MASTER

Improving the multi-item, multi-location spare parts stocking policy at PACCAR Parts Europe

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Improving the multi-item, multi-location spare parts stocking policy at PACCAR Parts Europe

Master Thesis

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Abstract

This research aims to improve the multi-item, multi-warehouse spare-parts stocking policy of the European warehouses of PACCAR Parts under capacity constraints. The problem is split up into two parts. Firstly, a stocking/non-stocking decision is made. Based on cost approximations for the expected PACCAR Parts fill rates (order fill rate), expected transshipment costs, and expected inventory costs, an integer programming model is proposed that decides per warehouse whether an item is stocked or not. In order to enable a smooth implementation of the proposed stocking/non-stocking model for PACCAR Parts, an additional heuristic has been proposed that is easier to implement for PACCAR Parts in the short term.
Hereafter, the optimal safety stock coverage levels are obtained via two different methods. The first method is a safety stock heuristic that minimizes the total expected inventory costs and obtains a minimal aggregated service level. The second method starts with proposing a new classification algorithm for spare parts that are evaluated via the PACCAR Parts fill rate (order fill rate). This classification algorithm classifies spare parts based on their degree of variability and the trade-off between the increase in aggregated service level and the increase in total inventory costs. Hereafter, a real-coded genetic algorithm determines the near-optimal safety stock coverage levels per class. The fitness values of the chromosomes are determined by simulation. To limit the computational time of this simulation-based real-coded genetic algorithm, efficient methods for initializing the population and executing the genetic operators are proposed.

Executive summary

This master's thesis project is conducted at the Demand Planning department of PACCAR Parts Europe in Eindhoven. PACCAR Parts Europe is responsible for the after-sales of spare parts for DAF trucks. This executive summary overviews the most crucial research outcomes for PACCAR Parts and its warehouse stocking policies.

Problem definition

The Demand Planning department is responsible for the inventory management of spare parts in the European warehouses of PACCAR Parts. Their goal is to maximize the availability of spare parts and minimize the total costs. PACCAR Parts measures this availability by using the PACCAR Parts fill rate. This Kep Performance Indicator (KPI) can be defined as the percentage of order lines that can be delivered immediately from stock. It is measured per warehouse individually and on an aggregated European level by considering transshipments. In the stocking policy, two main decisions have to be made. Firstly, it has to be decided per warehouse whether each item becomes stocking or not. In the current policy, this decision is made per item warehouse individually rather than making an aggregated decision that takes into account the effects of transshipments. Secondly, a level for the safety stock coverage in days has to be set for every item that is stocked. In the current policy, an item is classified in one of 9 classes based on a two-dimensional array that considers the number of order lines and Cost Of Goods Sold (COGS) in the last rolling year. However Wingerden, van, Tan and Houtum, van (2016) proved that having a one-dimensional $\frac{demand}{price}$-ratio outperforms a classification that is based on a two-dimensional array. Additionally, the findings of Teunter, Babai and Syntetos (2010) suggest that there is room for improvement in extending the number of classes. Furthermore, the current safety stock policy does not consider any variability, which is in contrast to the literature on safety stocks ((Zipkin, 2000)). It is concluded that the current stocking policies are sub-optimal. Accordingly, the main research question of this thesis is as follows:

How can the Demand Planning department improve the stocking policy of spare parts at the European warehouses of PACCAR Parts

Research design

In order to answer the main research question systematically, the problem is split up into three sub-research questions.

1. *What are the (simulated) performances of the current stocking policy in terms of total costs and availability?*
   In order to compare the performances of the current situation with the proposed improvements, a simulation model is made. A reliable and representative simulation model is obtained using empirical forecast, product, demand, and supply data.

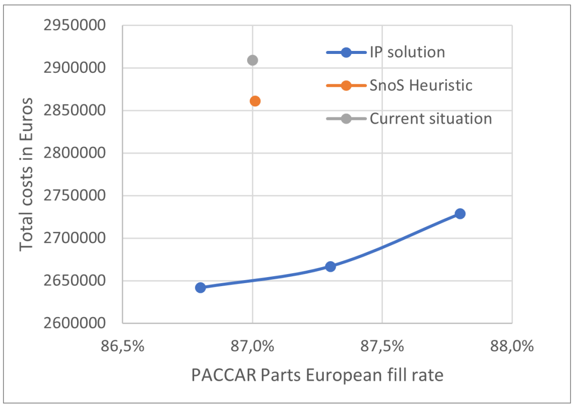
2. *How can the Demand Planning department improve the policy regarding the stocking/non-stocking decision?*
   It is concluded that an item can be stocked via 92 different stocking options across the warehouses if transshipments are taken into account. An IP model is proposed that allocates

one of these 92 stocking options to every item such that the total costs (inventory + transshipments) are minimized, the minimum expected PACCAR Parts fill rates are respected, and the capacity constraints of the warehouses are respected. Based on the analysis of the results of the IP model, a stocking/non-stocking heuristic (SnoS heuristic) is proposed that is more convenient to implement for PACCAR Parts.

3. *What is the near-optimal safety stock coverage level per item per warehouse?*
Two different methods are used to determine the safety stock coverage levels. The first method is the safety stock heuristic that is described by Donselaar, van, Broekmeulen and Kok, de (2021). The heuristic iteratively increases the SKU's safety stock level with the biggest increase in aggregated PACCAR Parts European fill rate relative to the increase in total costs until a target PACCAR Parts European fill rate is met. The second method starts by proposing a new classification algorithm based on the trade-off between the increase in aggregated service level and increase in total costs on the one hand and total variability on the other. Hereafter, a Real-Coded Genetic Algorithm (RCGA) is proposed that determines the near-optimal safety stock coverage levels per category. The fitness values of the chromosomes in the RCGA are determined utilizing simulation.

Results

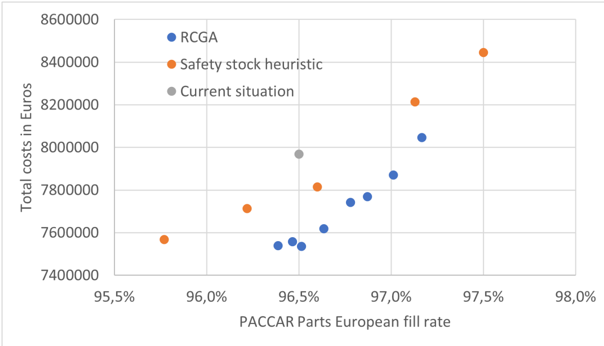
The output of the IP model proposes per item per warehouse whether an item is stocking or not. The IP does not consider items for which it is obvious to make the items stocking in all warehouses (when more than five order hits were observed in the last rolling year in every warehouse) or non-stocking in all warehouses (when there were no order hits observed in the last rolling year in any of the warehouses). Consider these items as group A items. The remaining items are considered by the IP model and referred to as group B items. Note that the PACCAR Parts European fill rate of items in group A affects the total aggregated PACCAR Parts European fill rate of items in groups A and B. Therefore, the IP model is executed for different scenarios of the expected PACCAR Parts European fill rates for items in group A. Figure 1 plots the performances of the current situation, the SnoS heuristic, and the IP solution for 2019. Note that the total costs in this figure include transshipment costs and inventory costs. The plots are obtained by applying the proposed stocking/non-stocking decisions in the simulation model. Note that this plot only considers items in group B since the performances of the items in group A are the same for all situations.



Note: *The different blue dots in the graph represent the different outputs that were obtained for different scenarios of the expected PACCAR Parts fill rates for items in group A.*

Figure 1: PACCAR Parts European fill rate versus total costs for the tested stocking policies in 2019

After the stocking/non-stocking decision has been made, the two methods for determining the safety stock coverage levels are executed and tested using the simulation model. Note that the simulations are based on the heuristically stocking/non-stocking decision. Figure 2 plots the performances of the current safety stock coverage levels and the ones that are proposed by the safety stock heuristic and the RCGA.



Note: *the different blue dots in the graph represent the different outputs that were obtained for different values of the target PACCAR Parts fill rates. These targets are a percentage of the current PACCAR Parts fill rates. From left to right these percentages were: 99.50%, 99.75%, 100%, 100.25%, 100.50%, 100.75%, 101%, and 101.25%.*

Figure 2: PACCAR Parts European fill rate versus total costs for current situation, safety stock heuristic, and RCGA in 2019

Conclusion and recommendation

This thesis investigated how PACCAR Parts can improve its current stocking policies. It is concluded that PACCAR Parts can improve its stocking policy in two ways:

1. **Improvements regarding the stocking/non-stocking decision**
   The proposed stocking/non-stocking heuristic slightly outperforms the current stocking/non-stocking decision, but the heuristic is relatively easy for PACCAR Parts to implement. On the other hand, the proposed IP model significantly outperforms the current stocking policy and the heuristic, but it is relatively harder to implement. Therefore, applying the stocking/non-stocking heuristic is recommended in the short term. Nevertheless, it is recommended to implement the IP model in the long term. The yearly cost savings of more than €200,000 are considered worth implementing the complex model. In both cases, a gradual implementation is recommended such that no unnecessary transportation costs are made and that the PACCAR Parts European fill rate is maximized.
2. **Improvements regarding the safety stock coverage levels**
   The proposed classification algorithm and the proposed safety stock coverage levels per class outperform the current situation and the safety stock heuristic. For this reason, it is recommended to implement this method to determine the safety stock coverage levels. Additionally, the proposed method is more accessible to implement for PACCAR Parts than the safety stock heuristic. For the proposed safety stock policy, it is recommended to test the stocking policy on a small set of items to enable a gradual implementation.

Table 1 represents the improvements that can be obtained if the SnoS heuristic and RCGA are implemented. The total cost improvements display the total cost improvements obtained compared to the current situation when the same PACCAR Parts European fill rate is obtained (vice versa for the PACCAR Parts European fill rate improvements).

	2019	**2020**	**2021**
Cost improvement	5.5%	4.7%	4.4%
PACCAR Parts European fill rate improvement (in percentage point)	0.68	0.74	0.78

Table 1: Improvements in costs and PACCAR Parts European fill rate when SnoS heuristic and RCGA are implemented

Preface

This thesis report marks the end of my master's study in Operations Management & Logistics at the Eindhoven University of Technology. I am thankful to the Demand Planning department of PACCAR Parts for providing me the opportunity to perform my master's thesis at this company. It has been a very interesting period at PACCAR Parts in which I gained a lot of valuable practical and theoretical knowledge that I can apply in my future career. For this, I would like to express my gratitude to numerous people.

First of all, I would like to thank my first supervisor Nico Dellaert for his guidance, endless enthusiasm, critical feedback, and the interesting discussions. Additionally, I would like to thank my second supervisor Karel van Donselaar for his critical feedback and great expertise in the field of inventory models. The feedback of both of you is extremely appreciated and improved the quality of this thesis significantly. Furthermore, your passion for doing research in this field kept me highly motivated during this period.

Secondly, I would like to thank my PACCAR Parts supervisor Ward Bekkers for his guidance, support, and practical insights. Whenever I had a problem, question, or request for data, you could often help me the same day. This enabled me to work efficiently on my project and ensured that I seldom got stuck in the project. Moreover, I want to thank all other employees of PACCAR Parts for their help and support.

Last but not least, I would like to thank my family, friends, and girlfriend for their great support and for offering me the possibility to relax from time to time.

Thomas Jacobs
Eindhoven, June 2022

List of abbreviations

Abbreviation	Definition
ADV	Annual Dollar Volume
B	Backorders
BUD	Budapest
COGS	Cost Of Goods Sold
CV	Coefficient of Variation
EIN	Eindhoven
EOQ	Economic Order Quantity
GA	Genetic Algorithm
IIDRV	Independent Identically Distributed Random Variables
I^{OH}	Inventory On Hand
IO	Inventory Order
IOH	Inventory On Hand
IP	Inventory Position
KPI	Key Performance Indicator
L	Lead time
LEY	Leyland
LP	Linear Programming
max_{cov}	Maximum Order Coverage
MAD	Madrid
min_{cov}	Minimum Order Coverage
min_{OQ}	Minimum Order Quanitty
MLO	Material Labor Overhead
MOQ	Multiple Order Quantity
OFR	Order Fill Rate
OQ	Order Quantity
RCGA	Real-Coded Genetic Algorithm
SnoS	Stocking/non-stocking
ss_{cov}	Safety Stock Coverage
SKU	Stock Keeping Unit

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Chapter 1

Introduction

This graduation project partially fulfills the requirements for the degree of Master of Science in Operations Management and Logistics. The graduation project is performed at the Demand Planning department of PACCAR Parts Parts Europe.

1.1 Report structure

This section describes the structure of this thesis. In the first chapter, an introduction to PACCAR Parts and the Demand Planning Department is given. Besides, the transportation network, stocking policy, replenishment policy, and Key Performance Indicators (KPIs) that are relevant for this thesis project are explained. Chapter 2 describes the problem statement, validates the problem quantitatively, and describes the research design. Hereafter, Chapter 3 explains how the simulation model that is used in this study is substantiated. Furthermore, this chapter validates the simulation model by comparing its outputs to those obtained in real life. Chapters 4, 6, and 7 describe the models that are used in this thesis thoroughly. After the models are implemented, their results are displayed and analyzed in Chapter 8. Lastly, in Chapter 9, an overall conclusion is drawn, explicit and practical recommendations for PACCAR Parts are given, a discussion of the contribution to the scientific literature is given, and the limitations and directions for future research are indicated.

1.2 Company context

PACCAR Parts is a division of the overarching company PACCAR. PACCAR Parts is a global leader in the distribution, sales, and marketing of aftermarket parts for heavy and medium-duty trucks, trailers, buses, and engines. With state-of-the-art distribution processes, award-winning sales and marketing programs, and industry-leading quality management, PACCAR Parts provides aftersales support to DAF, Kenworth, and Peterbilt dealers worldwide.

The European division of PACCAR Parts is responsible for the spare part availability on the after-sales market for DAF trucks. In other words, PACCAR Parts manages the inventory of DAF warehouses and dealers that store spare parts. This graduation project is performed at the Demand Planning department of PACCAR Parts Europe. Among other things, this department is responsible for the spare-part availability at 5 warehouses in Europe. The warehouses are located in Leyland, Eindhoven, Madrid, Budapest, and Moscow. Eventually, these warehouses deliver spare parts to DAF dealers who repair DAF trucks. Every DAF dealer is allocated to one warehouse (see Figure 1.1). However, in case of a stock-out, the dealers can be sourced by a backup warehouse they are not allocated to in the first instance.

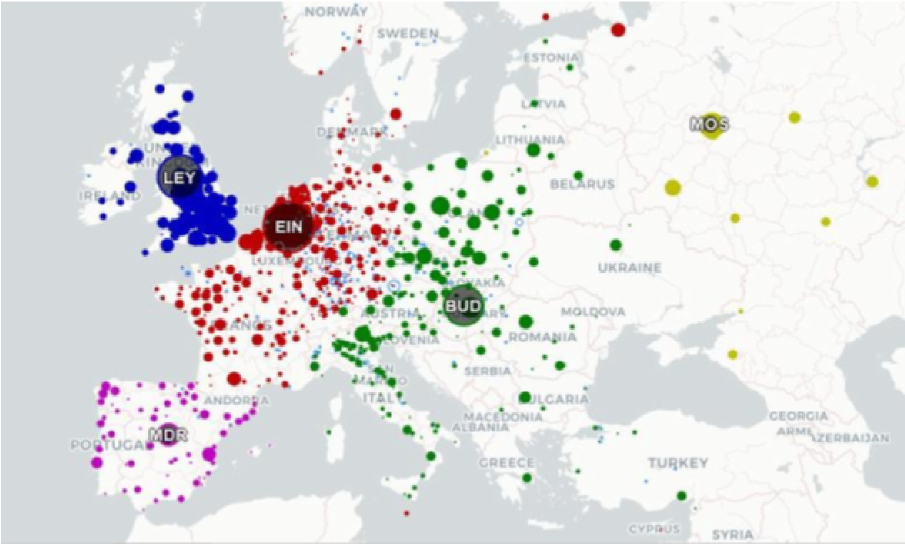


Figure 1.1: DAF dealer-warehouse allocation network in Europe

It is crucial to have high spare-part availability in the warehouses to satisfy the DAF customers. On the other hand, PACCAR Parts aims at having as low costs as possible. Hence, this graduation project's challenge is finding a proper trade-off between spare-parts availability and costs. In order to achieve this, the goal of the graduation project is to optimize the stocking policies of the European warehouses. In the next section, the PACCAR Parts Europe supply chain is explained in more detail by considering the flow of goods. Hereafter, the current stocking and replenishment strategies are discussed. At last, the KPIs that PACCAR Parts uses are explained.

1.3 Transportation network

Figure 1.1 displays which dealer is allocated to which warehouse. This section describes the supply chain in more detail by considering the flow of goods in the warehouse-dealer network.

1.3.1 From supplier to warehouse

Suppliers of PACCAR Parts deliver their goods to the warehouse that is located closest to their production facility. The warehouse to which the supplier delivers the goods is responsible for the ordering and distribution to the other warehouses. For example, consider a supplier of screws located in the Netherlands. This supplier delivers goods to the warehouse in Eindhoven. In this case, Eindhoven has to order items at this supplier for all of the European warehouses (see section 1.4 for more details about this). Once the goods arrive at the Eindhoven warehouse, they are redistributed to the other warehouses.

Most of the suppliers of PACCAR Parts deliver their goods to the warehouse in Eindhoven. Furthermore, this warehouse is centrally located in the supply chain network. For this reason, most of the transport streams are executed via Eindhoven. Every weekday, at least one truck travels back and forth between the warehouse in Eindhoven and every other warehouse in the supply chain. An exception to this is the transport stream from Madrid to Eindhoven. Due to the small number of suppliers that are allocated to the warehouse in Madrid, only three trucks a week travel to Eindhoven. Another exception is the warehouse in Moscow. The small number of DAF dealers in Moscow, in combination with the import/export restrictions due to political reasons, make the transport streams from and to Moscow more complicated than the other transportation streams. Since the Moscow warehouse is the most miniature warehouse with a relatively small demand share concerning the total demand, the complications are not considered worth taking into account in this research. For this reason, it has been decided to leave this warehouse out of the scope of this research.

In some cases, the cargo that must be transported does not fit into one truck. Then, it can be decided to send an extra truck. This is only done if the extra truck can be filled fully. If this is not the case, the cargo is transported the next day. The items that are delayed by one day are always stocking items meant to increase the stock level at other warehouses. Therefore, the single-day delays never cause stock-outs at the warehouses. Hence, no backorders are caused by the delay, and the service rates are not affected.

PACCAR Parts assumes that the internal lead time between all the warehouses in the supply chain, including administration, picking, and transportation, is always two weeks (i.e., 14 days).

1.3.2 From warehouse to dealer

Every day, the warehouses serve their dealers by sending the demanded order lines. An order line contains a specific item and its demanded order quantity. If an order line cannot be fully satisfied, it is not sent (i.e., no partial order lines are delivered). In this case, it is checked whether transshipments can complete the order line.

In classical inventory systems, inventory streams are only possible between separated echelons. However, inventory streams are also allowed between the same echelon when transshipments are allowed. In this way, members of the same echelon can pool their inventories. This leads to lower inventory costs, more flexibility, and, therefore, a higher service rate for the whole system (Paterson, Kiesmüller, Teunter & Glazebrook, 2011). For PACCAR Parts, this implies the following: once an order line that a dealer places cannot be satisfied by the warehouse to which the dealer is initially allocated, it is checked whether another warehouse can fulfill the order line. If this is the case, there are two options:

1. A dealer placed a stocking order. This means that the dealer needs the order line to increase their inventory level. In this case, a small delay does not affect the service level since there are no stock-outs and thus no backorders incurred. For these orders, the item is transshipped from one warehouse to the other via the usual transport channels. In this way, no extra costs for the transshipment are made apart from the regular transportation and material handling costs. It should be noted that the transshipment items are always cross-docked in Eindhoven. For example, when a transshipment is needed from Budapest to Madrid, the item is first sent from Budapest to Eindhoven, then from Eindhoven to Madrid. This holds since the warehouse in Eindhoven is the biggest warehouse with the most transportation streams to the other warehouses. Most of the suppliers deliver the goods to the Eindhoven warehouse. For this reason, there are existing transportation streams from Eindhoven to the other warehouses every day of the week.

2. A dealer placed a rush order. This means that the dealer needs the item as soon as possible. This happens when a truck cannot continue driving without the ordered part. In this case, the warehouse that has the order line on stock sends the item directly to the dealer via the postal service company DHL. Although the aggregated service rate is not affected since the dealer still gets his demanded items on time, extra transshipment costs are incurred due to the postal shipment. Hence, these transshipments are considered to be emergency transshipments with extra costs involved. More details about these costs are explained in section 4.3.1.

If transshipments cannot satisfy the order line, the order line is backordered.

1.4 Current replenishment policy

The warehouses use an (R, s, nQ)-policy to replenish their orders. Every night at 00:00, the Inventory Position (IP) at the end of the previous day is calculated. The IP can be calculated by taking the Inventory On Hand at the end of the period (IOH), adding the Inventory on Order (IO) to it and substracting the backorders (B) (Donselaar, van & Broekmeulen, 2014). Using the demand forecast that the Demand Planning department makes, it is checked at every review moment whether the forecasted demand during the lead time (L) plus review period drops below the safety stock level. When this is the case, a replenishment order is placed. In section 1.5, the determination of the safety stock level is explained in more detail.

A flowchart of the ordering process is summarized in Figure 1.2. The order quantity (OQ) is based on the Economic Order Quantity (EOQ) formula that is proposed by Harris (1913). In addition to the EOQ, rules regarding Minimum Order Quantity (min_{OQ}), Minimum Order Coverage (min_{cov}), Maximum Order Coverage (max_{cov}), and Multiple Order Quantity (MOQ) are applied. For the min_{OQ}, the OQ that the EOQ obtains is increased to min_{OQ} if the OQ is smaller than the min_{OQ}. The same logic holds for the min_{cov}. The min_{cov} is displayed in days and reflects how many days of demand should be covered minimally by the order placed. Using the demand forecast, the min_{cov} can be displayed in the number of items that should be ordered minimally. The max_{cov} works the same but for a maximum number of days that the OQ can cover. Lastly, the order quantity is set to a multiple of the MOQ. For this, a rounding factor of 0.85 is used. Consider the example where the OQ equals 14, and the MOQ equals 5. In this case, the remainder of 14/5 equals 0.8. Since 0.8 is smaller than the rounding factor of 0.85, only ten items (2×5) instead of 15 items (3×5) are ordered. Whenever this rounding factor suggests that 0 articles should be ordered, still the MOQ is ordered to prevent stock-outs.

