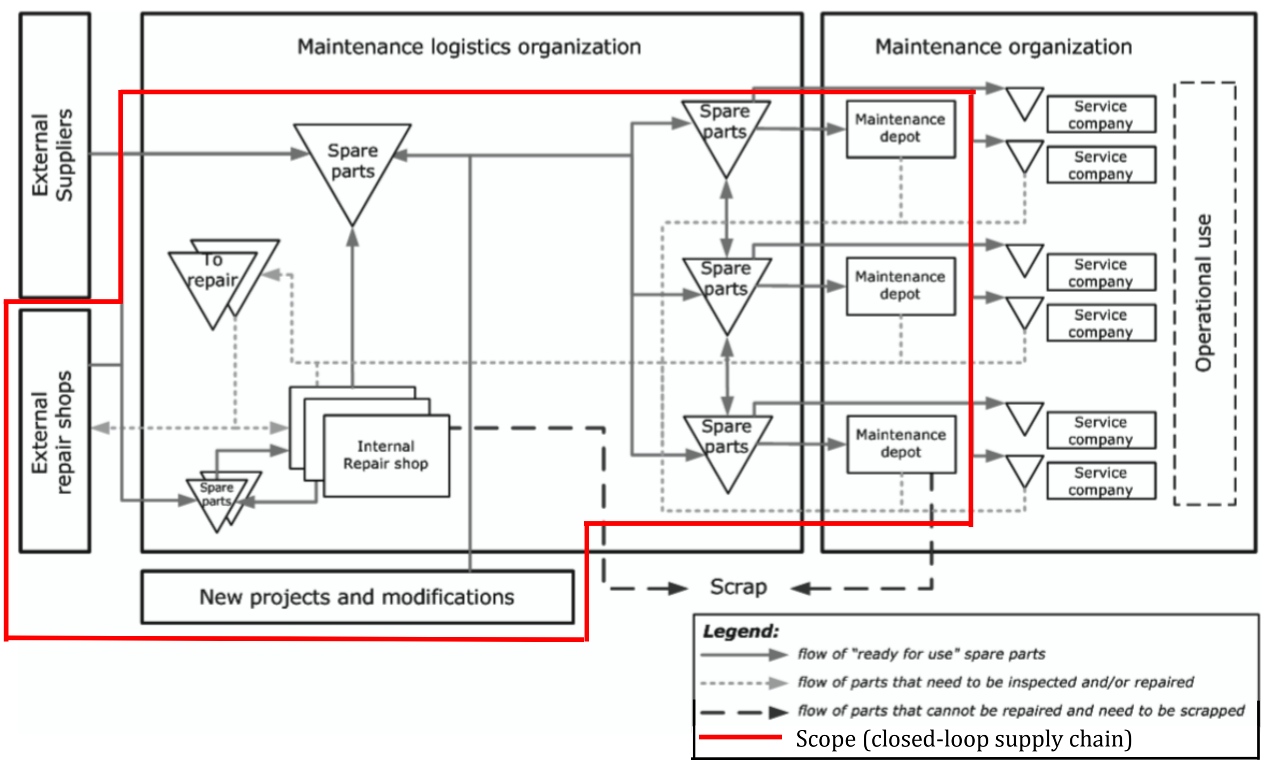

Figure 2.1: Process view of supply chain NedTrain (Arts and Driessen, 2011) (added scope)

3. Model for Planning of Spare Parts

3.1 Mathematical Models

The two main decisions that followed from discussions with management of SCO and NCB were the assignment of parts and expediting of parts that are in repair. The assignment of parts encompasses two elements: allocating the on-hand inventory to the demand that arrived from the two demand streams at the OB, and the decision to restrict part of the inventory to be allocated only to one of the two demand streams (rationing). Expediting the remaining time in repair for parts entails a two-step method: determining the number of spare parts wished to receive with all corresponding costs and the number of parts in repair considered, and determining which specific repair orders should be expedited to compound to the amount determined before. The ***MM0*** model overarches all the decisions and includes the entire planning of spare parts. However, the ***MM0*** model does not include all the calculations for each of the decisions. Three additional models are introduced to solve parts of the ***MM0*** model. Reasons for introducing these additional models were:

1. <u>Dependencies</u>: the calculations of a decision variable could require the input of another decision variable in the constraints or in the objective function. In our model, the expediting level has to be known before we can determine the repair orders that should be expedited. This can lead to complex models which could be very hard to solve.
2. <u>Timing</u>: not all decision variables are calculated at the same moment during the day. The expediting and rationing decisions are taken in the beginning of the working day whereas the assignment decisions are made later during the day when all demand is known. The timing of determining the values for all variables is further explained in section 3.3.
3. <u>Modular design</u>: for NedTrain it is of importance that it is possible to include or exclude some parts of the model at any time. This is mainly due to the fact that employees could resist implementing some of the policies or that policies which underperform in practice can be disabled.
4. <u>Solving method</u>: to determine the best value for each of the decision variables different methods have to be used. Methods range from performing some sort of dynamic programming to solving a MILP (Mixed Integer Linear Programming) problem.

The fact that deciding which repair orders to expedite requires the decision variable that determines the expediting level does not mean that it is unsolvable. It does, however, make determining the best values for both variables more complex. The number of possible outcomes when combined in one model is the product of the number of options for the expediting level and the respective number of combinations of repair orders. When these two decisions are separated, the number of calculations needed equals the number of options for the expediting level and once the number of combinations of repair orders for the chosen expediting level. We want to develop the model with the decision support tool in mind. Fewer calculations needed on average will generally lead to less computational time and thus faster output for the end-users of the tool.

The model is developed to assist the planners of SCO during their operations throughout a working day. The model has to supply them with the expediting and rationing information at the start of a working day (around 9:00AM) and assist them with the assignment decisions later that day (around 12:00PM), when the demand of that day is known. These decisions do not happen simultaneously. So, the calculations also happen at a different moment in time. Because of this, these calculations cannot be in the calculation module.

Although the rationing of inventory for unplanned demands that occur during ShCM seems like a logical policy to SCO because of the high corresponding backlog cost, they would like this policy to be optional in the model. The reasons behind this are further discussed in the implementation plan (section 5.4). Due to this, they want to be able to include or exclude this part of the model at any time. This requires the separation of the rationing calculations from the rest of the model.

Liu et al. (2015) state that in literature, dynamic inventory rationing problems are often addressed by applying dynamic programming. This can, however, be a critical challenge due to the curse of dimensionality. For both the rationing level and the expediting level, we developed an algorithm that uses some form of dynamic programming to evaluate how a certain level behaves over a given number of periods in the future. The fastest way to find the best combination of repair orders when we have determined the expediting level, is the transformation to a MILP problem. A MILP solver can be used to find the optimal value for these decision variables. The assignment of spare parts can be written as an MILP problem, but can also be translated to simple dynamics rules. This last option gives closed form expressions for the choice for both assignment decisions for the two possible scenarios.

The issues taken in consideration for deciding to introduce an additional model are summarized in Table 3.1.

Table 3.1: Reasons to create a separate model versus each of the decision variables

	Dependencies	Timing	Modular design	Solving method
Assignment of spare parts to the two demand streams	-	12:00PM	Always included	Dynamics rules
Determining rationing level	-	9:00AM	Optional	Dynamic programming
Determining expediting level	-	9:00AM	Always included	Dynamic programming
Determining the repair orders to expedite	Includes the expediting level	9:00AM	Always included	MILP

Based on the factors summarized in Table 3.1, we conclude that these four calculations need to be in an own calculation model. Figure 3.1 gives an overview of all different processes that lead to the combined planning of spare parts for the two demand streams in the OB. Each of the four models and their underlying processes are explained in this chapter.

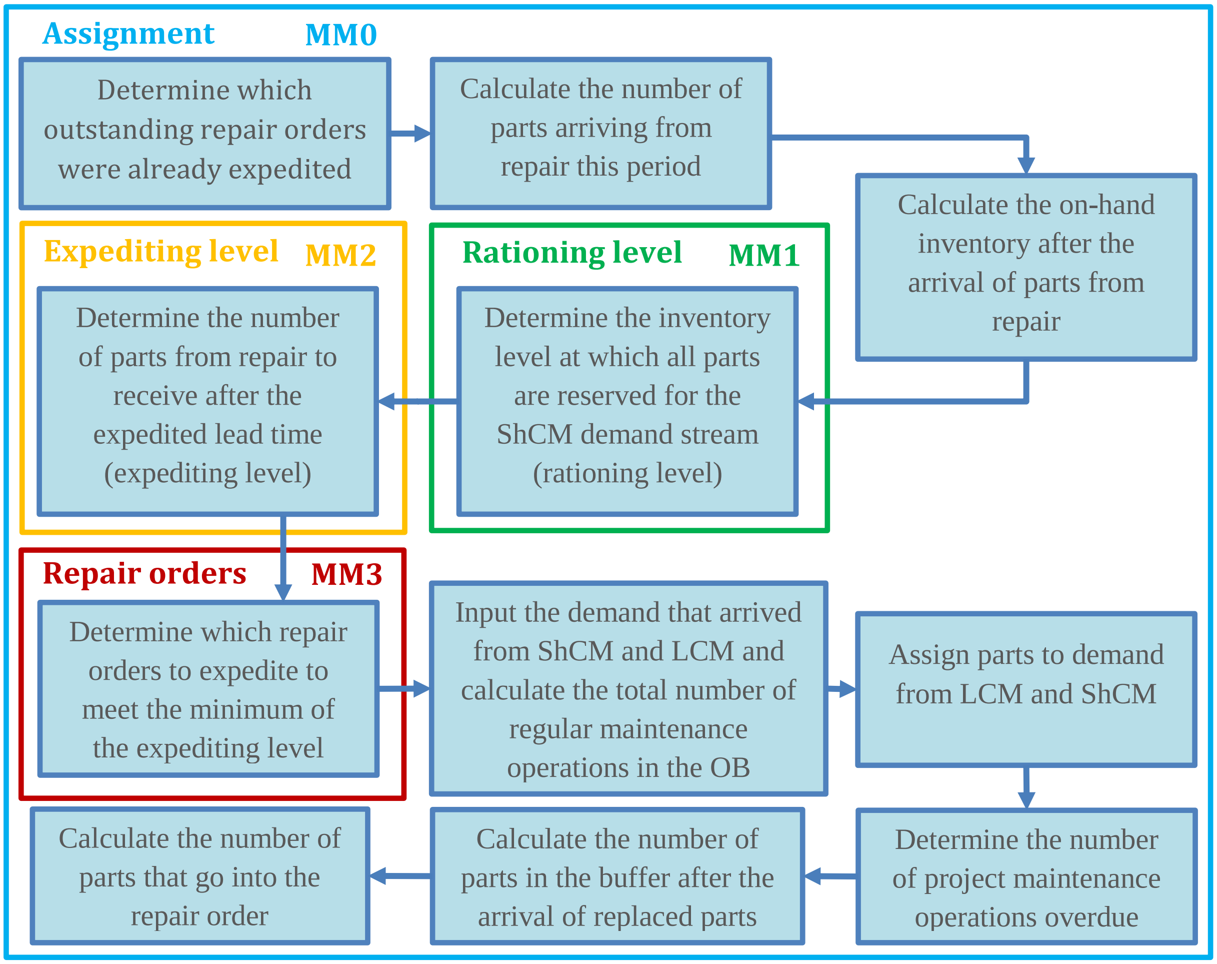

Figure 3.1: Processes for the planning of spare parts and the division of the four models

3.2 Model Variables

Decision variables

Notation	Variable description
$E_{i,t}$	Decision to expedite an outstanding repair order in period t that was supposed to arrive in period t+i and will now arrive in period t+Y with i≥Y
I_t^R	Rationing level for ShCM (when on-hand inventory is equal to or lower than the rationing level, the remaining inventory can only be used to satisfy demand from ShCM)
P_t	Number of parts assigned to a project maintenance operation in period t
R_t	Number of parts assigned to a regular maintenance operation in period t
X_t	Expediting level (minimal feasible number of spare parts required to receive in period t+Y with respect to all corresponding costs)

Variables

Notation	Variable description
$\mu_{dp,t}$	Mean of project demand for period t
μ_{dr}	Mean of regular demand for periods 1 to T
$\sigma_{dp,t}$	Standard deviation of project maintenance demand for period t
σ_{dr}	Standard deviation of regular maintenance demand for periods 1 to T
$A_{i,t}$	0 when the order initially arriving i periods from period t has already been expedited, 1

	otherwise
B_t	Number of parts in the buffer at the repair shop after receiving the replaced parts at the end of period t
$c_{E,i}$	Additional repair cost per part of expediting a repair that was supposed to arrive i periods from now
c_{DP}	Cost of delaying a LCM operation as a result of not assigning a spare part
c_{DR}	Cost of delaying a ShCM operation as a result of not assigning a spare part
c_P	Cost per period for unperformed maintenance outside project interval
c_R	Cost of a regular repair
c_U	Cost per period for unavailability of a train
D_t^P	Demand for spare parts for project maintenance that arrives in period t
D_t^R	Demand for spare parts for regular maintenance that arrives in period t
$D_{t,t}^{P*}$	Generated project demand in period t for period t consisting of a drawn value for the demand and the project demand delayed in $t-V$
$D_{t,t}^{R*}$	Generated regular demand in period t for period t consisting of a drawn value for the demand and the non-critical regular demand delayed in $t-V$
d_t^P	Random drawn value for the demand for project maintenance in t, estimated in t based on $\mu_{dp,t}$ and σ_{dp} and the project demand delayed in $t-V$
d_t^R	Random drawn value for the demand for project maintenance in t, estimated in t based on μ_{dr} and σ_{dr} and the non-critical regular demand delayed in $t-V$
F	Batch size for repairs at the repair shop
I_t	Inventory on hand at the beginning of period t after receiving the parts from repair and subtracting the number of parts assigned in period $t-1$
K	1 when part is critical and train cannot leave OB without replacement, 0 otherwise
L	Lead time of a defect product returning as a RFU under regular repair
M_t^R	Regular maintenance operations currently waiting in the OB after the arrival of regular demand in period t
N	number of periods after which it is possible to expedite an outstanding repair order
O_t	number of unfinished project maintenance operations after assigning parts to project maintenance in period t
PB	Period when the project begins
PE	Period when the project ends
Q_t^A	Number of parts arriving from repair at the start of period t
Q_t^D	Number of defective parts sent to repair at the end period t after determining B_t
Q_t^E	Number of parts in repair that can be expedited in period t
Q_t^T	Number of parts still in repair after the arrival of parts from repair at the beginning of period t
S	Total number of spare parts in the closed-loop supply chain
t^*	Tipping point of the assignment priority: period in which LCM receives the highest priority in the assignment of spare parts to maintenance operations
$TC(t)$	Total cost for the planning of spare parts in period t
$TC_D(t)$	Total cost of delaying maintenance operations in period t
$TC_P(t)$	Expected penalty cost for all delayed project maintenance in period t
$TC_R(t)$	Total cost for repairs in period t
$TC_U(t)$	Total cost for unavailability of trains in operation in period t
TP	Total maintenance operations in the project
V	Number of periods between two visits to the OB for a given expectation
Y	Expedited repair lead time, with $Y < L$

3.3 Sequence of Determining Values

The sequence of determining the values for all variables in the model is shown in Figure 3.2. A process view of determining the values for these variables can be found in *Appendix I*. The numbers in this section refer to the order and the numbers in the figure.

9:00AM

Every day starts with checking which repair orders already have been expedited (1). After the parts from repair have arrived (2), the on-hand inventory (3) at the OB is calculated. When the parts from repair have arrived, the total number of parts still in repair is calculated (4). The number of spare parts rationed (5) has to be calculated before the minimum number of spare parts that have to be ordered (6) can be determined. When this number is known, the model has to calculate which repair orders to expedite (7).

12:00PM

The trains that have arrived last night and those still in the OB are inspected. From these inspections, demand for regular maintenance can arrive (8). Also, maintenance workers can check whether the trains in the OB still need to undergo LCM (8). The number of regular maintenance operations in the OB (9) can be calculated when the demand for regular maintenance is known. The assignment of spare parts to both demand streams (10) happens after this. After it is known how many parts were assigned to project maintenance, the number of project operations overdue (11) can be determined.

At the end of the day, all replaced parts are sent to the repair shop and are added to the buffer (12), before they go into repair. From this buffer, defect parts go into a repair order in a multiple of the batch size for repairs (13).

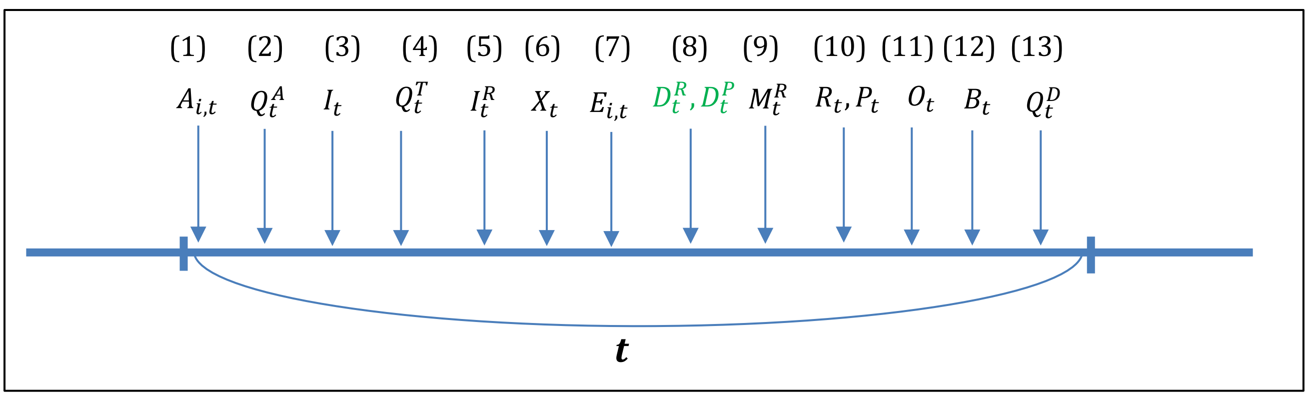

Figure 3.2: Order of determining variables (green variables: manual input)

3.4 MM0: Assignment

Assumptions

Some assumptions are presented to outline the scope and make simplifications in the model possible. Because the mathematical model created in this research will be converted into a decision support tool for operational use, these assumptions were formulated while keeping practice in mind.

1. **Project maintenance operations for a specific spare part are conducted in a single OB**
Because all 4 OBs are specialized in specific types of trains and maintenance operations, most of the projects take place in a specific OB. The exceptions to this will not be covered in the model because adding OBs brings the extra problem of allocating repaired parts to these OBs.
2. **When a spare part is assigned to a maintenance operation, there are always sufficient of the other required resources available to perform this maintenance**
The model would become too complex if the availability of human resources and tools have to be incorporated.
3. **At the starting date of a project, all spare parts within the closed-loop supply chain are RFU and in the inventory at the OB**
It is always the goal of SCO to have all spare parts repaired and in the local stock at the OB at the start of a project because of the increased demand during the project. When projects are planned well ahead of time, this requirement should be realizable.
4. **There is a maximum of one unplanned demand per train in a given period t**
The demand for spare parts from ShCM is equal to the number of trains that need corrective maintenance. We need this assumption for our unavailability cost calculations.
5. **The repair shop will send the maximum number of parts from the buffer in repair every period while taking batch size into account**
During the project period, the demand for the respective part is much higher than usual. To ensure enough inventory in the OB, replaced parts have to be sent to repair and be returned as RFU parts as quickly as possible. This comes down to maximum possible repairs per period.
6. **The repair shop can always revise defect parts into ready-for-use (RFU) parts (no condemnation)**
*The actual scrap rates at NedTrain's repair shop were around 3% in 2012 (*Table 0.1 *in Appendix B), so they are able to revise most parts that come in for repair. This assumption is vital for the next assumption. The number of parts has to stay constant and procurement of new parts is out of this project's scope.*
7. **The number of spare parts within this closed-loop supply chain is given and constant**
When new train series are acquired, NedTrain will procure an initial set of all spare parts needed for future maintenance. For most types of spare parts, this initial set is used for the maintenance over the complete lifetime of the series i.e. there are no other procurement moments.
8. **Repair lead time of a defect part at the repair shop is constant**
Each spare part type has a predetermined repair lead time which can be reached in practice if the repair shop holds the agreements made with SCO.
9. **The total demand for both demand streams for a day is known at some point during that day, after which there is still enough time left to perform the maintenance operations that day**
Trains arrive in the OBs at night, so inspections and other checks can start immediately in the morning. The total demand for each of the demand streams is known around noon, when there is still enough time left to execute the maintenance operations to which a part is assigned.

10. **Long Cycle Maintenance operations are always preventive during the duration of the project (even if once delayed), i.e. the parts that need replacement have not yet failed**
    The intention of performing LCM is to replace the respective parts before they fail. This assumption makes the distinction between LCM and ShCM (when parts are defect) clear and makes it possible to delay LCM.
11. **No extra visits (EBK's) take place for project maintenance**
    In some cases, SCO has to plan an extra visit to the OB to be able to perform the project maintenance before the project end date. According to Koen Dekkers, these extra visits are really expensive, so SCO uses these very infrequently. Because these happen so infrequently and are very hard to forecast, these will be left out of scope.
12. **The rationing of inventory is only used for the ShCM demand stream**
    The project end date is considered more a soft deadline than a hard deadline. When the assignment priority switches to LCM, all project maintenance operations are first in line to ensure that all project maintenance operations will be finished before this project end date. But because it is a soft deadline we want to prevent unnecessary unavailability of trains that need parts for ShCM and not use rationing for LCM.
13. **Number of periods after which an expedited order arrives is constant**
    If SCO makes a phone call to request the expedition of a repair order, these parts will arrive Y period later. When SCO and the repair shop make clear agreements, this is a realistic assumption according to the SCO management.
14. **Only a complete outstanding repair order can be expedited (not partial)**
    This assumption simplifies the expediting calculations and does not differ much from the current situation if a period t is equal to one working day (repair orders will not be very large).

Introduction

The ***MM0*** model includes the start and the ending of the planning of spare parts for the two demand streams at the OB. The start includes the calculation of the on-hand inventory at the OB at the start of the working day. Then, the priority of the two demand streams is determined by comparing the backlog costs of the two streams. When the ***MM1, MM2*** and ***MM3*** models have respectively determined the rationing level, expediting level and which repair orders to expedite, the ***MM0*** model requires the input of the total demand for both demand streams. This is known around noon on every working day. Following is the assignment of spare parts from the on-hand inventory to the two demand streams and the calculation of the number of replaced parts that go into the repair order sent to the repair shop. We assume that there still is enough time left after the assignment to perform the maintenance operations. The difference between the number of replaced parts and the size of the repair order goes into the buffer at the repair shop.

Model description

A single-item deterministic model is created for the operational planning of spare parts that incur demand from two demand streams: Short Cycle Maintenance (ShCM) and Long Cycle Maintenance (LCM). This planning includes the assignment of spare parts to these two demand streams and the control over the repair shop, as can be seen in *Figure 3.3*.