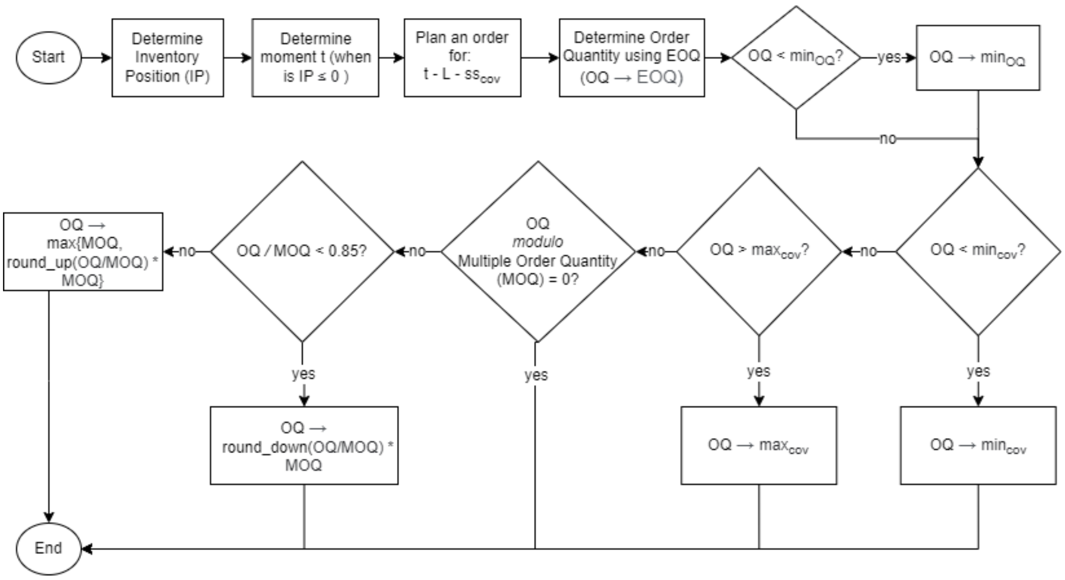


Figure 1.2: Flowchart of the ordering process

1.5 Current stocking policy

The decisions that are made in the current stocking policy at PACCAR Parts Europe are summarized in Figure 1.3. The stocking policy at the warehouses consists of three main decisions:

1. Firstly, it is decided whether the item is stored in the warehouse (i.e., stocking vs. non-

stocking). This decision is based on the product price and the number of order lines (hits) of the item in the last rolling year in the warehouse for which the decision has to be made.

2. When it is decided to stock an item, a demand forecast is made. Hereafter, a safety stock coverage level is determined. Since the demand for many products follows a non-stationary pattern, the safety stock is determined in days (i.e., safety stock coverage (ss_{cov})). Similar to the stocking/non-stocking decision, the safety stock coverage is based on the COGS and the number of order lines (i.e., hits) in the last rolling year. An example on how ss_{cov} is determined is displayed in Table 1.1.

3. When it is decided not to store an item locally, it can still be decided to store this item globally at the warehouse in Budapest. This decision determines whether there are enough order lines (hits) on a European level. It was chosen to facilitate the global storage in Budapest since this warehouse had the most unused capacity when the stocking policy was designed. Once it is decided to store an item globally, no forecast data on the item is available. Therefore, a base-stock policy controls the inventory of globally stocked items. This implies that the IP can only drop below the base stock level once actual demand occurs.

It should be noted that the used values for the parameters that are used in the stocking/non-stocking decision are different for every warehouse. Due to the different capacity restrictions per warehouse, the stocking decisions can be more lenient for warehouses with a higher capacity (and vice versa).

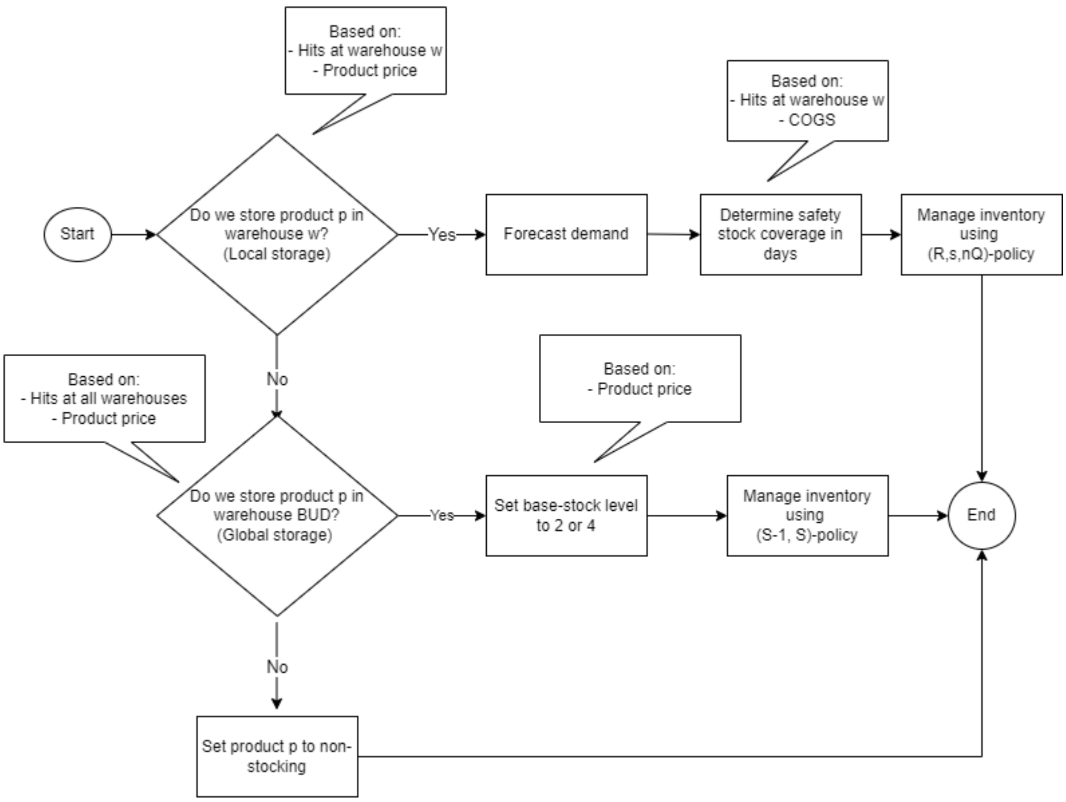


Figure 1.3: Flowchart of decision process current stocking policy

		COGS (in euros per year)		
		0 - 6000	6.000 - 75.000	75.000 - 999.999
Hits	0 - 150	28 days	14 days	14 days
	150 - 500	28 days	21 days	14 days
	500 - 9.999	35 days	28 days	14 days

Table 1.1: Example of safety stock determination matrix for items at the warehouse in Eindhoven

1.6 Key Performance Indicators

The Demand Planning department uses several KPIs to evaluate the performance of the stocking policy relevant to this project. This section discusses these KPIs. Note that in the traditional literature on inventory management, order costs and shortage costs are often considered while evaluating inventory strategies. However, the order costs are not influenced by the safety stock policy. Besides, PACCAR Parts assumes a minimum service level should be met rather than assuming shortage costs per missed order. Hence, order costs and shortage costs are not considered in this research.

1.6.1 Fill rate

PACCAR Parts uses the fill rate to measure their part availability performance. The PACCAR Parts fill rate differs somewhat from the fill rate that is defined in the traditional literature on inventory management that is described by Nahmias and Olsen (2015) and Silver, Pyke and Peterson and (1998). In this traditional literature, the fill rate is described as the percentage of demand that can be delivered immediately from the stock on hand (see Equation 1.1). Using this definition of the fill rate, it is implicitly assumed that delivering partial order lines is allowed. However, PACCAR Parts only satisfies order lines that can be delivered fully (i.e., no partial order lines). Recall that an order line contains a specific item and its demanded order quantity. Thus, an order line can only be satisfied if the whole order line can be delivered fully from stock. Therefore, the PACCAR Parts fill rate is defined as the percentage of satisfied order lines (see Equation 1.2).

$$\text{Volume fill rate} = \frac{\text{Total satisfied demand (in units)}}{\text{Total demand (in units)}} \tag{1.1}$$

$$\text{PACCAR Parts fill rate} = \frac{\text{Total number of satisfied order lines}}{\text{Total number of order lines}} \tag{1.2}$$

As an illustration, consider the data in Table 1.2. In the case of the volume fill rate, 8 items of Item A and 10 items of Item B can be delivered. Hence, the volume fill rate equals $\frac{8+10}{8+12} = 0.9$. For PACCAR Parts, the order line for item B would not be delivered since the order line cannot be satisfied fully. This means that only 1 out of the 2 order lines can be satisfied. Hence, the PACCAR Parts fill rate equals $\frac{1}{2} = 0.5$

	Inventory level	**Order line**
Item A	10	8
Item B	10	12

Table 1.2: Example data for PACCAR Parts fill rate calculation

PACCAR Parts measures the PACCAR Parts fill rate on two levels. Firstly, on a regional level, it is examined per warehouse individually what the availability performances are. Then, for each warehouse, it is determined which percentage of the order lines placed at the warehouse can be fully satisfied by its stock (Equation 1.3). Next to the regional fill rate that is determined per warehouse, an overall European fill rate is determined. Eventually, this fill rate is the most important one since it represents the performances of the whole European supply chain for which PACCAR Parts is responsible. The European fill rate determines which percentage of total order lines can be satisfied fully by any of the European warehouses (Equation 1.4). Note that the European fill rate considers order lines that are satisfied via (emergency) transshipments as satisfied order lines.

$$\text{PACCAR Parts regional fill rate} = \frac{\text{Total number of fully satisfied order lines by warehouse stock}}{\text{Total number of order lines placed at the warehouse}} \tag{1.3}$$

$$\text{PACCAR Parts European fill rate} = \frac{\text{Total number of fully satisfied order lines in Europe}}{\text{Total number of order lines placed in Europe}} \tag{1.4}$$

1.6.2 Total costs

The total costs that depend on the stocking policy consist of three components:

1. **The inventory costs** for an item depends on its sum of Material, Labor, and Overhead costs (MLO). The MLO is different for every item and depends on item properties such as purchasing price and volume. Eventually, the inventory value for an item at any moment in time is determined by multiplying its MLO with the IOH. In this way, the inventory values per warehouse individually can be calculated. The total European inventory value can be determined by summing these individual warehouse inventory values. PACCAR Parts assumes its inventory costs to be 12% of its inventory value per year.

2. **The regular transshipment costs** are determined based on the volume of an item. The trucks that drive between the warehouses have a fixed cost and a particular capacity in terms of volume. Since only full truckloads are used, it is assumed that the regular transshipment costs per item are proportionally distributed to its volume. Additionally, a fixed price per transshipment is assumed to include the warehouse's administration and order handling costs.

3. **The emergency transshipment costs** are determined based on the weight of an item. This holds since an external postal service takes care of the emergency transshipments. They calculate the costs based on the weight of an item. Again, a fixed price per transshipment is assumed to cover the warehouse's administration and material handling costs.

The three cost components that are briefly explained here are elaborated on further in section 4.3 of this thesis.

Chapter 2

Problem definition

The first step in the regulative problem solving cycle that is proposed by Aken van (2005) is to form a proper problem definition. This chapter provides the problem definition, including a problem statement, a description of the research scope, and research questions.

2.1 Problem setting

2.1.1 Problem context

In 2015, PACCAR Parts introduced a new planning system called JDA. JDA is responsible for all the inventory planning tasks involved in the operations of PACCAR Parts. Forecasting and replenishing are the most critical tasks for the Demand Planning department. JDA is initially developed for retail operations. Retail operations' characteristics differ from those of spare parts management at PACCAR. For many spare parts, demand is often relatively low and highly fluctuating. This makes it hard to fit distributions and forecasts the demand (Mo, Wang, Ho & Leung, 2022; Syntetos, Babai & Altay, 2012; Topan & Heijden, van der, 2020). In retail operations, products with low demand are often eliminated from the product portfolio. For this reason, JDA is not specialized in handling low-demand items. Moreover, JDA is a planning system rather than an inventory control system. Consequently, the initial stocking policies that were integrated into the JDA software were assumed to be too simplistic and, therefore, unsuitable for the operations at PACCAR Parts. As a result, PACCAR Parts designed and implemented the new stocking policy that is described in section 1.5. The stocking policy was designed to be easy to implement in the JDA software. Since the implementation of the new stocking policy in JDA, manual adjustments to individual safety stock settings have been made for items that perform poorly. As a result, the Demand Planning department believes that the stocking policy is not robust and sub-optimal in obtaining a proper trade-off between costs and service level.

2.2 Problem statement

The stocking policy's first step is determining whether an item is stocking or non/stocking. Currently, the stocking/non-stocking decision per warehouse is based on the number of hits in the specific warehouse in the in the last rolling year. For example, in the warehouse in Madrid, an article is set to stocking once it had at least three hits in the last rolling year. Some warehouses have an additional criterion that considers an article's price. For example, in the warehouse in Eindhoven, an article is considered to be stocking once it had at least three hits in the last rolling year and the price of the article is below 15 Euros. If the item is more expensive than 15 Euros, the article needs at least six hits in the last rolling year before it is considered to be stocking. This additional criterion is not used for every warehouse. Moreover, the minimum number of hits can differ per warehouse. The reason for these differences is related to capacity restrictions. The tighter the capacity in a warehouse is, the tighter its criteria are and vice versa. For this reason, the capacity restrictions are taken into account in this research.

Additionally, there is the option of global storage. Whenever a particular item is not stored in any of the warehouses, it is checked whether there were enough hits in the last rolling year on a European level. In this case, the item is stored globally in Budapest (see section 1.5). Note that the current stocking/non-stocking policy, in combination with the replenishment policy that is described in section 1.4 can lead to the following situation: A particular item had two hits in Madrid and two hits in Leyland in the last rolling year, in Eindhoven and Budapest there were zero hits. Based on the stocking/non-stocking policy, the item is not stored locally in any warehouses but globally in Budapest. If the supplier of this item delivers to the Eindhoven warehouse and has a high minimum/multiple order quantity, the warehouse in Eindhoven has to order more than is needed to stock the warehouse in Budapest. In this case, there could be inventory for the specific item in Eindhoven and Budapest, while there is no inventory in Leyland and Madrid. This situation is considered to be inefficient since unnecessary transportation costs are made.

After the stocking/non-stocking decision is made, the safety stock coverage has to be determined. Safety stock is meant to cover variation at the supply and demand side (Zipkin, 2000). Currently, the safety stock policy does not consider any variation characteristics. It is based on the number of expected order lines to increase the PACCAR Parts fill rate on the one hand and the COGS to decrease the inventory costs on the other. However, no demand or supply variation characteristics are taken into account. Furthermore, Wingerden, van et al. (2016) prove in their research that classifying inventory based on a one-dimensional $\frac{demand}{price}$-ratio outperforms the situation in which inventory is classified based on demand and price in a two-dimensional way in terms of inventory costs and service level. As has been explained in section 1.5, PACCAR Parts uses a two-dimensional method to classify the spare parts. It can be concluded that PACCAR Parts' current safety stock policy is not in line with the findings of Wingerden, van et al. (2016). Additionally, Teunter et al. (2010) show in their research that increasing the number of classification classes significantly impacts the performance of the policy in a positive way. Considering the large boundaries that PACCAR Parts uses (see table 1.1), there is room for improvement in expanding the size of this 9-grid.

The most important KPIs for the Planning Department are the PACCAR Parts European fill rate (Equation 1.4) and the total inventory costs. In the case of transshipments, additional costs incur that are not taken into account currently. In other words, the effects of transshipments are not considered explicitly in the current stocking policy. However, they influence the costs of the entire PACCAR Parts supply chain. Since the stocking policy directly affects the number of transshipments that take place, this research takes into account the costs that are involved regarding the transshipments.

Lastly, it is assumed that the internal lead times between the warehouses are always equal to exactly 14 days. The extent to which this assumption is valid is questionable. The processes regarding the administration and picking of the order lines for other warehouses differ across the warehouses. This is mainly due to the differences in size and work capacities of the warehouses. Moreover, the transportation times are different between all nodes in the supply chain network. This results in underestimation or overestimation of the actual lead times (see section 2.3 for the quantitative substantiation of this statement). Since the ordering policy suggests that an order is placed such that the demand during the expected lead time plus review period is covered, an incorrect lead time assumption leads to an incorrect order suggestion. When the lead time is overestimated, too much inventory is ordered, which increases the inventory costs and PACCAR Parts fill rate. This obstructs the design of an accurate stocking policy.

2.3 Problem validation

In order to validate that the described problem is indeed a problem, an initial data analysis has been performed. The PACCAR Parts fill rates (Figure 2.1) and warehouse inventory values (Figure 2.2) over the past five years have been visualized. Note that some less historical inventory value data is available compared to the historical PACCAR Parts fill rates data. Nevertheless, the limits of the x-axis are displayed on the same interval to enable a proper comparison between the two.

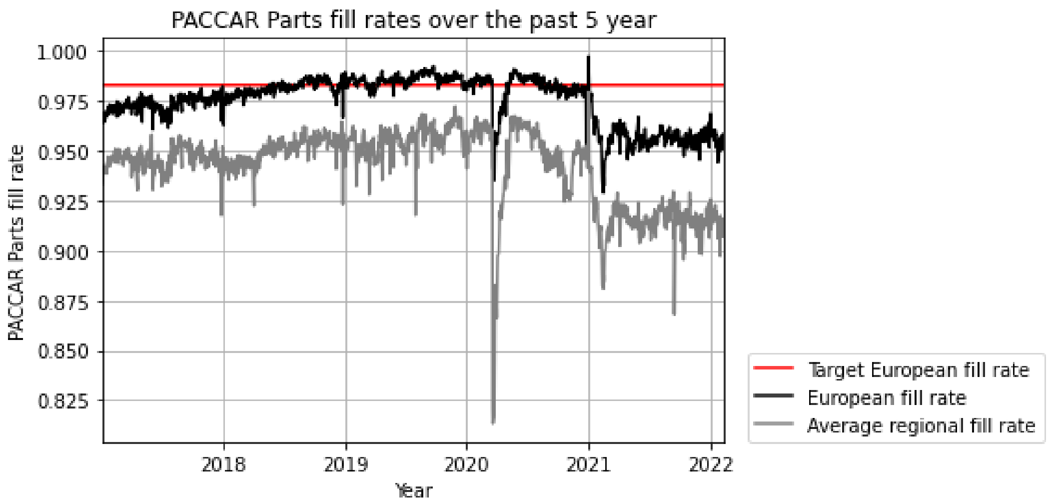


Figure 2.1: PACCAR Parts fill rates over the past five years

The on-time serving of customers is considered to be crucial for PACCAR Parts. Therefore, a relatively high target European fill rate of 98.3% is desired. From Figure 2.1, it can be derived that this target PACCAR Parts European fill rate is not satisfied most of the time. Therefore, it can be concluded that the described problem is valid. Around March 2020, steep decreases in the PACCAR Parts fill rates are observed. These decreases were caused by the supplier disruptions involved with the incipient COVID-19 pandemic. Around the start of 2021, the PACCAR Parts European fill rate decreased even more due to the worldwide microchip shortage in combination with the bullwhip effect caused by the COVID-19 uncertainties.

	2019	**2020**	**2021**
Average actual lead time (days)	48.91	50.93	53.13
Average standard deviation of actual lead times (days)	5.56	6.81	9.21

Table 2.1: Actual supplier lead times per year

Some interesting conclusions can be drawn by comparing the inventory values with the observations made from Figure 2.1. From 2017 until approximately 2020, the intuitive positive relationship between inventory value and PACCAR Parts fill rates can be observed. The small peak in inventory value around March 2020 reflects PACCAR Parts's response to the COVID-19 uncertainties. In order to deal with the uncertainties, the inventory levels were increased. Since more customers of the suppliers did this, a bullwhip effect on the supplier side was created. This bullwhip effect on the supply side caused high supply uncertainties. This, in combination with supply disruptions regarding the worldwide chip shortage, caused a decreased service level while the inventory value increased. From this, it can be concluded that in the last two years, the supply disruptions caused most problems for PACCAR Parts.

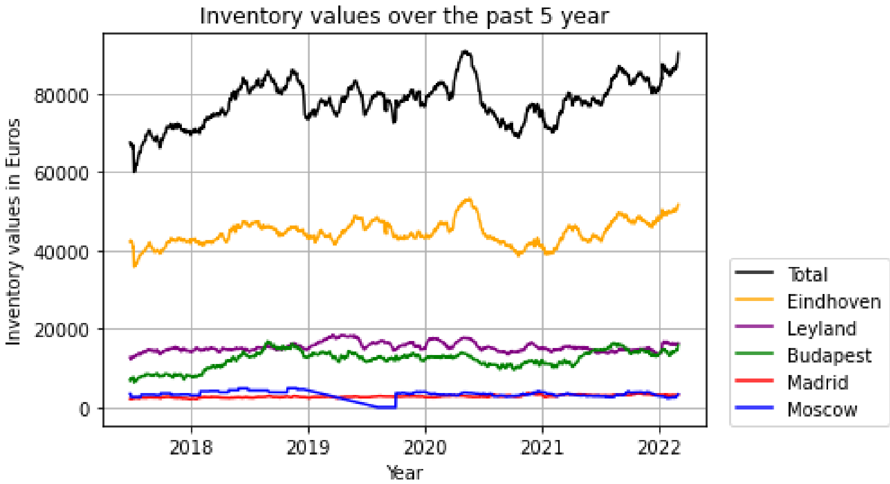


Figure 2.2: Inventory values over the past five years

As has been stated earlier, it can be decided to stock items globally in Budapest based on the aggregated demand in the last rolling year. Due to this policy, items can be stored in Budapest while there were no order hits in the last rolling year in the warehouse in Budapest itself. Therefore, table 2.2 validates that the mentioned case is not an exception. More than 60% of the globally stocked items in Budapest did not have any demand in Budapest itself the previous year.

	2019	**2020**	**2021**
#Items that were global stocking in Budapest	4035	4317	4138
#Items that had 0 demand in Budapest in the last rolling year	3087	3285	2481
%Global stocking items with 0 demand in Budapest in the last rolling year	76.5	76.1	61.5

Table 2.2: Global stocking in Budapest

Table 2.3 displays the actual average lead times between the warehouses. Note that the expected inter-warehouse lead time in the current ordering system is always assumed to be equal to 14 days. It can be concluded that this assumption is invalid in most cases. Recall that most suppliers deliver their goods to the warehouse in Eindhoven. From the table, it can be derived that the average actual lead times from Eindhoven to the other warehouses is lower than 14 days. This means that in most cases, the order suggestion on the number of goods ordered from the Eindhoven warehouse is overestimated.