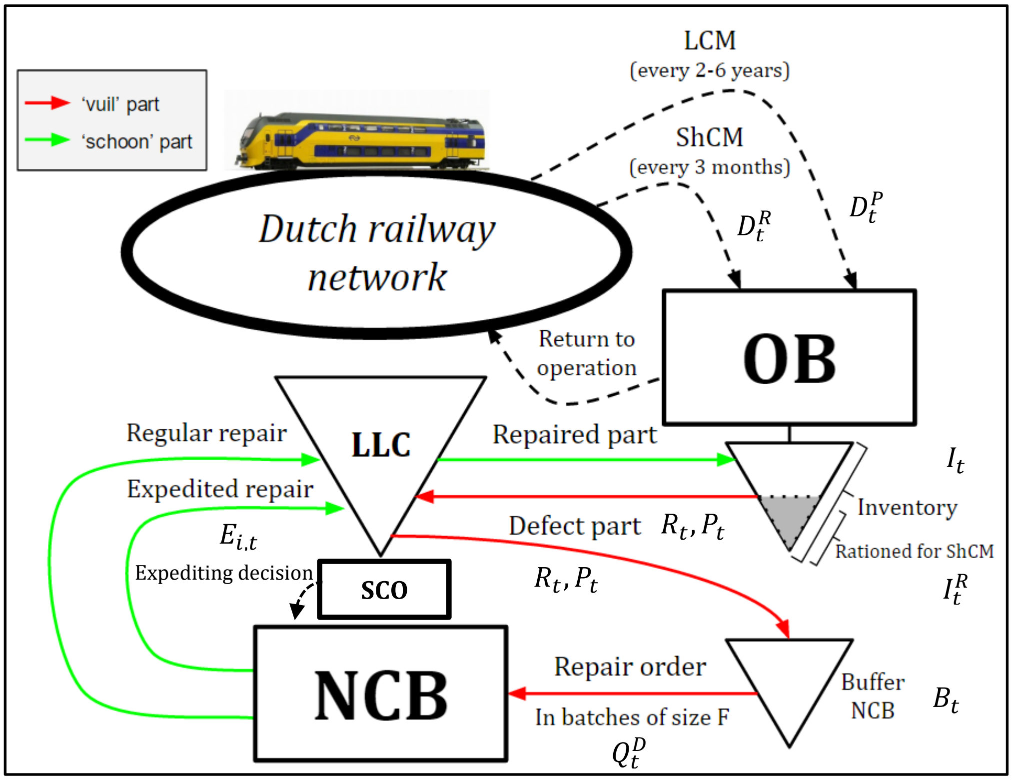

Figure 3.3: Spare part planning for two demand streams

The objective of the model is the minimization of the average total cost per period with a rolling horizon of $[t, t + t']$, with $t' \in \{0,1, \dots, \tau\}$ being the additional period on top of current period t and τ being the planning horizon of SCO [1]. The ***MM0*** model has a finite horizon of T, with T being the period in which all project maintenance operations are finished. This model will help SCO planners at NedTrain with their decisions regarding the planning of spare parts. Because this planning is part of their daily routine, one period is equal to one working day. The total cost consists of four components [2]:

- Repair cost (TC_R) [17]: all costs related to the repair of spare parts in the repair shops, including a normal repair cost for all repairs and incremental cost for every spare part that is expedited
- Unavailability cost (TC_U) [8]: cost incurred per period for a ShCM operation (if part is denoted as critical for operation) that does not get a part assigned and has to stay one or more extra days in the OB and will be unavailable for the transport of passengers
- Delaying maintenance cost (TC_D) [9]: cost incurred for LCM and ShCM (if part is denoted as non-critical for operation) that does not get a part assigned and has to be delayed
- Unfinished project maintenance outside the project interval cost (TC_P) [12]: penalty cost for all delayed project maintenance operations that are expected to return after the project end date (penalty cost incurred per day outside the project interval)

$$\min \frac{1}{\tau+1} \sum_{t'=0}^{\tau} TC(t+t') \qquad [1]$$

$$TC(t) = TC_R(t) + TC_U(t) + TC_D(t) + TC_P(t) \qquad [2]$$

The trains that come in for ShCM and LCM arrive at night at the OBs. Inspections can begin immediately every morning when maintenance workers come in for work. We assume that the total demand for both demand streams for a day is known at some point during that day, after which there is still enough time left to perform the maintenance operations.

Trains come in for ShCM approximately once every 3 months. During ShCM, several parts of the train are inspected. If they fail one of these inspections, meaning a part does not meet the requirements, the corresponding part has to be replaced. Demand for parts encountered during these inspections is called regular demand (D_t^R). The model considers one type of spare part at a time because it will be used for the planning of separate projects. A specific spare part can be defined as critical ($K = 1$) or non-critical ($K = 0$). A train has to stay in the OB and is not available for operation when a spare part which is defined as critical cannot be assigned to the regular demand stream. This means that the total demand from regular maintenance currently in the OB (M_t^R) in period t is [3]:

- For critical part ($K = 1$): regular demand in the OB after the arrival of regular demand in period $t-1$ minus the parts assigned to regular demand in period $t-1$ (R_{t-1}) plus the regular demand that arrived in period t
- For non-critical part ($K = 0$): regular demand that arrived in period t

$$M_t^R = (D_t^R + (M_{t-1}^R - R_{t-1}))K + D_t^R(1-K) \qquad [3]$$

Demand for the same spare part can also arise from LCM, which occurs every 2-6 years. In the case of LCM, a part is preventively replaced and has not failed yet. Because these maintenance operations are performed in large projects for multiple trains at once, its demand for spare parts is referred to as project demand (D_t^P).

We refer to a maintenance operation as the replacement of a single part. When a spare part is assigned to a maintenance operation, it replaces a part in the train. We use R_t to denote the number of parts assigned to regular maintenance (ShCM) in period t and P_t to project maintenance (LCM) in period t. Both R_t and P_t cannot be larger than the total demand for the respective demand streams [4 & 5]. The total number of parts in the buffer in period t after the replaced parts are sent to the repair shop (B_t) is equal to the total number of parts that were in the buffer at the end of period $t-1$ plus the total number of replaced parts in period t [6]. From this buffer, parts go into repair orders in a maximum multiple of the predetermined batch size (F) adding up to the total number of parts in the repair order Q_t^D [7].

$$R_t \leq M_t^R \qquad [4]$$

$$P_t \leq D_t^P \qquad [5]$$

$$B_t = B_{t-1} - Q_{t-1}^D + P_t + R_t \qquad [6]$$

$$Q_t^D = \left\lfloor \frac{B_t}{F} \right\rfloor F \qquad [7]$$

Periodic backlog costs for unavailability (c_U) are incurred for every period where no part is assigned to the regular demand stream [8]. These costs are based on an internal penalty structure within NedTrain and are different for each train series because of the different passenger capacities. When a spare part is defined as non-critical, regular maintenance can be delayed at a certain cost for delaying (c_{DR}). Delaying a maintenance operation means that the demand will be considered again during the train's next visit to the OB. The number of periods between two visits of a train to the OB based on a given expectation is defined as V. When a maintenance operation is delayed, the period V is used to improve the forecasts of demand in period $t + V$. The updated forecast is used to try to ensure that enough spare parts are in inventory when the delayed maintenance operation returns to the OB. Which value to choose for V is discussed in *Appendix K.* We assume that project maintenance is always preventive and that the parts in question have not yet failed. This means that LCM can always be delayed at a certain cost per delay (c_{DP}). These costs are based on the time it takes a maintenance engineer to fill out an approval form for the delaying of this maintenance operation and releasing the train from the OB. The total cost for delaying maintenance is the sum of the regular maintenance delay cost and the project maintenance delay cost [9].

$$TC_U(t) = (M_t^R - R_t)Kc_U \qquad [8]$$

$$TC_D(t) = (D_t^P - P_t)c_{DP} + (1 - K)(D_t^R - R_t)c_{DR} \qquad [9]$$

Projects have a begin date (PB), an end date (PE), and a total number of maintenance operations to perform (TP). Project maintenance operations which are not finished after the end date will incur overdue penalty cost per period per part not assigned (c_P). These penalty cost have to prevent that projects will be delayed endlessly. To increase punishment for projects the more they exceed the project deadline, the project penalty cost is incurred for every period it is expected to exceed this deadline. The total expected penalty cost in period t for delayed projects equals the product of the expected number of periods overdue when the delayed project maintenance returns, the number of project maintenance operations that do not get parts assigned in period t, and the penalty cost per day for performing the project outside the project interval [10].

$$TC_P(t) = \max(0, (t + V) - PE)(D_t^P - P_t)c_P \qquad [10]$$

The normal repair of a spare part has a cost per part (c_R) and a constant repair lead time (L). To make sure the OB receives enough parts from the repair shop, the possibility to expedite outstanding repair orders can be used. From the expediting policy Chiang (2010) proposes, we derived a customized policy for NedTrain's situation. The idea of splitting the lead-time into two segments, one with the possibility to expedite orders and one without, seems similar to our situation. Part of the repair lead-times are due to transport and time spent in different warehouses. When the part has not yet entered the repair process, it is not possible to expedite it. We will denote the number of periods after which expediting is possible with N. Contrary to Chiang (2010), we have multiple expediting moments instead of just one after N. The cost of expediting an order that is supposed to arrive i periods from now is given by $c_{E,i}$, with $c_{E,i} < c_{E,i+1}$, and $L - N \geq i \geq Y$, where Y is the number of periods after which an expedited repair order arrive [14]. We will also consider it to be expediting when an order that is supposed to arrive in Y periods according to its normal repair schedule is used to satisfy the amount of parts required to receive in period $t+Y$. There is, however, no incremental cost for the expedition of this order [15]. To prevent repair orders that already have been expedited being expedited again we introduce $A_{i,t}$, with i being the time from t after which the repair order was supposed to arrive without expediting. This binary variable checks the repair order's corresponding historic expediting decisions and gives the output 0 if it was already expedited [11]. An order that was sent to repair in $t-1$ and is supposed to arrive in $L-1$ periods from period t may not yet have been expedited [12]. To calculate the maximum number of parts that can be expedited in period t (Q_t^E), we have to take the sum of all the repair orders in the interval $[t+Y, t+L-N-1]$ that have not been expedited yet [13].

$$A_{i,t} = \begin{cases} 0, & \sum_{j=i}^{L-2} E_{j+1,t+i-j-1} = 1 \\ 1, & otherwise \end{cases} \qquad i \in \{0,1,\dots,L-2\} \tag{11}$$

$$A_{L-1,t} = 1 \tag{12}$$

$$Q_t^E = \sum_{i=Y}^{L-N-1} A_{i,t}\, Q_{t-L+i}^D \tag{13}$$

$$c_{E,Y} < c_{E,Y+1} < \cdots < c_{E,L-N} \tag{14}$$

$$c_{E,Y} = 0 \tag{15}$$

Every period, the minimum feasible number of spare parts expected to receive in period $t+Y$ (X_t) based on forecasts, is determined by ***MM2***. This model determines the best value for X_t by minimizing the corresponding backlog and expediting cost while considering the number of parts arriving from repair in the upcoming periods and the expected upcoming demand. The value for X_t is always feasible because it has an upper-bound of the maximum number of parts that can be expedited in period t (Q_t^E). When the value for X_t is determined, the repair orders that are expedited are calculated by ***MM3***. The binary decision (1=YES, 0=NO) of the model to expedite the repair order that is arriving i periods according to its normal repair schedule is presented by $E_{i,t}$ [16]. The total cost for repairs in period t includes the normal repair cost for all parts sent to repair in period t plus an incremental expediting cost for all parts of the expedited repair order [17].

$$E_{i,t} \in \{0,1\} \tag{16}$$

$$TC_R(t) = Q_t^D c_R + \sum_{i=Y}^{L-N-1} E_{i,t}\, A_{i,t} c_{E,i} Q_{t-L+i}^D \tag{17}$$

Using the expediting decisions made in the periods previous to t, the number of spare parts that arrive at the start of period t (Q_t^A) can be calculated. The number of spare parts that arrive in period t is equal to the product of all expediting decisions in period $t-Y$ and their respective repair orders plus the product of the repair order that was sent to repair in period $t-L$ and $A_{0,t}$ [18]. Then, the on-hand inventory at the start of period t is calculated. This is equal to the on-hand inventory in period $t-1$ minus the parts that were assigned to ShCM and LCM in period $t-1$ and the parts that arrive from repair in period t [19]. The sum of the parts that are assigned to ShCM and LCM in period t has to be smaller than or equal to the on-hand inventory in period t [20]. When the parts from repair have arrived and the on-hand inventory in period t is calculated, we can calculate the total number of parts that are still in repair (Q_t^T). We calculate Q_t^T by subtracting the on-hand inventory in period t and the number of parts currently in the buffer from the constant number of parts in the closed-loop supply chain (S) [21]. Equation [21] is used in the validation of the model in *Appendix N*.

$$Q_t^A = \sum_{i=Y}^{L-N-1} E_{i,t-Y}\, Q_{t-Y-L+i}^D + A_{0,t} Q_{t-L}^D \qquad [18]$$

$$I_t = I_{t-1} - R_{t-1} - P_{t-1} + Q_t^A \qquad [19]$$

$$R_t + P_t \leq I_t \qquad [20]$$

$$Q_t^T = S - I_t - (B_{t-1} - Q_{t-1}^D) \qquad [21]$$

To ensure enough inventory for unplanned demand until the arrival of the expedited orders Y periods later, we use the idea of a rationing level as proposed by Dekker et al. (1998) and Liu et al. (2015). When the on-hand inventory is equal to or below the rationing level, the remaining parts in inventory can only be used to satisfy ShCM demand. We choose to do this only for ShCM because of the higher backlog cost throughout the largest part of most projects and because the project end date (PE) is rather a soft deadline than a hard deadline. In ***MM1*** this will be further explained. The difference with the suggested policies in literature is the replenishment of new parts. Both the policies of Dekker et al. (1998) and Liu et al. (2015) assume unlimited order quantities, whereas our model has the supply limitations of a closed-loop supply chain. In our situation, however, we know exactly how many orders arrive from repair in every period, $Y-1$ periods in the future. The inventory level rationed for ShCM demand (I_t^R) is determined by ***MM1*** and depends on the expected upcoming demand for both demand streams and the incoming spare parts from repair.

We refer to the sequence in which the demand from ShCM and LCM is satisfied as the assignment priority. The assignment priority is based on the backlog cost for the two demand streams. So, this priority can change during a project and can be considered a dynamic priority. We define the tipping point in time of the dynamic priority as t^*. This tipping point can be found with the following inequality: $c_{DP} + (t^* + V - PE)c_P > c_U$. At the start of a project ($t \leq t^*$), ShCM has a higher priority and is considered first when assigning spare parts [22a,23a]. When the delay cost for project demand plus the expected penalty cost for the project being overdue outweighs the unavailability cost of ShCM ($t > t^*$), LCM has the highest priority [22b,23b].

$\boldsymbol{c_U \geq c_{DP} + \max(0, (t+V) - PE)\, c_P}$		$\boldsymbol{c_U < c_{DP} + \max(0, (t+V) - PE)\, c_P}$	
$R_t = \min(I_t, M_t^R)$	[22a]	$P_t = \min(I_t, D_t^P)$	[22b]
$P_t = \min(\min(I_t - R_t, \max(0, I_t - I_t^R - R_t)), D_t^P)$	[23b]	$R_t = \min(I_t - P_t, M_t^R)$	[23b]

The variables for the rationing level, number of parts in the buffer, parts assigned to regular and project maintenance, and the number of projects maintenance overdue have to be integers [25] and cannot be negative [24]. We start every project with all parts which are in the closed-loop supply chain in the inventory at the OB [26]. This also means that there were no parts sent to repair [26], no demand left in the OB [28], no parts in the buffer [29], and no parts in the repair process [30] previous to the start.

$$I^R, B_t, X_t, R_t, P_t, O_t \geq 0 \qquad [24]$$

[25]

$$I^R, B_t, X_t, R_t, P_t, O_t \in \mathbb{Z} \qquad [25]$$

$$Q_0^D = 0 \qquad [26]$$

$$I_0 = S \qquad [27]$$

$$M_0^R = 0 \qquad [28]$$

$$B_0 = 0 \qquad [29]$$

$$Q_0^T = 0 \qquad [30]$$

Model equations

This section includes the equations that add up to the MM0 model. The objective function of the model is displayed first, followed by the 'subject to' (s.t.) equations. A description of all these numbered equations can be found in *Appendix A*.

Objective function:

$$\min \frac{1}{\tau+1} \sum_{t'=0}^{\tau} TC(t+t') \qquad [1]$$

$$TC(t) = TC_R(t) + TC_U(t) + TC_D(t) + TC_P(t) \qquad [2]$$

$$TC_R(t) = Q_t^D c_R + \sum_{i=Y}^{L-N-1} E_{i,t} A_{i,t} c_{E,i} Q_{t-L+i}^D \qquad [21]$$

$$TC_U(t) = (M_t^R - R_t) K c_U \qquad [8]$$

$$TC_D(t) = (D_t^P - P_t) c_{DP} + (1-K)(D_t^R - R_t) c_{DR} \qquad [9]$$

$$TC_P(t) = \max(0, (t+V) - PE)(D_t^P - P_t) c_P \qquad [10]$$

Decision variables:

$$P_t, R_t$$

Constraints:

$$R_t \le M_t^R \qquad [4]$$

$$P_t \le D_t^P \qquad [5]$$

$$R_t + P_t \le I_t \qquad [20]$$

$$E_{i,t} \in \{0,1\} \qquad [16]$$

$$I_t^R, B_t, X_t, R_t, P_t, O_t \ge 0 \qquad [24]$$

$$I_t^R, B_t, X_t, R_t, P_t, O_t \in \mathbb{Z} \qquad [25]$$

Dynamics:

$\boldsymbol{c_U \ge c_{DP} + \max(0, (t+V) - PE)\, c_P}$	$\boldsymbol{c_U < c_{DP} + \max(0, (t+V) - PE)\, c_P}$
$R_t = \min(I_t, M_t^R)$ [22a] $P_t = \min(\min(I_t - R_t, \max(0, I_t - I_t^R - R_t)), D_t^P)$ [23b]	$P_t = \min(I_t, D_t^P)$ [22b] $R_t = \min(I_t - P_t, M_t^R)$ [23b]

$$B_t = B_{t-1} - Q_{t-1}^D + P_t + R_t \qquad [6]$$

$$Q_t^D = \left\lfloor \frac{B_t}{F} \right\rfloor F \qquad [7]$$

$$Q_t^A = \sum_{i=Y}^{L-N-1} E_{i,t-Y}\, Q_{t-Y-L+i}^D + A_{0,t} Q_{t-L}^D \qquad [18]$$

$$Q_t^E = \sum_{i=Y}^{L-N-1} A_{i,t}\, Q_{t-L+i}^D \qquad [13]$$

$$Q_t^T = S - I_t - B_{t-1} + Q_{t-1}^D \qquad [21]$$

$$I_t = I_{t-1} - R_{t-1} - P_{t-1} + Q_t^A \qquad [19]$$

$$M_t^R = (D_t^R + (M_{t-1}^R - R_{t-1}))K + D_t^R(1-K) \qquad [3]$$

$$A_{i,t} = \begin{cases} 0, & \sum_{j=i}^{L-2} E_{j+1,t+i-j-1} = 1 \\ 1, & otherwise \end{cases} \qquad i \in \{0,1,\dots,L-2\} \qquad [11]$$

$$A_{L-1,t} = 1 \qquad [12]$$

$$c_{E,Y} < c_{E,Y+1} < \cdots < c_{E,L-N} \qquad [14]$$

$$c_{E,Y} = 0 \qquad [17]$$

$$Q_0^D = 0 \qquad [28]$$

$$I_0 = S \qquad [27]$$

$$M_0^R = 0 \qquad [28]$$

$$B_0 = 0 \qquad [29]$$

$$Q_0^T = 0 \qquad [30]$$

3.5 MM1: Rationing level

Introduction

In sections 3.5 and 3.6, a stepwise approach is presented to determine which values we should use for the decisions I_t^R (***MM1***) and X_t (***MM2***). The choice for both variables depends on the expected upcoming demand. The future demand for both demand streams is stochastic, so we will generate daily demand for ShCM ($D_{t,t}^{R*}$) and LCM ($D_{t,t}^{P*}$) to create demand patterns for the given intervals over which the calculations are performed. The generated demand consists of two elements: drawn values for either ShCM (d_t^R) or LCM (d_t^P) based on their respective mean and standard deviation $(\mu_{dr}, \sigma_{dr}, \mu_{dp,t}, \sigma_{dp,t})$, and the returning projects that were delayed in period $t-V$ [31,32]. The intervals for both algorithms are shown in Figure 3.4 and will be further explained in the next section. The mean of LCM ($\mu_{dp,t}$) depends on the number of project maintenance operations that remain to be done and the time that remains until the end of the project [33].

$$D_{t,t}^{R*} = d_t^R + (1-K)(D_{t-V}^R - R_{t-V}) \qquad [31]$$

$$D_{t,t}^{P*} = d_t^P + (D_{t-V}^P - P_{t-V}) \qquad [32]$$

$$\mu_{dp,t} = \frac{TP - \sum_{t\prime=PB}^{t} P_{t\prime}}{PE - t} \qquad \forall t, t \geq PB \qquad [33]$$

Because we do not want to rely on a single generated demand pattern for our calculations, we consider multiple patterns for both demand streams. We refer to the number of demand patterns and their corresponding calculations as the number of iterations of the algorithm (n). The number of iterations that should be chosen is discussed in *Appendix L*. The algorithm makes assignment decisions for every iteration over the length of the interval and based on the respective demand pattern. These assignment decisions are based on the same cost functions as presented in the model and are based on equations [22a,22b,23a,23b]. Note that when parts are assigned in the algorithms, new repair orders are also created in the simulation, based on the number of parts replaced and the batch size. Following is a description of the two algorithms. A schematic overview of the two algorithms can be found in *Appendix E*.

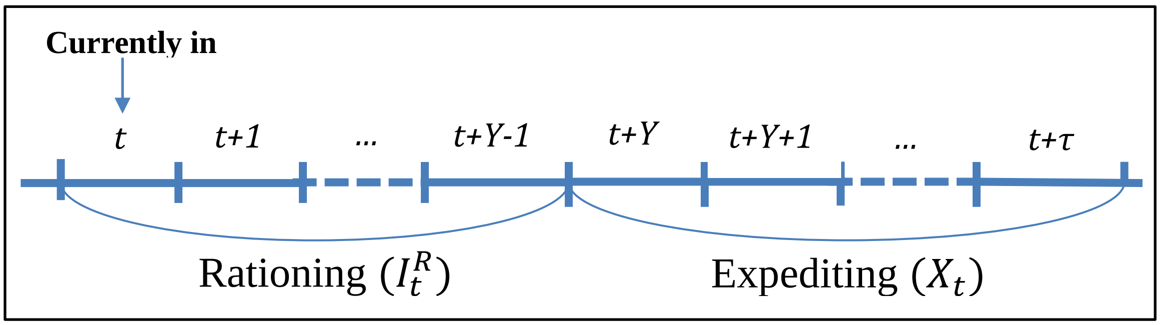

Figure 3.4: Periods considered in the calculations of I_t^R and X_t

Model description

Algorithm 1 is used to determine the inventory level at or below which only demand from ShCM can be satisfied, based on the difference in backlog cost for ShCM and LCM. We refer to this as the rationing level (I_t^R). The rationing level has an upper-bound of the total number of parts in the closed-loop supply chain (S). In general, an increased rationing level leads to satisfying more ShCM demand and less LCM demand. To compare the different rationing levels in this algorithm, we use an average cost per period function, based on the service levels of both demand streams. These service levels are similar to fill rates (percentage of demand satisfied from on-hand inventory). The difference is that both delayed demand that returns to the OB and ShCM demand that is still in the OB the next period, is considered a demand arrival. Increasing the rationing level will not only lead to a shift in service levels of the two demand streams, it will generally also lead to satisfying less demand overall. This is due to the fact that there is no guarantee that the expected ShCM demand for which is rationed will actually arrive, but there is a guarantee that when the on-hand inventory is below the rationing level, all LCM demand will be delayed. For this reason, we mainly want to rely on the expediting of repairs to handle demand fluctuations and only use rationing when really needed. This means that we only consider all periods up to and excluding the arrival of the expedited orders in period t. This gives us the interval $[t, t + Y - 1]$ for **Algorithm 1**. The algorithm assumes that I_t^R is the same over the interval $[t, t + Y - 1]$.

We use the variable M_t^{R*} in the algorithms to denote the number of ShCM maintenance in the OB in period t based on the generated demand and the assignment decision in period *t-1* [34]. When **Algorithm 1** has made the assignment decisions for $[t, t + Y - 1]$ in every iteration, the service level for ShCM (α_i) [35] and LCM (β_i) [36] per iteration can be calculated. The final service level that is used in the calculations is the mean of all serice levels per iteration [37,38].

$$M_t^{R*} = \left(D_t^{R*} + (M_{t-1}^{R*} - R_{t-1})\right) K + D_t^{R*}(1-K) \tag{34}$$

$$\alpha_i = \sum_{i=1}^{n} \left(\frac{\sum_{t'=0}^{Y-1} R_{t+t'}}{\sum_{t'=0}^{Y-1} M_{t+t'}^{R*}} \right) \tag{35}$$

$$\beta_i = \sum_{i=1}^{n} \left(\frac{\sum_{t'=0}^{Y-1} P_{t+t'}}{\sum_{t'=0}^{Y-1} D_{t,t+t'}^{P*}} \right) \tag{36}$$

$$\alpha = \frac{\sum_{i=1}^{n} \alpha_i}{n} \tag{37}$$

$$\beta = \frac{\sum_{i=1}^{n} \beta_i}{n} \tag{38}$$

After the algorithm has calculated the two service levels for a proposed rationing level, we can calculate the average cost per period over $[t, t+Y-1]$ for this rationing level. This average cost per period is equal to the probability that ShCM is not satisfied $(1-\alpha)$ times the unavailability cost and the probability that LCM is not satisfied $(1-\beta)$ times the delay cost plus the average project penalty cost over $[t, t+Y-1]$ [39]. When the algorithm has calculated the average cost per period for all proposed rationing levels, it will choose the rationing level with the lowest cost.

$$\begin{aligned} &Average\ cost\ per\ period\ over\ [t, t+Y-1]: (1-\alpha)c_U + (1-\beta)c_{DP} \\ &+ \frac{1}{Y} TC_P(t, t+Y-1) + \frac{1}{Y} TC_R(t, t+Y-1) \end{aligned} \tag{39}$$

The rationing level will only be used if regular maintenance has priority over project maintenance. When the end of a project is nearing, it could be more expensive to delay a project and incur penalty cost for being overdue than a train being unavailable because of unplanned demand. We defined t^* as $c_{DP} + (t^* + V - PE) > c_U$. For $t \geq t^*$, the model will always assume that there is no rationing for ShCM and thus $I_t^R = 0$. It is also possible that t^* falls within the interval $[t, t+Y-1]$. When this is the case, the algorithm will calculate two values for I_t^R: one for the interval $[t, t^*-1]$ and one for $[t^*, t+Y-1]$. These three scenarios can be seen in Figure 3.5.

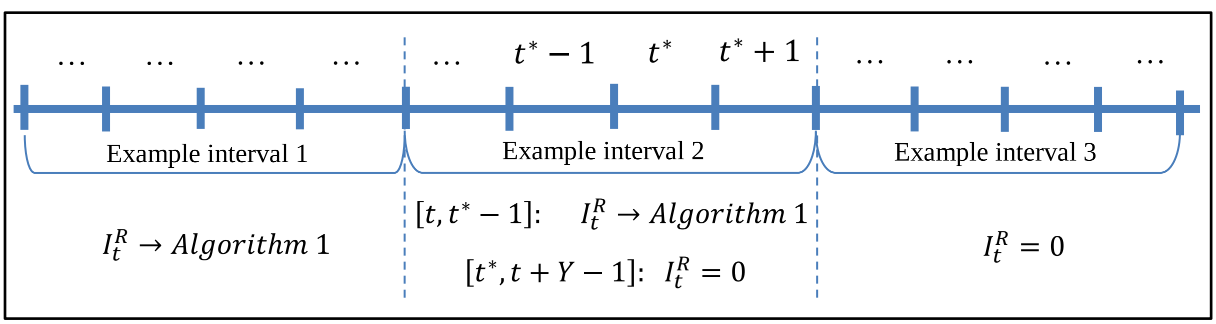

Figure 3.5: Three scenarios for determining IRt

Algorithm 1: Rationing Algorithm

***Step* 1** $\quad For\ every\ iteration, draw\ random\ values\ for\ D_{t,t}^{P*}\ and\ D_{t,t}^{R*}\ for\ [t, t+Y-1]$

***Step* 2** $\quad Take\ a\ value\ for\ I_t^R, I_t^R \in \{0,1,\ldots,S\}$

***Step* 3** $\quad Determine\ if\ t^* is\ in\ the\ interval\ [t, t+Y-1].\ If\ so, let\ the\ algorithm\ determine\ I_t^R$ $for\ [t, t^*-1]\ and\ choose\ I_t^R = 0\ for\ [t^*, t+Y-1]$

***Step* 4** $\quad Make\ assignment\ of\ spare\ parts\ for\ [t, t+Y-1]\ for\ all\ iterations\ by\ using$ $equations\ [22a, 22b, 23a, 23b]$

$Note\ that: I_t = I_{t-1} - R_{t-1} - P_{t-1} + Q_t^A$

	t	**t+1**	**...**	**t+Y-1**
Rationing level	I_t^R	I_t^R	**...**	I_t^R
Arrive from repair	Q_t^A	Q_{t+1}^A	**...**	Q_{t+Y-1}^A
Demand ShCM	M_t^{R*}	M_{t+1}^{R*}	**...**	M_{t+Y-1}^{R*}
Demand LCM	$D_{t,t}^{P*}$	$D_{t,t+1}^{P*}$	**...**	$D_{t,t+Y-1}^{P*}$

Assignment:

Assign to ShCM	R_t	R_{t+1}	**...**	R_{t+Y-1}
Assign to LCM	P_t	P_{t+1}	**...**	P_{t+Y-1}

***Step* 5** $\quad Calculate\ the\ average\ fraction\ of\ maintenance\ operations\ that\ get\ a\ part\ assigned$ $per\ period\ with\ the\ proposed\ value\ of\ I_t^R\ for\ ShCM\ (\alpha)\ and\ LCM\ (\beta)$

$$\alpha_i = \sum_{i=1}^{n} \left(\frac{\sum_{t'=0}^{Y-1} R_{t+t'}}{\sum_{t'=0}^{Y-1} M_{t+t'}^{R*}} \right) \qquad \beta_i = \sum_{i=1}^{n} \left(\frac{\sum_{t'=0}^{Y-1} P_{t+t'}}{\sum_{t'=0}^{Y-1} D_{t,t+t'}^{P*}} \right)$$

$$Average\ cost\ per\ period\ over\ \ [t, t+Y-1]: (1-\alpha)c_U + (1-\beta)c_{DP} + \frac{1}{Y}TC_P(t, t+Y-1) + \frac{1}{Y}TC_R(t, t+Y-1)$$

***Step* 6** $\quad Calculated\ the\ cost\ for\ all\ proposed\ values\ for\ I_t^R, I_t^R \in \{0,1,\ldots,S\}$

$Yes \rightarrow Continue\ to\ step\ 6,\ \ No \rightarrow Return\ to\ step\ 2$

***Step* 7** $\quad Choose\ value\ for\ I_t^R\ with\ lowest\ average\ cost\ per\ period$

3.6 MM2: Expediting level

When we have determined the rationing level, we can determine the expediting level (X_t). The expediting level is defined as the minimal feasible number of spare parts required to receive in period $t+Y$ with respect to all corresponding costs.

Model description

Algorithm 2 is used to find the best value for the expediting level. This algorithm uses the results (demand patterns, parts assigned to ShCM and LCM, and inventory levels) generated in **Algorithm 1** for the optimal value of I_t^R and extends the demand patterns for the demand with $[t+Y, t+\tau]$, for every iteration. The value that should be chosen for τ is discussed in *Appendix M.* The number of spare parts arriving after period Y is unknown. We want to determine the value for X_t under the assumption that the amount expedited in period t has to be enough to satisfy demand until period $t+\tau$. So, we assume that no other expedited orders arrive until period $t+\tau$ and all parts arrive according to their normal repair schedule. This means that the number of spare parts that arrive in period $t+j$ equals Q^D_{t+j-L}, for $j \in \{Y+1, \dots, \tau\}$. Because repair orders that are supposed to arrive until period $t+L-N-1$ could already have been expedited and arrived in the OB, we need the variable $A_{i,t}$ to check for this. When **Algorithm 2** has made the assignment decisions for $[t+Y, t+\tau]$ in every iteration, the service level for ShCM (α_i) [40] and LCM (β_i) [41] per iteration can be calculated. Equations [37] & [38] can be used to calculate the average service levels (α & β) over all iterations. We choose to compare the average cost over the entire period $[t+Y, t+\tau]$ for every possible value of X_t, so that we can place the total expediting cost in perspective. The total cost function takes the cost function for rationing [39], which it multiplies by the number of periods in the interval $(\tau+1-Y)$ and adds the total expediting cost depending on the value chosen for X_t and the project penalty cost over $[t+Y, t+\tau]$ [42]. The expediting cost is calculated the way as in the mathematical model, by minimizing [17] with [15] as a constraint.

$$\alpha_i = \sum_{i=1}^{n} \left(\frac{\sum_{t'=0}^{\tau} R_{t+t'}}{\sum_{t'=Y}^{\tau} M^{R*}_{t+t'}} \right) \tag{40}$$

$$\beta_i = \sum_{i=1}^{n} \left(\frac{\sum_{t'=Y}^{\tau} P_{t+t'}}{\sum_{t'=Y}^{\tau} D^{P*}_{t,t+t'}} \right) \tag{41}$$

$$\begin{aligned} \textit{Average cost over } [t+Y, t+\tau]&: \big((1-\alpha)c_U + (1-\beta)c_{DP}\big)(\tau+1-Y) \\ &+ TC_R(t+Y, t+\tau) + TC_P(t+Y, t+\tau) \end{aligned} \tag{42}$$

The optimal value for X_t does not necessarily have to be equal to the actual number of parts that are expedited in period t. The value for X_t denotes the minimal number of parts we want to receive in period $t+Y$ to be able to satisfy the upcoming demand and has an upper limit of the maximum number of parts that can be expedited in period t (Q^E_t). When the optimal value for X_t is determined, the model will find the combination of repair orders that can be expedited and add up to the lowest combination of expediting cost for that period. Because the model is only allowed to expedite an entire repair order and not separate parts within the order, it is possible that the actual number of parts expedited is larger than X_t.

Algorithm 2: Expediting Algorithm

***Step* 1** $\quad$ *Take results for every iteration from* **Algorithm 1**, *and extend drawn values for every iteration with drawn values for* $D_{t,t}^{P*}$ *and* $D_{t,t}^{R*}$ *for* $[t+Y, t+\tau]$

***Step* 2** $\quad$ *Take a value for* $X_t, X_t \in \{0,1,\dots,Q_t^E\}$ *and make the following assumptions*:

1. $Q_{t+j}^{A} = X_t$ $\quad$ *for* $j = Y$
2. $Q_{t+j}^{A} = Q_{t+j-\mathrm{L}}^{D} A_{j,t}$ $\quad$ *for* $Y + 1 \leq j \leq L - N - 1$
3. $Q_{t+j}^{A} = Q_{t+j-\mathrm{L}}^{D}$ $\quad$ *for* $j \geq L - N$

***Step* 3** $\quad$ *Make assignment of spare parts for* $[t+Y, t+\tau]$ *for all iterations by using equations* $[22a, 22b, 23a, 23b]$

Note that: $I_t = I_{t-1} - R_{t-1} - P_{t-1} + Q_t^A$

	t+Y	**…**	**t+L-N-1**	**…**	**t+τ**
Rationing level	I^R	**…**	I^R	**…**	I^R
Arrive from repair	X_t	**…**	$Q_{t+L-N-1}^{D} A_{L-N-1,t}$	**…**	$Q_{t+\tau-L}^{D}$
Demand ShCM	M_{t+Y}^{R*}	**…**	$M_{t+L-N-1}^{R*}$	**…**	$M_{t+\tau}^{R*}$
Demand LCM	$D_{t,t+Y}^{P*}$	**…**	$D_{t,t+L-N-1}^{P*}$	**…**	$D_{t,t+\tau}^{P*}$

Assignment:

Assign to ShCM	R_{t+Y}	**…**	$R_{t+\mathrm{L-N-1}}$	**…**	$R_{t+\tau}$
Assign to LCM	P_{t+Y}	…	$P_{t+\mathrm{L-N-1}}$	…	$P_{t+\tau}$

***Step* 4** $\quad$ *Calculate the average fraction of maintenance operations that get a part assigned per period with the proposed value of* X_t *for ShCM* (α) *and LCM* (β)

$$\alpha_i = \sum_{i=1}^{n} \left(\frac{\sum_{t'=0}^{\tau} R_{t+t'}}{\sum_{t'=Y}^{\tau} M_{t+t'}^{R*}} \right) \qquad \beta_i = \sum_{i=1}^{n} \left(\frac{\sum_{t'=Y}^{\tau} P_{t+t'}}{\sum_{t'=Y}^{\tau} D_{t,t+t'}^{P*}} \right)$$

Average cost over $[t+Y, t+\tau]$ *of proposed* X_t

$$= \big((1-\alpha)c_U + (1-\beta)c_{DP}\big)(\tau + 1 - Y) + TC_R(t+Y, t+\tau) + TC_P(t+Y, t+\tau)$$

***Step* 5** $\quad$ *Calculated the cost for all proposed values for* $X_t, X_t \in \{0,1,\dots,Q_t^E\}$

Yes $\rightarrow$ *Continue to step* 6, *No* $\rightarrow$ *Return to step* 2

***Step* 6** $\quad$ *Choose value for* X_t *with lowest average cost over* $[t+Y, t+\tau]$

3.7 MM3: Repair orders

Model description

When the expediting level (X_t) is determined in ***MM2***, we can calculate the best combination of repair orders to expedite in order to meet this level. The sum of the number of parts in the repair orders that get expedited has to be equal to or larger than the expediting level [43].

$$X_t \leq \sum_{i=Y}^{L-N-1} A_{i,t} E_{i,t}\, Q_{t-L+i}^{D} \qquad [43]$$

By using this as a restriction in the MILP (Mixed Integer Linear Programming) problem that minimizes the expediting cost, we can find all combinations of repair orders to expedite to meet the expediting level. Because the expediting repair cost component of the repair cost function [17] is part of the minimization objective function, the model will always choose the optimal combination of repair orders to expedite. In *Appendix D*, two examples are presented in which this part of the model is demonstrated. The other constraints for the model include the expediting decision to be binary [19] and that there are no incremental cost for expediting a repair order from which the remaining repair lead time is equal to the expedited repair lead time [15]. Note that all values for $A_{i,t}$ and Q_{t-L+i}^{D} for $i \in \{Y, Y+1, \dots, L-N-1\}$ are calculated in ***MM0***. All values for $c_{E,i}$ are determined externally. We use the Solver Add-in from MS EXCEL to solve this MILP problem. This solver uses the Branch & Bound method as proposed by Land and Doig (1960) to find the optimal solution.

Model equations

Objective

$$\min \sum_{i=Y}^{L-N-1} E_{i,t}\, A_{i,t} c_{E,i} Q_{t-L+i}^{D} \qquad [17]$$

Constraints

$$X_t \leq \sum_{i=Y}^{L-N-1} A_{i,t} E_{i,t}\, Q_{t-L+i}^{D} \qquad [43]$$

$$c_{E,Y} = 0 \qquad [15]$$

$$E_{i,t} \in \{0,1\} \quad for\ i \in \{Y, \dots, L-N-1\}, \forall t \qquad [19]$$

4. Implementation

To be able to use the mathematical model, including the two algorithms, in the daily operations, it was converted into a decision support tool. This tool uses the model and algorithms as presented in chapter 3. The verification and validation of the decision support tool can be found in *Appendix N*.

4.1 Decision Support Tool

The aim of developing a decision support tool was to help SCO with their daily operational decisions. The tool should provide guidance, based on statistical analysis of the upcoming demand for both demand streams in the OB. Because the coding that serves as the core of this tool is quite complex and the calculations are not always that simple, the main objective during the development was to display all output and input in a straightforward and understanding way. The end-user should not be required to have any experience with algorithms or coding to be able to use it.

After contemplating with the involved parties at NedTrain, it was decided that the tool should be developed in MS EXCEL for two important reasons. First, all computers at NedTrain are equipped with the MS Office package by default, including MS EXCEL. This means that no extra software packages have to be installed in order to open the tool. The second reason is that the planners at SCO, the main end-users, already use MS EXCEL in their daily operations. They understand how to find data in these files and how different cells or sheets could be linked.

We used the Visual Basic (VBA) programming language in MS EXCEL to perform all calculations (VBA code in *Appendix O*). Most output and intermediate steps can be found in the different sheets of the file. For example, the calculations for the rationing and expediting levels require the simulation of many different demand patterns. The final value for each of these levels is determined by choosing the proposed value with the lowest cost function. But when the user is interested in the service levels and total costs of the other proposed values, this is saved in separate sheets. Every period, the VBA code determines whether regular demand still has priority over project demand or if the project end is nearing and will be more expensive to delay project maintenance. This outcome determines which of the two demand streams has priority and whether we will use rationing for regular maintenance. We also use the Solver Add-in function of MS EXCEL for the separate problem of choosing which repair orders to expedite. The solver minimizes the expediting cost under the requirement that the number of parts expedited should be equal to or bigger than X_t.

The sheets in the MS EXCEL file either have a green or a black label. A green label is used to address the sheets in which the user is allowed to input data and receives the output needed for operations. The sheets with a black label contain data for extra insights. Following is a description of all sheets in the MS EXCEL file of the decision support tool:

- 'Dashboard': main sheet of the decision support tool in which the user is supposed to input the daily demand for ShCM and LCM. After running the tool, the user is presented with the rationing level of that day and a list of repair orders that should be expedited. This sheet also contains a number of graphs which show the progress of the active project and projections for the remainder of the project.

- ‘Instellingen’ (settings): sheet that is mainly used at the start of a new project to change the part-specific parameters. Three different colors are used to indicate the varying changeability of the corresponding cells. Green cells are free to change, orange cells need some consideration before changing, and red cells are determined automatically and should only be changed when the user is completely certain of his decision. This sheet also contains a demand generation tool, if the user is interested in simulating a longer period of time.
- ‘Onbeschikbaarheid’ (unavailability): sheet containing a table with the different costs for unavailability per train series. If user selects the train series in the ‘Instellingen’ sheet, the corresponding unavailability cost per day will automatically be inserted.
- ‘Rationing’: sheet containing the service levels for ShCM and LCM and total cost for all possible values of I_t^R for every period.
- ‘Xvalue’: sheet containing the service levels for ShCM and LCM and total cost for all possible values of X_t for every period.

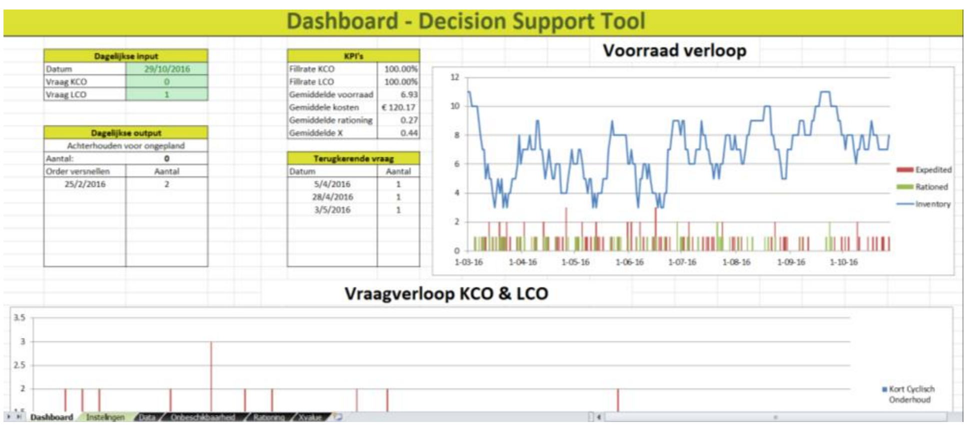

Figure 4.1: Screenshot of dashboard page of decision support tool

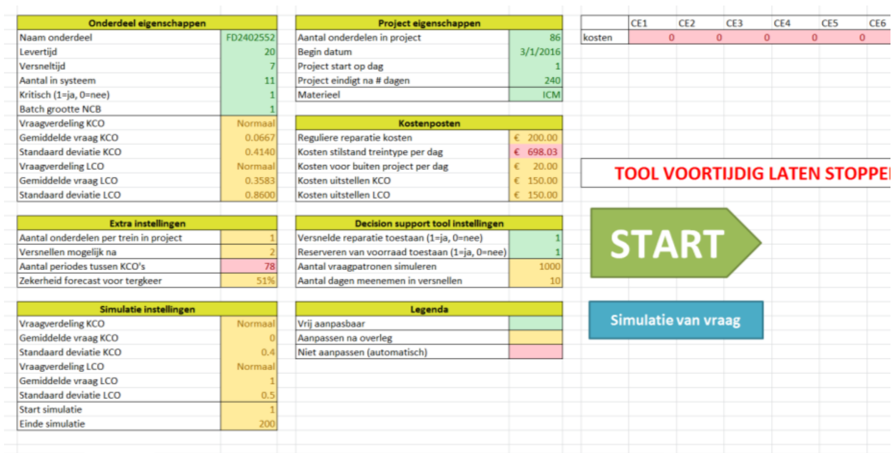

Figure 4.2: Screenshot of settings page of decision support tool

4.2 Implementation Plan

The implementation of the decision support tool involves the following three phases: (1) presentation and training phase, (2) initializing phase, and (3) evaluation phase. The first phase will occur just once and the second and third phases are iterative for every project.

A presentation will be held for the SCO management and planners to explain what the decision support tool can be used for and how it should be used. This will include a brief explanation of this research and the mathematical model that was developed. Then, all the sheets in the MS EXCEL file are discussed. The different inputs and outputs of the tool are explained. After the presentation, an interactive training session will make the users get a feeling with the tool. The case study conducted in this research is presented, which the users will have to perform themselves. They will be provided with the parameters, but have to enter the values on their own. They will be allowed to ask questions if they get stuck somewhere. This interactive moment is not only to get them familiar with the usage, but also to obtain feedback for possible adjustments of the tool. All users will also be provided with a step-by-step manual for the initialization of the decision support tool. The steps will be presented in clear actions accompanied with screenshots of the tool. Next to the set-up steps, the manual also provides an overview of how the output of the tool should be interpreted and where the users can find certain values.

When SCO will use the tool for the first time on a new project, the initializing of all parameters is of great importance. The first step is to make estimations of the mean and standard deviation of the daily unplanned and planned demand. The estimations for unplanned demand can be derived from historic demand and the estimations for planned can be based on finished projects for similar spare parts. Then the SCO planner has to make agreements with the planner at the repair shop about the lead times of normal and expedited repairs. The decision support tool includes an additional functionality to generate simulated demand patterns for a given period. SCO and the repair shop can simulate how different parameters will work out over the course of the project before it has even started. This can be used in discussions about e.g. the expedited repair lead time, number of parts in the closed-loop supply chain, the project duration, or the planned number of project maintenance operations per week. The final step is the input of all project parameters, including a starting and ending date, and the total number of parts needed to finish the entire project. All parameters described above can be changed throughout the project.

After every finished project, especially after the first, the output of the tool should be evaluated. If the tool gave output at some point which in hindsight seems unusual or illogic, the cause should be examined. When the demand pattern of a finished project is known, it is very simple to perform a complete new analysis with altered values for some parameters. When this new analysis achieves better results for the finished project, it might be worth trying these new parameters for the next project. Parameters that can be easily changed and can have a big impact on the outcomes of the model are: expected time between two visits to the OB, expedited repair lead time, normal repair lead time, all cost parameters, and the end date of the project.

After the tool is implemented, some parts of the daily routine of the planners at SCO and the workers in the OB will change. Some parts of their daily routine will now be performed by the tool.

Figure 4.3 shows the difference in the phase before the start of the project and the daily routine during the project between the as-is and to-be situations.