		To			
		Eindhoven	**Madrid**	**Leyland**	**Budapest**
From	**Eindhoven**	N/A	11.1	12.5	12.3
	Madrid	13.1	N/A	14.3	15.3
	Leyland	13.4	11.2	N/A	17.1
	Budapest	9.3	12.5	14.5	N/A

Table 2.3: Average actual lead times between warehouses in days

2.4 Research design

2.4.1 Scope

This thesis aims at improving the stocking policies of the European warehouses that the demand Planning Department of PACCAR Parts is responsible for. These warehouses include Eindhoven, Leyland, Budapest, Madrid, and Moscow. Nonetheless, the warehouse in Moscow differs from the regular operations at PACCAR Parts due to Russia's legal export and import restrictions. This limits the transshipment possibilities that Moscow has. Furthermore, the supply process of the warehouse in Moscow is somewhat more complex than the others. On the other hand, the warehouse share of Moscow in terms of PACCAR Parts European fill rate and inventory costs is relatively low compared to the other warehouses. The extra complexity involved when the warehouse in Moscow would be included in this research does not outweigh its benefits in terms of an increase in aggregated PACCAR Parts European fill rate and total inventory costs. Hence, it is decided to exclude the warehouse in Moscow from this study and thus only consider the warehouses in Eindhoven (EIN), Budapest (BUD), Leyland (LEY), and Madrid (MAD).

Forecasting is considered to be a crucial element of the stocking policy (see Figure 1.3). During the execution of this research at PACCAR, additional research is performed by another researcher focusing on improving the forecasting methods. Therefore, it is decided to exclude forecasting from this research. Conclusively, the scope of this research is primarily focused on determining the safety stock coverage per item per warehouse. This safety stock coverage should be set in such a way that the important KPIs for PACCAR Pars are improved. These KPIs include European fill rate (Equation 1.4), Regional fill rate (Equation 1.3), and total costs. These costs consist of inventory costs and transshipment costs. PACCAR Parts considers the inventory costs to be 12% of the inventory value per year.

2.4.2 Research questions

Based on the problem statement and scope definition of this research, the main research question can be formulated as follows:

How can the Demand Planning department improve the stocking policy of spare parts at the European warehouses of PACCAR Parts?

As mentioned, the improvements are examined by considering the European fill rate, Regional fill rate, and total costs. To answer the main research question systematically, it is split up into 3 sub-research questions that are discussed below.

1. What is the (simulated) performance of the current stocking policy in terms of total costs and availability?
In order to examine the value of potential improvements for the current stocking policy, the current stocking policy needs to be evaluated. In this way, a fair comparison between the potential improvements and the current situation is enabled. PACCAR Parts keeps track of some of the KPIs that are considered in this research (PACCAR Parts fill rates and inventory costs). This actual KPI data can be used to validate the simulation model.

2. How can the Demand Planning department improve the policy regarding the stocking/non-stocking decision?
As shown in Figure 1.3, the first decision in the stocking policy that needs to be made is whether or not to stock an item (stocking vs. non-stocking). Eventually, it is the goal to determine per item per warehouse whether the item should be stocked or not.

3. What is the near-optimal safety stock coverage level per item per warehouse?
After the stocking/non-stocking decision is made, the near-optimal safety stock coverage per item that is stocked needs to be determined. Intuitively, there is a positive relationship between inventory costs and PACCAR Parts fill rate. For this reason, it is desired to provide a set of Pareto-optimal solutions to answer this sub-research question. This can be done by minimizing the total costs constrained to several values for the PACCAR Parts fill rates.

2.5 Research methods

The research design and proposed research methods are displayed in Figure 2.3. Firstly, a simulation model is made to evaluate the performances of the current stocking and safety stock policies. Secondly, to improve the stocking/non-stocking decision, an Integer Programming (IP) model is proposed that makes a stocking decision such that total costs are minimized, warehouse capacity restrictions are met, and minimum PACCAR Parts fill rates are met. Since implementing the proposed IP model into the planning systems of PACCAR Parts is complex, a Stocking/non-Stocking (SnoS) heuristic is developed based on the outcomes of the IP model. The outcomes of the IP model and the SnoS heuristic are tested in isolation from the proposed improvements regarding the safety stock settings via the simulation model. Thirdly, using the stocking/non-stocking decision made via the SnoS heuristic, the heuristic proposed by Donselaar, van et al. (2021) is used to calculate the optimal safety stock levels. Again, these safety stock settings are tested via the simulation model. Lastly, a Genetic Algorithm (GA) is proposed that determines the near-optimal safety stock coverage levels for each class that is distinguished via a pre-defined classification algorithm. Also, for the GA, the SnoS heuristic is used to make the stocking/non-stocking decision. The safety stock heuristic can be used to compare and validate the results of the GA. Also, for the GA, the simulation model is used to calculate the fitness values.

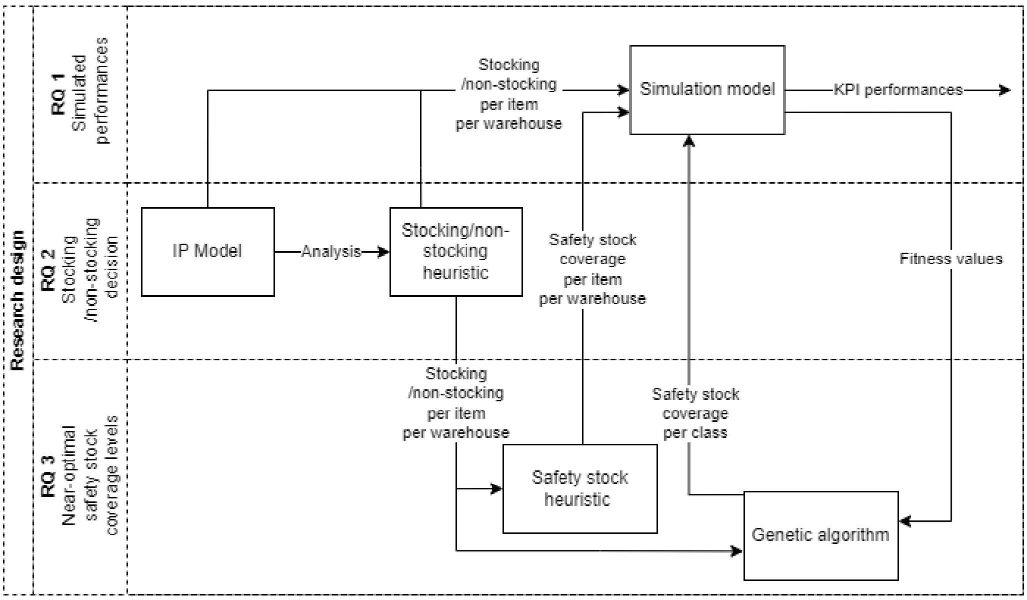


Figure 2.3: Research design and methods

2.6 Theoretical contribution

The problem studied in this thesis is a multi-item, single-echelon, multi-location spare parts inventory model with transshipments and warehouse capacity restrictions. The problem is considered multi-item since it aims to optimize an aggregated service level, single-echelon since only one echelon is reviewed, and multi-location since multiple warehouses that can facilitate transshipments are studied.

Firstly, a stocking/non-stocking decision is proposed in this thesis. In most of the multi-item, single-location problems in a spare parts environment, ABC classification is used to determine whether a certain part is stocking or non-stocking (Silver et al., 1998; Nahmias & Olsen, 2015). The intuition behind this approach is that a fair trade-off is enabled between inventory costs and aggregate service level. However, it is complex to make this trade-off in a multi-location case. This holds since the implication of transshipment changes the aggregate service level and total costs (i.e., a higher service level can be obtained at fewer costs). The literature available on the stocking/non-stocking decision for multi-item, multi-location problems is limited. Wong, Houtum, van, Cattrysse and Oudheusden, van den (2005) and Archibald, Sassen and Thomas (1997) both propose a multi-item, multi-location policy. Both papers conclude that optimally solving the problem is infeasible for large problem instances due to the computational time. These studies use Lagrangian-based heuristics with the assumption of a demand process that is Poisson distributed. For spare parts, the latter assumption is often invalid (Mo et al., 2022). Furthermore, these papers do not consider the warehouse capacity restrictions present at PACCAR Parts.

Most of the transshipment inventory models in the literature that study transshipments are single-item. Service levels for a single item are optimized, which decreases the complexity of the problem compared to a multi-item situation (Paterson et al., 2011). Papers that consider multi-item optimization models are often focused on finding the optimal number of transshipments rather than the optimization decisions regarding stocking/non-stocking and the optimal safety stock level (Mo et al., 2022; Topan & Heijden, van der, 2020; Patriarca, Costantino & Di Gravio, 2016). Besides, most multi-item models focus on a small number of items compared to the number of items that need to be considered in the spare-parts environment at PACCAR Parts. The complexity of the problem at PACCAR Parts is related to the enormous number of spare parts in the product portfolio that can potentially be stored in each location (over 100,000). Compare this to the five items that are considered by Paterson, Teunter and Glazebrook (2012) or the three items that are considered by Patriarca et al. (2016) in their multi-location inventory models with transshipments.

Transshipment inventory models are often based on known demand distribution which enables the derivation of analytical models accordingly (Boucherie, Houtum, van, Timmer & Ommeren, van, 2018; García-Benito & Martín-Peña, 2020; Chen & Lu, 2011; Feng, Moon & Ryu, 2017; H. Li & Jiang, 2012; Z. Li, Li & Xu, 2019; Nakandala, Lau & Ning, 2016; Nakandala, Lau & Zhang, 2017; Nakandala, Lau, Zhang & Gunasekaran, 2018; Yu, Zhou & Zhang, 2020; Zelibe & Bassey, 2021; Gholamian & Nasri, 2019). Analytically optimizing the transshipment inventory models is only possible for relatively small cases with a few items or one or two echelons (Paterson et al., 2011). When multiple items or echelons are considered, optimizing the models analytically becomes impossible due to the increased complexity. Simulation-based optimization techniques are used in these situations to optimize the problem (Cesarelli, Scala, Vecchione, Ponsiglione & Guizzi, 2021; Gholamian & Nasri, 2019; Gu, Zhou & Zhang, 2020; Hochmuth & Köchel, 2012; Meissner & Senicheva, 2018; Purnomo, 2011; Ri-Hong, Peng-Cheng, Jiang-Sheng & Cheng-Ying, 2012). Nevertheless, these models rely on known demand distributions that assume stationary demand. In spare parts inventory management, the demand distribution is often unknown due to the intermittent demand for several items (Paterson et al., 2011; Mo et al., 2022). Additionally, many items at PACCAR Parts follow a seasonal pattern which contradicts the assumption of stationary demand.

To summarize, the complexity of the problem at PACCAR Parts is related to an aggregate service level that needs to be optimized across a large number of spare parts and multiple locations with a limited capacity. Therefore, it can be concluded that this research fills the gap of stocking policy optimization in a multi-item, single-echelon, multi-location spare parts inventory model with transshipments and warehouse capacity restrictions.

Chapter 3

Simulation model

A simulation model is needed for all of the research questions that are defined. In Figure 3.1, a schematic representation of the simulation model is given. Using the proposed simulation model, performances of the important KPIs that are given as output can be simulated for different values of the safety stock coverage per item per warehouse.

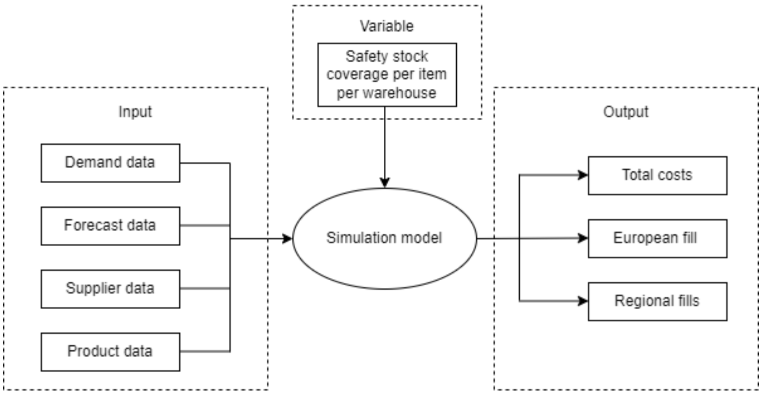


Figure 3.1: Simulation model

3.1 Input data

The purpose of safety stock is to deal with variations in the demand and supply of items (Zipkin, 2000). In order to create a reliable simulation model, the input data has to simulate the real-life variation as correctly as possible. This section describes the input data for the simulation that enables the proper representation of reality.

3.1.1 Product data

The actual product data that is needed to calculate the costs, simulate the ordering process, and simulate the stocking policy are used (see sections 1.4 and 1.5). Additionally, some products were removed from the product data set. As has been explained in section 2.4.1, the warehouse in Moscow is not considered in this research. There are some products for which Moscow serves as the supplying warehouse. These products are excluded from the data set. Additionally, some products in the data set are not sold any more because other products in the product portfolio replace them. In the data, it is not retrievable from which moment onward these products were not available for the dealers to order anymore. Therefore, these products are also excluded from the research. These products are also excluded from the demand, forecast, and supplier reliability data sets.

3.1.2 Forecast data

Since forecasting is out of the scope of this research project, the historical forecasts that the Demand Planning department made are used. The Demand Planning department makes a forecast for every 4-week period. In this way, they can adopt the seasonal patterns available in the data. Approximately 25% of the items are forecasted according to a seasonal forecasting method. In section 1.5, it has been explained that forecasts are only made for articles that were stocked locally in the warehouses. No forecasts were needed for globally stocked, and non-stocking items since these items were not ordered based on a forecast. Nevertheless, the forecasts of all items are considered in this research. The items that do not have a forecast are items with relatively low demand. Whenever the Demand Planning department makes a forecast for items with relatively low demand, simple exponential smoothing with a smoothing constant of 0.1 is used. In order to make a forecast for all items, the simple exponential smoothing method is applied to all the items that did not have a forecast yet.

3.1.3 Demand data

Due to the seasonality involved in the demand data, it is invalid to assume stationary demand patterns. Moreover, fitting a distribution on items with only a few demand hits per year is inaccurate. Hence, empirical data is used to simulate the demand. For every 4-week period, two empirical distributions per SKU are derived. One empirical distribution represents the daily number of order lines. The other empirical distribution represents the order size. The 4-week periods for which the empirical distributions are derived match the periods for which the forecasts are made. This way, the historical forecast data can be used, and the seasonal patterns are considered. For every day in the simulation horizon, the empirical daily order line distribution is used to simulate the number of orders that comes in. Whenever an order is generated, the empirical order size distribution is used to simulate the size of the order.

3.1.4 Supplier reliability

For every order that has been placed at the supplier, the Demand Planning department keeps track of the delivery time. With this data, an empirical distribution of the actual lead time per item can be derived. This empirical supplier reliability data is used to simulate the variation at the supply side. As has been concluded in section 2.3, the supplier reliability is time-dependent. Based on the conclusions that were drawn in section 2.3, three scenarios can be distinguished:

1. The period before COVID-19 (i.e., up until 2019). In this period, the supplier reliability was relatively stable, and no extreme outliers in the actual supplier lead times were observed.
2. The first year of COVID-19 (i.e., 2020). This year, the first COVID-19 lock-downs were announced, which eventually resulted in a high level of supply uncertainty.
3. The period with the remaining effects of COVID-19 in combination with the chip shortage (i.e., 2021). This year, the chip shortage occurred, causing even more supply problems.

For this reason, three empirical supplier reliability functions are derived that can be tested. In the simulation, every time an order is placed, a random observation of the actual lead time per SKU is picked out of the historical data per period. This way, the supply side variation is adopted into the simulation model. The main goal of this research is to develop a stocking policy that is suitable for the situation with relatively stable supplier reliability (scenario 1). Nevertheless, the solution will be tested in scenarios 2 and 3 to examine the robustness of the model concerning situations with extreme supply reliability outliers.

Recall that the lead times between the warehouses are also variable. Therefore, the empirical lead time data between the warehouses are also used to simulate the variability in the lead time between the warehouses. These actual inter-warehouse lead times are drawn randomly in the same manner as is described above for the actual supplier lead times.

3.2 Simulation

3.2.1 Generic process

For every day in the simulation, the same process is executed. To start with, the items that another warehouse supplies are considered. For each of these items, the desired Order Quantity (OQ) is ordered at the supplying warehouse by applying the replenishment policy that is explained in section 1.4. Once this is done for all warehouses, it is checked at the supplying warehouse whether it can satisfy all of the orders that are placed by the other warehouses. A supplying warehouse can only send the number of items from a specific part left from the IP after subtracting the safety stock and forecasted demand until the next potential delivery moment. Whenever this amount is not enough to satisfy all orders from the other warehouses fully, the warehouses are served partly based on their relative share in the total forecasted demand until the next potential delivery moment. Hereafter, the warehouses that order their items with the external suppliers place their orders. After all of the orders are placed, the outstanding backorders from dealer demands are considered. Firstly, it is checked whether the warehouse at which the order is placed initially can deliver the backorders. Hereafter, it is checked whether the backorders can be satisfied by one of the other warehouses. Every warehouse has a fixed sequence representing the order in which the other warehouses' inventories are checked (Table 3.1). Lastly, the daily demand is checked the same way as the backorders. After all of the days are simulated, the total costs and PACCAR Parts fill rates are computed. In Appendix A, the high-level flowchart is displayed of the used simulation model.

	1	2	3
Eindhoven	Leyland	Budapest	Madrid
Madrid	Eindhoven	Leyland	Budapest
Leyland	Eindhoven	Budapest	Madrid
Budapest	Eindhoven	Leyland	Madrid

Table 3.1: Sequence of transshipment opportunities per warehouse

3.2.2 Starting values

It is desired to set the starting values in combination with the warm-up period to obtain a stable system. On the other hand, it is also desired to minimize the warm-up period since this increases the computational time of the simulation. Especially when executing the GA described in Chapter 7, it is crucial to minimize the computational time for the simulation. This holds since the simulation model is used to calculate the fitness values in the GA.

The starting values for the I^{OH}, IT, and B are set to 0 for each SKU at the beginning of the simulation. Then, the warm-up period for each SKU is defined. The warm-up period is assumed to be equal to the item's lead time plus an additional 30 days to warm up. The lead time accounts for the filling of the inventory pipeline of each SKU. The additional 30 days account for the stabilization of the system. Note that for SKUs that another warehouse supplies, the lead time used here is equal to the lead time of the supplying warehouse plus the lead time between the supplying and receiving warehouse. In this way, the inventory pipeline between the supplier and supplying warehouse is also filled correctly. After the warm-up period, stable starting values are obtained. Using these values, a simulation time of a full year is run to calculate the KPIs. By considering a full year of simulation, the seasonal patterns are adopted equally.

3.2.3 Simulation versus reality

There are two crucial differences between the input data that is used in the simulation, and the data was used in real life:

1. At PACCAR Parts, so-called templates are used to increase safety stock for parts that perform poorly. A template reflects an extra safety-stock coverage that is added to the safety-stock coverage obtained by applying the heuristic explained in section 1.5. For example, when a supplier delivers its goods often too late, a template can be added to the products that this supplier delivers. These templates are temporary and can only be positive. Consider the example of the poorly performing supplier. PACCAR Parts will try to find a solution to prevent from having over time deliveries by the supplier. Once these problems are solved, the templates are removed. Only data is available on the templates that are applied currently (i.e., no historical template data). For this reason, it is chosen to simulate one situation with the current templates and one without the current templates. Table 3.2 displays the impact of the templates.

SKUs that had at least one demand hit in 2019, 2020, or 2021	146466
Number of these SKUs on which a template is applied currently	41574
% of SKUs with demand in 2019, 2020, or 2021 with a template	28.38

Table 3.2: SKUs with templates

2. Besides the templates, manual adjustments are made to the inventory of certain parts. Extra inventory is ordered by the inventory planners of PACCAR Parts based on practical knowledge. For example, when the United Kingdom left the European Union (Brexit), it was chosen to increase the inventory for items in Leyland and the inventory for items that the warehouse in Leyland was supplying. This was done to anticipate import/export restrictions. There is also no historical data on these events, implying that they cannot be simulated.

It can be concluded that there are inevitably differences between the actual performances and the simulated performances due to the use of templates and manual adjustments. Nonetheless, it is still decided to use the simulation model since it properly tests the proposed stocking policies according to the simulation validation that is explained in more detail in Appendix B. This validation concludes that the current templates are not representative and applicable to the older data sets. Therefore, the templates are not considered in the rest of this study.

3.3 Current performance

The simulated performances regarding the PACCAR Parts fill rates that the simulation model obtains are displayed in Table 3.3. Additionally, the total yearly costs are obtained using the simulation model (see Table 3.4). These costs include the inventory costs, which are assumed to be 12% of the average inventory value per year. Furthermore, the transshipment costs of regular and rush orders are calculated based on the transshipped product and its volume or weight, respectively (see section 1.6.2). Additionally, Table 3.5 display the demand characteristics for the periods that are simulated. The intuitive positive effect between the total costs and sales turnover can be observed from the tables. Furthermore, it can be observed that it is worthwhile to take into account the transshipment costs. Namely, they account for more than 30% of the total costs. Besides, a higher inventory level reduces the transshipment costs. This can be observed for all years when comparing the simulation including templates with the situation excluding templates.

	2019			2020			2021		
	Actual	**Simulation**		**Actual**	**Simulation**		**Actual**	**Simulation**	
		Inc. T	*Exc. T*		*Inc. T*	*Exc. T*		*Inc. T*	*Exc. T*
European	0.987	0.973	0.966	0.985	0.972	0.962	0.962	0.964	0.949
Eindhoven	0.970	0.955	0.942	0.962	0.952	0.937	0.970	0.938	0.918
Madrid	0.940	0.936	0.915	0.932	0.934	0.908	0.935	0.924	0.894
Leyland	0.966	0.953	0.935	0.950	0.950	0.929	0.921	0.943	0.914
Budapest	0.944	0.958	0.943	0.943	0.953	0.933	0.905	0.939	0.916

Inc. T: including templates. Exc. T: excluding templates

Table 3.3: PACCAR Parts fill rates in current situation

	2019		2020		2021	
	Inc. T	*Exc. T*	*Inc. T*	*Exc. T*	*Inc. T*	*Exc. T*
Inventory costs	6722	5597	8137	5488	8204	6772
Transshipment costs rush order	1509	1853	1243	1615	2078	2548
Transshipment costs regular orders	460	655	464	665	638	860
Total	8691	8105	9844	7768	10920	10180

Inc. T: including templates, Exc. T: excluding templates

Table 3.4: Total yearly costs simulation (in thousands of euros)

	Order lines (per thousand)			Quantity (in thousands)			Turnover (in thousands €)		
	2019	*2020*	*2021*	*2019*	*2020*	*2021*	*2019*	*2020*	*2021*
European	26419	25408	27981	274993	246535	288669	27308	26237	33919
Eindhoven	10566	10074	10945	129004	116805	135719	13327	13093	17380
Madrid	2194	2172	2405	15953	14889	16500	1274	1308	1546
Leyland	9092	8801	9820	82891	72169	85121	8000	7338	8987
Budapest	4566	4362	4812	47144	42672	51330	4707	4498	6007

Table 3.5: Demand characteristics

Chapter 4

Stocking/non-stocking IP model

The first decision that needs to be made in the stocking policy deals with the stocking/non-stocking decision. This chapter describes the model that is proposed for making this decision.

4.1 ABC classification

In spare parts inventory management, many companies use an ABC classification to decide whether an item is stocking or non/stocking (Wingerden, van et al., 2016). When applying ABC classification, parts are categorized across the three categories 'A', 'B', and 'C'. Class A parts are considered to be the most important parts receiving the closest attention, while class C parts are considered to be the least important ones (Teunter et al., 2010). Part B parts are the remaining articles. By categorizing spare parts in such a way, companies can differentiate between different SKUs while having a simple policy for all spare parts (Wingerden, van et al., 2016). There have been extensive studies on how to classify spare parts. Wingerden, van et al. (2016) conclude that there are three main classification criteria that are often used. The first classification criterion that is often used is the Annual Dollar Volume (ADV). The ADV is a one-dimensional criterion representing the demand rate multiplied by its price. The second classification criterion is also one-dimensional and considers a rate equal to the demand divided by the price. The last classification criterion is two-dimensional and classifies the articles based on price and demand. PACCAR Parts's current stocking policy is an example of this classification (Table 1.1). These three classifications aim to make a proper trade-off between service level and inventory costs. Parts with a high demand contribute relatively more to the aggregated service level, while relatively expensive parts contribute relatively more to the inventory costs. Ideally, it is desired to stock items with high demand and low prices. However, these classification criteria do not consider the effect of transshipments and capacity restrictions present at PACCAR Parts. Hence, an algorithm is proposed for a multi-item, multi-location stocking problem with transshipments and capacity restrictions.

With the philosophy of the ABC classification in mind, an algorithm is proposed that is based on the historical demand data. The algorithm uses historical data from the last rolling year to make decisions for the current year. This one-year interval is chosen so that the newest sales trends are considered and no outdated data is used. Additionally, choosing an interval that captures a full year prevents the occurrence of seasonal biases. The proposed algorithm consists of two main steps. In the first step, an initial classification is made that is similar to the ABC categorization in the sense that three main categories are proposed based on the number of sales in the last rolling year. The categorization that is used in this algorithm is summarized in Figure 4.1. Additionally, to get an impression of the distribution of the number of parts per category, Table 4.1 displays the number of parts per category for 2018, 2019, and 2020. Note that the table only displays the parts that can still be ordered by the dealers (i.e., active parts).

Firstly, parts that did not have any demand in the four warehouses are filtered out. These parts are set to non-stocking in every warehouse. Hereafter, parts that did have a high number of demand hits in the last rolling year across all warehouses are set to stocking. As has been explained in section 1.5, the current stocking policy is based on the number of demand hits in the last rolling year and the price of a part. For the most expensive parts, a part is only set to stocking when it has six or more hits in a year. In this case, PACCAR Parts states that it is necessary to stock the item to be customer friendly. Therefore, this same boundary is applied as classification criteria for items set to stocking in all warehouses. In other words, a part is considered stocked in every warehouse if it had six or more hits in the last rolling year. Note that in the case that the threshold of 6 hits is not met for every of the considered warehouses, the part is not considered to be stocking in every warehouse. This holds since, in this case, it may be beneficial not to stock the item in every warehouse but only in some of the warehouse(s). The demand of the other warehouses could, in this case, still be met by transshipments. For the remaining parts, an IP model is proposed that decides for every part, for every warehouse individually, whether it is set to stocking or non-stocking. The IP model is described in the next section.

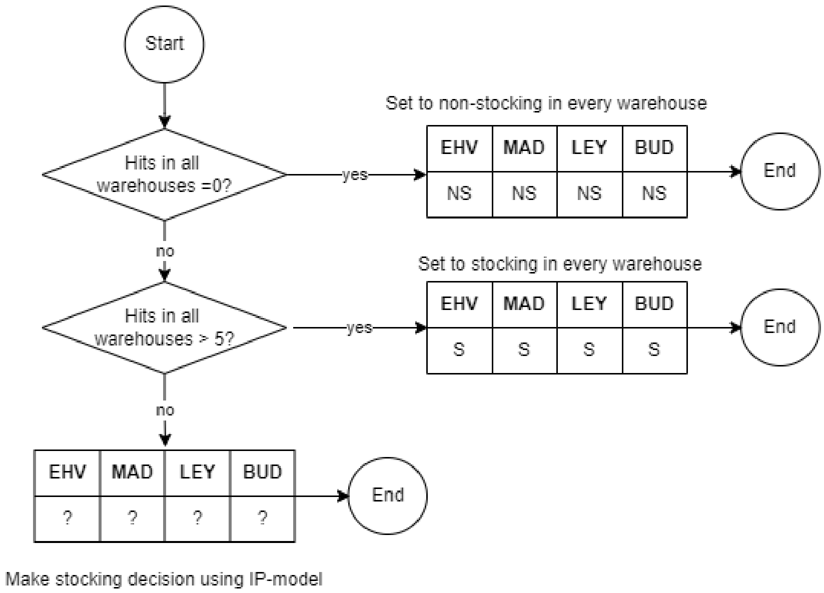


Figure 4.1: Stocking/non-stocking decision model

	2018	2019	2020
Total active parts	166307	166307	166307
Hits = 0 in all warehouses	117065	117308	117024
Hits > 5 in all warehouses	17169	15907	16323
Considered in IP model	32073	33092	32960

Table 4.1: Number of parts per category

4.2 IP model

An IP model is proposed for the parts for which a stocking decision has not been made yet. The goal of the IP model is to decide per part per warehouse whether the part needs to be stocked or non-stocked.

Consider the yearly demand for item i at warehouse w ($d_{i,w}$). For every warehouse w, there are three options regarding how the item i can be stocked:

1. Stock $d_{i,w}$ in warehouse w itself.
2. Stock $d_{i,w}$ in another warehouse v (where $v \neq w$). Note that this is only possible if the other warehouse v already stocks the item.
3. Do not stock $d_{i,w}$.

With the four warehouses that are considered in this study, 92 different stocking options for a part can be defined. A stocking option displays per warehouse whether an item is stocked or not. Additionally, it displays whether the warehouse stocks the demand for one or more other warehouse(s). All the stocking options are displayed in Appendix D. A snapshot from this appendix is displayed in Table 4.2. To clarify, consider the following example of how to interpret a stocking option: for stocking option 44, the warehouse in Madrid stocks such that it can meet its own demand and the demand from the warehouse in Budapest. In Leyland, the demand for Leyland and Eindhoven is stocked. This means that no items are stocked in Eindhoven and Budapest. Nevertheless, the demand for these warehouses can still be satisfied by the warehouses which store the demand for these warehouses. For stocking option 45, it can be seen that only Leyland stocks the item. It stocks the item for itself and Eindhoven. This means that the demand for Madrid and Budapest is expected to be lost in this case. Note that it can still be possible that a part is stocked in none of the warehouses (stocking option 1) or in all of the warehouses (stocking option 9). It can also be possible that one warehouse stocks the demand for all warehouses.

	Stocking warehouse			
Option	**EHV**	**MAD**	**LEY**	**BUD**
1				
...	...	...	...	...
9	EHV	MAD	LEY	BUD
43		MAD-BUD	LEY	
44		MAD-BUD	LEY-EHV	
45			LEY-EHV	
46		MAD	LEY-EHV	
...	...	...	...	...
89	EHV-MAD-LEY-BUD			

Table 4.2: Example of stocking opportunities

The IP model aims to allocate 1 of the 92 stocking options to each part so that the total costs are minimized, the minimum expected PACCAR Parts European and individual fill rates are obtained, and such that the capacity constraints of the warehouses are respected. To make this decision, some parameters need to be estimated per item per warehouse. The following two sections explain the sets and parameters that are used in the IP model.

4.2.1 Sets

The sets that are used in the IP model are listed in this section.

- The set I represents the items for which a stocking decision needs to be made by the IP model.
- The set W represents the set of warehouses (i.e., Eindhoven, Madrid, Leyland, and Budapest).
- As has been stated in the previous section, every item can be stocked via 1 of the 92 stocking options. The set S represents these 92 stocking options.
- At PACCAR Parts, three types of storage locations can be distinguished: small-sized storage locations for products with a volume up to 0.01 m^3, medium-sized storage locations for products with a volume between 0.01 and 0.25 m^3, and large-sized products with a volume that is larger than 0.25 m^3. The set T represents the set of these three storage location types.

- A set of individual PACCAR Parts fill rates F is considered. For the IP model, every individual item needs to be stocked according to a stocking option and according to an individual PACCAR Parts fill rate. This implies that the IP model has I × S × F decision variables. The more decision variables an IP model has, the more computational time is needed to solve the IP model. Therefore, to reduce the model's computational time, there needs to be a limited number of individual PACCAR Parts fill rate options. On the other hand, more individual PACCAR Parts fill rate options improve the model's accuracy. Teunter et al. (2010) studied the differences between having three or six classes in inventory classification. It was concluded that six classes yield more accurate results than only three classes. Nevertheless, the number of decision variables in the IP model doubles if six instead of three classes are chosen. Furthermore, the demand for items considered in the IP model is relatively low. For items with low demand, there is likely overlap in the minimum safety stock levels that need to be set to obtain a minimum individual PACCAR Parts fill rate. In these cases, the model becomes more complex while the accuracy does not improve. Therefore, as a proper trade-off between complexity and accuracy, the line of reasoning by Wingerden, van et al. (2016) is followed by using 3 fill rate options (80%, 90%, and 97.5%).

4.2.2 Parameters

In this section, the parameters that are used in the IP model are listed. In order to explain the parameters that are used in the IP model, consider the example data of the last rolling year for an arbitrary item in Table 4.3. Note that the dealers are closed on Sundays, implicating that they cannot order on those days (i.e., there are 313 days on which orders can be placed in the example of Table 4.3).

Warehouse	Hits	Daily order quantities	Empirical demand distribution
EHV	6	1-1-2-4-1-2	$P(D_1 = 0) = 307/313$ $P(D_1 = 1) = 3/313$ $P(D_1 = 2) = 2/313$ $P(D_1 = 4) = 1/313$ 0 otherwise
MDR	1	1	$P(D_1 = 0) = 312/313$ $P(D_1 = 1) = 1/313$ 0 otherwise
LEY	4	2-1-2-1	$P(D_1 = 0) = 309/313$ $P(D_1 = 1) = 2/313$ $P(D_1 = 2) = 2/313$ 0 otherwise
BUD	5	2-4-1-3-2	$P(D_1 = 0) = 308/313$ $P(D_1 = 1) = 1/313$ $P(D_1 = 2) = 2/313$ $P(D_1 = 3) = 1/313$ $P(D_1 = 4) = 1/313$ 0 otherwise

Table 4.3: Example empirical data of the last rolling year for an arbitrary item

- For every item i, it is calculated for every stocking option s, what the expected costs are if a minimum individual PACCAR Parts fill rate f is obtained ($c_{i,s}^{f}$). In the next section 4.3, it is explained how the individual PACCAR Parts fill rate and its associated total costs are approximated.

- For every item i, it is calculated for every stocking option s, what the expected number of satisfied hits is if a minimum individual PACCAR Parts fill rate f is obtained ($h_{i,s}^{f}$). Consider the example data in Table 4.3. If for this arbitrary item, stocking option 44 is used (see Table 4.2), it is expected that the hits of all warehouses can be satisfied since the demand for all items is stocked. This means that in theory, 6+1+4+5 = 16 hits for item i can be satisfied. Nevertheless, if a minimum individual PACCAR Parts fill rate of for example 90% is desired, only 90% of the hits can be met in theory. Note that discrete demand distributions are used for the calculation of the minimum PACCAR Parts fill rate.

For this reason, it does not necessarily mean that a minimum individual PACCAR Parts fill rate of exactly 0.9 is obtained. In theory the obtained PACCAR Parts fill rate is slightly higher than 0.9. For the example, suppose that this PACCAR Parts fill rate level is 0.912, this means that $h^2_{i,44}$ = (6+1+4+5) × 0.912 = 14.592 for item i when stocking option 44 and minimum PACCAR Parts fill rate option 2 are used. To clarify, if stocking option 45 is applied, the demand for Madrid and Budapest is assumed to be lost. In that case, $h^2_{i,45}$ = (4+6) × 0.912 = 9.12.

- Donselaar, van and Broekmeulen (2022) describe the effect of honeycombing in warehousing. This effect implies that partially filled unit loads still occupy full unit-load capacities. Especially for spare parts, where there are many small-sized items, the honeycombing effect induces that the warehouse capacity is mainly determined by the number of items that are stored per warehouse. For this reason, capacity constraints at PACCAR Parts are determined using the number of items stored per warehouse per storage type. The binary variable $x^t_{i,s,w}$ indicates whether an item i occupies a storage location of type t in warehouse w when stocking option s is used. Eventually, this variable is used to set a constraint on the maximum number of items stored per location type per warehouse.

4.3 Cost approximations

A crucial assumption for the IP-model deals with the approximation of the transshipment and inventory costs. This subsection describes how the costs of the stocking options are approximated.

4.3.1 Transshipment costs

The first cost assumption deals with the transshipment costs. Recall that a dealer places a rush order if the item is needed immediately. This happens when a truck cannot be used without the needed parts. In this case, every second the truck is not operating can cause extra costs for the transportation company. It is concluded that the occurrences of rush transshipments happen intermittently. For this reason, it is assumed that the probability for a transshipment to be a rush one is equal to the total number of rush transshipments divided by the total number of transshipments. From Table 4.4, it can be concluded that the percentage of rush orders is relatively stable over time. In contrast to the demand data, there are no trends in the percentage of rush orders over time. For this reason, it is decided to take the average over five years of 10.25% rush orders that are used for the transshipment cost calculations.

Year	Normal	Rush	Total	Fraction rush
2017	4518788	502139	5020927	0.1000
2018	4676432	546939	5223371	0.1047
2019	4607176	517342	5124518	0.1010
2020	4375508	493463	4868971	0.1013
2021	4909345	578219	5487564	0.1054
Average	4617450	527620	5145070	0.1025

Table 4.4: Number of normal and rush orders

For every of the 92 stocking options, it can be estimated how many orders need to be transshipped. If we consider the example data again with stocking option 45, Leyland stocks the demand for Eindhoven. It is expected that there are six demand hits in Eindhoven. This implies that we expect that a transshipment must be performed six times from Leyland to Eindhoven. Note that we do not take into account the PACCAR Parts fill rate here, since backorders also need to be transshipped eventually. Using the empirical demand data on the average order size, the expected order size of a demand hit can be calculated. Using this order size, a shipment's expected volume or weight can be calculated. These values can be used in combination with equations 4.1 and 4.2 to calculate the expected costs for a rush and regular transshipment respectively. Recall that the rush orders are transshiped via DHL who charge a fee based on the weight of the package. Besides, the regular orders are only shipped in full trucks (see section 1.3). This explains the linear form of equations 4.1 and 4.2. Both equations represent the costs of transshipping a single order line for item i from warehouse w to another warehouse v.

$$Costs_{i,w,v}^{Rush\ transshipment} = Cost^{Order\ Handling} + Cost_{w,v}^{Shipment\ per\ kg} \times Weight_{i,v}^{kg}. \tag{4.1}$$

$$Costs_{i,w,v}^{Regular\ transshipment} = Cost^{Order\ Handling} + Cost_{w,v}^{Shipment\ per\ m^3} \times Volume_{i,v}^{m^3}. \tag{4.2}$$

If equation 4.1 and 4.2 are used in combination with the probability of having a rush transshipment, the total expected transshipment costs for transshipping a single order line of item i from warehouse w to another warehouse v can be calculated (equation 4.3). This way, the expected transshipment costs for every stocking option can be calculated.

$$E[Costs_{i,w,v}^{transshipment}] = 0.1025 \times Costs_{i,w,v}^{Rush\ transshipment} + 0.8975 \times Costs_{i,w,v}^{Regular\ transshipment}. \tag{4.3}$$

4.3.2 Inventory costs

For the inventory costs, a more elaborate approach is needed since the inventory costs depend on the reorder level. To approximate the reorder levels, PACCAR Parts fill rates, and the average inventory levels, the theory on stochastic inventory models for a single item at a single location that is described by Donselaar, van and Broekmeulen (2014) is used. However, Donselaar, van and Broekmeulen (2014) propose formulas for the volume fill rate (see Equation 1.1). Since PACCAR Parts uses a fill rate that measures the performances regarding the number of satisfied order lines, the theory on order fill rates described by Larsen and Thorstenson (2008) is used. The described order fill rate used in this paper has the same definition as the PACCAR Parts fill rate (see Equation 1.2). In literature, the order fill rate is only described for situations in which a base-stock policy is applied (Rosling, 2002; Song, 1998; Tempelmeier, 2000; Larsen & Thorstenson, 2008). For this reason, new functions for the order fill rate (PACCAR Parts fill rate) are derived for discrete demand distributions in case of an (R, s, nQ)-policy. These functions are based on the studies of Donselaar, van and Broekmeulen (2014) and Larsen and Thorstenson (2008). Before the approximations of the reorder levels, PACCAR Parts fill rates, and average inventory levels are explained, the most important assumptions are discussed:

- The paper of Donselaar, van and Broekmeulen (2014), uses an (R, s, nQ)-system that assumes a fixed s and Q throughout the year. In sections 1.5 and 1.4, it is explained that an adjusted form of the (R, s, nQ)-policy is used at PACCAR Parts, where s and Q depend on the forecasted demand which is seasonal (i.e., s and Q are not completely stable throughout the year). Nevertheless, the values for s and Q increase or decrease in the same direction when the forecasted demand increases or decreases, respectively. Therefore, the theory that is described by Donselaar, van and Broekmeulen (2014) is still considered to serve as a good approximation to calculate the average inventory levels throughout the year.
- Donselaar, van and Broekmeulen (2014) and Larsen and Thorstenson (2008) assume that unsatisfied orders are backordered and that inter-arrival times and order sizes are independently and identically distributed. These assumptions are also valid for the case at PACCAR Parts.
- Donselaar, van and Broekmeulen (2014) and Larsen and Thorstenson (2008) assume deterministic lead times. The lead times at PACCAR Parts are, in reality, not deterministic. In order to enable a clear explanation, the derived formulas in this section also assume deterministic lead times in the first instance. Nonetheless, this assumption is relaxed in section 4.3.4.

Consider the random variable J that describes the order sizes under a base-stock policy with a fixed level S and lead time L. Furthermore, consider the random variable D_t that describes the aggregate demand in the time interval $[\tau - t, \tau]$ for any instant τ at which demand occurs. Note that D_t and the demand at time instant τ (represented by the random variable J) are independent. Whenever a customer order arrives, there is a probability of $P(D_L = n)$ that the net inventory on hand at the time of the arrival equals $S - n$. With probability $P(J \leq S - n)$, the whole customer order can be delivered from stock (Larsen & Thorstenson, 2008). Hence, Larsen and Thorstenson (2008) describe the following formula for the order fill rate (OFR) in case of a continuous reviewed base-stock policy:

$$OFR(S) = \sum_{n=0}^{S-1} P(D_L = n)P(J \leq S - n). \tag{4.4}$$

In the paper of Donselaar, van and Broekmeulen (2014), the IP just after a potential delivery is used to derive the formulas for the KPIs in an (R, s, nQ)-policy. By using the IP, the property that is proved by Hadley and Whitten (1963) can be used. This property is valid in cases where an (R, s, nQ)-policy is used where the IP just before ordering has to be strictly below s and demand is discrete. In this case, the property states that the IP just after a potential delivery is uniformly distributed on the interval $(s, s - 1 + Q)$ (see Equation 4.5).

$$P(IP = s + i) = \frac{1}{Q} \text{ for } i = 0,\ 1,\ \dots\ ,\ Q - 1 \text{ and zero elsewhere.} \tag{4.5}$$

Note that in the case of Larsen and Thorstenson (2008), in which a continuous base stock policy is used, the IP is always equal to the base-stock level S. If Equation 4.4 is derived via the logic that is applied in the paper of Donselaar, van and Broekmeulen (2014):

$$\begin{aligned}
\text{OFR(S)} &= P(J \leq IP(\tau) - D_L) \\
&= P(J \leq S - D_L) \\
&= \sum_{n=0}^{\infty} P(D_L = n)P(J \leq S - n) \\
&= \sum_{n=0}^{S-1} P(D_L = n)P(J \leq S - n).
\end{aligned} \tag{4.6}$$

Now, consider an arbitrary moment Z in the interval $(\tau + L, \tau + L + R)$ for an (R, s, nQ)-policy (see Figure 4.2. The random variable of the aggregated demand from the last potential delivery moment until the moment Z at which a potential demand could occur is described by D_z (see Figure 4.2. Using the property of Equation 4.5, the following expression for the OFR (and thus PACCAR Parts fill rate) can be derived for moment Z:

$$\begin{aligned}
\text{PACCAR Parts fill rate at moment Z} &= P(J \leq IP(\tau) - D_{L+Z}) \\
&= \sum_{k=0}^{\infty} P(IP = k)P(J \leq k - D_{L+Z}) \\
&= \frac{1}{Q} \sum_{k=s}^{s+Q-1} P(J \leq k - D_{L+Z}) \\
&= \frac{1}{Q} \sum_{k=s}^{s+Q-1} \sum_{n=0}^{\infty} P(J \leq k - n)P(D_{L+Z} = n) \\
&= \frac{1}{Q} \sum_{k=s}^{s+Q-1} \sum_{n=0}^{k-1} P(J \leq k - n)P(D_{L+Z} = n).
\end{aligned} \tag{4.7}$$

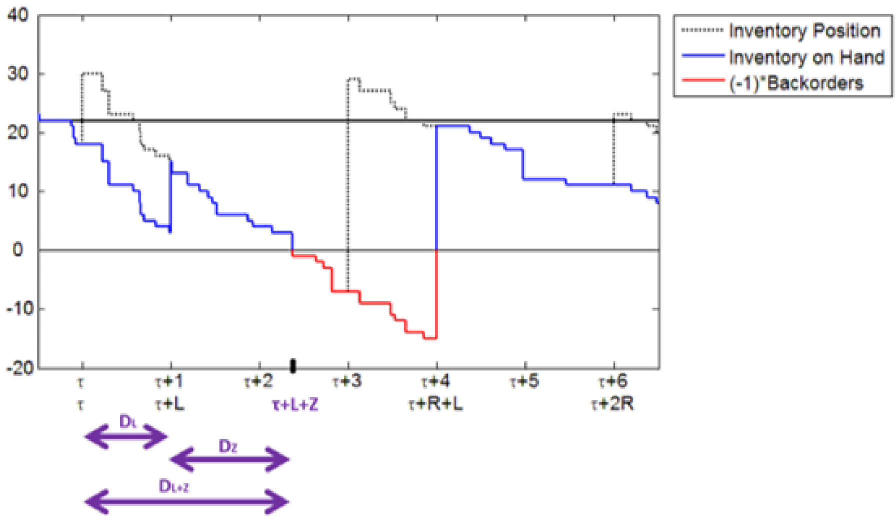


Figure 4.2: Sample path of an (R, s, nQ) inventory system with $R = 3$, $s = 22$, $Q = 12$, and $L = 1$

Figure is derived from Donselaar, van and Broekmeulen (2014)

In order to obtain an expression for the PACCAR Pats fill rate during the potential delivery cycle, the average value of Equation 4.7 across all possible time units during the potential delivery cycle of length R should be calculated. Note that in the case of PACCAR Parts, $R = 1$. Besides, the historical demand data is saved per day (i.e., it is unknown at which moment of the day the demand order arrived). Because of this and the fact that R has a value of 1, the PACCAR Parts fill rate is assumed to be equal to Equation 4.7. In a more generic case where demand, R, and L are discrete and in which $R \neq 1$, the estimated average OFR is represented in Equation 4.8.

$$\text{PACCAR Parts fill rate} = \frac{1}{R}\sum_{t=1}^{R}\Big(\frac{1}{Q}\sum_{k=s}^{s+Q-1}\sum_{n=0}^{k-1} P(J \leq k-n)P(D_{L+t} = n)\Big). \tag{4.8}$$

For the average level for the expected I^{OH}, Donselaar, van and Broekmeulen (2014) derived a formula that is valid for all cases where items are non-perishable, items are backordered in case of a stockout, lead times are deterministic, an (R, s, nQ)-policy is used, and demand is stationary. Hence, the expression for the expected I^{OH} applies to the case at PACCAR Parts. The expression for the expected I^{OH} on moment t is defined as follows:

$$E[I^{OH}(\tau + t)] = \frac{1}{Q}\sum_{i=0}^{Q-1}\sum_{d=0}^{s+i-1}(s + i - d)P(D_t = d). \tag{4.9}$$

Donselaar, van and Broekmeulen (2014) state that the average inventory value during the potential delivery cycle can be calculated by taking the average value across the interval $(\tau + L, \tau + L + R)$. Therefore, the average inventory value is approximated by taking the average value of $E[I^{OH}(\tau + L)]$ and $E[I^{OH}(\tau + L + R)]$ (i.e., $\frac{E[I^{OH}(\tau+L)]+E[I^{OH}(\tau+L+R)]}{2}$). Note that at PACCAR Parts, R is equal to 1. Since this model is only executed for items with relatively low demand, the differences between $E[I^{OH}(\tau + L)]$ and $E[I^{OH}(\tau + L + R)]$ are negligible in most cases.