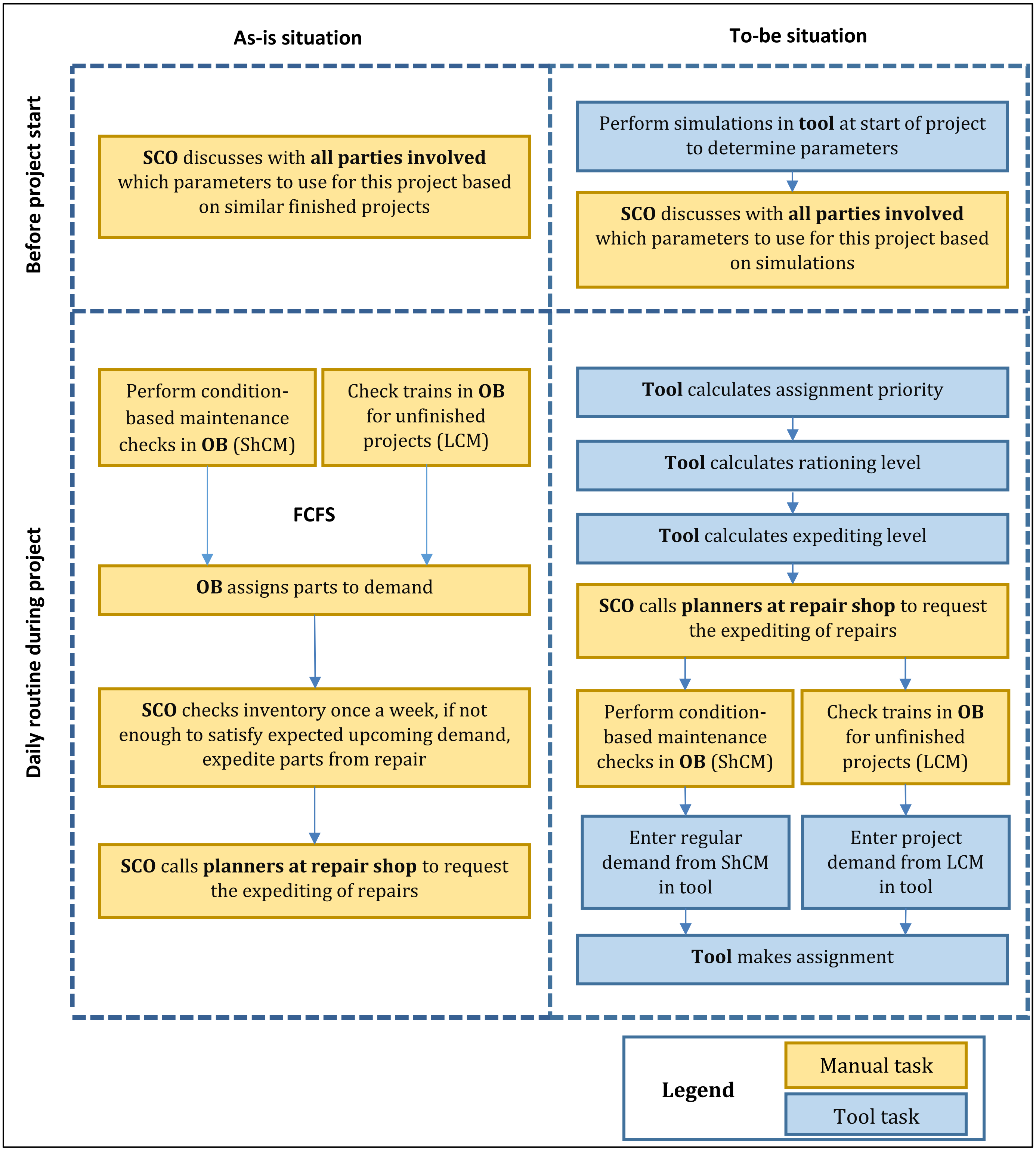

Figure 4.3: Implementation: as-is situation vs to-be situation

5. Case Study

To evaluate and validate the functionalities of the decision support tool, a case study of one specific spare part will be conducted. The first section presents the requirements for choosing the spare part of this case study and explains how the data was collected. In the second section, we will examine the output and results of the decision support tool for a set of different scenarios. We will then discuss the results in this section and evaluate the performance of the rationing and expediting algorithms. Finally, we will perform a sensitivity analysis on two parameters: the number of parts in the supply chain and the expedited repair lead time.

5.1 Introduction

There are currently around 300 spare parts that incur demand from both LCM and ShCM. However, not all of these parts were suited to conduct this case study. To be able to test both the rationing and expediting algorithm at once, we have some requirements regarding the characteristics of the spare part. The requirements for the spare part that will be used in this case study were:

- Critical part: spare part should be critical for the functioning of the train, otherwise demand from ShCM could be delayed and there would not be any priority in the assignment.
- Repairable part: the spare part should be repairable to evaluate the effects of the expediting policy.
- Project length at least 6 months: demand data should be over a longer period of time to evaluate demand fluctuations and returning projects that were delayed.
- Large projects: projects with around 3-4 replacements planned per week are considered large by SCO. This will create a high velocity of spare parts moving through the closed-loop supply chain. Overall, a higher velocity will trigger more expediting if the number of parts in the closed-loop supply chain stays constant.
- Significant unplanned demand (ShCM): during the duration of the project there should have been some cases of regular demand, so that we can study the effects of rationing.

These requirements were discussed with Koen Dekkers of SCO. He proposed a toilet module for the ICM (InterCity Materieel) trains (article number: FD2402552). These modules consist of a large cabin with a toilet and a sink, including a complete system for internal waste disposal. These modules are considered as one part and are replaced as a whole. An example of a toilet module for trains can be seen in Figure 5.1. Due to the high procurement cost of a new module, NedTrain aims to completely revise replaced modules for future replacements. The project started in March 2016 and lasted until the end of October 2016 (8 months) and was completely performed in the OB in Onnen, the Netherlands. During this project, 86 modules were replaced and there were 16 unplanned demands. An unplanned demand meant that an important part of the module was defect and the entire module was labelled as inoperable, meaning that passengers are not allowed to use it anymore. The ICM train series is not allowed to leave the OB with an inoperable toilet. The demand per month for ShCM and LCM was exported from the supply chain software *Xelus Parts* and is presented in Table 5.1. SCO does not have data available of the exact days this demand arrived.

Figure 5.1: Example of a toilet module for trains*

The original plan was to perform 4 planned replacements per week for 22 consecutive weeks. Because there are only 11 modules within NedTrain's closed-loop supply chain, some delays of project maintenance operations were allowed. The normal repair lead time of this part is 20 days. SCO made agreements with the NCB (internal repair shop) that this part had increased priority during the duration of the project and that modules in repair could be received in 7 days after a decision to expedite.

Table 5.1: Demand for ShCM and LCM of FD2402552 in March '16 – October '16

	ShCM	LCM
March '16	1	18
April '16	1	13
May '16	0	16
June '16	7	10
July '16	3	7
August '16	0	10
September '16	2	2
October '16	2	10
TOTAL	**16**	**86**

The aim of the decision support tool is to be used in the daily operations. The input for the tool will therefore be the demand for a specific spare part that arrived that day from both ShCM and LCM. Because we only have the monthly historic demand of both demand streams and do not exactly know on which days it arrived, we need to make a simulation of the daily demand patterns. These daily demand patterns need to be based on some stochastic distribution that fits the sample. If we are able to fit a negative binomial distribution to the monthly sample, we can use this distribution to generate daily demand. We use the statistical computing software *RStudio*, based on the programming language *R*, to fit our samples to a negative binomial distribution and find the corresponding parameters. *RStudio* includes the *fitdistr* function to fit univariate distributions with maximum-likelihood and allowing parameters to be held fixed if desired. The outputs of this

* Source: http://www.azom.com/article.aspx?ArticleID=11061

function are two parameters: *mu* (μ) and *size*. A negative binomial distribution can also arise as a mixture of Poisson distributions with mean distributed as a gamma distribution with shape parameter *size*. All results from *RStudio* are presented in *Appendix F*.

We will assume that every month has 30 working days because the OBs are in operation throughout the whole week. To get the daily parameters for the Gamma-Poisson mixture, we divide the obtained parameters by 30. Both the monthly and daily parameters are shown in Table 5.2.

Table 5.2: Mu and size parameter Gamma-Poisson mixture of ShCM and LCM during project

	ShCM	LCM
μ (per month)	2.000	10.750
μ (per day)	0.067	0.358
Size (per month)	1.69168	7.4647
Size (per day)	0.0564	0.2488

We use a Chi-squared test to test whether our sample fits a negative binomial distribution. We compare our observed sample to a generated sample with the Gamma-Poisson mixture and the parameters in Table 5.2. Our null hypothesis for both the observed ShCM and LCM sample is that they follow a negative binomial distribution for $\alpha=0.05$. The test led to a p-value of 0.616 for the ShCM sample and 0.326 for the LCM sample. This means that we cannot reject the null hypotheses, and can safely assume that our sample follows a negative binomial distribution. All results from the Chi-squared test can be found in *Appendix F*.

We will draw random values for the daily demand, based on the two daily parameters (*mu & size*) in Table 5.2. *RStudio* includes the function *rnbinom* to generate random negative binomial values based on the derivation of gamma mixtures of Poissons (Devroye, 1986). The *RStudio* code for generating demand patterns is shown in *Appendix F*. We generate multiple different demand patterns to generalize the results of the simulations. As can be seen in *Appendix L* and Table 0.6, performing calculations for one week of demand under the proposed number of iterations takes 0:48min. The whole project will then take about 27 minutes to perform all calculations. To prevent the computing times becoming longer than one day, we will consider a total of 50 different demand patterns to evaluate the different policies.

The unavailability of an ICM train costs 698 EUR per day. This cost is based on an internal penalty structure within NedTrain and does not equal a day of missed revenue. NedTrain does not have estimations of the cost related to delaying LCM. The delay cost is based on the time it takes a maintenance worker in the OB to request a delay and a maintenance engineer to process this request. The total time is estimated at 2 hours per delay. If we assume that one hour of work will cost NedTrain about 75 EUR, we obtain an estimation for the total delay cost of 150 EUR. We determined the penalty cost of an overdue project to be 18.5 EUR per day. This way, projects will receive priority over regular maintenance when a delay means that it will be at least 1 month over the project end date (delay will cost at least $150 + 30 \cdot 18.5 = 705$ EUR). For the number of periods after which it is possible to expedite an order (N) we chose 2 days. This covers the time the module is in transport from the OB to the LLC and from the LLC to the NCB and the time until the repair process starts. An overview of all parameters used for the case study can be found in *Appendix G*.

5.2 Results

To evaluate the performance of the decision support tool, this case study considers the six following policies:

1. Include both the expediting and rationing algorithm (complete decision support tool)
2. Only include the expediting algorithm
3. Only include the rationing algorithm
4. Exclude both the expediting and rationing algorithm
5. Expedite maximum number of spare parts every period and exclude rationing
6. Only include an expediting policy that simulates current practice

The first 3 policies test the different functionalities of the tool and deliver their separate and combined results. The fourth policy simulates the situation where all parts are repaired according to the normal repair lead time and no rationing is used. To study the maximum effect that the expediting of repairs can have, we expedite the maximum number of parts every period in policy five ($X_t = Q_t^E$). With the sixth policy, we try to approximate the as-is situation at NedTrain.

Currently, SCO does not use any rationing policies and only expedites parts from repair when the on-hand inventory is lower than the expected number parts needed. The SCO managers evaluate the on-hand inventory at the OBs on average once a week. When they see that this level is too low to satisfy incoming demand, they make a call to the planners at the repair shop and request shorter repair lead times. Because they aim to have enough on-hand inventory to satisfy the total weekly demand, we use this amount as a parameter in this policy. We assume that we solely look at the current on-hand inventory at the review moments and not consider the planned incoming repair orders. The planned weekly demand was estimated at 4 parts and we choose an order-up-to-level of 5 to include unplanned demand and uncertainty. So, every 7 days we look at the on-hand inventory and expedite the difference between the on-hand inventory at that moment and the order-up-to-level. Furthermore, we assume the same expedited repair lead times and cost parameters.

The different policies are compared by looking at the following Key Performance Indicators (KPI's): service levels ShCM and LCM, average on-hand inventory, total expediting cost, total unavailability cost, total delay cost, expected project penalty cost, average cost per period, average rationing level (I^R) per period, and the average value for X_t per period. The expected project penalty cost is based on estimations of the period when delayed projects return and what the corresponding penalty cost is when these arrivals are outside the project interval. In this case study, we do not have any data of arrivals outside the project interval. So, we assume that the delayed projects outside the project interval can always be performed and is not delayed again for the estimations of the project penalty cost. We left the regular repair cost out because these are paid anyway in every policy. An overview of the results is given in Table 5.3 over the duration of the project. We assumed that a month contains 30 days, so the total duration of the 8 month project is 240 days. The service levels are determined as follows:

$$Service\ level\ ShCM = \sum_{t=1}^{240} \frac{R_t}{M_t^R} \qquad\qquad Service\ level\ LCM = \sum_{t=1}^{240} \frac{P_t}{D_t^P}$$

Table 5.3: Key Performance Indicators (KPI's) over the duration of the project (8 months)

	Including X_t and I^R	Including X_t excluding I^R	Excluding X_t including I^R	Excluding X_t and I^R	$X_t = Q_t^E$ excluding I^R	Current practice
	1	2	3	4	5	6
Service level ShCM	100.00%	98.02%	100.00%	78.88%	100.00%	91.98%
Service level LCM	99.09%	99.17%	70.02%	84.21%	100.00%	88.33%
Average on-hand inventory	6.23	6.01	5.10	4.07	7.09	4.26
Average rationing Level	0.51	0.00	2.09	0.00	0.00	0.00
Average value for X_t	0.46	0.42	0.00	0.00	0.53	0.14
Total expediting cost	€ 5691.09	€ 5455.84	€ 0	€ 0	€ 6847.21	€ 2181.67
Total unavailability cost	€ 0	€ 351.77	€ 0	€ 2499.01	€ 0	€ 1211.39
Total delay cost	€ 162.29	€ 133.09	€ 3958.54	€ 2302.74	€ 0	€ 1395.12
Expected project penalty cost	€ 195.33	€ 182.42	€ 3240.16	€ 2725.28	€ 0	€ 1789.64
Total cost	**€ 6048.71** (index)	**€ 6123.12** (1%)	**€ 7198.70** (19%)	**€ 7527.03** (24%)	**€ 6847.21** (13%)	**€ 6577.82** (9%)

The first things that stand out are the almost identical results for the policy that includes both algorithms and the one that only includes the expediting algorithm. This can either mean that the expediting algorithm on itself works really well and is able to cope with most demand fluctuations, or that the rationing algorithm does not add a lot of value to the model. This last interpretation does not seem valid, because the rationing does seem to ensure that there is always enough inventory available for unplanned demand when no expediting is allowed and the average on-hand inventory level drops by 20% (policy 3). We also observe that the total cost for policy 3 are less than that of policy 4, despite the significantly increased total delay cost and expected project penalty cost. We learn from this that when expediting is not possible and the spare part is critical, implementing the rationing for unplanned demand can decrease cost because the high unavailability cost of a train are avoided.

With respect to policy 2, we also notice that the service level of ShCM is lower than that of LCM, even though there is still an assignment priority because of the higher backlog cost. This is probably due to the fact that there is less total demand for ShCM over the project period. One time not assigning a part to the regular demand has a bigger impact on the service level over all periods.

We see that when the rationing algorithm is used, the average values for X_t and on-hand inventory increase. This makes sense, because the expediting algorithm calculates how many spare parts should be ordered for all incoming demand. If part of that demand is only allowed to use part of the inventory, the total inventory has to increase, which is achieved by expediting earlier or more.

If we solely look at the service levels of ShCM and LCM, policy 5 performs the best with perfect service levels for both demand streams over the 50 generated demand patterns. This policy has the highest average on-hand inventory due to its high expediting levels. However, the high expediting cost that come along with the high expediting levels do not seem to weigh against the unavailability and delay cost of policy 1. This also confirms that the expediting algorithm does not just expedite excessive quantities for the purpose of preventing backlog cost, but rather considers all related costs in the model.

We also plotted the inventory levels throughout a whole project for one demand pattern for all 6 policies (*Appendix I*). Studying the inventory graphs for the five different policies also leads to some interesting insights. In Figure 0.1 we see a quite even distribution of the size and frequency of the expediting moments during the project. We can also see the priority switch between ShCM and LCM in the last weeks of the project when delaying project maintenance gets too expensive and there is no more rationing. Figure 0.3 also stands out, with the overall rationing levels being higher and adding up to the entire on-hand inventory when it gets to 3 parts or less. This is not because the model expects that there will be 3 unplanned demands on that day, but because it wants to hold that inventory back for the unplanned demand that can potentially arrive in the upcoming periods. Expediting the maximum repair orders every period in policy 5 leads to a more jigsaw pattern and higher average inventory, as can be seen in Figure 0.5. This is caused by the more frequent arrival of smaller repair orders. The inventory of the policy that simulates the current practice is shown in Figure 0.6. We can clearly distinct the weekly expediting moments and their larger average size.

5.3 Sensitivity Analysis

We perform a sensitivity analysis on two main parameters in the mathematical model to study alternatives. We chose the expediting period (Y) and the number of spare parts in the closed-loop supply chain (S) for this analysis, because these parameters are usually the easiest to change by SCO. The sensitivity analyses were simulated over the same 50 demand patterns that were created in section 4.1.

Increasing the expedited repair lead time obviously never leads to problems at the repair shop. They would have more time to finish the repair than they have with the current agreements. Decreasing this period could perhaps lead to some problems due to a lack of resources and/or time. The offset between this period and the service levels for both LCM and ShCM are displayed in Figure 5.2 and the exact numbers in Table 0.3 in *Appendix H*. We can see that for all expedited repair lead times of around 10 and lower, the service levels stabilize and slowly converge to 100%. This means that choosing an expediting repair lead time of 10 days would not affect the performance of the tool that much compared to the current situation ($Y = 7$). For a lead time of 5 days, the tool achieved perfect service levels over all 50 generated demand patterns. The expediting cost seems to move in a similar trend as the expediting lead time. The three functions are not very smooth, but do show some sort of trend. We expect that if we consider more demand patterns in our analysis, the smoothness of these functions will increase, as they become more generalized.

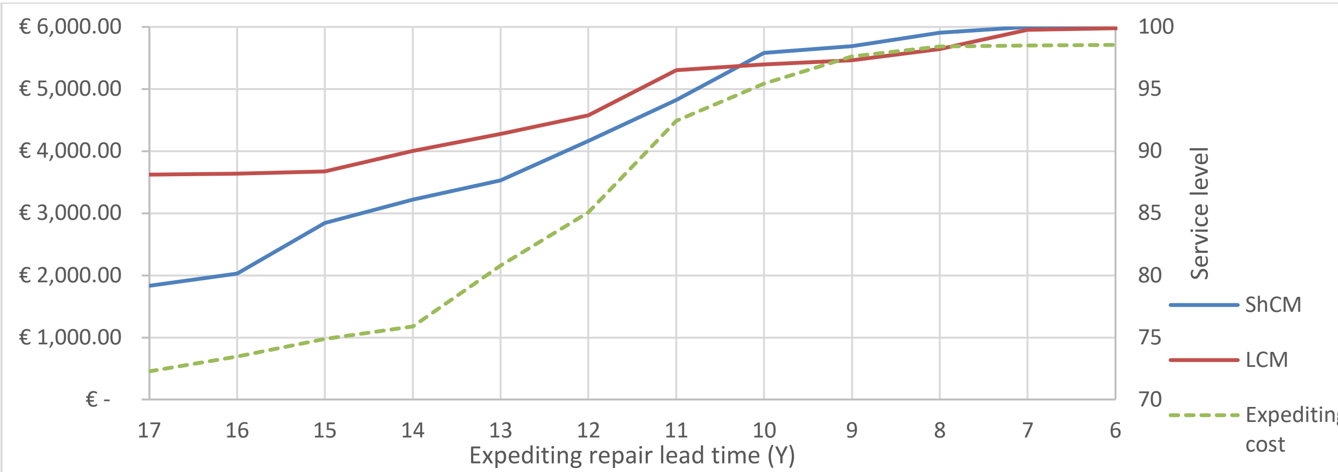

Figure 5.2: Sensitivity analysis of the expediting period (Y) versus the service levels and cost

For the number of units in the supply chain, the incremental cost of an extra unit is given. So, managers at SCO could easily make a trade-off between this procurement cost and the increased service levels. If they think the procurement of an extra toilet module for 90,000 EUR weighs against these better service levels, expanding their turn-around stock may be a good decision. Because the service levels of both ShCM and LCM were already very high for the current number of units in the system when both the algorithms are used, we choose to perform this sensitivity analysis for the situation that both algorithms are turned off. This means that all parts arrive back from repair according to their normal lead time and no rationing is used. The service levels for an increasing number of units in the supply chain are presented in Figure 5.3 and the numbers in Table 0.2 in *Appendix G*. With a total of 17 toilet modules in NedTrain's closed-loop supply chain, this project could have been performed with very high service levels and without using either expediting or rationing. The procurement cost of a toilet module is confidential, but procuring 6 extra units would be significantly more expensive than using the proposed expediting policy to manage the closed-loop supply chain and ensure that enough parts are in inventory at the OB.

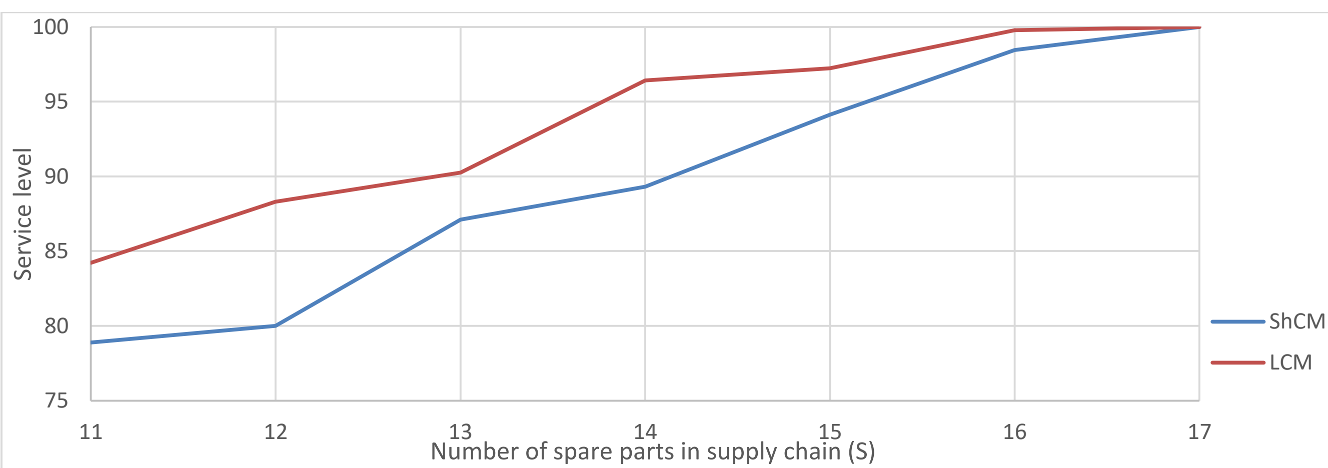

Figure 5.3: Sensitivity analysis of number of units in supply chain (S) versus the service levels

To test the limits of the decision support tool, we perform simulations on three extreme demand patterns (Table 5.4) that are based on the original demand pattern (Table 5.1). We take the original demand pattern as a starting point and add the same value to every month to reach total demands which are about 150%, 200%, and 400% of the original total demands. Because the LCM demand stream is much larger than the ShCM demand stream we start with 150% for LCM and respective 200% and 400% for ShCM in the first and second extreme demand pattern. To push the tool really to its limits, the third demand pattern will be 400% for ShCM and 200% for LCM.