4.3.3 Total costs calculation

Now that the formulas for the cost approximations are given, the total cost functions can be calculated for every item i, stocking option s, and target PACCAR Parts fill rate f. Firstly, Equation 4.7 is used to calculate the minimum s level needed to obtain the target PACCAR Parts fill rate level. This s level is plugged into Equation 4.9 to calculate the expected inventory levels. PACCAR Parts assumes that the expected inventory costs equal 12% of the inventory value per year.

Seasonality plays a vital role in the operations of PACCAR Parts. As stated before, approximately 25% of the items at PACCAR Parts are forecasted via a seasonal pattern. By using the demand and order size distributions for a whole year, variation would be overestimated for seasonal products. This could lead to an overestimation of the needed safety stock levels in order to obtain a minimum PACCAR Parts fill rate, leading to an overestimation of the costs of having inventory. The seasonality at PACCAR Parts is complex. Different types of seasonal patterns at PACCAR Parts can be identified. Weather conditions, sales targets, and holiday periods are the leading causes of the seasonal patterns. Since the seasonal patterns differ per item, it is complex to include seasonality in an aggregated model. Nevertheless, for most items, the seasonality is based on the weather conditions. Therefore, the empirical demand and order distributions are separately derived for the four seasons. Accordingly, the minimum safety stock levels and corresponding expected inventory costs to obtain the minimum PACCAR Part fill rates are calculated separately. Eventually, an average value for the expected inventory costs is taken across the four seasons.

These expected inventory costs are added to the expected transshipment costs of Equation 4.3 in order to obtain the total costs regarding an item, stocking option, PACCAR Parts fill rate combination.

4.3.4 Stochastic lead times

Up to now, it has been assumed that the lead times are deterministic. It has been explained that the empirical demand data of the demand during one day is used to obtain the convolution of the demand during the deterministic lead time. However, when the lead time is also assumed to be a stochastic variable, the empirical lead time data in combination with the demand convolution can be used to calculate the convolution of the demand during the lead time. For example, consider a certain empirical lead time distribution that has an equal probability of the lead to be 14 or 15 days (i.e., $P(L = 14) = 0.5$ and $P(L = 15) = 0.5$). In this case, the empirical distribution of the demand during the lead time can be obtained by multiplying both the demand convolution of the demand during 14 days and the demand during 15 days by 0.5 and adding the probabilities together. Note that this method can only be applied when the lead times are discrete random variables. The empirical lead times derived from the PACCAR Parts database are discrete and can therefore be applied.

The empirical lead time distributions are based on the data in the last rolling year in this research. Recall that the calculation for the cost approximations is performed for every season to consider the seasonality. This enables us to update the empirical lead time data every season (i.e., use the empirical lead time data of quarters two, three, and four of 2019 and quarter one of 2020 to do the calculations for quarter two of 2020).

4.3.5 Lead time selection

The formulas that are derived in the previous subsection can be used to approximate the costs per stocking option for each item. When doing so, it is crucial to select the proper lead time to derive the demand distributions used in the formulas. For example, consider Figure 4.3 in which the examples of the lead times for an arbitrary part are displayed. For this part, the supplier delivers the goods to the warehouse in Budapest, which cross-docks the parts to Leyland. Also, consider stocking option 45 again, where the item is only stocked in Leyland. When calculating the costs for this option, the L that is used to calculate D_{L+R} or D_L for the warehouse in Leyland should consider that the item is cross-docked in Budapest. This means that instead of setting L equal to 15, L should be set equal to 15+28 in this case. In this case, the convolutions of the two empirical lead time distributions are used (i.e., the empirical lead time distributions from supplier to BUD and BUD to LEY).

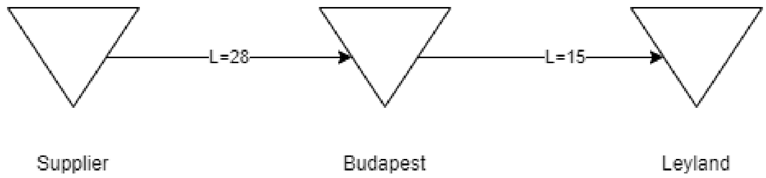


Figure 4.3: Example of lead times

4.4 Mathematical formulation

On the next page, the mathematical formulation of the IP model is displayed. The objective function 4.10 minimizes the total expected costs of the network. Note that for every stocking opportunity, the total costs, including inventory and transshipment costs, are calculated beforehand. Constraint 4.11 ensures that every item is stocked via exactly one stocking opportunity - PACCAR Parts fill rate combination. Constraint 4.12 ensures that a minimum PACCAR Parts European fill rate is obtained. Using the total number of expected order lines and the desired PACCAR Parts European fill rate, it can be calculated how many order lines should be satisfied in order to obtain the desired PACCAR Parts European fill rate. By subtracting this with the number of order lines that is expected to be satisfied by the parts that are already stocking, a minimum number of order lines that need to be satisfied by the IP model is obtained. The same logic is applied in equation 4.13 for each warehouse individual to obtain the minimum desired PACCAR Parts individual fill rates. Constraint 4.14 ensures that no more than a certain number of items can be stored per storage location type per warehouse (i.e., the capacity constraints). The last constraint 4.15 defines the binary decision variable in the model. Note that the binary decision variable is not dependent on w, implicating that the PACCAR Parts fill rate cannot differ between warehouses for the same item. If the IP model allowed the PACCAR Parts fill rates between the four warehouses, the number of decision variables in the IP model would quadruple. At the same time, it is likely that the majority of the items only become stocking in one or two warehouses due to the low demand in combination with the capacity restrictions. Hence, it is considered that quadrupling the number of the decision variables does not outweigh its benefits since no significant changes in the outcome will be noticed.

Sets

I	Set of items that is considered by the IP model
W	Set of warehouses
S	Set stocking options
F	Set of PACCAR Parts fill rate options
T	Set of types of storage locations

Parameters

$c_{i,s}^{f}$	Total costs of item i when stocking option s and PACCAR Parts fill rate option f are used
$h_{i,s}^{f}$	Expected number of hits of item i that are satisfied when stocking option s and PACCAR Parts fill rate option f are used
$h_{i,s,w}^{f}$	Expected number of order hits of item i at warehouse w that are satisfied by warehouse w itself when stocking option s and PACCAR Parts fill rate option f are used
$x_{i,s,w}^{t}$	Binary parameter that equals 1 if an item i occupies a storage location of type t in warehouse w when stocking option s is used, and 0 otherwise
H^{EUR}	Total number of hits on a European level for all items
H_{w}^{IND}	Total number of hits at warehouse w for all items
H_{A}^{EUR}	Total number of hits on a European level for items that are already stocked (i.e., group A items)
$H_{A,w}^{IND}$	Total number of hits at warehouse w for all items that are already stocked (i.e., group A items) in warehouse w
u_{w}^{t}	Maximum number of items that can be stored in storage locations of type t at warehouse w
a_{w}^{t}	Number of items that are already stocked in storage location type t in warehouse w
F^{EUR}	Minimum value for PACCAR Parts European fill rate
F_{w}^{IND}	Minimum value for PACCAR Parts individual fill rate for warehouse w
F_{A}^{EUR}	Value for PACCAR Parts European fill rate parts that are already stocked (i.e., group A items)
$F_{A,w}^{IND}$	Value for PACCAR Parts individual fill rates for parts that are already stocked (i.e., group A items) at warehouse w

Decision variables

$y_{i,s}^{f}$	Binary variable that equals 1 if an item i is stocked via stocking option s and PACCAR Parts fill rate option f, and 0 otherwise

IP model

$$\min \sum_{f=1}^{F} \sum_{i=1}^{I} \sum_{s=1}^{S} c_{i,s}^{f} y_{i,s}^{f} \tag{4.10}$$

Subject to

$$\sum_{f=1}^{F} \sum_{s=1}^{S} y_{i,s}^{f} = 1 \qquad \forall i \in \mathrm{I} \tag{4.11}$$

$$\sum_{f=1}^{F} \sum_{i=1}^{I} \sum_{s=1}^{S} h_{i,s}^{f} y_{i,s}^{f} \geq F^{EUR} H^{EUR} - (H_{A}^{EUR} F_{A}^{EUR}) \tag{4.12}$$

$$\sum_{f=1}^{F} \sum_{i=1}^{I} \sum_{s=1}^{S} h_{i,s,w}^{f} y_{i,s}^{f} \geq F^{IND} H_{w}^{IND} - (H_{A,w}^{IND} F_{A,w}^{IND}) \qquad \forall w \in \mathrm{W} \tag{4.13}$$

$$\sum_{f=1}^{F} \sum_{i=1}^{I} \sum_{s=1}^{S} x_{i,s,w}^{t} y_{i,s}^{f} \leq u_{w}^{t} - a_{w}^{t} \qquad \forall w \in \mathrm{W}, \forall t \in \mathrm{T} \tag{4.14}$$

$$y_{i,s}^{f} \in \{0,1\} \qquad \forall f \in \mathrm{F}, \forall i \in \mathrm{I}, \forall s \in \mathrm{S} \tag{4.15}$$

Chapter 5

Stocking/non-stocking heuristic

There are some challenges regarding the implementation of the IP model that is proposed in the previous section. The calculations that are needed to approximate the expected PACCAR Parts fill rates and inventory values per stocking option are relatively complex and computationally expensive. Additionally, a solver is needed for the IP model to solve while no solver is included in PACCAR Parts' planning system. For this reason, a simple heuristic is proposed that is more convenient to implement for PACCAR Parts. This heuristic is based on the analysis of the stocking options proposed by the IP model. Section 8.1.4 describes this analysis in more detail. The most important conclusions are summarized below:

1. The IP model gains the most cost reductions by reallocating stock from Budapest to Eindhoven or Leyland. The reduction in transshipment costs mainly drives these cost reductions.
2. To enable this reallocation and still respect the capacity constraints, Eindhoven and Leyland have to free up space by setting some other items to non-stocking.
3. The targets regarding individual PACCAR Parts fill rates are met relatively easily in Eindhoven and Leyland.
4. Transshiping items between Eindhoven and Leyland is cheaper than transshipping from Budapest to these warehouses.

Based on these conclusions, the following intuition forms the base of the proposed stocking/non-stocking (SnoS) heuristic: *for some items with relatively low demand, it may be beneficial to store the item only in Eindhoven or Leyland instead of in both warehouses. In this way, space is created for items that are currently stocked in Budapest and that have high expected transshipment costs.* In the remaining part of this chapter, the heuristic is explained. Note that the heuristic is executed separately for the three stocking location types (small, medium, and large). Additionally, in Appendix J, the pseudo-code of the SnoS heuristic is displayed.

Step 1: Create space in Leyland and Eindhoven

Recall that in section 1.5, it is explained that an item's current stocking/non-stocking decision is based on its price and the number of order lines in the last rolling year. For example, in Eindhoven, an item is set to stocking when it had more than three demand hits strictly in the last rolling year, and the price of the item was less than 15 euros. The first step in the heuristic is to increase the hits boundaries by one (i.g., an item whose price is less than 15 euros now needs four or more hits). This way, space is created in the warehouses by removing the items with the least number of order hits. The effect of this stricter stocking policy is displayed in Table 5.1.

	Small		**Medium**		**Large**	
	EHV	*LEY*	*EHV*	*LEY*	*EHV*	*LEY*
Current policy	18251	17136	4098	3807	402	337
Stricter policy (+1 hit)	16772	15399	3826	3496	362	302
Difference	1479	1737	272	311	40	35

Table 5.1: Stocking items per storage location in 2019 for Eindhoven and Leyland

Step 2: Add the removed items to the global stocking items

The removed items are added to the set of global stocking items. At this moment, we consider the set of items needs to be allocated to the free stocking locations in the warehouses in Budapest, Eindhoven, and Leyland. Note that some items removed from the warehouse in Eindhoven and Leyland are the same. In other words, among the 1479 and 1737 small items that were removed from Eindhoven and Leyland, respectively, some parts are the same.

Step 3: Consider 4 stocking options per item
Now, the set of items that need to be allocated to the created free spots in the three warehouses is considered. An item in this set can be stored in one of the three warehouses. Additionally, it may be beneficial to store the items in both Eindhoven and Leyland because, in these warehouses, most of the demand occurs. Also, recall that some products that were removed in step 1 were stocked both in Eindhoven and Leyland. To summarize, we consider the following four stocking options: BUD, LEY, EHV, and LEY+EHV.

Step 4: Calculate the expected transshipment costs
The expected cost function that was used in the IP model consists of inventory and transshipment costs. When an item is allocated to a warehouse in this heuristic, it will stock the demand for all warehouses (i.e., global stocking). This implies that the same amount will be stocked for every stocking option. Therefore, there are no differences in inventory costs between the stocking options. An exception to this is the option in which the item is both stored in Leyland in Eindhoven. Nevertheless, due to the small demand for the items that are considered in this heuristic, these effects are considered to be negligible. Hence, this heuristic only takes into account the expected transshipment costs. These expected transshipment costs are calculated in the same way as has been explained in section 4.3.1

Step 5: For every item, calculate the expected savings per stocking option compared to stocking option of stocking in Budapest
For every item, calculate the expected cost savings for the three stocking options: Leyland, Eindhoven, and Eindhoven+Leyland (i.e., the potential savings that can be made when the stocking option is used instead of the stocking option in Budapest). This can be calculated for a particular stocking option by subtracting the expected transshipment costs for stocking a particular item in Budapest by the expected transshipment costs of the other stocking options.

Step 6: Select the item stocking-option possibility that yields the highest savings
Select the item-stocking option combination that yields the highest expected savings according to the calculations in the previous section. Note that the option can only be selected if space is left in the warehouse(s) where the item should be stocked according to the stocking option. Hereafter, delete the allocated item from the list of items to be allocated to a warehouse and update the free spots in the warehouses. Note that the savings obtained for the stocking option Eindhoven+Leyland are divided by two since twice as much capacity is needed compared to the other stocking options.

Step 7: Stop the algorithm once the capacity of the warehouses is full
Eventually, all items that are considered in the heuristic need to be allocated to at least one warehouse. In this way, the expected PACCAR Parts European fill rate cannot decrease compared to the current situation. However, on the other hand, the warehouse capacities have to be respected. Therefore, whenever the amount of free spots in the warehouses equals the number of items that need to be allocated to a warehouse, the option of stocking the item in both Leyland and Eindhoven is not considered anymore.

Note that the warehouse to which the item is assigned will stock the demand for all other warehouses. Whenever the stocking option of stocking in Leyland and Eindhoven is chosen, Leyland stocks its own demand and Eindhoven the rest of the demand. This holds since it is cheaper to tranship from Eindhoven to Madrid and Budapest than from Leyland.

Chapter 6

Safety stock heuristic

After the stocking/non-stocking decision is made, the next step in this research is to calculate the optimal safety stock coverage levels for all SKUs that are stocking (i.e., for both the items that were considered by the IP model and the items that were not). In the previous chapter, safety stock levels were only determined for stocking items considered by the IP model (i.e., not for items that had over five hits in every warehouse in the last rolling year). Note that the safety stock levels that the IP model determined only considered three targets PACCAR Parts fill rates per item. Furthermore, these PACCAR Parts fill rate targets were assumed to be the same for every warehouse in which the item is stocked. In order to obtain accurate results for an aggregated model that considers all SKUs individually, a new safety stock setting approach is desired.

As a first method for calculating the optimal safety stock levels, the heuristic that is described by Donselaar, van et al. (2021) is tested. The heuristic aims to set reorder levels in periodic review inventory systems with an aggregated service constraint. This chapter explains the model that is designed by Donselaar, van et al. (2021), adjusts it to the problem at hand at PACCAR Parts, discusses its assumptions, and explains the greedy approach that is proposed by Sherbrooke (2006) to solve the model efficiently.

6.1 Optimization problem

The model that is proposed by Donselaar, van et al. (2021) can be described as an optimization problem. The objective of the optimization model is to minimize the total expected holding costs for a set of items I, subject to the restriction that an aggregated minimum service level is obtained. In the case of PACCAR Parts, this aggregated service level is the PACCAR Parts European fill rate. The mathematical model is expressed as follows:

$$\min \sum_{i=1}^{I} c_i E[I_i^{OH}] \tag{6.1}$$

Subject to

$$\sum_{i=1}^{I} w_i \times \text{PACCAR Parts fill rate}_i \geq \text{PACCAR Parts fill rate}^*, \tag{6.2}$$

$$\sum_{i=1}^{I} w_i = 1, \tag{6.3}$$

where:

- c_i reflects the holding costs for item i.

- $E[I_i^{OH}]$ reflects the average expected inventory on hand for item i.
- PACCAR Parts fill rate$_i$ reflects the individual PACCAR Parts fill rate for item i.
- PACCAR Parts fill rate* reflects the target aggregated European fill rate.
- w_i reflect the weight in the fill rate calculation for item i.

In this model, $E[I_i^{OH}]$ and PACCAR Parts fill rate$_i$ depend on the reorder level s of item i (s_i). Therefore, s_i is the decision variable in the model. In section 4.3, expressions for the PACCAR Parts fill rate and $E[I_i^{OH}]$ are given (equations 4.9 and 4.7). These expressions are also used in this model. Additionally, Donselaar, van et al. (2021) describe two approaches for determining the weights. Namely, one based on the order volumes and one on the turnover. At PACCAR Parts, the weights for the aggregated PACCAR Parts European fill rate depend on the number of order hits. Hence, the weight definition in the model that is used in this research is as follows: $w_i = \frac{h_i}{\sum_i^I h_i}$, where h_i are the number of order hits in the last rolling year for item i. A crucial difference between the model that is described by Donselaar, van et al. (2021) and its implementation in this thesis deals with the stocking/non-stocking decision. In the model that Donselaar, van et al. (2021) use, it is assumed that reorder levels can take the value of zero. If an item its reorder level takes the value of 0, it implies that the item is non-stocking. This study already makes the stocking/non-stocking decision before the safety stock heuristic is executed. Since the non-stocking items are considered in the aggregated PACCAR Parts fill rate calculation, they have to be taken into account in the model to obtain reliable results. By considering both the stocking and non-stocking items in set I, the weights are calculated based on their contribution to the aggregated PACCAR Parts fill rate for all articles. Note that the PACCAR Parts fill rate of non-stocking articles are always equal to 0.

6.2 Assumptions

6.2.1 Multi-location problem

Initially, the heuristic that is proposed by Donselaar, van et al. (2021) is designed for single-location problems (i.e., without transshipments). Nevertheless, in the stocking/non-stocking decision, the stocking options that are selected per product indicate how the expected transshipment streams are organized. Therefore, the multi-location problem is approximated by treating it as a single-location model that uses the aggregated demand and order size distributions for items that are stocked via a stocking policy that suggests shared inventory. In this way, a constraint can be set on the aggregated service level (i.e., PACCAR Parts European fill rate). Note that in this case, the individual PACCAR Part fill rates are not taken into account. Also, note that the expected transshipment costs are independent of the reorder level. This holds since items that cannot be transshipped immediately if they are not on stock need to be back-ordered eventually. For this reason, the expected transshipment costs are not considered in this model.

6.2.2 Seasonality

Recall that seasonality plays a vital role in the operations of PACCAR Parts. In the same line of reasoning as in section 1.6.2, the model is executed for the four seasons separately. These models' safety stock levels are translated into safety stock coverage levels expressed in days (see Equation 6.4). Across the four seasons, the mean value of the four safety stock coverage levels is taken. Since the forecasts per item consider the seasonal patterns, the safety stock coverage can adapt to the seasonal patterns better than the numerical safety stock levels. Another advantage of using safety stock coverage levels over numerical safety stock levels comes with the nature of the spare-parts industry. The relatively large share of low-demand items with high variability makes it hard to set accurate safety stock levels one year in advance. When using the numerical safety stock levels, the numerical safety stock levels have to be set one year in advance in order to adapt to the seasonality. In contrast, the forecast is updated every month. Hence, using up-to-date forecasts with the safety stock coverage levels is more likely to yield accurate results than numerical safety stock levels that are calculated one year in advance.

$$\text{Safety stock coverage (in days)} = \text{Numerical safety stock level} \times \frac{\text{Number of days in period}}{\text{Demand during period}}. \tag{6.4}$$

6.2.3 Deterministic lead times

Especially in the past two years, supply disruptions and variations played a significant role in the operations of PACCAR Parts. As explained in 2.3, the COVID-19 situation and chip shortage caused supply disruptions in the PACCAR Parts supply chain. In order to take into account the stochastic lead times, the empirical lead time distributions are used to derive the probability functions for the demand during the lead time. This is done in the same way as explained in section 4.3.4.

6.3 Greedy approach

The described optimization model is time-consuming to solve. Sherbrooke (2006) describe a greedy approach that solves the optimization problem more efficiently. Donselaar, van et al. (2021) conclude that the greedy approach yields nearly as good as the optimal solution that is obtained by solving the optimization model exactly. Therefore, the greedy approach is used in this thesis. The greedy approach starts by setting every reorder level equal to one. Note that this heuristic is only executed for the items that are considered to be stocking. For every item, the ratio between the increase in PACCAR Parts European fill rate and the increase in total costs is calculated (see equation 6.5). Iteratively, the safety stock level of the item with the highest ratio is increased by one. The algorithm stops once the desired PACCAR Parts European fill rate is obtained.

$$ratio_i = \frac{w_i\Big(\text{PACCAR Parts fill rate}_i(s+1) - \text{PACCAR Parts fill rate}_i(s)\Big)}{c_i\Big(E[I_i^{OH}](s+1) - E[I_i^{OH}](s)\Big)}. \tag{6.5}$$

Chapter 7

Genetic algorithm

In the previous chapter, the safety stock heuristic that is proposed by Donselaar, van et al. (2021) has been described. Regarding the implementation of this heuristic at PACCAR Parts, there are some disadvantages. Firstly, the heuristic decides on an item's individual safety stock level based on its empirical demand distribution of the last rolling year. For most of the items in the spare parts industry, there are only a few order hits per year. This means that the safety stock decision for most items is based on an empirical demand distribution with only a few observations. The accuracy of these distributions is therefore questionable. Note that the model that is described in Chapter 4 also uses the empirical demand distributions from the last rolling year. Nevertheless, this model uses the empirical demand distributions to make cost approximations that serve as an input for an IP model that makes a binary decision. The empirical demand distributions in the safety stock heuristic are used directly to make a numerical decision. In the latter case, having accurate demand distributions is crucial. In the method proposed in this chapter, no empirical demand and lead time distributions are used to estimate individual safety stock coverage levels. Moreover, the management of PACCAR Parts prefers a model that is easy to implement in the planning system JDA. The safety stock heuristic encounters the same problem as the IP model. Namely, the complex cost calculations are hard to implement into the planning system JDA. The management of PACCAR Parts prefers a metric that is easy to implement in JDA, such as the 9-grid table that is currently used (see Section 1.5). Hence, this chapter proposes a new classification method for PACCAR Parts that is relatively easily implementable for PACCAR Parts. Furthermore, a Real Coded Genetic Algorithm (RCGA) is used to determine the near-optimal safety stock coverage levels per class.

7.1 Classification

In section 2.1, it was concluded that the current classification method PACCAR Part uses is sub-optimal. For the renewed inventory classification, an important trade-off has to be made. On the one hand, it is desired to have enough categories to propose a safety stock coverage level that is representative of each item in the category. On the other hand, it is desired to restrain the number of categories in order to limit the complexity of the RCGA and the implementation. Besides, a high number of categories can lead to over-fitting within each category. In literature, much research is performed on the best way to classify spare parts inventory. The classification methods that are used in this thesis are based on the studies of Wingerden, van et al. (2016), Teunter et al. (2010), and Williams (1984). The proposed classification method is based on two criteria explained in the next two subsections. The first classification criterion deals with the trade-off between service level and inventory costs, while the second classification criterion deals with the variability of an item.

7.1.1 PACCAR Parts fill rate and inventory costs trade-off

Recall that most classification methods in the literature rely on ABC classification (see section 4.1). The intuition behind ABC classification is that items with relatively high demand and relatively low prices are the most efficient to stock since they contribute the most to the aggregated service level relative to their contribution to the total costs. Wingerden, van et al. (2016) investigated which classification criteria captures this trade-off the best. It was concluded that the one-dimensional $\frac{demand}{price}$−ratio was the most efficient method to capture the trade-off. This criterion outperformed the two-dimensional classification strategy in which items are classified based on a matrix for different demand and price intervals. Wingerden, van et al. (2016) state that the two-dimensional classification method can also capture the trade-off to some extent, although it does not directly capture the trade-off for each SKU individually. Furthermore, more classes are needed since a two-dimensional matrix is used.

An important difference between the case in the study of Wingerden, van et al. (2016) and PACCAR Parts comes with the service level definition. Wingerden, van et al. (2016) use the volume fill rate definition instead of the order fill rate definition that is used at PACCAR Parts. Regarding the volume fill rate, demand divided by price reflects the trade-off between service level and costs properly since each demand unit of a particular item contributes proportionally to the aggregated volume fill rate and total inventory costs. However, regarding the order fill rate, a demand unit is not contributing proportionally to the order fill rate and costs (i.e., one order hit can consist of multiple demand units). For this reason, the classification criterion is adjusted to the order fill rate. Equation 7.1 reflects the new classification criteria. Using this criterion, the trade-off between order fill rate and inventory costs is made by weighting the number of hits to the expected price of holding inventory of one hit (which is equal to the price times the expected customer order size). Teunter et al. (2010) use a similar criterion to classify the inventory in which they include the average order quantity per SKU (Q) in their classification criterion. In this study, a fixed cost per backorder is taken into account. Since Teunter et al. (2010) prove that the expected number of backorders depends on Q, they include this variable in their classification criterion. This thesis assumes no backorder costs, and a constraint is set on the minimum desired PACCAR Parts fill rates. In that case, the value of Q only influences the cycle stock costs. Since these costs are irrelevant when evaluating the safety stock policy, Q is not considered in the classification criterion.

$$\text{Classification criterion} = \frac{Hits}{Price \times E[OS]}. \tag{7.1}$$

To clarify, consider the example data in Table 7.1. Item A, B, and C had the same aggregated demand in the previous year. Additionally, the price is the same for the items. The only difference between the items is the number of hits and expected order sizes. For example, item A was only ordered in one order line time while Item B was ordered in ten order lines. If the classification criterion that is originally proposed by Wingerden, van et al. (2016) is used, both items items would get the same classification score. However, item B contributes ten times as much to the aggregated PACCAR Parts fill rate as item A. Intuitively, it is illogical to give the same score to A en B in this case. Therefore, the proposed classification criterion distinguished the parts based on their trade-off between contribution in aggregated PACCAR Parts fill rate and total inventory costs. Teunter et al. (2010) investigated the effects of having three or six classes in a classification

	Item A	**Item B**	**Item C**
Demand	10	10	10
Price	5	5	5
E[OS]	10	1	2
Hits	1	10	5
$\frac{Demand}{Price}$	2	2	2
$\frac{Hits}{Price \times E[OS]}$	0.02	2	0.50

Table 7.1: Example data for classification criteria

based on demand and price. Naturally, having six classes outperformed the case in which three classes were distinguished. Additionally, Teunter et al. (2010) showed that the advantage of having six over three classes increases with the number of SKUs considered. Since the number of SKUs at PACCAR Parts is relatively high, it is decided to use six classes. Furthermore, Teunter et al. (2010) explained a rule of thumb for setting the boundaries of the six classes. This rule of thumb states that the class sizes should increase in the opposite direction of the service level per class that is needed. More specifically, 4% of the SKUs with the highest classification value are considered to be the most important and need the highest safety stock level, followed by the next 7%, and so on. Eventually, the increasing class sizes should contain 4%, 7%, 10%, 16%, 25%, and 38% of the SKUs, respectively. In this way, the desired service level per class moves in the opposite direction of the class sizes. Table 7.2 displays the lower boundaries for the classification criterion per year when the class sizes that are proposed by Teunter et al. (2010) are used. It is observed that the boundaries are stable across the years. In order to make a robust classification and compare the safety stock coverage levels per class across the years, the same boundaries are used for each year. These boundaries are set to the average in Table 7.2.

	4%	**7%**	**10%**	**16%**	**25%**	**38%**
2019	25.44	10.03	4.52	1.80	0.50	0.00
2020	25.32	10	4.51	1.76	0.49	0.00
2021	25.74	10.11	4.55	1.77	0.49	0.00
Average	25.50	10.05	4.53	1.78	0.49	0.00

Table 7.2: Lower boundaries classification criterion per year

7.1.2 Variability

Since six classes are created for the trade-off between PACCAR Parts fill rate and inventory costs, every classification regarding the variability six-folds the total number of classes. In order to limit the number of total classes, it is desired to have a one-dimensional classification with only three classes for the variability. Williams (1984) proposes a simple method for defining the variability of a certain part during the lead time. This method considers the variability due to the number of orders arriving during the lead time, the variability due to the order sizes, and the variability due to the lead time. Assume that the numbers of orders arriving in successive units of time per SKU are Independent, Identically Distributed Random Variables (IIDRV) with mean $\bar{n}$ and variance $var(n)$. Furthermore, assume that the order sizes are IIDRV with mean $\bar{j}$ and variance $var(j)$. Finally, suppose that the lead times are IIDRV with mean $\bar{L}$ and variance $var(\bar{L})$. Note that the three IIDRVs are also independent of each other. Williams (1984) derive a dimensionless expression for the coefficient of variation during the lead time (C^2_{DDLT}):

$$C^2_{DDLT} = \frac{C^2_n}{\bar{L}} + \frac{C^2_j}{\bar{n}\bar{L}} + C^2_L, \tag{7.2}$$

where C_n is the coefficient of variation of the number of orders that arrive per time unit (the time unit is days in this case), C_j is the coefficient of variation of the order size, and C_L is the coefficient of variation of the lead time. This equation enables one to give a single score for the variability of a part. This variability score can be combined with the six classification criteria defined in the previous subsection. This way, a two-dimensional matrix is obtained for which the near-optimal safety stock coverage levels are determined using the RCGA explained in the next section.

The rule of thumb that is proposed by Teunter et al. (2010) is not appropriate to use in the context of variability since it is based on a trade-off between two parameters (i.e., demand and price). In the case of variability, no trade-off is made, and the classification criterion just gives a score to the total variation during the lead time. In literature, no unanimous method is used for determining the class sizes or boundaries for spare parts classification based on the coefficient of variation (CV). However, most of the studies assume 3 or 4 classes (Williams, 1984; Syntetos, Boylan & Croston, 2005; do Rego & De Mesquita, 2015; Boylan, Syntetos & Karakostas, 2008). Additionally, cut-off values of 0.5 and 1.0 for the CV^2 are often used as class boundaries. Whenever the CV^2 exceeds the value of 1.0, items are often referred to as highly-variable or sporadic items. In order to find out whether the same boundaries can be applied to the case at PACCAR Parts, Table 7.3 displays the distribution of two different settings for the boundaries of CV^2. It can be seen that the boundaries of 0.5 and 1.0 yield distributions in which almost 70 % of the items are covered in the first class, while less than 0.5 % is covered in the last class. It is considered that this highly unbalanced distribution cannot classify the SKUs properly in terms of variation. Therefore, other boundaries were tested. Eventually, the boundaries of 0.4 and 0.7 are assumed to yield more of a convenient classification from a practical point of view (see Table 7.3). Namely, the majority of the SKUs are in classes 1 and 2. This way, a distinction can be made between items with a low and a high level of overall variability. Additionally, somewhat more than 5% of the items with an extremely high level of variability are classified in class 3. Consider Equation 7.2, due to the division by $\bar{L}$ and $\bar{n}\bar{L}$ in the first and second term respectively, an extremely high value of C^2_{DDLT} ($\geq$0.7) is almost always due to the lead time variability. Therefore, the items in class 3 are considered to be the items that have a high probability of having supply disruptions. As has been proven in section 2.3, the supply disruptions drastically influence the stocking policy's performance. Hence, the SKUs with the highest risk of supply disruptions are considered separately in class 3.

	Boundaries of 0.5 and 1.0			**Boundaries of 0.4 and 0.7**		
	$CV^2 < 0.5$	$0.5 \leq CV^2 < 1$	$CV^2 \geq 1$	$CV^2 < 0.4$	$0.4 \leq CV^2 < 0.7$	$CV^2 \geq 0.7$
2019	68.8%	31.0%	0.2%	45.4%	48.9%	5.7%
2020	68.6%	31.0%	0.3%	45.5%	48.6%	6.0%
2021	66.2%	32.9%	0.5%	42.6%	50.4%	7.0%

Table 7.3: Distribution of SKUs per category for different boundaries of CV^2

The two classifications are combined into a two-dimensional matrix. The resulting matrix consists of 18 classes. The classes are numbered and can be found in Table 7.4. The detailed distributions of the SKUs per class per year are displayed in Appendix M.

		$Hits/(Price \times E[OS])$					
		[0,00, 0.49)	[0.49, 1.78)	[1.78, 4.53)	[4.53, 10.05)	[10.05, 25.50)	[25.50, ∞)
C^2_{DDLT}	[0, 0.4)	1	4	7	10	13	16
	[0.4, 0.7)	2	5	8	11	14	17
	[0.7, ∞)	3	6	9	12	15	18

Table 7.4: Class number per classification interval

7.2 Real-Coded Genetic Algorithm

After the classes are defined, the safety stock coverage levels per class need to be determined. Ideally, all combinations for the safety stock coverage levels per class are simulated. This way, the combination of safety stock coverage levels that yield the lowest total costs and respect the PACCAR Parts fill rate constraints can be selected. However, simulating all different combinations of safety stock coverage levels would be highly time-consuming. Hence, an algorithmic approach is needed to find near-optimal solutions efficiently. This same conclusion is drawn by authors that also study optimal safety stock setting in multi-location problems. Namely, these problems are considered NP-hard, and the possibilities to solve them exactly are limited (Feng et al., 2017; Gu et al., 2020; Hochmuth & Köchel, 2012). Meissner and Senicheva (2018) and Paterson et al. (2012) concluded that using dynamic programming is computational too expensive for large problem sizes such as the problem at PACCAR Parts. Problems with similar sizes that also consider transshipments often use Genetic Algorithms (GAs) to solve their problems (Nakandala et al., 2016; Yu et al., 2020; Feng et al., 2017; Gu et al., 2020; Hochmuth & Köchel, 2012). Genetic

Algorithms (GAs) are algorithms based on the natural evolution of biological systems. The GA is a combination of classical Darwinian evolutionary theory, the selectionism of Weismann, and the genetics of Mendel (Du & Swamy, 2016). The idea of the algorithm is to combine several good solutions to get a better one. By iteratively combining good solutions using crossovers, mutations, and selection, a near-optimal solution is found in an efficient way (H. Li & Jiang, 2012). Hence, it has been decided to use this approach to solve the problem at PACCAR Parts.

Conventionally, GAs are based on binary problems (Du & Swamy, 2016). However, the problem of determining the safety stock coverage levels is not a binary problem. Therefore, a special type of GA is needed to solve the problem. This type is called a Real-Coded Genetic Algorithm (RCGA). In RCGA, every decision variable is displayed directly in the vector (i.e., for every class, a numerical safety stock coverage level). Figure 7.1 displays the vector representation that is used in the proposed RCGA at PACCAR Parts. Note that the safety stock coverage is a floating-point number in this case. RCGA has several advantages over binary-coded GA. RCGA is faster, more consistent from run to run, and provides higher accuracy than binary-coded GA (Du & Swamy, 2016).

In a GA, the population consists of several chromosomes, representing a solution to the problem.

S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	...	...	S_x

S_x = Safety stock coverage for products in category x

Figure 7.1: Vector representation in RCGA for Paccar Parts case per category

A chromosome consists of genes representing a class's safety stock coverage levels. To clarify, the vector displayed in Figure 7.1 is called a chromosome, and the vector elements are called genes. For each of the chromosomes, the fitness value is calculated using the simulation model that is represented in Figure 3.1. These fitness values are based on the total costs that the simulation model obtains if the safety stock coverage levels of the chromosome are used. Additionally, penalty costs are added whenever constraints regarding the minimum PACCAR Parts fill rates are violated. Hereafter, crossover and mutation operators serve to improve the solution and explore the solution space (Deb, 2000). Finally, if the solution converges, the algorithm is stopped. The following subsections explain the steps that are used in the proposed RCGA in more detail.

7.2.1 Initialize population

The first step in the GA is to define the initial population. The size of the initial population is often between 20 and 100 chromosomes. Du and Swamy (2016) argue that increasing the population size increases the genetic diversity, enabling the algorithm to discover the full solution space. There is no need to discover the full solution space for the case at hand due to the substantiation of the chromosomes. Consider the six classification scores that are obtained using the classification criterion of Equation 7.1 to be represented by the set P. Moreover, consider the three variability scores that are obtained by using Equation 7.2 to be represented by the set Q. The classification that is represented in the set P relies on the theory that is proposed by Teunter et al. (2010). They state that the lower an item's classification score, the less the aggregated service level can increase relative to the increase in total costs when more safety stock is kept. Based on this, the solutions that the RCGA considers have to respect the following property:

Lemma 1 *For every element q in the set Q it holds that:* $S_{1,q} \leq S_{2,q} \leq S_{3,q} \leq S_{4,q} \leq S_{5,q} \leq S_{6,q}$,

where $S_{p,q}$ represents the safety stock coverage of items that have a classification score p and variability score q. Items with a higher level of variability need a higher safety stock level to obtain the same service levels (Zipkin, 2000). Hence, it also follows that:

Lemma 2 *For every element p in the set P it holds that:* $S_{p,1} \leq S_{p,2} \leq S_{p,3}$.

For this reason, the solution space that needs to be discovered only needs to take into account solutions in which the safety stock coverage levels respect Lemmas 1 and 2.

For the case at PACCAR Parts, the fitness value of every chromosome needs to be calculated via simulation. This implies that the computational time increases when the population size increases. For this reason, it is chosen to set the population size to a relatively small number (25) and to use crossover and mutation operators such that only new offspring chromosomes are created that respect Lemmas 1 and 2 (see sections 7.2.4 and 7.2.5).

Usually, the chromosomes in the initial population are obtained by choosing random values for the genes in the chromosomes (Du & Swamy, 2016). The disadvantage of this approach is that it takes significantly more iterations before the RCGA finds an optimal solution. This holds since the RCGA is not searching in the right direction. In the RCGA that is proposed for this research, it is desired to have as few iterations as possible because of the computationally expensive fitness evaluation. It is therefore decided to choose the initial population not wholly random. This way, the possible solutions are already in the right direction, and fewer iterations are needed (Altiparmak, Gen, Lin & Paksoy, 2006).

The initial population is built up by considering five different intervals of safety stock coverage levels from which six random genes are drawn. The randomly generated genes are sorted in non-decreasing order. The obtained six values are used to form the safety stock coverage levels of the group with the lowest variation score per class (i.e., classes 1, 4, 7, 10, and 13 in Table 7.4). The solution space is diversified by using five different intervals from which random numbers can be drawn. For each of the six safety stock coverage levels that are obtained by now, two random numbers between 0 and 25 are drawn and sorted in non-decreasing order. These two numbers are added to the safety stock level of the group with the lowest variation score per class and represent the two other variability groups within a class. In this way, Lemmas 1 and 2 are respected when the initial population is created. The upper bound of 25 is chosen so that the solution space is not made unnecessarily big by allowing illogical solutions. This could increase the computational time significantly. Note that the solutions obtained by the safety stock heuristic or the safety stock levels proposed by the IP model cannot be used here. This holds since the proposed classification algorithm is not adopted in these two models, implying Lemmas 1 and 2 are not respected.

7.2.2 Calculate fitness value

In GAs or RCGAs, the fitness value is usually calculated by filling in a single formula. In the proposed form of the RCGA, the fitness value is calculated via simulation. The challenge regarding this comes with computational time. Namely, for every chromosome, a simulation needs to be run. Moreover, in every iteration of the RCGA new offspring or mutated chromosomes are obtained for which the simulation needs to be run again. On the one hand, the number of parts that are considered in the simulation should be minimized to reduce the computational time. On the other hand, the more parts that are considered, the more representative the simulation model is. Although simulating too many items could cause overfitting.

Figure 7.2 represents the run times for different values of the number of parts that are considered in the simulation. It can be seen that there is a linear relationship between the run time and the number of parts that are considered. In total, there are approximately 35000 unique parts per year that are stocked. Simulating 3500 of these parts is chosen to calculate the fitness value. In this way, approximately 10% of the parts are simulated in approximately 5 minutes. This is considered to give the proper trade-off between having a representative sample, minimizing the computational time, and preventing overfitting. Eventually, the RCGA is run five times using the simulation model with 10% of the items. A representative safety stock coverage level per class is obtained by taking the average value of the outcomes. The random parts are chosen so that the representation per class is equal to the percentages in Table M.1. If only the stocking articles were simulated, incorrect PACCAR Parts fill rates would be obtained since the backorders resulting from non-stocking articles are neglected. For this reason, the obtained PACCAR Parts fill rates are subtracted by the percentages that are displayed in Table 7.5. The PACCAR Parts fill rate losses due to the non-stocking items are displayed in this table. As an illustration, in 2019, in 0.65% of the cases, an incoming order line was backordered immediately because the item was non-stocking in all European warehouses.

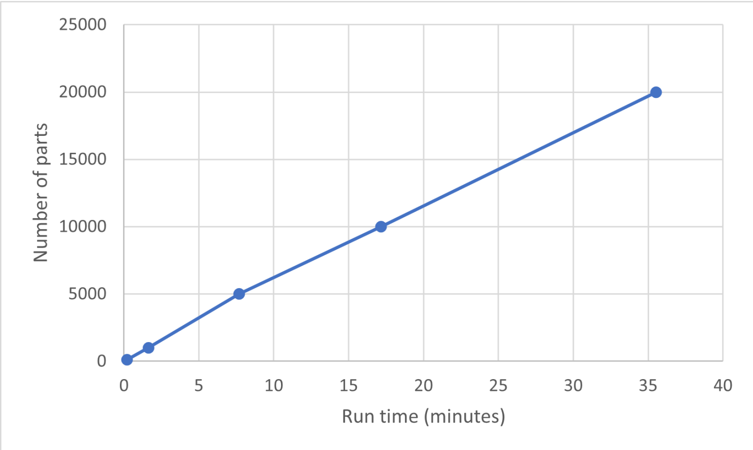


Figure 7.2: Simulation run times for different values of the number of parts considered

	2019	**2020**	**2021**
European	0.65%	0.67%	0.63%
Eindhoven	2.64%	2.88%	2.67%
Madrid	1.61%	1.65%	1.50%
Leyland	1.83%	1.88%	1.55%
Budapest	1.00%	1.03%	1.16%

Table 7.5: PACCAR Parts fill rates losses due to non-stocking items

The fitness value has to represent a single value to compare the fitness of the chromosomes (Du & Swamy, 2016). For the case of PACCAR Parts, this value has to consider the total costs and the extent to which the PACCAR Parts fill rates targets are respected. In most of the GA applications in the literature, a penalty function method has been used to consider constraints. In this way, infeasible solutions are penalized. The challenge regarding this method comes with the definition of the penalty function. A simplistic way of setting the penalty function is by using the so-called death penalty. In this approach, infeasible solutions are penalized with a big value M that ensures that the fitness value is so bad that the solution is eliminated by the GA (Du & Swamy, 2016). The disadvantage of this approach is that it does not distinguish between nearly infeasible and very infeasible solutions. Consequently, valuable information on the nearly infeasible solutions is lost. In order to make a distinction between infeasible solutions, a dynamic penalty approach can be used. This approach multiplies the amount of constraint violation j with a penalty parameter R_j. However, the advantage of this approach is that the penalty parameter has to be defined. For this reason, Deb (2000) proposed an efficient constraint handling method that overcomes the disadvantages of the death penalty and dynamic penalty approaches. Three main requirements for the penalty function are defined:

1. Any feasible solution is preferred to an infeasible solution.
2. Among two feasible solutions, the one having a better objective function is preferred.