Table 5.4: Three extreme demand patterns to test the limits of the decision support tool

	Pattern 1		**Pattern 2**		**Pattern 3**	
	ShCM	**LCM**	**ShCM**	**LCM**	**ShCM**	**LCM**
Added demand	+2	+5	+5	+5	+5	+10
March '16	3	23	6	23	6	28
April '16	3	18	6	18	6	23
May '16	2	21	5	21	5	26
June '16	9	15	12	15	12	20
July '16	5	12	8	12	8	17
August '16	2	15	5	15	5	20
September '16	4	7	7	7	7	12
October '16	4	15	7	15	7	20
TOTAL	**32 (±200%)**	**126 (±150%)**	**56 (±400%)**	**126 (±150%)**	**56 (±400%)**	**166 (±200%)**

All simulations of these demand patterns were performed with both the expediting and rationing algorithm included. The average KPI's of the simulation of the 3 extreme demand patterns are shown in Table 5.5. These results show that the rationing algorithm is still able to satisfy almost all ShCM demand in demand pattern 1, even though the total demand increased with about 55%. The service level for LCM for pattern 1 is with almost 80% also still relatively good, considering the increase in demand. For pattern 2 and 3, the tool is not able anymore to sustain any service levels in the 95-100% region. The rationing levels keep increasing, but it seems that some of the times there is not enough on-hand inventory available to even satisfy any demand in the OB. For demand pattern 1 the average value for X_t is lower than the maximum expediting policy in the case study, even though more parts are visiting the repair shop due to more replacements. This implies that the expediting algorithm still does not expedite the maximum number of parts every period for pattern 1. The average levels for X_t increase a lot for patterns 2 and 3, so we assume that in those cases, the expediting algorithm expedites the maximum number of parts from repair.

Table 5.5: Results from the simulation of the three extreme demand patterns

	Pattern 1	**Pattern 2**	**Pattern 3**
Service level ShCM	99.03%	93.55%	86.86%
Service level LCM	79.68%	70.87%	62.61%
Average on-hand inventory	3.10	2.49	2.01
Average rationing level	1.08	1.14	1.55
Average X per period	0.49	0.62	0.71

6. Conclusions & Discussion

This final chapter concludes the research with a conclusion and discussion. In the first section, we will answer the five main research questions. The next section discusses the limitations this research has. Finally, we present suggestions for future research, based on extensions that we left out of scope.

6.1 Conclusion

The objective of this research was improving the planning of spare parts for the two demand streams that arrive in the OB. We explain the findings of this research, based on the five main research questions, as presented in section 2.2.

1. ***How does withholding spare parts for upcoming maintenance operations affect the total cost?***

The withholding or rationing of inventory for certain demand classes is only effective when these demand classes have a higher priority than the other classes. This priority can be presented in the form of different levels for aggregate service levels or penalty cost. The more significant the difference in shortage cost is, the more effect rationing will have (Dekker, Klein & Rooij, 1998). The rationing of inventory will in general produce lower aggregate service levels for the demand classes with lower priorities. So, the first question that was asked was: is there a significant difference in priority between the ShCM and LCM demand streams? The management of SCO, who is responsible for handling these two demand streams, argued that there was a significant difference in the penalty cost between ShCM and LCM. This is due to the potential unavailability of a train if demand from ShCM is not satisfied and only administrative delay cost when this is the case for LCM. However, the difference in priority changes as the project progresses. Because projects have a clear start and end date, they cannot be delayed endlessly. We decided that the model will decide until when during the project we will use rationing, based on the penalty cost for LCM to be performed outside the project interval.

To express the value of the rationing policy as its effect on the total cost, we will look at the results of the case study in Table 5.3. We see that both the policies which include the rationing algorithm have lower average total cost per period than the respective policies without rationing. For the policies that include the expediting algorithm, this difference is about 65 EUR (± 1% decrease) for the entire project. When the expediting policy is excluded, the added value of rationing is more and adds up to 329 EUR (± 5% decrease). What must be noted is that these costs were based on estimations for the costs in the case study.

2. ***How can an expediting repair policy that considers expected demand arrivals be used to improve the assignment of spare parts?***

After reviewing literature concerning the expedition of repairs, the research by Arts et al. (2016) immediately stood out. The expediting policy he describes in this paper was developed and tested at NedTrain. It works within NedTrain's closed-loop supply chain and also includes a Markov modulated demand to incorporate a part's different states of degradation. However, this policy describes the situation in which expedition is triggered by a replacement. According to Koen Dekkers (manager SCO), the expediting of parts can happen at any moment during its repair in practice. Because the objective of this research is to develop a tool which can be used in the daily operations, we want to describe practice as close as possible.

This led to a customized expediting policy with a daily moment to expedite, based on the forecasts for upcoming demand, the current on-hand inventory and the number of periods it takes an expedited repair order to arrive at the OB. This expediting repair lead time is called Y and is assumed to be constant. We developed an algorithm that determines the value for the minimum number of parts expected to receive in period $t + Y$ and thus the minimum number of parts to expedite in period t. From the results of the case study, we see that the average parts expedited per period and the total cost for expediting repairs are much higher for the policies with this algorithm included than for the as-is expediting policy. However, the total costs of the policies that include the developed expediting policy are lower due to the significant decrease in cost for unavailability and delaying of trains.

3. ***How can the mathematical model be transformed into a decision support tool for SCO to help them with the assignment of spare parts?***

The mathematical model, as presented in chapter 3, was used to develop an interactive decision support tool in MS EXCEL. The largest part of the calculations is performed on the backend side of the file in the Visual Basic (VBA) programming language of MS EXCEL. The part where we calculate which specific repair orders should be expedited to minimize the cost, is done by using the Solver Add-in function in the sheets of the MS EXCEL file.

Every day, the user has to enter the demand from LCM and ShCM that arrived in the OB. The tool will do the calculations and give the user the following output: number of parts from the on-hand inventory that should be rationed for unplanned demand and which specific repair order should be expedited. On the dashboard of the tool, the user is provided with more insights regarding the progress of the project and estimations of the returning of delayed project maintenance operations. The tool also has a settings page in which the user is able to tweak some parameters.

4. ***How does the developed model function within the closed-loop supply chain of NedTrain compared to the as-is situation?***

We conducted a case study in this research in which we compared the developed model to policies that only include parts of the model and to the current practice. In this case study we modelled the current situation of spare parts expediting with a constant review period and an order-up-to-level. This policy also does not allow the rationing of inventory. When comparing this policy to the policy that includes both the rationing and expediting algorithm, the difference is quite significant. The average service level of ShCM and LCM is almost 10% less in the modelled as-is situation. This is due to the lower expediting levels and, as a consequence, lower average on-hand inventory. Also, there is a decrease in the total project cost of 9% in the proposed model, compared to the as-is situation.

5. ***How can a decision support tool to compute the assignment of spare parts and give repair orders be implemented for further use?***

The implementation of the decision support tool involves three phases. The first phase is the presentation and training phase, in which the users and others involved are presented with the findings of this research and get a demonstration of the tool. The second phase is the initializing of parameters and the development of agreements between SCO and the repair shop to make sure the set parameters will be achieved. The third phase is the evaluation of the tool by looking at the results at the end of a finished project. Because there was a lack of time to test the tool in practice during the full duration of a project, its actual value to the supply chain has yet to be evaluated.

Overall conclusion

This research combines a rationing policy and an expediting policy in the environment of a closed-loop supply chain with two demand streams that have a dynamic priority. Both the expediting and rationing policy showed to have a positive effect on the total cost within the closed-loop supply chain. The dynamic priority of the two demand streams ensures that during the first part of a project the focus lies on satisfying all unplanned demand, due to its high backlog cost. In the last part of the project, when it is nearing its end date, the dynamic priority switches and all remaining project maintenance operations are first in line to receive spare parts at the OB. This priority switch is triggered by the variable project penalty cost that increase as the period after which delayed project maintenance operations will likely return to the OB increases.

As far as our literature review went, we did not encounter any articles that combined a rationing and an expediting policy for multiple demand streams. We conclude that when there is a significant difference in the backlog cost of the demand streams, the rationing policy proves to be able to save cost in the long term by preventing the backlog cost of the higher priority demand stream. The expediting policy we developed was customized for the situation at NedTrain. We were not able to find an expediting policy for outstanding (repair) orders in literature that fitted our situation. Our policy is therefore also an addition to the current literature on expediting. The customized expediting policy includes a period after which it is possible to expedite an outstanding repair order. After this period, it is possible to expedite the remaining repair lead time of an outstanding repair order to a deterministic fixed number of days (less than the regular repair lead time).

The case study we conducted showed very positive results of these new policies. The use of the decision support tool that was developed with the mathematical model created in this research, lead to a cost reduction of around 9% compared to current practice. We advise NedTrain to implement this decision support tool in their future projects by following the implementation plan provided in this research. We also advise SCO and NCB to use the simulation functionalities of the tool at the start of a new project to make lead-time and other agreements.

6.2 Limitations

The main limitations of this research are:

Constant lead time: When clear agreements are made between SCO and the repair shop, the assumption of a constant lead-time could hold up pretty good in practice. However, in practice this lead time will always have some variance due to disruptions in the repair process or priority of other parts.

Case study of multiple spare parts: Because the analysis of a single project in the case study made up for a large portion of the research, we were not able to look at other projects. The studying of multiple projects for spare parts could perhaps lead to more insights in the way projects progress or in the fine-tuning of the tool parameters.

Cost parameters: We were only able to obtain estimations by NedTrain for the unavailability cost for each train series. For all other cost parameters we had to make our own estimations, based on the processes that lead to these costs. These cost parameters are essential in both algorithms and in the assignment of spare parts. Better estimations for these parameters will improve the model.

6.3 Future Research

The main recommendations for future research are:

Link the decision support tool to live data: It is already possible to export inventory levels and the progress of repairs from the system. But implementing these data feeds into our model was deemed too difficult. Future research could look into these opportunities to obtain more accurate forecasts of the arrival of trains to the OB, the breakdown of parts, and the returning of spare parts from the repair shop.

Multi-item model: It could well be possible that a train has to undergo multiple project maintenance during the same period. For trains with unplanned demand it could also be the case that other types of critical spare parts failed and replacing one of them still does not lead to the train leaving the OB. To consider all these dependencies, the model has to be extended to allow multiple items.

Multiple OBs: Even for some of the larger spare parts, replacements can happen in multiple OBs. Including multiple OBs in the model will increase the complexity significantly. The model not only has to cope with more demand streams (2 for every OB), but also has to worry about to which OB the RFU parts have to go when they come out of the repair shop.

Holding cost: When a warehouse is nearing its capacity, its remaining storage space will become more valuable and thus more costly. An extension of the tool could be to include this fact and let the decision support tool decide whether to store a part at the repair shop, at the LLC (central warehouse), or at the OB.

Allow procurement of new parts: our model assumes that the repair shop is able to revise all parts that go into repair and thus that the number of parts in the closed-loop supply chain stays constant. An extension of the model could be that this assumption is relaxed and parts can be rated unrepairable. The model should then decide whether the procurement of a new part, with a certain delivery lead time and procurement cost, would be a feasible decision.

List of abbreviations

EBK	Extra BinnenKomst
ICM	Type of intercity train (Dutch: InterCity Materieel)
LCM	Long Cycle Maintenance or project maintenance (Dutch: Lang Cyclisch Onderhoud)
NCB	NedTrain Components Company (Dutch: NedTrain Componenten Bedrijf)
NS	Dutch Railways (Nederlandse Spoorwegen)
NSR	Planning department Dutch Railways (NS Reizigers)
OB	Maintenance Depot (Onderhouds Bedrijf)
RFU	Ready-for-use: part which are repaired and can be used for replacements
R&O	Refurbishment and Overhaul Workshop
SB	Service Company (Dutch: Service Bedrijf)
SCO	Supply Chain Operations
ShCM	Short Cycle Maintenance or regular maintenance (Dutch: Kort Cyclisch Onderhoud)

Glossary

As-is	Present state of the organization's process
Backlog cost	The cost for not being able to satisfy demand
Buffer	Virtual queue in which replaced spare parts wait before they enter the repair process in multiples of their batch size
Carriage	Separate car of a train
Closed-loop supply chain	Supply chain with goods flowing back upstream the chain after usage/failure. In NedTrain's case, the cycle of spare parts being used in trains and revised after replacement for future replacements
Expedited repair	Accelerated repair that is faster and more expensive than a regular repair
Life cycle of spare parts	Series of stages through which the part passes during its lifetime
Outstanding repair order	Repair order which is currently in repair and will not arrive in the current period
Penalty cost	Cost incurred when a spare part is not available for a maintenance operation
Rationing	The act of reserving a part of the on-hand inventory to solely satisfy unplanned demand
Repair order	Collection of a specific spare part which was sent to repair in the same period
Rolling stock	Wheeled vehicles used by businesses on roadways/railways (in this case: trains)
Scope	The extent to which certain subjects or activities are relevant for the project
Scrap rate	Fraction of the total number of parts that go into repair that is classified as unrepairable
Service level	In this research: the sum of all parts assigned to a demand stream divided by the sum of the daily demands of that demand stream over the same period of time
To-be	Future (proposed) state of the organization's process
Turn-around stock	Number of units in NedTrain's closed-loop supply chain of a specific spare part

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Appendix

Appendix A: Equation descriptions

[1] The objective is the minimization of the average cost per period for the planning of spare parts for two demand streams from period 1 to period T

[2] The total cost include the cost for repairs, unavailability, delaying and unfinished project maintenance outside the project interval

[3] If spare part defined as critical (K=1): the number of regular (ShCM) maintenance operations in the OB in period t after the arrival of demand and adding the maintenance operations from previous periods still waiting for a part. If the spare part is defined as non-critical (K=0): number of maintenance operations in period t is equal to demand arrived in period t from ShCM

[4] The number of parts assigned to regular maintenance (ShCM) in period t cannot be larger than the maintenance operations waiting for a spare part in the OB in period t after the arrival

[5] The number of parts assigned to project maintenance (LCM) in period t cannot be larger than the demand from LCM in period t

[6] The number of parts in the buffer at the repair shop at the end of period t before the parts go into repair is equal to the number of parts in the buffer at the end of period t-1 plus the number of replaced parts for regular and project maintenance in period t minus the parts sent to repair at the end of period t-1

[7] The number of spare parts sent to repair in period t is equal to the round down number of 'parts in the buffer divided by the batch size' times the batch size

[8] The total cost for unavailability include the number of unfinished ShCM maintenance operations (trains) currently in the OB at time t minus the parts assigned to these operations times the cost per period for unavailability (note: only incurred when spare part is defined as critical (K=1))

[9] The total cost for delaying include the cost for delaying LCM and ShCM (only if part is defined as non-critical (K=0)), these cost are incurred once per train that does not get a part assigned.

[10] The total expected cost for unfinished project maintenance outside the project interval equals the product of the number of periods overdue when the delayed project maintenance returns, the number of project maintenance operations that do not get parts assigned in period t, and penalty cost

[11] Binary variable that is 0 when the corresponding outstanding repair order that arrives i periods from period t has ever been expedited and 1 if it was never expedited

[12] A repair order which was sent to repair in period t-1 cannot have been expedited yet

[13] The total number of spare parts that can be expedited in period t to receive in period t+1

[14] It is more expensive to expedite a repair order that is supposed to arrive in i+1 periods than a repair order that is supposed to arrive in i periods

[15] The cost of expediting an order that will arrive in Y periods and was supposed to arrive in Y period is equal to zero

[16] The decision to expedite an order in period t ($E_{i,t}$) is binary

[17] The total cost for repairs include the regular repair cost for all parts being sent to repair at the end of period t and the additional expediting repair cost for all parts expedited in period t

[18] The total number of parts which arrive in period t is equal to all parts expedited in period t-Y plus the parts that were sent to repair in period t-L times the variable that checks whether this repair order was ever expedited and thus already arrived

[19] The inventory on hand at the beginning of period t is equal to the inventory on hand in period t-1 minus the parts assigned to regular and project maintenance in period t-1 plus the parts arriving from repair in period t

[20] The number of parts assigned to regular maintenance (ShCM) plus the number of parts assigned to project maintenance (LCM) have to be smaller than or equal to the inventory on hand in period t

[21] The total number of spare parts in the closed-loop supply chain is equal to the on hand inventory at the start of period t after receiving parts from repair plus the total number of parts in repair at the start of period t plus the buffer size at the end of period t-1

[22] [a] Number of parts assigned to ShCM in period t is equal to the minimum of the on-hand inventory in period t and the number of ShCM maintenance operations in the OB in period t

[b] Number of parts assigned to LCM in period t is equal to the minimum of the remaining parts in inventory for LCM and the demand from LCM in period t

[23] [a] Number of parts assigned to LCM in period t is equal to the minimum of the on-hand inventory in period t and the demand from LCM in period t.

[b] Number of parts assigned to ShCM in period t is equal to the minimum of the remaining parts in inventory for ShCM and the ShCM maintenance operations in the OB in period t

[24] Non-negative constraint

[25] Integer constraint

[26] There were no parts sent to repair in period 0

[27] The on hand inventory in period 0 is equal to all spare parts in the closed-loop supply chain

[28] There are no regular maintenance operations in the OB in period 0

[29] There are no defect spare parts in the buffer in period 0

[30] There are no parts in repair in period 0

[31] The generated regular demand in period t for period t consists of a drawn value for the demand and the non-critical regular demand delayed in $t - V$

[32] The generated project demand in period t for period t consists of a drawn value for the demand and the project demand delayed in $t - V$

[33] The mean of LCM is equal to the remaining number of project maintenance operations divided by the number of periods remaining until the end of the project

[34] Number of ShCM maintenance operations in the OB in period t, based on the generated demands

[35] Service level ShCM per iteration of the rationing algorithm

[36] Service level LCM per iteration of the rationing algorithm

[37] Average servive level ShCM over all n iterations

[38] Average servive level LCM over all n iterations

[39] Average cost per period calculated with the service levels that depend on the rationing level

[40] Service level ShCM per iteration of the expediting algorithm

[41] Service level LCM per iteration of the expediting algorithm

[42] Total cost over $[t+Y, t+\tau]$ calculated with the service levels and the expediting cost that depend on the expediting level

[43] The number of parts expedited in period t, to receive in period t+Y, has to be equal to or larger than the minimal required number of parts to receive in period t+Y. The possible outstanding repair orders that can be expedited range from the orders that are supposed to come in i periods from now up until L-N periods from now (with N being the number of periods after which it is possible to expedite an order)

Appendix B: Scrap rates of parts in the NCB in 2012

In this context, the scrap rate at NedTrain's internal repair shop equals the fraction of the total number of spare parts that go into repair and are classified as unrepairable. Parts are classified as unrepairable when it is physically impossible to repair it, or when it makes financially more sense to procure a new part. The scrap rates for NedTrain's internal repair shop (NCB) of 2012 can be found in Table 0.1. This table comes from the Master thesis of Martijn van Aspert (Van Aspert, 2013) which was also conducted at NedTrain. Because this data is several years old, we tried to recreate it with more recent data. We were able to obtain all scrap data per part and per product group of 2016. However, we were not able to collect any data about the total repairs that were conducted in the same period per part or product group. This made it impossible to calculate the actual scrap rates.

Table 0.1 is used to justify *Assumption 6* in section 3.4. Because the average scrap rate is just at 3.5%, we feel safe to assume that the repair shop is able to repair all replaced spare parts and thus the number of spare parts in the closed-loop supply chain stays constant.

Table 0.1: Scrap rates of parts in the NCB in 2012 (Van Aspert, 2013)

Cluster	Scrapped	Ordered	Scrap rate (%)	Average Scrap Rate (%)	Standard Deviation (%)
Air Conditioners	3	172	0.4	2.0	10.0
Mechanics	159	12191	1.3	6.0	18.0
Electronics	717	9545	7.5	9.0	22.0
Pneumatics	450	15366	2.9	3.9	10.8
Total	**1329**	**37814**	**3.5**	**6.3**	**17.1**

Appendix C: Literature Review – Summary of Articles

This appendix includes a summary of all articles used in the literature review (Konings, 2016) conducted for this research. Important parts from this review can be found in section 1.4

	General description	Closed-loop supply chain	Expedited repair	Demand differen-tiation	Spare parts	Inventory reservations (rationing)
Sherbrooke (1967)	The METRIC model is a two-echelon, multi-item mathematical model for recoverable items. The METRIC model has the following three purposes: optimization of the system, redistribution of inventory and assessing performance and investment costs.	+	-	-	+ (multi-item)	-
Basten & Ryan (2015)	Inventory system with two types of demand with different priorities: high and low. Low priority demand is observed before the ordering decision and high priority demand after the ordering decision.	-	-	+	+	-
Kranenburg & Van Houtum (2004)	Single warehouse with multiple stock-keeping units to serve multiple customers. Customers are divided into multiple customer classes with different aggregate fill rates. Multi-item, single-stage spare part inventory model is proposed to minimize the inventory investment.	-	-	+	+ (multi-item)	-
Díaz & Fu (1996)	Inventory control model of repairable items with limited repair capacities. Approximations are introduced that can deal with limited repair facilities under single-class and multi-class scenarios.	-/+	-	-	+	-
Arts et al. (2016)	Repairable items facing Markov modulated Poisson demand. Opportunity to expedite the repair of failed parts at the start of the repair. Decision depends on number of items in regular repair and the state of the exogenous Markov process.	-/+	+	-	+	-
Luoit et al. (2010)	Dynamic control system for the service rate in an M/M/1 queueing system. The inventory of critical spare parts can be controlled by expediting or slowing down the repair rate in the facility. Decision depends on number of units in operation.	+	+ (repair rates)	-	+	-
Verrijdt, Adan & De Kok (1998)	Emergency repair model with Poisson arrivals. If on-hand stock of spare parts exceeds the emergency trigger level, failed part is sent into normal repair. If level is below or equal to this trigger level, the part is sent into an emergency repair.	+	+	-	+	-
Allen & D'Esopo (1968)	Ordering policy with an additional quantity called the expediting level. When on-hand stock is reduced to this level, an outstanding order will be expedited and received in R periods (less than normal lead-time L).	+	+ (outstanding orders)	-	-	-
Chiang (2010)	Single-item continuous-review order expediting policy. Lead-time split into two parts: transport and manufacturing. After transport part is finished, there is an opportunity to expedite outstanding repairs, depending on expedite-up-to level.	+	+ (outstanding orders)	-	-	-
Topkis (1968)	Inventory system with *n* demand classes of varying importance. Rationing is used to satisfy demand from a more important class between two procurement moments. Critical rationing levels are determined. If on-hand stock falls below this level, remaining stock can only be used to satisfy demand of higher priority.	-	-	+	-	+
Dekker, Kleijn & de Rooij (1996)	Demand is classified into critical and non-critical demand, depending on the criticality of the respective equipment. A stocking policy is proposed where some of the stock is reserved for critical demand.	-	-	+	+	+
Liu et al. (2015)	Dynamic inventory rationing policy for multiple demand classes. A two-step approach proposed, based on the equivalence principle, to tackle the computational problems of dynamic programming.	-	-	+	+ (multi-item)	+

Appendix D: Mathematical model: Explanatory examples

Some examples are given to show how (parts of) the mathematical model works:

Expediting (1)

Assume that the deterministic repair lead time (L) is 4, the number of periods after which an expedited order arrives (Y) is 2, and the number of periods after which it is possible to expedite an outstanding order (N) is 0. It is also assumed that none of the orders before period 3 have been expedited. As can be seen in the table below, the minimum number of parts required to order (X) in period 3 is equal to 3 ($X_3 = 3$). This order will arrive 2 (Y) periods later. To satisfy X_3, the parts sent to repair in period 1 (2 parts) and period 2 (1 part) are expedited (note that the parts sent to repair in period 1 were already supposed to arrive in period 5 and thus incur no additional expediting cost, $c_{EY} = 0$).

T	Sent to repair (Q^D)	Inventory on hand (I)	Min. ordered (X)	$E_{Y,t}$	$E_{Y+1,t}$
1	2	..	..	..	..
2	1	..	..	..	..
3	2	..	3	1	1
4	1	..	..	..	..
5	4	(+3)	..	..	..
6	2	..	..	..	..