3. Among two infeasible solutions, the one having a smaller constraint violation is preferred.

Based on these requirements, the efficient constraint handling equation (Equation 7.3) is proposed. Note that the function is adjusted to the case of PACCAR Parts.

$$F(x) = \begin{cases} f(x) & \text{if solution is feasible,} \\ f_{worst} + g_1(x)f(x) + \frac{1}{4}\sum_{j=2}^{\mathrm{J}} g_j(x)f(x), & \text{otherwise,} \end{cases} \tag{7.3}$$

where:

- J is the set of constraints. The first constraint ($j = 1$) represents the PACCAR Parts European fill rate constraint, and the remaining constraints represent the PACCAR Parts regional fill rate constraints.
- $F(q)$ is the fitness value of chromosome q.
- $f(q)$ is the value for the total costs of chromosome q that the simulation model obtains.
- f_{worst} is the highest value for the total costs among the chromosomes that yield a feasible solution.
- $g_j(q)$ represents the percentage that constraint j is violated by chromosome q.

The main advantage of this method is that no parameter has to be set. Therefore, in the case of PACCAR Parts, this is the most efficient method for constraint handling. The only drawback for the PACCAR Parts case is that some constraints are not equally scaled. In other words, the PACCAR Parts European fill rate is more critical than the PACCAR Parts regional fill rates. For this reason, violations in PACCAR Parts regional fill rates are penalized less than in the PACCAR Parts European fill rate.

7.2.3 Selection

The driving force of GA is the selection of individuals based on their fitness value to generate a new generation (Du & Swamy, 2016). In the proposed RCGA, elitism selection is used. Elitism ranks all parent chromosomes based on their fitness value. The 17 chromosomes with the highest fitness value are selected for the next generation. The remaining eight chromosomes are created via genetic operators. It is chosen to generate eight new chromosomes per iteration because the laptop on which the RCGA code must run has eight logical processors. This implies that eight simulations at the same time can be run using the multiprocessing library in Python. In other words, per iteration, eight new chromosomes (offsprings) can be simulated without increasing the computational time per iteration significantly.

The crossover operators that produce the eight new offspring chromosomes have to replace the eight worst chromosomes in the current population. In order to obtain the offspring chromosomes, parent chromosomes have to be selected that undergo crossover operations. These parent chromosomes are selected via roulette-wheel selection. A roulette wheel is spun twice, and chromosomes with a higher fitness value are more likely to get selected. The probability of getting selected is proportional to the fitness value of the fitness value (Du & Swamy, 2016). In other words, the fitter the chromosome is, the higher the probability of getting selected as a parent chromosome. For each crossover operation that is proposed in section 7.2.4, two new parents are selected out of the population. Note that the parents need to be different from each other. When the first parent is selected, it is excluded from the roulette wheel selection of the second parent.

7.2.4 Crossover

Once the parents are selected, genetic operations can be executed. The genetic operation that yields the most significant results is the crossover operation (Du & Swamy, 2016). In total, it is desired to create eight new offspring chromosomes be created by crossovers and mutations due to the eight logical processors. Since the crossovers are considered to yield the most significant results, it is chosen to obtain six new offsprings from crossover operations such that space for two new offsprings from mutations is left. RCGA can use other crossover operators than the ones that are used in binary-coded GA. The RCGA crossover operators can push the algorithm towards a better solution more efficiently since less randomness is involved (Du & Swamy, 2016). In the proposed RCGA, linear crossover operators are suggested. Linear crossover operators provide a linear combination between one or more parent chromosomes. By using linear crossovers, crossovers can be used without violating Lemmas 1 and 2. There are two types of linear crossovers suggested:

1. **Problem-oriented crossover**. To every chromosome c_q in the set of chromosomes Q, a weight (w_q) is allocated that allows to create a new offpsring ($c^{'}$) in the following manner:

$$c^{'} = \sum_{q=1}^{Q} c_q w_q. \tag{7.4}$$

   The weights are determined using a simple Linear Programming (LP) model that minimizes the total costs constraint to the PACCAR Parts fill rate constraints. The LP model is defined as follows:

   Sets, parameters, and decision variable

Q	Set of chromosomes in the population
J	Set of PACCAR Parts fill rates in the population
F^*_j	Target PACCAR Parts fill rate level for j
t_q	Total costs of chromosome q (inventory + transshipments)
$F_{q,j}$	Value of PACCAR Parts fill rate j of chromosome q
w_q	Decision variable representing the weight of chromosome q in the new offspring

$$\min \sum_{q=1}^{Q} t_q w_q \tag{7.5}$$

   Subject to

$$\sum_{q=1}^{Q} F_{q,j} w_q \geq F^*_j \qquad \forall j \in \text{J} \tag{7.6}$$

$$\sum_{q=1}^{Q} w_q = 1 \tag{7.7}$$

$$0 \leq w_q \leq 1 \qquad \forall q \in \text{Q} \tag{7.8}$$

2. **Random linear crossover** Consider the vector of parent 1 and 2 as c_1 and c_2 respectively. The offsprings $c^{'}_1$ and $c^{'}_2$ of c_1 and c_2 respectively can be obtained in the following manner:

$$c^{'}_1 = \lambda c_1 + (1-\lambda)c_2, \tag{7.9}$$

$$c^{'}_2 = \lambda c_2 + (1-\lambda)c_1, \tag{7.10}$$

   where $0 < \lambda < 1$. The next two offsprings are created by choosing a random value for λ. If $\lambda = 0.5$, only one offspring is created. In this case, the process is repeated until $\lambda \neq 0.5$.

The problem-oriented crossover is used to generate the first out of the desired six offspring chromosomes. The random linear crossover creates the other five chromosomes. However, in some cases, the LP model assigns a weight equal to 1 to a certain chromosome. This implies that the problem-oriented crossover creates no new offspring. In that case, all six offspring chromosomes are created via the random linear crossover.

7.2.5 Mutation

After the crossover operations, the population undergoes mutation operations. Mutations add differences to the solution space (Ray, Singh, Isaacs & Smith, 2009). The new offspring chromosome can be obtained by replacing one or more genes in chromosome c (Du & Swamy, 2016). Consider $c_i fori = 1, ..., n$, with n the number of genes in a chromosome. In RCGA, the Gaussian mutation method is usually applied (Srinivas & Patnaik, 1994). It adds a Gaussian random number to one a gene in chromosome c and produces the offspring chromosome c' in the following manner:

$$c_i{}' = c_i + N(0, \sigma_i), \tag{7.11}$$

where $N(0, \sigma_i)$ is a random number drawn from the normal distribution with mean 0 and standard deviation σ_i. Traditionally, σ_i is a decreasing function with respect to the number of generations t. The following function for σ_i is used:

$$\sigma_i(t) = \frac{1}{\sqrt{1+t}}. \tag{7.12}$$

In some exceptional cases, it can happen that after a mutation operation, Lemmas 1 and 2 are violated. In these cases, the offspring chromosome is rejected. As stated in the previous subsection, it is desired to have a maximum of eight new offspring chromosomes per iteration to reduce the computational time. Since the crossover operations create six offsprings, the mutation operation can create two offsprings. Therefore, two random chromosomes are selected which genes undergo a mutation with a probability of $\frac{1}{18}$. Whenever none of the genes undergoes a mutation, the process is repeated until at least one gene in the chromosome undergoes a mutation.

7.2.6 Termination criteria

At some point, the population's best fitness value converges. In other words, the best solution that is found per iteration does not improve anymore. At this moment, it is often decided to stop the algorithm and conclude that the best solution has been found. However, it is not desired to stop immediately once the solution has not improved for one iteration. It could be, due to the randomness that is involved, that the solution still improves after a few iterations without any improvements. Therefore, the algorithm is only stopped once the iteration has not improved over ten successive iterations.

Chapter 8

Results

The models regarding the stocking/non-stocking decision and safety stock coverage levels that were described in the four previous chapters have been executed and tested using the simulation model. This chapter describes the results of the proposed models. The first section describes the results of the stocking/non-stocking decision. Hereafter, the results regarding the safety stock heuristic and RCGA are described in the second and third sections.

8.1 Stocking/non-stocking decision

As has been explained at the beginning of Chapter 6, the exact safety stock coverage levels that were proposed by the IP model are not used (i.e., they are only used to approximate the costs that the IP model used to make the stocking/non-stocking decision). Moreover, the SnoS heuristic does not propose any safety stock levels. Hence, in order to enable a comparison between the two methods and evaluate the proposed stocking/non-stocking policies in isolation from the safety stock coverage levels improvements that are proposed in Chapters 6 and 7, the current safety stock settings are used. This implies that for every part set to stocking by the IP model or SnoS, the safety stock coverage is determined using the data from the last rolling year on the number of hits and COGS (see section 1.5). Note that if a stocking option is selected, that implies that one warehouse has to store for multiple warehouses. In this case, the sums of the hits and COGS of all SKUs stored at the warehouse determine the safety stock coverage level.

Recall that in the current policy, the only stocking option in which there is shared inventory is the global stocking option in Budapest. In this stocking option, the aggregated European demand is relatively low. If this were not the case, the item would have become stocking in one of the warehouses based on its regional number of order hits in the last rolling year. Because of the relatively low aggregated demand, the globally stocked items are stocked via a base-stock policy with base-stock level 2 or 4 (see section 1.5). However, the IP model's stocking options contain multiple options with a shared inventory. In these options, it is not always the case that the aggregated demand is relatively low. For example, the IP model can decide to stock the demand for the warehouse of Madrid in Eindhoven for a particular item. The expected demand in Madrid is likely relatively low in this case (otherwise, this stocking option would yield high transshipment costs, and the IP model would not choose it). If the demand in Eindhoven is relatively high, stocking this item via a base-stock policy with a base-stock level of 2 or 4 is inefficient. The base-stock policy does not consider the forecasts and only orders when the physical inventory level drops below 2 or 4. When the lead time and demand are relatively high, the item will often be out of stock. Therefore, all items that the IP model stocks are assumed to be controlled via an (R, s, nQ)-policy. For the SKUs for which there were no historical forecasts available, the historical forecasts were obtained using the assumption explained in section 3.1.2 (i.e., using exponential smoothing with a smoothing constant of 0.1).

8.1.1 Group A and B items

The first step in the stocking/non-stocking policy that is proposed is to filter out the items that had 0 hits in every warehouse or strictly more than five order hits in every warehouse (see Figure 4.1). These items are referred to as group A items in the remaining part of this thesis. The other items in the product portfolio of PACCAR Parts are referred to as group B items. Note that for part A items, the stocking decision is the same as in the current situation. In other words, the performances of the part A items are the same for the current and proposed stocking policies. The differences in performance between the proposed stocking policies and the current stocking policy can be identified by simulating the items in group B. Table 8.1 displays that the fraction of total costs regarding items in group B is relatively high compared to its contribution to the PACCAR Parts European fill rate (i.e., fraction of order lines). Although this is an already known characteristic of the spare parts industry, it demonstrates the importance of considering the items in group B.

	Fraction of total order lines		**Fraction of total costs**	
	Group A	*Group B*	*Group A*	*Group B*
2019	0.863	0.137	0.641	0.359
2020	0.866	0.134	0.617	0.383
2021	0.867	0.133	0.705	0.295

Table 8.1: Distribution of number of total order lines and total costs between group A and B

8.1.2 PACCAR Parts fill rates

The target PACCAR Parts fill rates are parameters that must be set before the IP model can be executed. Recall that the cost approximations rely on empirical demand and lead time data from the last rolling year. Also, recall that this empirical data may not fully represent SKUs with a relatively low number of observations. For this reason, the actual PACCAR Parts fill rate performances are expected to be worse than the PACCAR Parts fill rate performances that the IP model expects. For this reason, the target PACCAR Parts fill rates used in the IP model are somewhat higher than the actual desired PACCAR Parts fill rates. By experimenting with several values for the target PACCAR Part fill rates, it was observed that the difference between the expected and actual PACCAR Parts fill rates is approximately 1%. For this reason, the target aggregated PACCAR Parts fill rates that are set in the IP model, are equal to the current simulated performances (see section 3.3) plus an additional 1%.

Although the IP model only considers the items in group B, the aggregated PACCAR Parts fill rate targets depend on the items in groups A and B. In other words, the higher the PACCAR Parts fill rates of the items in group A, the lower the PACCAR Parts fill rates in group B need to be to obtain the aggregated PACCAR Parts fill rate levels. Therefore, the IP model is run for three different scenarios for the PACCAR Parts fill rates of the items in group A. In scenario 2, the PACCAR Parts fill rate performances of group A are equal to the current performances of items in group A. In scenario 1 and 3, these performances are decreased and increased by 0.1% respectively (see Appendix F for the exact targets that are used).

8.1.3 IP validation

In order to validate the IP model and the cost approximations on which it is based, the IP output values for the PACCAR Parts fill rates, and objective function are compared with the values that the simulation model obtained. Table 8.2 shows the validation data of the IP model for 2019 for the items in group B. The validation for the data sets of 2020 and 2021 can be found in Appendix G. From these tables, the same conclusions can be derived as can be from this table.

Firstly, it can be observed that the individual PACCAR Parts fill rates are met relatively easily in the IP model. For the low-demand items in group B, the savings that can be made by pooling the inventory across several warehouses do not weigh up against the extra costs needed for transshipments. In other words, it is always cheaper to store the demand for a particular item in warehouse w, in warehouse w itself rather than storing this demand in one of the other warehouses. This implies that the total warehouse capacity is always used for all warehouses. Because of this, the individual PACCAR Parts fill rates are met relatively easily, and the bottleneck is the PACCAR Parts European fill rate. Secondly, it can be noted that the PACCAR Parts fill rates that the IP model obtains are somewhat lower than those that the simulation model obtains. These differences can be explained by the empirical demand and lead time distributions from the last rolling year that are used. This also explains the higher costs that the simulation model obtains. These are mainly due to the extra transshipment costs that are caused by the differences between the expected and actual observations of the demand and lead times.

		Scenario								
		1			**2**			**3**		
		Target	*IP*	*Sim*	*Target*	*IP*	*Sim*	*Target*	*IP*	*Sim*
PACCAR Parts fill rates for B items	*European*	0.886	0.886	0.878	0.880	0.880	0.873	0.874	0.874	0.868
	Eindhoven	0.847	0.862	0.839	0.841	0.856	0.831	0.835	0.892	0.828
	Madrid	0.795	0.831	0.790	0.788	0.828	0.784	0.782	0.819	0.779
	Leyland	0.807	0.866	0.795	0.801	0.857	0.793	0.795	0.855	0.788
	Budapest	0.867	0.875	0.856	0.861	0.925	0.853	0.855	0.922	0.850
Total costs per year for part B items (×1000€)			2431	2909		2296	2729		2228	2667

Table 8.2: Validation of IP model for data of 2019

8.1.4 Analysis

Eventually, the IP model allocated 1 out of the 92 stocking options to every part that is considered in the IP model. Figure 8.1 compares the allocation in the current situation with the allocation proposed by the IP model for 2019 for the different scenarios of the PACCAR Parts fill rates of items in group A. In Appendix H, the same figures are displayed for 2020 and 2021. From these figures, the same conclusions can be drawn. Note that stocking option 0 (non-stocking in every warehouse) is not included in the figures for clarity. This stocking option has a high frequency and therefore decreases the clarity of the other bars in the chart. In addition, they do not add a large amount of added value to the comparison between the two situations since the frequency that this stocking option is selected, is more or less the same for both situations. Note that in the current situation, stocking options 17 up to and including 91 did not exist. Only stocking option 92 (global stocking in Budapest) was available.

The stocking options that are interesting for this analysis are highlighted by the numbers of the stocking options in the graph in Figure 8.1. In addition, Table 8.3 explains these stocking options. The most important observations that can be derived from stocking option comparison are listed below:

- It can be observed that the lower the expected PACCAR Part fill rates of items in group A, the more stocking options that involve transshipments are selected (i.e., stocking options from stocking option 16 on-wards). This makes sense since more hits should be satisfied in group B when fewer hits are satisfied in group A. At the same time, the same number of total order hits should be met to satisfy the PACCAR Parts fill rates constraints. In order to still respect the capacity constraints, more items are forced to have shared inventory by the IP model.

- Stocking options 2 and 14 are chosen fewer times by the IP model compared to the current situation. On the other hand, stocking options 22, 24, and 56 are chosen more often. This implies that the IP model often chooses to have a shared inventory between Eindhoven and Leyland. An explanation for this can be that it is relatively cheap to transship between Eindhoven and Leyland. Moreover, Leyland and Eindhoven relatively have the highest demand rates. This implies that stocking in one of these warehouses is often desired since this minimizes the amounts to transshipment.

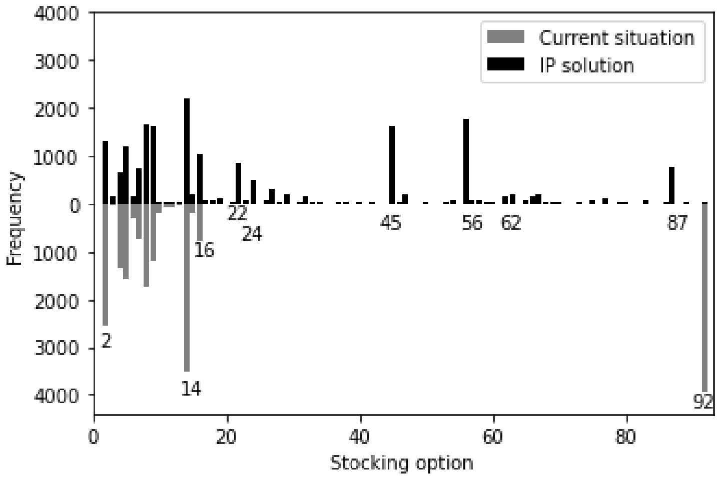
- Due to the capacity constraints, not all items can be stored in Eindhoven or Leyland. The warehouse in Budapest relatively has the biggest capacity compared to its demand. For this reason, stocking options 56, 62, and 87 have a high occurrence frequency in the IP solution. In these options, Budapest stores the demand for Eindhoven and/or Leyland. On the other hand, stocking option 92 is not highly frequent in the IP solution. This holds since this option assumes that demand is stocked for all warehouses. Since the warehouse in Madrid has a relatively low demand, it is not common that there was demand in all of the warehouses for items in group B. Hence, stocking option 92 has a low frequency of occurring.

- The stocking options in which Madrid stocks demand from other warehouses are selected seldom by the IP model. This holds because the demand in Madrid is relatively low, and the capacity in this warehouse is relatively tight.

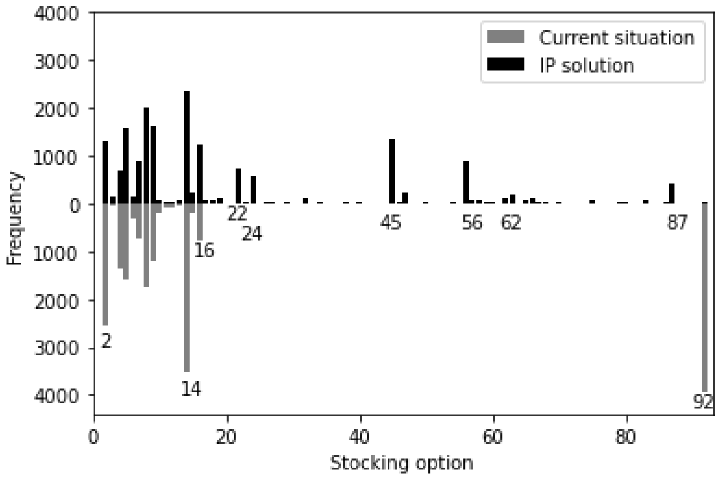
	Stocking warehouse			
Option	**EHV**	**MAD**	**LEY**	**BUD**
2	EHV			
14			LEY	
16				BUD
22	EHV-LEY			
24	EHV-LEY			BUD
45			LEY-EHV	
56				BUD-EHV
62				BUD-LEY
87				BUD-LEY-EHV
92				BUD-EHV-MAD-LEY

Every row in this table displays one of the stocking opportunities for a specific item. Per warehouse, it is displayed for which warehouses the demand is stocked. Note that white space in a cell indicates that the item is non-stocking for this warehouse. For example, consider option 24. The interpretation of this stocking option is as follows: Eindhoven stocks the demand for itself and Leyland, Budapest stocks its own demand and the demand for Madrid is assumed to be lost.