In mathematical formulas:

$$X_t \leq \sum_{i=Y}^{L-N-1} A_{i,t} E_{i,t}\, Q^D_{t-L+i}$$

$$X_3 = 3$$

$$3 \leq \sum_{i=2}^{4-0-1} A_{i,3} E_{i,3}\, Q^D_{3-4+i}$$

$$3 \leq A_{2,3} E_{2,3} Q^D_1 + A_{3,3} E_{3,3} Q^D_2$$

$$3 \leq E_{2,3} 2 + E_{3,3} 1$$

$$E_{2,3} = 1 \quad \& \quad E_{3,3} = 1$$

$$I_t = I_{t-1} - R_{t-1} - P_{t-1} + \sum_{i=Y}^{L-N-1} E_{i,t-Y}\, Q^D_{t-L+i-Y} + A_{0,t} Q^D_{t-L}$$

$$I_5 = (\dots) + \sum_{i=2}^{4-0-1} E_{i,5-2}\, Q^D_{5-4+i-2} + 0$$

$$I_5 = (\dots) + E_{2,3} Q^D_1 + E_{3,3} Q^D_2 = (\dots) + 3$$

Expediting (2)

Assume that the deterministic repair lead time (L) is 5, the number of periods after which an expedited order arrives (Y) is 2, and the number of periods after which it is possible to expedite an outstanding order (N) is 0. The costs of expediting outstanding repair orders that are supposed to arrive I periods from t are given for each possible I in the following table:

i	C_{Ei}
2	0
3	1
4	2

The minimization of the total cost, including the cost of repairs, will always ensure that the best combination of repair orders is expedited. The minimum number of parts required to order (X) in period 4 is equal to 3. To satisfy X, the parts sent to repair in period 1 (2 parts) and period 3 (2 part) are expedited. The model calculated that this combination will lead to the lowest possible cost.

T	Sent to repair (Q^D)	Inventory on hand (I)	Min. ordered (X)	$E_{Y,t}$	$E_{Y+1,t}$	$E_{Y+2,t}$
1	2	..	..	..	..	..
2	5	..	..	..	..	..
3	2	..	..	..	..	..
4	1	..	3	1	0	1
5	4	..	..	..	..	..
6	2	(+4)	..	..	..	..

In mathematical formulas:

$$3 \leq \sum_{i=2}^{5-0-1} A_{i,4} E_{i,4}\, Q_{4-5+i}^{D}$$

$$\min \frac{1}{T}\sum_{t=1}^{T} TC(t)\left(= TC_R(t) + TC_U(t) + TC_D(t) + TC_P(t)\right)$$

$$TC_R(t) = Q_t^D c_R + \sum_{i=Y}^{L-N-1} E_{i,t}\, A_{i,t} c_{Ei} Q_{t-L+i}^{D}$$

$$TC_R(t) = (\dots) + \sum_{i=2}^{5-0-1} E_{i,4}\, A_{i,4} c_{Ei} Q_{4-5+i}^{D}$$

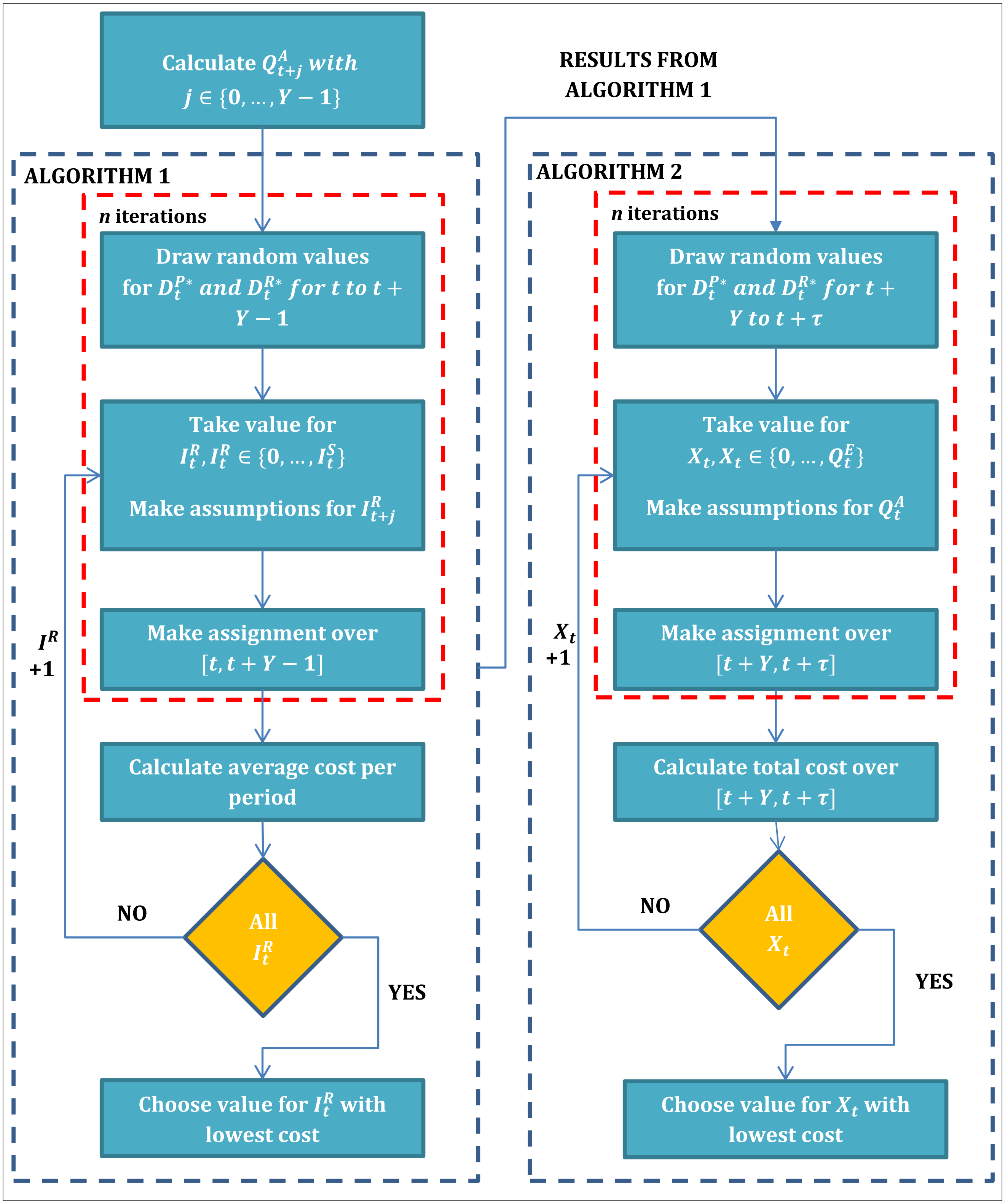
$$TC_R(t) = (\dots) + E_{2,4}A_{2,4}c_{E2}Q_1^D + E_{3,4}E_{3,4}c_{E3}Q_2^D + E_{4,4}A_{4,4}c_{E4}Q_3^D$$

$$TC_R(t) = (\dots) + E_{2,4}(1)(0)(2) + E_{3,4}(1)(1)(5) + E_{4,4}(1)(2)(2)$$

$$E_{2,4} = 1 \quad \& \quad E_{3,4} = 0 \quad \& \quad E_{4,4} = 1$$

Appendix E: Schematic Overview of Algorithms

See **Algorithm 1** and **Algorithm 2** in sections 3.5 and 3.6 for a stepwise description.



Appendix F: Case Study: RStudio output

In the case study in section 5.1, we want to assume that the monthly data we obtained for ShCM and LCM follows a negative binomial distribution so that we can generate daily demand patterns. We used the statistical computing software *RStudio* to first fit the negative binomial parameters to our samples. Then, we use a Chi-squared test to check whether we can assume our samples indeed follow a negative binomial distribution. The p-values from the Chi-squared test indicate that we cannot reject the null hypothesis and both samples can be considered negative binomially distributed. All results from *RStudio* are displayed below.

ShCM sample

```
> a <- c(1,1,0,7,3,0,2,2)
> MASS::fitdistr(a,"negative binomial")
     size          mu
  1.6916852   2.0000006
 (1.6927765) (0.7386226)
```

LCM sample

```
> b <-c(18,13,16,10,7,10,2,10)
> MASS::fitdistr(b,"negative binomial")
     size          mu
   7.464705   10.750000
 ( 6.947287) ( 1.810773)
```

Chi-squared test

```
> chisq.test(factor(a),factor(c))

        Pearson's Chi-squared test

data:  factor(a) and factor(c)
X-squared = 10, df = 12, p-value = 0.616
```

```
> chisq.test(factor(b),factor(d))

        Pearson's Chi-squared test

data:  factor(b) and factor(d)
X-squared = 16.889, df = 15, p-value = 0.3255
```

Creating daily demand patterns

```
> e <- rnbinom(240, mu = 2/30, size = 1.6916852/30)
> f <- rnbinom(240, mu = 10.75/30, size = 7.464705/30)
```

Appendix G: Case Study: Decision Support Tool parameters

All settings for the decision support tool in the case study are presented below. A discussion about how we arrived at these values is presented in the introduction of the case study in section 4.1.

Variable	Value
Normal repair lead time (L)	20 days
Expedited repair lead time (Y)	7 days
Number of periods after which expediting is possible (N)	2 days
Number of spare parts in closed-loop supply chain (S)	11 parts
Batch size for repairs (F)	1 parts
Number of parts per train for LCM (W)	1 parts/train
Critical spare part (K)	1 (=YES)
Number of spare parts in project (TP)	86 maint. op.
Starting period of project (PB)	1st day
Ending period of project (PE)	240th day
Expected time between two visits to the OB (V)	78 days
Mean of demand from ShCM	0.067
Standard deviation of demand from ShCM	0.414
Mean of demand from LCM	0.358
Standard deviation of demand from LCM	0.860
Cost of a regular repair (Cr)	200 EUR
Cost of unavailability of train per day (Cu)	698 EUR
Cost per unperformed project outside project interval per day (Cp)	18.50 EUR
Cost of delaying LCM (Cdp)	150 EUR
Cost of expediting repairs that are supposed to arrive in {7,8,9,10,11,12,13,14,15,16,17} days	{0,30,35,40,45,50,60 ,65,70,75,80} EUR
Number of iterations for the algorithms (n)	5000 iterations
Number of periods considered for Xt (τ)	9 days

Appendix H: Case Study: Sensitivity Analysis

The service levels for ShCM and LCM for Figure 5.2 and Figure 5.3 in section 4.3 of the case study can be found in respective Table 0.2 and Table 0.3. These outcomes are discussed in section 4.3

Table 0.2: Service levels for different number of units in supply chain (S)

S	ShCM	LCM
11	88,89%	87,21%
12	90,01%	89,76%
13	90,55%	92,19%
14	92,97%	96,41%
15	94,12%	99,23%
16	98,45%	99,78%
17	100%	100%

Table 0.3: Service levels for different lengths of the expediting period (Y)

Y	ShCM	LCM
5	100%	100%
6	100%	99.89%
7	100%	99.77%
8	99.53%	98.22%
9	98.44%	97.32%
10	97.9%	96.99%
11	94.12%	96.51%
12	90.81%	92.88%
13	87.65%	91.38%
14	86.11%	90.02%
15	84.21%	88.37%
16	80.15%	88.19%
17	79.17%	88.11%

Appendix I: Case Study: Inventory graphs

To give a visual representation of the 6 different policies for the case study (section 4.2), we plotted the inventory graphs for all the different policies for a specific demand pattern over the duration of the project. These graphs also include the amount expedited and rationed for every period. <u>A discussion per graph is presented in section 4.2.</u>

Policy 1: With expediting and rationing algorithm

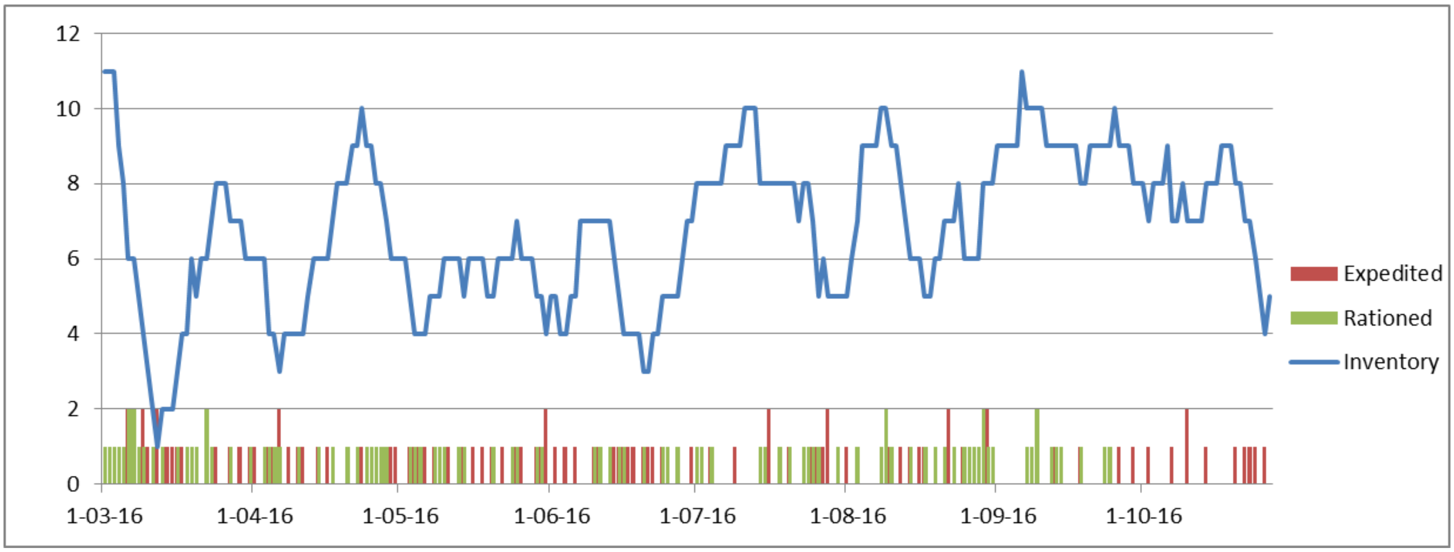


Figure 0.1: Inventory during project of policy 1 of one demand pattern

Policy 2: Only with expediting algorithm

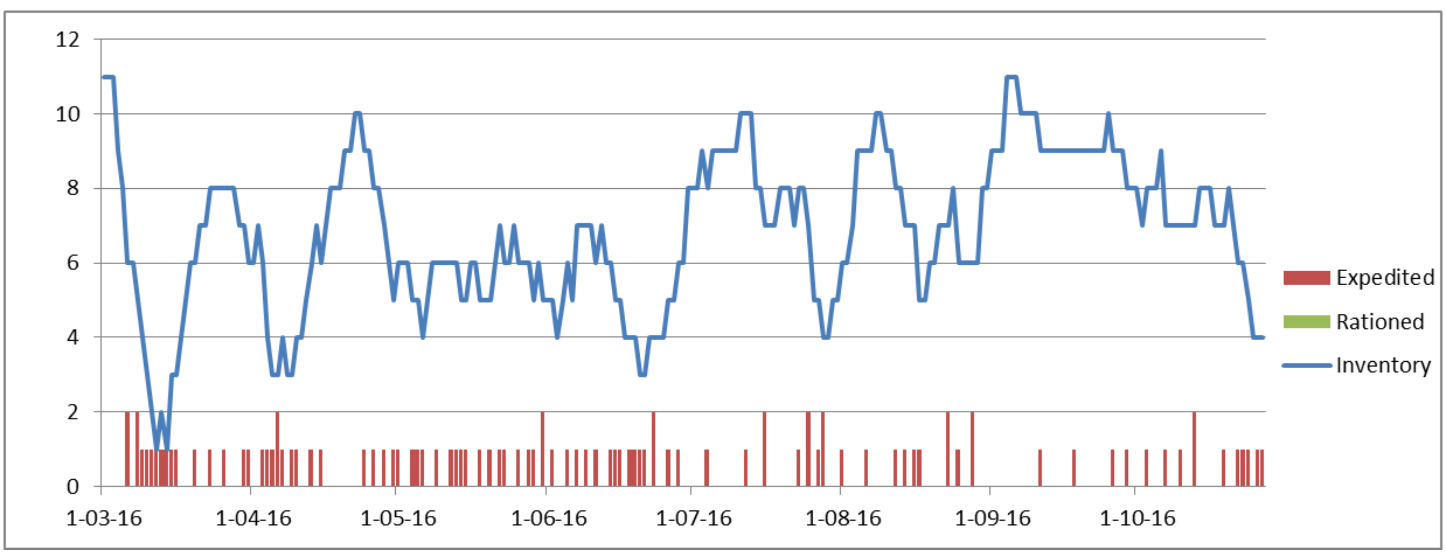


Figure 0.2: Inventory during project of policy 2 of one demand pattern

Policy 3: Only with rationing algorithm

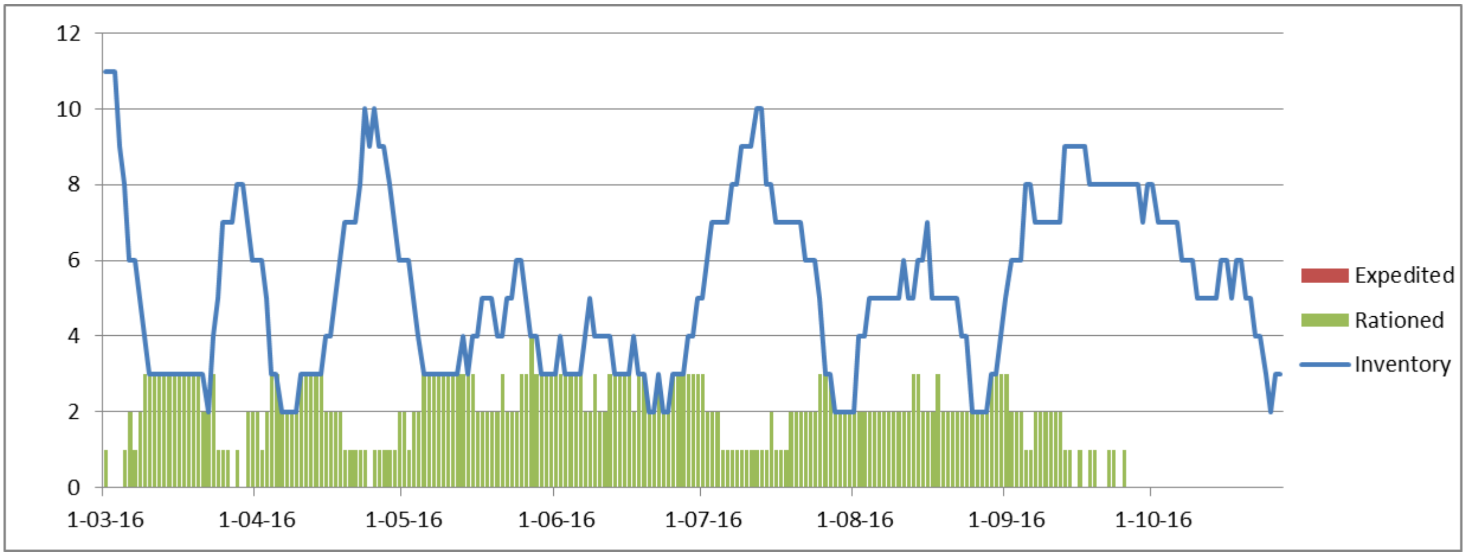


Figure 0.3: Inventory during project of policy 3 of one demand pattern

Policy 4: Without expediting and rationing algorithm

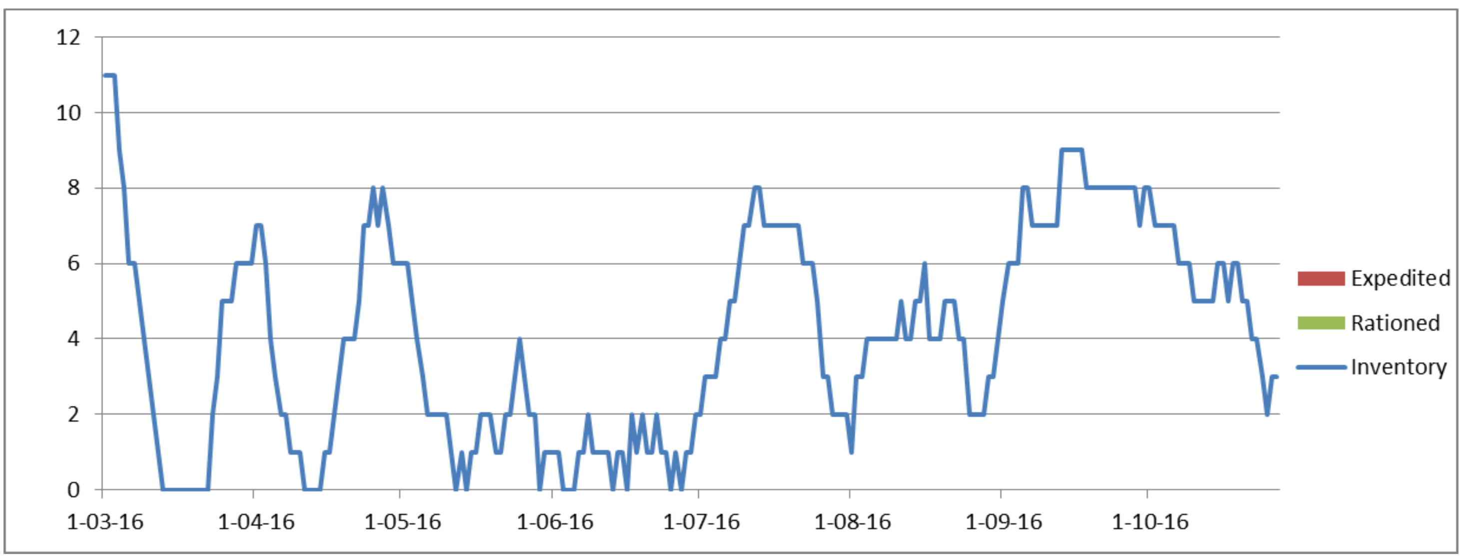


Figure 0.4: Inventory during project of policy 4 of one demand pattern

Policy 5: Maximum expediting policy

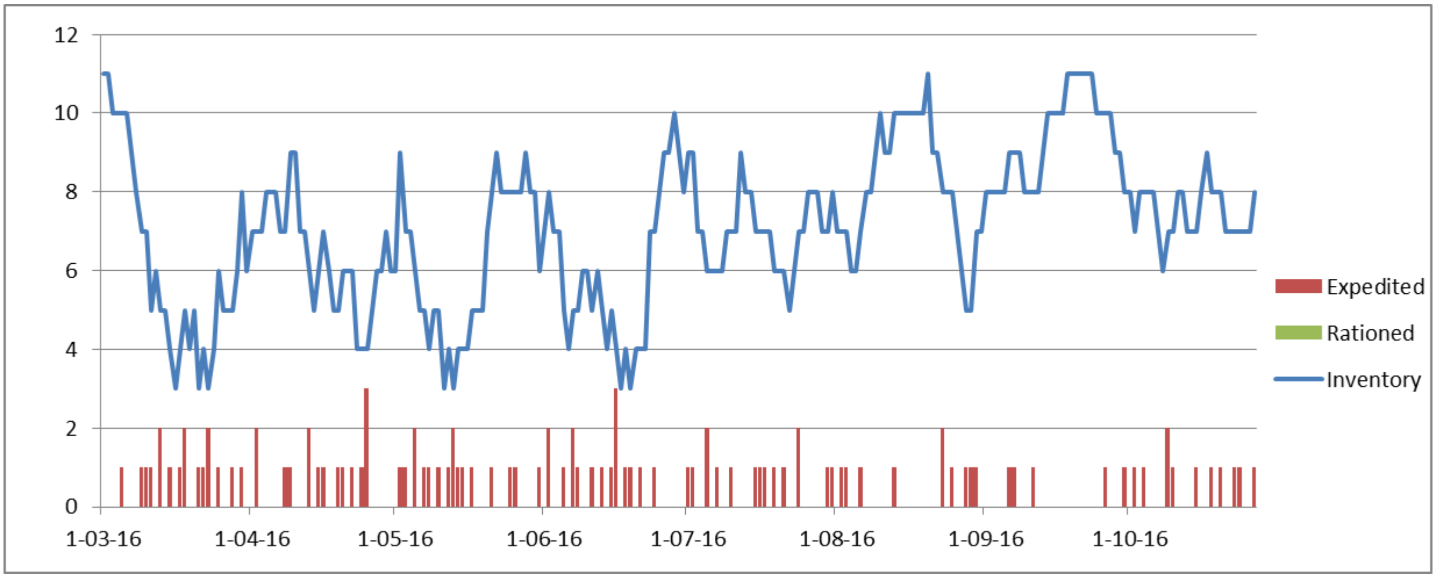


Figure 0.5: Inventory during project of policy 5 of one demand pattern

Policy 6: Customized expediting policy (current practice)

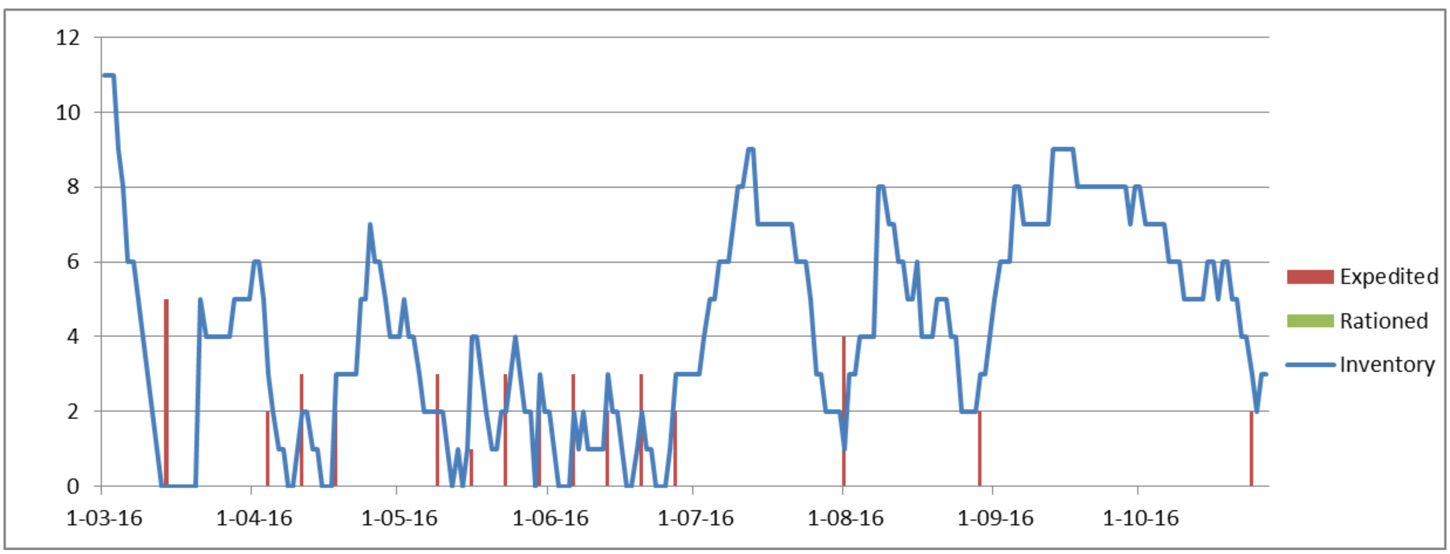
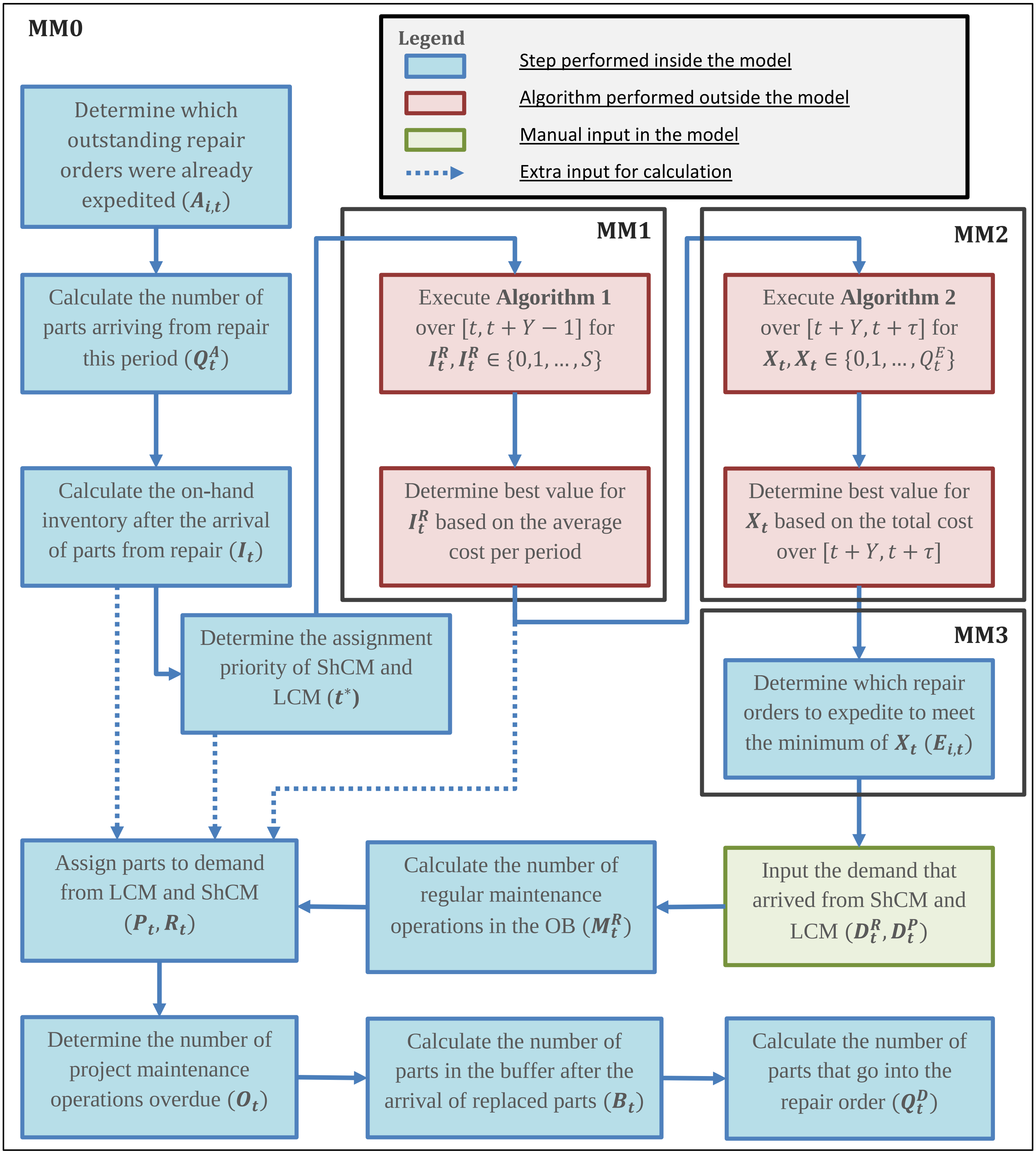


Figure 0.6: Inventory during project of policy 6 of one demand pattern

Appendix J: Mathematical Model & Algorithms: Process View

A process view of all the steps inside the mathematical model and the algorithms calculated outside the model. A detailed description of the model and algorithms can be found in sections 3.4-3.7. A schematic overview of both algorithms is presented in *Appendix E*.



Appendix K: Time between two visits to the OB (ICM and VIRM)

The parameter for the number of days between two visits of a train to the OB (V) is used to forecast the returning demand of a delayed maintenance operation. The model uses this information to try to make sure there will be enough on-hand inventory in the OB when the delayed maintenance returns, so that it does not have to be delayed again. As mentioned before, the time between two visits is about 3 months, but can deviate. If we want to be on the safe side and choose V to be a couple of weeks before the expected arrival, we are almost certain that we have a spare part on-hand when the train with delayed project demand returns to the OB. This will, however, lead to higher cost for expediting, because parts will be needed back from repair earlier on average. On the other hand, when SCO tries to prevent high expediting cost and choose V to be on or above the average number of days, it leads to more delays and thus higher delay cost. To give SCO more perspective in choosing the right value for V, we want to find out how these visits are distributed. With this information, it would be possible for them to determine the number of days between two visits, based on the likelihood that the forecast is before or on the day the train's actual return to the OB.

We conducted an analysis of the arrival of around 300 VIRM (double deck) train series and 100 ICM (InterCity Materieel) train series at the different OBs for ShCM in the last 3 years. After cleaning the raw data files, we were able to calculate the number of days between consecutive visits. According to Thomas van Haperen (Reliability Engineer of the VIRM series), the VIRM and ICM series should have the same arrival patterns to the OB. This also showed from the analysis of the two datasets, with the two series having almost identical means and standard deviation for the number of days between two visits. Because of the same patterns of the two series, we decided to merge the two datasets for further analysis. The first step was to plot a histogram, to check for normality. If we look at Figure 0.7, we can roughly distinct the bell-curve of the normal distribution. So, we will assume that the data is normally distributed. The next step was the calculation of the mean and standard deviation of the dataset (Table 0.4).

Table 0.4: Mean and standard deviation of the number of days between two visits to the OB

Number of periods between two visits to the OB	
Mean	78.51
Standard deviation	13.20

Because the cleaning of the raw datasets and the performing of all analyses was very time intensive, we only looked at the VIRM and ICM series. Further research could analyze the other train series.

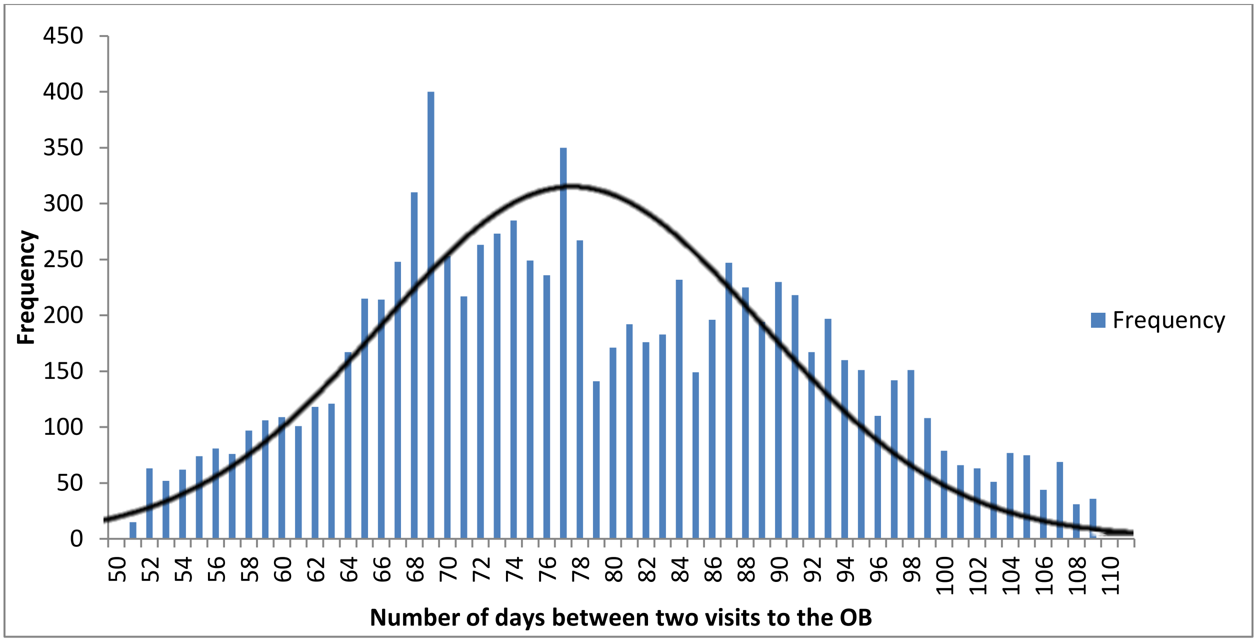


Figure 0.7: Histogram of time between two visits to the OB (ICM and VIRM)

Table 0.5: Table frequencies of time between two visits to the OB (ICM and VIRM)

Days	*Frequency*	*Days*	*Frequency*	*Days*	*Frequency*
50	0	**70**	253	**90**	230
51	15	**71**	217	**91**	218
52	63	**72**	263	**92**	167
53	52	**73**	273	**93**	197
54	62	**74**	285	**94**	160
55	74	**75**	249	**95**	151
56	81	**76**	236	**96**	110
57	76	**77**	350	**97**	142
58	97	**78**	267	**98**	151
59	106	**79**	141	**99**	108
60	109	**80**	171	**100**	79
61	101	**81**	192	**101**	66
62	118	**82**	176	**102**	63
63	121	**83**	183	**103**	51
64	167	**84**	232	**104**	77
65	215	**85**	149	**105**	75
66	214	**86**	196	**106**	44
67	248	**87**	247	**107**	69
68	310	**88**	225	**108**	31
69	400	**89**	194	**109**	36

Appendix L: Determining the number of iterations (n)

Both algorithms will simulate how the proposed value for the respective policy behaves over n generated demand patterns in the form of service levels for ShCM and LCM. If n is chosen large enough, the service levels should converge to a certain value. To determine what the minimal amount of iterations should be to obtain the converged value every time we use the algorithm, we will investigate the outcomes of the two algorithms for different values of n. It makes sense that if we keep increasing n, the outcomes of the two algorithms will keep getting more accurate. Increasing n will, however, also lead to longer computing times, as can be seen in Table 0.6.

Table 0.6: Computing times of a week of demand for different values of n

	n=1000	n=2000	n=5000	n=10000	n=20000
Computing time week of demand	0:09min	0:21min	0:48min	2:17min	7:09min

We generated a random demand pattern and let the algorithms determine the service levels for LCM for I_t^R and X_t for 10 periods for $n \in \{1000,2000,5000,10000,20000\}$ (Table 0.7, Table 0.8). We choose to analyze $I_t^R = 6$ and $X_t = 0$, because these appeared over all 10 periods. When we look at the results from both algorithms, we can see a clear convergence when n gets closer to 20,000 instances. It shows that the difference between the service levels of n=5,000 and n=20,000 are within 0.005 or 0.5%. We also notice in Table 0.6 that the generation of 4 times as many demand patterns will lead to about 7 times longer computing times. This is probably caused by an overload of calculations in MS EXCEL and/or in the CPU.

We feel that an error margin of 0.5% for the calculation of the service levels is acceptable because it will not affect the calculation of the total cost that much. This implies that it will also not influence the choice of the rationing and expediting levels. Also, the increased computing times for higher values of n are not really significant if we calculate a week or a day, but they will be when we consider a project of a couple of months. So, we used 5,000 iterations for all our calculations in the case study. This number can always be changed on the settings page of the decision support tool.

Table 0.7: Service levels for IRt=6 for 10 periods under different values for n

t	n=1000	n=2000	n=5000	n=10000	n=20000
1	0.866	0.865	0.864	0.863	0.863
2	0.769	0.750	0.759	0.755	0.756
3	0.758	0.746	0.756	0.754	0.754
4	0.764	0.758	0.757	0.755	0.755
5	0.602	0.613	0.602	0.606	0.605
6	0.487	0.484	0.485	0.485	0.485
7	0.529	0.523	0.527	0.526	0.526
8	0.560	0.630	0.552	0.560	0.563
9	0.654	0.690	0.577	0.585	0.585
10	0.511	0.537	0.460	0.464	0.462

Table 0.8: Service levels for Xt=0 for 10 periods under different values for *n*

t	n=1000	n=2000	n=5000	n=10000	n=20000
1	0.998	0.997	0.997	0.997	0.997
2	0.990	0.990	0.991	0.991	0.991
3	0.992	0.993	0.992	0.992	0.992
4	0.986	0.993	0.990	0.991	0.991
5	0.974	0.980	0.978	0.978	0.978
6	0.976	0.977	0.977	0.980	0.979
7	0.984	0.979	0.978	0.978	0.978
8	0.979	0.992	0.978	0.977	0.978
9	0.994	0.989	0.981	0.980	0.980
10	0.978	0.976	0.976	0.976	0.976

Appendix M: Determining τ (tau)

For the calculation of the expediting level in *Algorithm 2* we have to choose a value for τ, to indicate how many periods in the future we want to include in the calculations. This value for τ has to be equal to or larger than the expedited repair lead time (Y), because we want to examine the effect of an expediting decision after the corresponding expedited order has arrived. We assume for all periods beyond Y and up to τ that repair orders arrive according to their normal repair lead time. This implies that the parts that arrive according to their normal repair schedule in this period plus the number of parts in the expedited order has to be large enough to satisfy all incoming demand. In other words, the number of periods between τ and Y will be more or less equal to the number of periods between two expediting moments.

There is a daily opportunity to make expediting decisions. So, in the optimal case, this opportunity is considered every day to be able to cope with fluctuating demand and be as versatile as possible. This leads to the advice to set τ equal to Y and only consider the expected demand in the period that the expedited parts from repair arrive at the OB. However, the planners at the repair shop urge us to consider additional factors involved. They refer to potential start-up cost and decreasing repair times for a larger number of expedited parts due to efficiency in the process. They are not able to provide us with quantitative data, but they say they prefer somewhat less frequent expediting requests.

In our model, there will always be a daily opportunity to expedite repair orders. However, when we increase the period τ, the number of parts expedited from repair in one period will increase because the expected demand of more periods is considered. This will then lead to less frequent, but larger expediting decisions on average. To determine whether we should extend τ, and if so, by how many periods, we perform simulations of the case study under different values of τ and compare the service levels of both demand streams. These results are displayed in Table 0.9. What can be immediately noted are the decreasing service levels of the two demand streams as the length of τ increases. This can be asserted to the fact that the expediting policy becomes less able to handle heavy fluctuations in the demand patterns because of the extended average period between two expediting moments. While keeping this in mind, we feel that the results from the period $\tau = Y + 2$ do not differ much from the results of $\tau = Y$. Choosing τ larger than $Y + 2$, leads to a steeper drop in the service levels per period increase. We feel that choosing τ to be equal to $Y + 2$ is a good way to meet the needs of the planners at the repair shop while not compromising too much on the service levels. Because the periods in our model are equal to days, this leads to 3 days of expected demand being considered for the expediting decision. On average, this will lead to expediting decisions every 3 days.

Table 0.9: Service levels for the two demand streams under different values of tau

	$\tau = Y$	$\tau = Y + 1$	$\tau = Y + 2$	$\tau = Y + 3$	$\tau = Y + 4$	$\tau = Y + 5$
Service level ShCM	100.00%	100.00%	100.00%	99.96%	99.91%	99.87%
Service level LCM	99.09%	99.07%	99.07%	99.01%	98.96%	98.92%

Appendix N: Verification & Validation of Decision Support Tool

Verification

To confirm that the decision support tool is correctly implemented with respect to the conceptual model we have to perform some verification steps. We have to check whether it matches the specifications and assumptions that were made. In the upcoming sections, we perform a consistency check and an extreme value check to verify our mathematical model.

Consistency check

One of the main dynamics in our model is that the sum of the number of parts at different locations within our closed-loop supply chain equals the total number of parts in this supply chain [21]. With the different locations in NedTrain's supply chain we refer to the following three locations: the inventory at the OB, the buffer at the repair shop, and the repair process in which parts can be located. Because we assume that all parts can be repaired and there is no scrap during the repair process, we indirectly assume that the sum of the number of parts in all three locations is a constant.

Number of parts in the closed loop supply chain = number of parts in the inventory at the OB
+ number of parts in the buffer at the repair shop
+ number of parts currently in repair

To test if we modelled this central statement in our model correctly in the decision support tool, we will look at the simulation results of our case study. The assumption that at the start of every project, all parts are repaired and in the inventory at the OB leads to 11 parts at the OB, 0 parts in the buffer at the repair shop and 0 parts in repair in period 1. The fastest method to check the consistency is to look at the last period in all of our simulations and determine whether the sum of the parts at all three locations adds up to 11. This is the case for all simulations. Because this does not prove it is consistent throughout the entire simulation, we will generate the sum of the number of parts at all three locations for every period in the simulation as an output in a MS EXCEL file. All generated values are equal to 11 without any exemptions. This concludes that the central dynamics of the flow of parts in our tool functions accordingly.

Extreme value check

The extreme value check has to determine whether the output of the model makes sense when we input extreme or unlikely values. For most variables, we can hypothesize what the logical consequence of inputting an extreme value would be on the output of the model. If the actual output of the model differs from our hypothesis, this can indicate a modelling error. We will test both extreme low and extreme high values for every variable we analyze. For all analyses we use the parameters as presented in the case study as base values.

Number of parts in the closed-loop supply chain

In this check, we will input extreme values for the number of parts in the closed-loop supply chain to analyze the effects on rationing, expediting and the number of times demand is backlogged. Starting with the extreme low value of 1 part, we generate the extreme shortage scenario. The first thing we notice is that the rationing level is fixed at 1 and the overall backlogged demand increases significantly. It also seems that every time this part is sent to repair, a decision is made to expedite its repair lead time. The increasing backlogged demand and expedition of repair orders would be a logical result of an extreme shortage of parts.

We will now test the scenario that we have an abundance of parts in our supply chain by setting the number on 999. The opposite happens to our results. Rationing and expediting levels stay at 0 throughout the entire project. We are also able to satisfy all incoming demand and thus incur no backlogged demand.

Both scenarios behave like expected. All decision variables analyzed are on opposite sides of the spectrum for both extremes.

Expediting cost

When we use extreme high values for the expediting cost we see that the model never chooses to expedite an outstanding repair. This makes sense because the cost of expediting does not weigh against the unavailability or delay cost that can possibly be prevented. On the other hand, removing all costs to expedite repair orders leads to an expediting policy which expedites all repair orders at the first period possible. In practice, when the repair shop would offer to expedite the repair lead time at no additional cost, we would expect the same results.

Unavailability cost

Using an extreme high value for the unavailability cost results in rationing levels being equal to the number of parts in the supply chain (maximum rationing level possible). The assignment priority is fixed at ShCM throughout the whole project. On the other side, removing the unavailability cost leads to a fixed priority for LCM and no rationing in the project interval. Both these findings seem a logical result of the extreme values because it either is extremely expensive to not satisfy ShCM or completely free to do so.

Project penalty cost
In the scenario that there are no penalty cost incurred for project maintenance operations which are performed outside the set project interval, we see that there is no assignment priority switch at any point during the simulation. This can be explained by the fact that both the delay cost for LCM and the unavailability cost for ShCM are fixed and the variable project penalty cost are removed from the equation that determines the priority. When we introduce the project penalty cost, at an extremely high value, we see that the moment the assignment priority switches moves somewhat forward. This moment is however limited by the expected number of periods after which the train returns to the OB.

Validation

We have to validate our decision support tool to check how accurately it represents the real system. It should be resolved whether the conceptual model is a correct representation of the system by taking the objectives of this research into account. Both subjective and statistical tests can be used to test a model's validity. We use the face validity test to test our model.

Face validity
Sargent (2005) defines face validity as "asking people knowledgeable about the system whether the model and/or its behavior are reasonable". This technique can determine whether the logic in the model is correct and if the model's input-output relationships are reasonable. The people that know the process of spare part planning for the two demand streams in the OB the best and are also the end-users of the tool are the planners and management of SCO.

We invited one manager and two planners of SCO for demonstrations of the decision support tool. We were mainly interested in their thoughts regarding the output of the decision variables and the assumptions made to develop the model. The output of our case study and the specific decision variables were discussed with the SCO employees. They were able to recollect the project of the toilet module of the ICM and thought the output and improvements the tool offers seemed realistic. They also agreed that the assumptions made regarding e.g. repair lead times, expedited repair lead times, expediting levels, and assignment decisions seemed reasonable. Because they never used the rationing of inventory before, they could not evaluate what the results of this policy would be in practice.

Appendix O: Decision Support Tool: VBA code

```
Attribute VB_Name = "Assignment"
Sub Assignment()

' For the loops
Dim i As Integer
Dim j As Integer
Dim t As Integer
Dim zero As Integer
Dim loop1 As Integer
Dim loop2 As Integer
…
Dim loop21 As Integer
Dim loop22 As Integer

' Decision variables
Dim E() As Integer
Dim P() As Integer
Dim R() As Integer

' Variables
Dim stdevP As Single
Dim stdevR As Single
Dim A() As Integer
Dim B() As Integer
Dim CE() As Single
Dim CDP As Single
Dim CDR As Single
Dim CP As Single
Dim CR As Single
Dim CU As Single
Dim DP() As Integer
Dim DR() As Integer
Dim DPt() As Single
Dim DRt() As Single
Dim F As Integer
Dim Inv() As Integer
Dim IR() As Integer
Dim K As Integer
Dim L As Integer
Dim MR() As Integer
Dim N As Integer
Dim O() As Integer
Dim PB As Integer
Dim PE As Integer
Dim QD() As Integer
Dim QE() As Integer
Dim QT() As Integer
Dim S As Integer
Dim TC() As Double
Dim TCD() As Double
Dim TCP() As Double
Dim TCR() As Double
Dim TCU() As Double
Dim TP As Integer
Dim V As Integer
```

```
Dim W As Integer
Dim X() As Integer
Dim Y As Integer
Dim meanR As Single
Dim meanP As Single

' Other variables
Dim SimStart As Integer
Dim SimEnd As Integer
Dim AIT As Integer
Dim arrive_in_t As Integer
Dim temprange As String
Dim temprange2 As String
Dim clean As String
Dim diff As Integer
Dim QTT As Integer
Dim QTE As Integer
Dim QDtemp As Integer
Dim QY() As Integer
Dim PV() As Integer
Dim datetoday() As Date
Dim nextday As Date
Dim no_delayed As Integer
Dim date_return() As Date

' Constant variable settings
F = Worksheets("Instellingen").Range("C8").Value
K = Worksheets("Instellingen").Range("C7").Value
L = Worksheets("Instellingen").Range("C4").Value
N = Worksheets("Instellingen").Range("C18").Value
PE = Worksheets("Instellingen").Range("F6").Value + L
PB = Worksheets("Instellingen").Range("F5").Value
S = Worksheets("Instellingen").Range("C6").Value
TP = Worksheets("Instellingen").Range("F3").Value
V = Worksheets("Instellingen").Range("C19").Value
W = Worksheets("Instellingen").Range("C17").Value
Y = Worksheets("Instellingen").Range("C5").Value
' Cost settings
CDP = Worksheets("Instellingen").Range("F14").Value
CDR = Worksheets("Instellingen").Range("F13").Value
CP = Worksheets("Instellingen").Range("F12").Value
CR = Worksheets("Instellingen").Range("F10").Value
CU = Worksheets("Instellingen").Range("F11").Value

If L > 20 Then
Exit Sub
Else
End If

ReDim CE(20) As Single
For loop12 = 1 To 20
CE(loop12) = Worksheets("Instellingen").Cells(3, 8 + loop12).Value
Next
' Demand settings
meanR = Worksheets("Instellingen").Range("C10").Value
meanP = Worksheets("Instellingen").Range("C13").Value
stdevR = Worksheets("Instellingen").Range("C11").Value
```

```
stdevP = Worksheets("Instellingen").Range("C14").Value

' Simulation interval & duration
SimStart = L
SimEnd = PE
diff = 999

' New dimensions
ReDim E(20, diff) As Integer
ReDim P(diff) As Integer
ReDim R(diff) As Integer
ReDim A(21, diff) As Integer
ReDim B(diff) As Integer
ReDim DP(diff) As Integer
ReDim DR(diff) As Integer
ReDim DPt(diff) As Single
ReDim DRt(diff) As Single
ReDim Inv(diff) As Integer
ReDim IR(diff) As Integer
ReDim MR(diff) As Integer
ReDim O(diff) As Integer
ReDim QD(diff) As Integer
ReDim QE(diff) As Integer
ReDim QT(diff) As Integer
ReDim TC(diff) As Double
ReDim TCD(diff) As Double
ReDim TCP(diff) As Double
ReDim TCR(diff) As Double
ReDim TCU(diff) As Double
ReDim X(diff) As Integer
ReDim QY(diff) As Integer
ReDim PV(diff) As Integer
ReDim datetoday(diff) As Date
ReDim date_return(diff) As Date

For zero = 0 To diff - 1
    Inv(zero) = S
    For loop4 = 0 To 20
        E(loop4, zero) = 0
        A(loop4, zero) = 1
    Next
Next

' Clear Excel sheets
For loop7 = 2 To 999
clean = "D" & loop7 & ":" & "I" & loop7
Worksheets("Data").Range(clean).ClearContents
Next
For loop8 = 2 To 999
clean = "K" & loop8 & ":" & "N" & loop8
Worksheets("Data").Range(clean).ClearContents
Next
Worksheets("Data").Range("A2:A1000").ClearContents
Worksheets("Data").Range("CZ2:DA1000").ClearContents
Worksheets("Data").Range("P2:BH1000").ClearContents
Worksheets("Rationing").Range("A3:BL1000").ClearContents
Worksheets("Xvalue").Range("A3:BL1000").ClearContents
```

```
Worksheets("LCO").Range("A2:B1000").ClearContents

'
****************************************************************************
**

'                               SIMULATION START

'
****************************************************************************
**
For t = SimStart To SimEnd
datetoday(t) = DateAdd("d", t - SimStart,
Worksheets("Instellingen").Range("F4"))
nextday = DateAdd("d", 1, datetoday(t))
Worksheets("Data").Cells(t - SimStart + 2, 1).Value = datetoday(t)
Worksheets("Dashboard").Range("C4").Value = nextday

    arrive_in_t = 0
    For i = Y To L - N - 1
    arrive_in_t = arrive_in_t + E(i, t - Y) * QD(t - L + i - Y)
    Next
    ' Calculations for inventory on hand at the beginning of period t
    Inv(t) = Inv(t - 1) - R(t - 1) - P(t - 1) + arrive_in_t + A(1, t - 1) *
QD(t - L)
    Worksheets("Data").Cells(t - SimStart + 2, 4).Value = Inv(t)
    QTT = 0
    For j = 1 To L - 1
        AIT = 0
        For loop2 = j To L - 2
            AIT = AIT + E(loop2 + 1, t + j - loop2 - 1)
        Next
        If AIT > 0 Then
            A(j, t) = 0
        Else
            A(j, t) = 1
        End If
            A(L - 1, t) = 1
        Worksheets("Data").Cells(t - SimStart + 2, 40 + j).Value = A(j, t)
        QTT = QTT + A(j, t) * QD(t - L + j)
    Next
    ' Calculations for the total number of parts in repair
    QT(t) = S - Inv(t) - B(t - 1) + QD(t - 1)
    Worksheets("Data").Cells(t - SimStart + 2, 7).Value = QT(t)
'______________________________________________________________________

'                    START SIMULATION FOR IR(t) (MM1)
'______________________________________________________________________
Dim DR_sim() As Long
Dim DP_sim() As Long
Dim InvSim() As Long
Dim Rsim() As Long
Dim Psim() As Long
Dim DRtotal() As Double
Dim DPtotal() As Double
Dim Rtotal() As Long
Dim Ptotal() As Long
```

```
Dim fillrate_R() As Single
Dim fillrate_P() As Single
Dim cost_sim() As Double
Dim iMin As Double
Dim iCount As Long
Dim iterations As Integer
Dim withoutIRt As Integer
Dim tau As Integer

' number of iterations determines the number of demands patterns generated
(advised: 5000)
iterations = Worksheets("Instellingen").Range("F19").Value
' tau is equal to the number of periods considered for X(t) with tau >= Y
tau = Worksheets("Instellingen").Range("F20").Value + 1

ReDim DR_sim(iterations, tau) As Long
ReDim DP_sim(iterations, tau) As Long
ReDim InvSim(iterations, tau, S) As Long
ReDim Rsim(iterations, tau, S) As Long
ReDim Psim(iterations, tau, S) As Long
ReDim cost_sim(Inv(t)) As Double
ReDim Rtotal(Inv(t)) As Long
ReDim Ptotal(Inv(t)) As Long
ReDim fillrate_R(Inv(t)) As Single
ReDim fillrate_P(Inv(t)) As Single
ReDim DRtotal(Inv(t)) As Double
ReDim DPtotal(Inv(t)) As Double

' Determining whether to start with project or regular maintenance with
assignment based on long term cost

withoutIRt = 1 - Worksheets("Instellingen").Range("F18").Value

If withoutIRt = 0 Then
If CU >= (CDP + WorksheetFunction.Max(t - SimStart + 1 + V - PE, 0) * CP)
Then
    For loop20 = 1 To iterations
        For loop19 = 1 To Y
                DR_sim(loop20, loop19) =
WorksheetFunction.Round(WorksheetFunction.Max(0,
WorksheetFunction.NormInv(TakeRnd, meanR, stdevR)) + DRt(t + loop19 - 1), 0)
                DP_sim(loop20, loop19) =
WorksheetFunction.Round(WorksheetFunction.Max(0,
WorksheetFunction.NormInv(TakeRnd, meanP, stdevP)) + DPt(t + loop19 - 1), 0)
            For loop18 = 0 To Inv(t)
                InvSim(loop20, 0, loop18) = 0
                Rsim(loop20, 0, loop18) = 0
                Psim(loop20, 0, loop18) = 0
                InvSim(loop20, loop19, loop18) = InvSim(loop20, loop19 - 1,
loop18) - Rsim(loop20, loop19 - 1, loop18) - Psim(loop20, loop19 - 1, loop18)
+ PV(t + loop19 - 1 - Y)
                InvSim(loop20, 1, loop18) = Inv(t)
            ' Check whether the assignment prioirty switches in the rationing
interval (if so, assume IR(t)=0 after switch)
                If CU >= (CDP + WorksheetFunction.Max(t - SimStart + loop19 +
V - PE, 0) * CP) Then
```

```
                IR(t) = WorksheetFunction.Min(InvSim(loop20, loop19, loop18),
loop18)
                Else
                IR(t) = 0
                End If
            ' Assigning parts to two demand streams (first determine
assignment priority)
                If CU >= (CDP + WorksheetFunction.Max(t - SimStart + loop19 +
V - PE, 0) * CP) Then
                    Rsim(loop20, loop19, loop18) =
WorksheetFunction.Min(DR_sim(loop20, loop19), InvSim(loop20, loop19, loop18))
                    Psim(loop20, loop19, loop18) =
WorksheetFunction.Min(WorksheetFunction.Min(InvSim(loop20, loop19, loop18) -
Rsim(loop20, loop19, loop18), WorksheetFunction.Max(0, InvSim(loop20, loop19,
loop18) - IR(t) - Rsim(loop20, loop19, loop18))), DP_sim(loop20, loop19))
                Else
                    Psim(loop20, loop19, loop18) =
WorksheetFunction.Min(DP_sim(loop20, loop19), InvSim(loop20, loop19, loop18))
                    Rsim(loop20, loop19, loop18) =
WorksheetFunction.Min(InvSim(loop20, loop19, loop18) - Psim(loop20, loop19,
loop18), DR_sim(loop20, loop19))
                End If

                Rtotal(loop18) = Rtotal(loop18) + Rsim(loop20, loop19,
loop18)
                Ptotal(loop18) = Ptotal(loop18) + Psim(loop20, loop19,
loop18)
                DRtotal(loop18) = DRtotal(loop18) + DR_sim(loop20, loop19)
                DPtotal(loop18) = DPtotal(loop18) + DP_sim(loop20, loop19)
            Next
        Next
    Next
    For loop21 = 0 To Inv(t)
        ' Calculation of the fillrates and average cost per period
        fillrate_R(loop21) = Rtotal(loop21) / DRtotal(loop21)
        fillrate_P(loop21) = Ptotal(loop21) / DPtotal(loop21)
        cost_sim(loop21) = (1 - fillrate_R(loop21)) * CU + (1 -
fillrate_P(loop21)) * CDP
        Worksheets("Rationing").Cells(3 + t - SimStart, 2 + 3 * loop21).Value
= fillrate_R(loop21)
        Worksheets("Rationing").Cells(3 + t - SimStart, 3 + 3 * loop21).Value
= fillrate_P(loop21)
        Worksheets("Rationing").Cells(3 + t - SimStart, 4 + 3 * loop21).Value
= cost_sim(loop21)
    Next
    iMin = WorksheetFunction.Min(cost_sim)
    iCount = WorksheetFunction.Match(iMin, cost_sim, 0)
    IR(t) = iCount - 1
Else
End If
Else
    IR(t) = 0
End If

' Finding the lowest average cost per period and take respective value for
IR(t) as optimal value
Worksheets("Data").Cells(t - SimStart + 2, 8).Value = IR(t)
```

```
Worksheets("Dashboard").Range("C11").Value = IR(t)
Worksheets("Rationing").Cells(3 + t - SimStart, 1).Value = t - SimStart + 1
'______________________________________________________________________

'                        END SIMULATION FOR IR(t)
'______________________________________________________________________

' Calculations for number of parts possible to expedite
QTE = 0
For loop9 = Y To L - N - 1
QTE = QTE + A(loop9, t) * QD(t - L + loop9)
Next
QE(t) = QTE

'______________________________________________________________________

'                   START SIMULATION FOR X(t)(MM2)
'______________________________________________________________________
'
Dim TCRsim As Single
Dim IRsim As Integer
Dim index As Integer
Dim QDsim As Integer
Dim order As Integer
Dim withoutX As Integer
Dim weekend As Integer

ReDim cost_sim(QE(t)) As Double
ReDim Rtotal(QE(t)) As Long
ReDim Ptotal(QE(t)) As Long
ReDim fillrate_R(QE(t)) As Single
ReDim fillrate_P(QE(t)) As Single
ReDim DRtotal(QE(t)) As Double
ReDim DPtotal(QE(t)) As Double

If Weekday(datetoday(t)) = 1 Or Weekday(datetoday(t)) = 7 Then
    weekend = 1
Else
    weekend = 0
End If

withoutX = 1 - Worksheets("Instellingen").Range("F17").Value

If withoutX = 0 Then
If weekend = 0 Then

For loop17 = 1 To iterations
    For loop16 = Y + 1 To tau
        For loop15 = 0 To QE(t)
            PV(t) = loop15
            InvSim(loop17, loop16, loop15) = InvSim(loop17, loop16 - 1,
loop15) - Rsim(loop17, loop16 - 1, loop15) - Psim(loop17, loop16 - 1, loop15)
+ PV(t + loop16 - 1 - Y)
            DR_sim(loop17, loop16) = WorksheetFunction.Max(0,
WorksheetFunction.NormInv(TakeRnd, meanR, stdevR)) + DRt(t + loop16 - 1) +
DR_sim(loop17, loop16 - 1) - Rsim(loop17, loop16 - 1, loop15)
```

```
            DP_sim(loop17, loop16) = WorksheetFunction.Max(0,
WorksheetFunction.NormInv(TakeRnd, meanP, stdevP)) + DPt(t + loop16 - 1)

            IRsim = 0
            ' Assigning parts to two demand streams (first determine
assignment priority)
            If CU >= (CDP + WorksheetFunction.Max(t - SimStart + loop16 + V -
PE, 0) * CP) Then
                Rsim(loop17, loop16, loop15) =
WorksheetFunction.Min(DR_sim(loop17, loop16), InvSim(loop17, loop16, loop15))
                Psim(loop17, loop16, loop15) =
WorksheetFunction.Min(WorksheetFunction.Min(InvSim(loop17, loop16, loop15) -
Rsim(loop17, loop16, loop15), WorksheetFunction.Max(0, InvSim(loop17, loop16,
loop15) - IR(t) - Rsim(loop17, loop16, loop15))), DP_sim(loop17, loop16))
            Else
                Psim(loop17, loop16, loop15) =
WorksheetFunction.Min(DP_sim(loop17, loop16), InvSim(loop17, loop16, loop15))
                Rsim(loop17, loop16, loop15) =
WorksheetFunction.Min(InvSim(loop17, loop16, loop15) - Psim(loop17, loop16,
loop15), DR_sim(loop17, loop16))
            End If

            PV(t + loop16 - 1) = Rsim(loop17, loop16, loop15) + Psim(loop17,
loop16, loop15)
            Rtotal(loop15) = Rtotal(loop15) + Rsim(loop17, loop16, loop15)
            Ptotal(loop15) = Ptotal(loop15) + Psim(loop17, loop16, loop15)
            DRtotal(loop15) = DRtotal(loop15) + DR_sim(loop17, loop16)
            DPtotal(loop15) = DPtotal(loop15) + DP_sim(loop17, loop16)
        Next
    Next
Next
    ' Calculation of the fillrates and average cost per period
For loop22 = 0 To QE(t)
    index = 0
    QDsim = 0
    TCRsim = 0
    Do While QDsim < loop22
        If index > L - Y Then
            Exit Do
        End If
        QDsim = QDsim + QD(t + Y - L + index) * A(Y + index, t)
        TCRsim = TCRsim + QD(t + Y - L + index) * CE(Y + index) * A(Y +
index, t)
        index = index + 1
    Loop

    fillrate_R(loop22) = Rtotal(loop22) / DRtotal(loop22)
    fillrate_P(loop22) = Ptotal(loop22) / DPtotal(loop22)
    cost_sim(loop22) = ((1 - fillrate_R(loop22)) * CU + (1 -
fillrate_P(loop22)) * CDP) * (tau - Y) + TCRsim
    Worksheets("Xvalue").Cells(3 + t - SimStart, 2 + 3 * loop22).Value =
fillrate_R(loop22)
    Worksheets("Xvalue").Cells(3 + t - SimStart, 3 + 3 * loop22).Value =
fillrate_P(loop22)
    Worksheets("Xvalue").Cells(3 + t - SimStart, 4 + 3 * loop22).Value =
cost_sim(loop22)
Next
```

```
' Finding the lowest average cost per period and take respective value for
X(t) as optimal value
iMin = WorksheetFunction.Min(cost_sim)
iCount = WorksheetFunction.Match(iMin, cost_sim, 0)
X(t) = iCount - 1
Else
X(t) = 0
End If

Else
X(t) = QE(t)
End If

' Code for simulation of current practice with review period and order-up-to-
level
'Dim review As Single
'Dim reviewperiod As Integer
'reviewperiod = 7
'review = (t - SimStart + 1) / reviewperiod
'
'If review = Int(review) Then
'    If Inv(t) < 5 Then
'        X(t) = WorksheetFunction.Min(QE(t), 5 - Inv(t))
'    Else
'        X(t) = 0
'    End If
'Else
'    X(t) = 0
'End If
'Else
'X(t) = 0
'End If

Worksheets("Data").Cells(t - SimStart + 2, 9).Value = X(t)
Worksheets("Xvalue").Cells(3 + t - SimStart, 1).Value = t - SimStart + 1

'______________________________________________________________________

'                        END SIMULATION FOR X(t)
'______________________________________________________________________


' Copying QD() values to Excel sheet
For loop3 = 1 To L - 1
QDtemp = QD(t - L + loop3)
Worksheets("Data").Cells(t - SimStart + 2, 80 + loop3).Value = QDtemp
Next

' Using solver to find best combination of repair orders to expedite (MM3)
Worksheets("Data").Activate
SolverReset
SolverOK SetCell:=Cells(t - SimStart + 2, 15), MaxMinVal:=2, ValueOf:="0",
ByChange:=Range(Cells(t - SimStart + 2, 20 + Y), Cells(t - SimStart + 2, 40))
SolverAdd CellRef:=Range(Cells(t - SimStart + 2, 20 + Y), Cells(t - SimStart
+ 2, 40)), Relation:=5
```

```
SolverAdd CellRef:=Cells(t - SimStart + 2, 10), Relation:=3,
formulaText:=Cells(t - SimStart + 2, 9)
SolverSolve True

' Obtaining values for E(i,t) from Excel sheet
For loop5 = Y To 20
E(loop5, t) = Worksheets("Data").Cells(t - SimStart + 2, 20 + loop5).Value
Next

' Obtaining demand for Regular and Project maintenance from Excel sheet
DR(t) = Worksheets("Data").Cells(t - SimStart + 2, 2).Value
DP(t) = Worksheets("Data").Cells(t - SimStart + 2, 3).Value

' Use the following values for demand if simulated demand patterns are used
to include returning projects
'If t >= V Then
'DP(t) = Worksheets("Data").Cells(t - SimStart + 2, 3).Value + (DP(t - V) -
P(t - V))
'End If

MR(t) = MR(t - 1) - R(t - 1) + DR(t)
Worksheets("Data").Cells(t - SimStart + 2, 11).Value = MR(t)

' Determining whether to start with project or regular maintenance with
assignment based on long term cost
If CU >= (CDP + WorksheetFunction.Max(t - SimStart + 1 + V - PE, 0) * CP)
Then
' Assigning to regular maintenance (ShCM)
    R(t) = WorksheetFunction.Min(Inv(t), MR(t))
    Worksheets("Data").Cells(t - SimStart + 2, 5).Value = R(t)
' Assigning to project maintenance (LCM)
    P(t) = WorksheetFunction.Min(WorksheetFunction.Min(Inv(t) - R(t),
WorksheetFunction.Max(0, Inv(t) - IR(t) - R(t))), DP(t))
    Worksheets("Data").Cells(t - SimStart + 2, 6).Value = P(t)
' When delaying project maintenance is more expensive in the long term
Else
' Assigning the project maintenance
    P(t) = WorksheetFunction.Min(Inv(t), DP(t))
    Worksheets("Data").Cells(t - SimStart + 2, 5).Value = R(t)
' Assigning to regular maintenance
    R(t) = WorksheetFunction.Min(Inv(t) - P(t), MR(t))
    Worksheets("Data").Cells(t - SimStart + 2, 6).Value = P(t)
End If

' Calculate returning projects
If DP(t) - P(t) > 0 Then
no_return = no_return + 1
date_return(no_return) = DateAdd("d", V, datetoday(t))
Worksheets("LCO").Cells(1 + no_return, 1).Value = date_return(no_return)
Worksheets("LCO").Cells(1 + no_return, 2).Value = DP(t) - P(t)
Else
End If

' Calculations for number of project operations overdue
temprange2 = "F" & 2 & ":" & "F" & t + 1
    If t < PE Then
    O(t) = 0
```

```
    Else
    O(t) = WorksheetFunction.Max(0, TP -
WorksheetFunction.Sum(Range(temprange2)))
    End If
    Worksheets("Data").Cells(t - SimStart + 2, 12).Value = O(t)

' Calculations for the buffer size
B(t) = B(t - 1) + P(t) + R(t) - QD(t - 1)
Worksheets("Data").Cells(t - SimStart + 2, 13).Value = B(t)
' Calculations for repair order size
QD(t) = WorksheetFunction.RoundDown((B(t) / F), 0) * F
Worksheets("Data").Cells(t - SimStart + 2, 14).Value = QD(t)

'Calculating costs
TCR(t) = QD(t) * CR + Worksheets("Data").Cells(t - SimStart + 2, 15)
TCU(t) = (MR(t) - R(t)) * K * CU
TCD(t) = (DP(t) - P(t)) * CDP + (1 - K) * (DR(t) - R(t)) * CDR
TCP(t) = WorksheetFunction.Max(0, (t + V) - PE) * (DP(t) - P(t)) * CP
TC(t) = TCR(t) + TCU(t) + TCD(t) + TCP(t)
Worksheets("Data").Cells(t - SimStart + 2, 16).Value = TCR(t)
Worksheets("Data").Cells(t - SimStart + 2, 17).Value = TCU(t)
Worksheets("Data").Cells(t - SimStart + 2, 18).Value = TCD(t)
Worksheets("Data").Cells(t - SimStart + 2, 19).Value = TCP(t)
Worksheets("Data").Cells(t - SimStart + 2, 20).Value = TC(t)

'Updating forecasts with delays
DPt(t + V) = DPt(t + V) + DP(t) - P(t)
DRt(t + V) = DRt(t + V) + (DR(t) - R(t)) * (1 - K)

'Number of products expedited
PV(t) = Worksheets("Data").Cells(t - SimStart + 2, 10).Value

Worksheets("Data").Cells(t - SimStart + 2, 104).Value =
Worksheets("Data").Cells(t - SimStart + 1, 104) + P(t)
Worksheets("Data").Cells(t - SimStart + 2, 105).Value = TP -
Worksheets("Data").Cells(t - SimStart + 2, 104)
Worksheets("Data").Cells(t - SimStart + 2 + V, 106).Value = DP(t) - P(t)
Next

End Sub
' Function to prevent the random generated number to be 0 and make the
NormInv function crash
Function TakeRnd()

Dim random As Double

random = Rnd()
Do While random = 0
random = Rnd()
Loop
TakeRnd = random

End Function
)
```