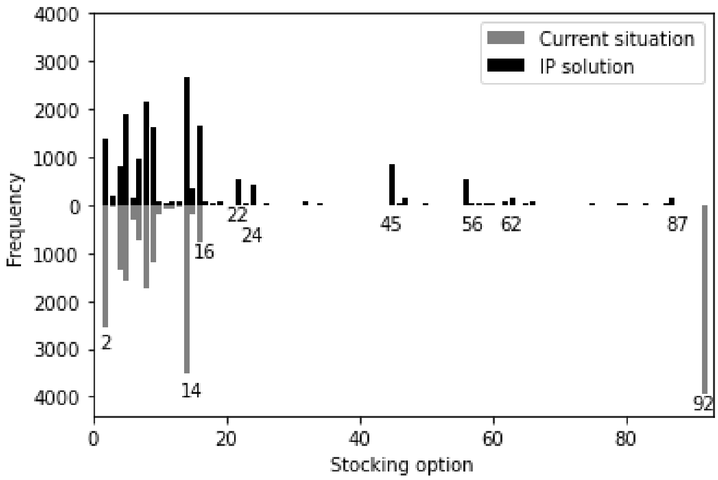
Table 8.3: Relevant stocking opportunities for IP solution



(a) Scenario 1



(b) Scenario 2

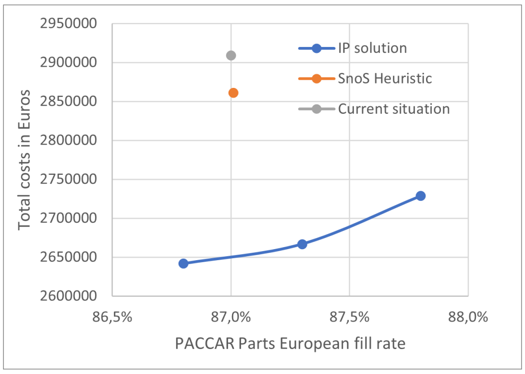


(c) Scenario 3

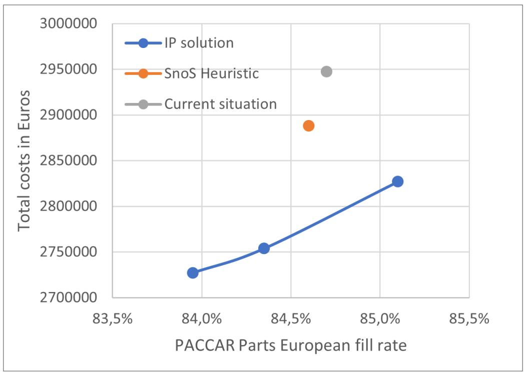
Figure 8.1: Frequency of stocking options for different scenarios of the PACCAR Parts fill rate of items in group A for 2019

8.1.5 Performances

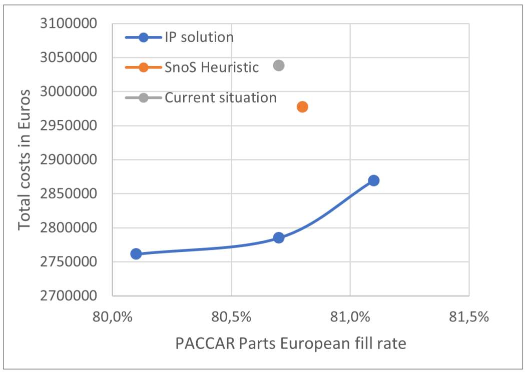
This subsection reflects on the performances of the current situation, IP model, and SnoS heuristic. Recall that for group A items, there are no differences between the current situation, the IP model, and the proposed heuristic. The performances of the items in this group are displayed in Appendix K. The performances of the IP model and SnoS heuristic can be compared to the current situation by considering the items in group B. Figure 8.2 displays the PACCAR Parts European fill rate against the total yearly costs for every policy. Note that the IP solution has three dots in the graph, these dots reflect the different scenarios for the expected PACCAR Parts fill rates for items in group A. It can be observed that the IP solution outperforms the current policy in terms of costs and PACCAR Parts European fill rate. On the other hand, the simple heuristic also outperforms the current situation. However, the SnoS heuristic only optimizes a part of the total problem which results in a worse performance compared to the IP solution.



(a) 2019



(b) 2020



(c) 2021

Figure 8.2: PACCAR Parts fill rate versus total costs for the tested stocking policies

In order to study the performances in more detail, the PACCAR Part fill rates and the costs of the policies are analyzed in more detail. In Appendix I, the detailed performances for the data sets of 2019, 2020, and 2021 are displayed. From these tables, the same conclusions can be drawn. It can be concluded that the higher the value of the expected PACCAR Parts fill rate for items in group A, the lower the PACCAR Part fill rates are for items in group B. This makes sense since, eventually, a total PACCAR Parts fill rate needs to be obtained by the model. For this reason, a higher level of expected PACCAR Parts fill rates for items in group A means that fewer hits need to be satisfied by the items in group B. This results in lower inventory costs since fewer items are stocked in group B. Considering the transshipment costs, it is somewhat more complicated. On the one hand, there is less inventory available to transship. On the other hand, more transshipments are needed since there are more warehouses with shared inventory in case of a higher value of the expected PACCAR Parts fill rate for items in group A. Nevertheless, we see a slight decrease in the transshipment costs when the value of the expected PACCAR Parts fill rate for items in group A increases. This implies that the first-mentioned effect outweighs the second one. Another relevant observation deals with the average inventory values in the warehouses. If the IP model is compared to the current situation, the inventory value in Budapest is increased while the inventory value in Eindhoven and Leyland is decreased. In general, more expensive parts are more expensive to transship. This holds since they are often bigger and heavier. In section 8.1.4, it was concluded that the IP model tends to swap inventory with high expected transshipment costs from Budapest to Eindhoven and Leyland. From these two observations together, it can be concluded that it is often more efficient to stock relatively cheap items with high demand in Leyland and Eindhoven. While in this case, the relatively expensive items with a low demand can be stored in Budapest. The same effect is observed in the solution that is obtained by the heuristic. Lastly, it is observed that the total transshipment costs decrease significantly. This emphasizes that it is worthwhile to consider the expected transshipment costs when making a stocking decision.

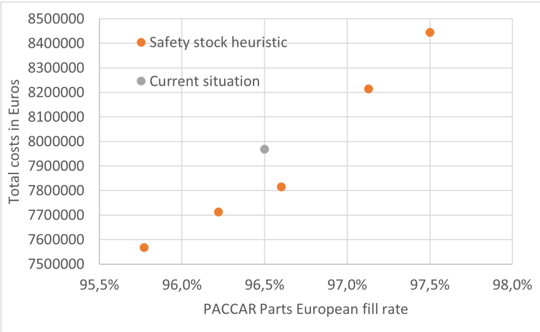
8.2 Safety stock heuristic

As explained in Chapter 5, it is hard for PACCAR Parts to implement the IP model in their planning system. It is more likely that the SnoS heuristic will be implemented. For this reason, the safety stock heuristic and GA are tested using the stocking/non-stocking decision obtained by applying the SnoS heuristic.

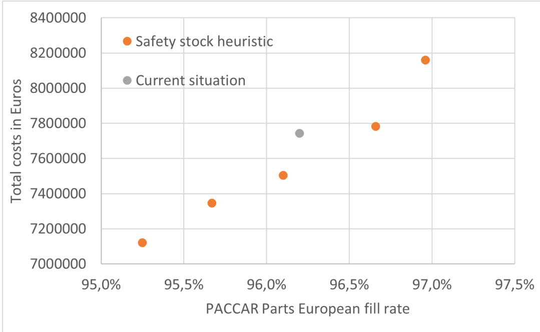
The safety stock heuristic is executed for different values of the target PACCAR Parts European fill rate. Again, the PACCAR Parts European fill rates are set 1% higher than the actual desired PACCAR Parts European fill rates. Figure 8.3 displays the outcomes of the safety stock heuristic for the different settings for the target PACCAR Parts European fill rate for the different years. The figure compares the PACCAR Parts European fill with the total costs, including the inventory and transshipment costs. It can be observed that the safety stock heuristic outperforms the current policy. The detailed data for 2019, 2020, and 2021 are displayed in Appendix L. Based on the analysis of these tables, the following observations are made:

- The transshipment costs that are obtained when the safety stock heuristic is implemented are higher than in the current situation. Recall that the safety stock heuristic decides on an item's safety stock level based on its demand distributions from the last rolling year. Especially for items with relatively low demand, it is likely that this distribution is not very accurate. As a result, the safety stock levels for some parts in some warehouses are either underestimated or overestimated. In order to compensate for this, transshipments are needed. This also explains the observation that the PACCAR Parts European fill rates that were obtained by simulation are lower than the target PACCAR Parts European fill rate levels that were expected by the safety stock heuristic.

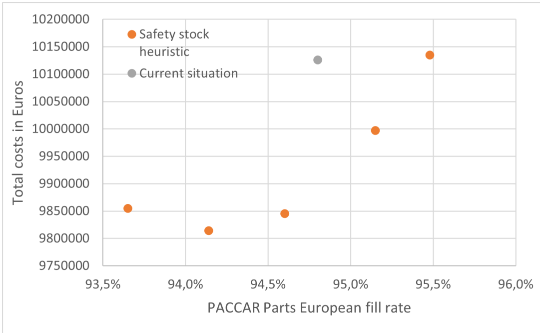
- The PACCAR Parts regional fill rate of the warehouse in Madrid is relatively low compared to the other warehouses. The same holds for the average inventory value. Recall that the safety stock heuristic only optimizes the aggregated PACCAR Parts European fill rate. The warehouse in Madrid has relatively the lowest demand compared to the other warehouses. Due to this, there are fewer demand observations for most of the items in Madrid compared to the other warehouses. Therefore, the demand variability in Madrid is higher than in the other warehouses. This implies that more safety stock is needed in Madrid to obtain the same PACCAR Parts fill rate level as in other warehouses. In other words, increasing the inventory in Madrid is more expensive to obtain the same service level as in other warehouses. Hence, the safety stock heuristic prefers to increase the inventory in the other warehouses first. This effect is strengthened by the fact that lower demand results in a lower weight to the total PACCAR Parts European fill rate. In other words, the 'bang for the buck' that is the driving force behind the greedy approach is often lower for items stored in Madrid's warehouse.



(a) 2019



(b) 2020



(c) 2021

Note: *The different orange dots in the graph represent the different outputs that were obtained for different values of the* target PACCAR Parts European fill rate. These values can be found in Appendix F.

Figure 8.3: PACCAR Parts European fill rate versus total costs for current situation and safety stock heuristic

8.3 Real-coded genetic algorithm

In contrast to the safety stock heuristic, the RCGA takes into account both the European and individual PACCAR Parts fill rates. In order to obtain a set of Pareto-optimal solutions, the proposed RCGA is executed for different values of the target PACCAR Parts fill rates. The different targets for which the RCGA is executed are set based on the current performances of the stocking policy. Namely, different percentages of the current PACCAR Parts fill rates are taken to set the target PACCAR Parts fill rates that are used in the RCGA. The percentages that are tested are 99.50%, 99.75%, 100%, 100.25%, 100.50%, 100.75%, 101%, and 101.25%. Note that a percentage that is higher than 100% implies that higher target PACCAR Parts fill rates are set compared to the current performances.

8.3.1 Analysis of generations

Recall that the RCGA is executed on five different data sets that contain a random sample of 10% of the stocking parts. Figure 8.4 displays the evaluation of the best fitness value for each data set over the generations. This figure is based on the runs of 2019, where the target PACCAR Parts fill rates are equal to the current targets (i.e., 100% of the current PACCAR Parts fill rates). It can be seen that the RCGA makes relatively big improvements in the first iterations of the algorithm.

During the algorithm's execution, it was observed that the big improvements were caused by the crossover operators rather than the mutation operators. This is in line with the findings of Du and Swamy (2016). Nonetheless, the mutation operators often caused small improvements that can be observed towards the end of the algorithm.

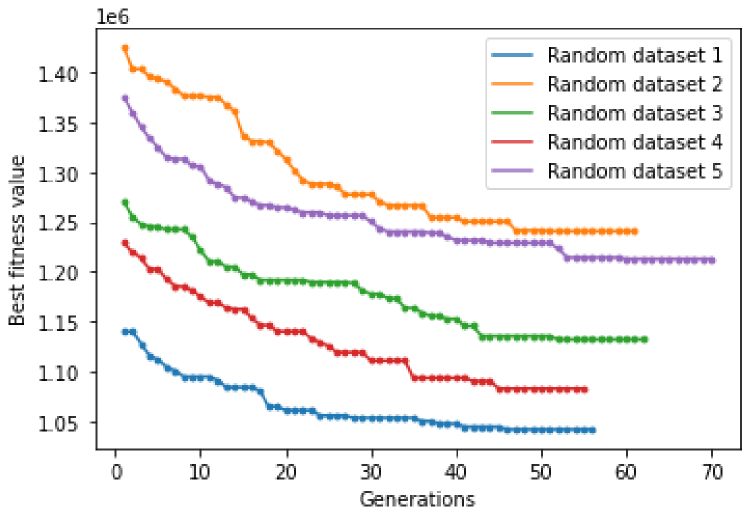
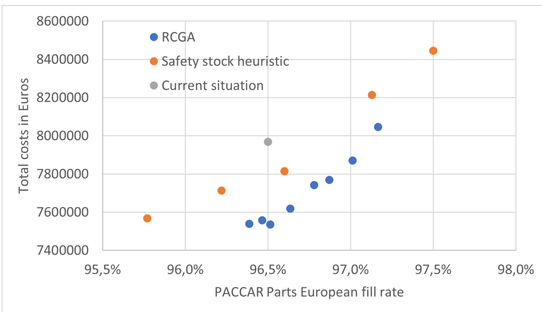
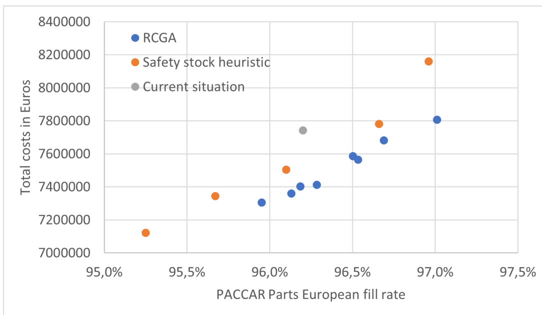


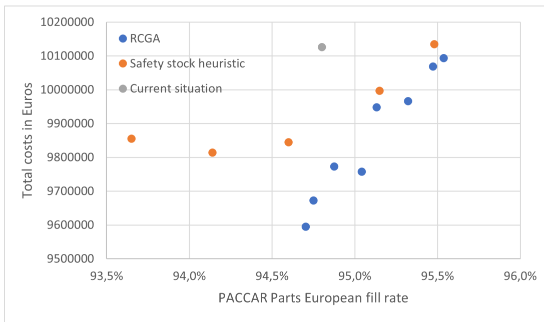
Figure 8.4: Example of best fitness value under different generations



(a) 2019



(b) 2020



(c) 2021

Note: *The different blue dots in the graph represent the different outputs that were obtained for different values of the target PACCAR Parts fill rates. These targets are set as a percentage of the current PACCAR Parts fill rates. From left to right these percentages were: 99.50%, 99.75%, 100%, 100.25%, 100.50%, 100.75%, 101% and 101.25%.*

Figure 8.5: PACCAR Parts European fill rate versus total costs for current situation, safety stock heuristic, and RCGA

8.3.2 Performances

In Figure 8.5, the results of the RCGA are added to the results of the current situation and the safety stock heuristic. In this way, the three policies can be compared. The detailed results of the RCGA are displayed in Appendix M. Additionally, the proposed safety stock coverage levels per class are displayed in Appendix N. It can be seen that the RCGA outperforms the safety stock heuristic and the current policy. Recall that a drawback of the safety stock heuristic was Madrid's low PACCAR Parts regional fill rate. In the RCGA, constraints were set on these regional PACCAR Parts fill rates. For this reason, the PACCAR Parts regional fill rate of Madrid that the RCGA obtains is significantly higher than that obtained by the safety stock heuristic. Because of this, fewer transshipments were needed to Madrid in the case of the RCGA. This resulted in lower transshipment costs for the RCGA compared to the safety stock heuristic.

8.3.3 Sensitivity analysis stocking/non-decision

As has been explained before, it is more likely that PACCAR Parts will implement the SnoS heuristic in the short term than the IP model due to extra investments that are needed in the planning system. For that reason, the stocking/non-stocking decision used to test the RCGA is set to the one proposed by the SnoS heuristic. The sensitivity analysis in this section aims to investigate the potential savings that can be obtained when the IP model solution is used as an input for the RCGA instead of the SnoS heuristic. In this way, PACCAR Parts can decide whether the costs of implementing the IP model outweigh its benefits. The analysis is performed on the data set of 2019, where the target PACCAR Part fill rates are set equal to the current performances. Additionally, The IP solution of scenario two is used. Recall that the expected PACCAR Parts fill rate for items in group A was equal to the current performances in this scenario.

In Table 8.4, the total costs that are obtained by the RCGA are displayed for the cases in which the SnoS heuristic and IP are used to determine the stocking/non-stocking decision. In both cases, the PACCAR Parts European fill rate is equal to the PACCAR Parts European fill rate obtained in the current situation (96.5%). It can be observed that an additional cost saving of 71478 euro can be obtained when the IP model is used to determine the stocking/non-stocking decision instead of the SnoS heuristic.

	SnoS	**IP**	Difference
Total costs per year (€)	7535337	7463858	71478
Cost reduction compared to current situation	5.44%	6.34%	0.90

Table 8.4: Total costs for RCGA when SnoS and IP are used

In Appendix M, the detailed results of the sensitivity analysis that is described in this subsection are displayed in Table M.5. Additionally, Figure 8.5a is expanded by the result of the RCGA that is obtained when the IP model is used for the stocking/non-stocking decision (see Figure M.1).

Chapter 9

Conclusion

This chapter draws an overall conclusion of this research and answers the main research question on how PACCAR Parts can improve its current stocking policy. Additionally, recommendations are given to PACCAR Parts on how to implement the suggested solutions taking into account the practical challenges. Moreover, conclusions on the contribution to the scientific literature are given. Lastly, the main limitations of this researcher are discussed based on which directions for future research are suggested.

9.1 Conclusion

This research has been conducted at the Demand Planning Department of PACCAR Parts Europe. Eventually, it was the goal to improve the current spare parts stocking policy of the European warehouses of PACCAR Parts. In order to achieve this, the problem has been split up into two parts. Firstly, the stocking/non-stocking decision per item per warehouse was made. Hereafter, the near-optimal safety stock coverage levels had to be determined. The complexity of this study came with the allowance of transshipments, capacity restrictions, high levels of supply variability, seasonality, and lumpy or intermittent demand patterns.

For each part in the product portfolio of PACCAR Parts, 92 different stocking options were defined. For each of these 92 stocking options, cost approximations that take into account the expected inventory and transshipment costs were estimated for different scenarios of the individual PACCAR Part fill rate levels per part. Hereafter, an IP model was proposed that assigned one of the 92 stocking options to each part. The IP model minimized the total costs such that constraints regarding the warehouse capacities and PACCAR Part fill rate levels were respected. Eventually, the outcomes of the IP model were analyzed such that a heuristic was proposed that is more convenient for PACCAR Parts to implement in their planning system.

After the stocking/non-stocking decision was made, two approaches were tested to determine the safety stock coverage levels. Firstly, the safety stock heuristic that is proposed by Donselaar, van et al. (2021) was tested. This heuristic determines optimal reorder levels for each SKU individually by constraining on a minimum target PACCAR Parts European service level. It was concluded that the empirical demand and lead time distributions used to estimate the PACCAR Part fill rates and expected inventory costs yielded somewhat inaccurate results for SKUs with a low number of empirical demand and lead time observations. Lastly, the PACCAR Parts individual fill rate for the warehouse in Madrid was relatively low due to its low contribution to aggregated service level and high level of demand variability. The second approach for determining the safety stock coverage levels started with a classification. The SKUs were classified on the service level versus cost trade-off and the total variability. A safety stock coverage level was determined for each category using an RCGA. Simulation results showed that this approach for determining the safety stock coverage levels outperformed the safety stock heuristic and PACCAR Parts' current approach for determining safety stock coverage levels. When the SnoS and the RCGA are implemented, Table 9.1 shows the improvements in total costs and PACCAR Parts European fill rates that were obtained per year. The total cost improvements display the improvements that can be obtained compared to the current situation when the same PACCAR Parts European fill rate is obtained (vice versa for the PACCAR Parts European fill rate improvements).

	2019	**2020**	**2021**
Cost improvement	5.5%	4.7%	4.4%
PACCAR Parts European fill rate improvement (in percentage point)	0.68	0.74	0.78

Table 9.1: Improvements in costs and PACCAR Parts European fill rate when SnoS heuristic and RCGA are implemented

9.2 Recommendation

Based on the outcomes of this research, a set of recommendations are proposed for the Demand Planning Department of PACCAR Parts. The first two recommendations deal with the implementation of the proposed methods regarding the stocking policies. Hereafter, two general recommendations are explained that can be used in PACCAR Parts' operations and analyses.

- **Gradually implement the SnoS heuristic or IP model.**
  This research proposed two methods for improving the stocking/non-stocking decision. Ideally, the IP model is implemented to make this decision since it can save over 70,000 euros per year when it is used in combination with the RCGA compared to the situation in which the RCGA is used in combination with the SnoS heuristic. However, due to its complex calculations and required planning system changes, it may be more convenient to implement the SnoS heuristic in the short term. Nevertheless, in both cases, the implementation has to be performed gradually. This holds since the items that are currently occupying the warehouses have to be taken into account when a new policy is implemented. It is suggested that once a month, the stocking/non-stocking is made (by running the IP model or by executing the safety stock heuristic). By running the model once per month, the newest sales trends of the past year are taken into account. This way, a list with the optimal item allocation per warehouse is obtained every month. From this, per warehouse, it can be derived which items are stocked, although this is in contrast with the optimal item allocation. Additionally, per warehouse, which items are not stocked can be derived, although this is in contrast with the optimal item allocation. Whenever an item that is set to non-stocking becomes out of stock in a particular warehouse, a spot is freed up, and it can be filled by one of the items that still needs to be stocked. In order to fill this spot, it is suggested to prioritize items stocked in none of the warehouses over items already stocked in one of the other warehouses. In this way, the PACCAR Parts European fill rate is maximized. Furthermore, no unnecessary transportation costs are made by gradually shifting from the current SKU allocation per warehouse to the proposed one.

- **Gradually implement the proposed safety stock classification and its safety stock coverage levels.**
  It is suggested to implement the proposed classification together with its corresponding safety stock coverage levels. Unlike the stocking/non-stocking decision, this implementation can be performed immediately. Namely, every time an item is ordered, its safety stock can be determined by the proposed policy. However, this approach may be too radical. It is suggested first to implement the proposed safety stock policy on a small set of SKUs. By analyzing the performances of this small set, it can be checked whether the simulated results match the results in real life. This way, a gradual implementation is enabled, and minor adjustments can be made to the proposed safety stock coverage levels if necessary. It should

be noted that this small set of SKUs should have the same distribution over the classes as the distribution that has been proposed in this thesis. This holds since the model is an aggregated model. Distorted results can be obtained whenever the distributions over the classes are not kept the same.

- **Use the actual inter-warehouse lead times to analyze and execute the current stocking policy.**
  It was shown in this research that the lead times between the warehouses are, in reality, not equal to 14 days. By considering the actual inter-warehouse lead times, more accurate analyses can be performed, and more reliable order suggestions can be calculated.

- **Take into account the costs of transshipments when analyzing or evaluating the performances of the stocking policy.**
  Currently, transshipment costs are not considered in the analyses and evaluation of the stocking policies. This research showed that the transshipments' costs contribute more than 30% to the total costs. It is, therefore, crucial to take into account these costs in order to make an accurate and reliable costs analysis.

9.3 Contribution to Scientific Literature

This thesis contributed to the scientific literature in multiple fields. Below is how this thesis explicitly contributes to the existing literature.

- **Stocking/non-stocking decision in a multi-item, multi-location setting with capacity constraints.**
  Most studies in the literature that make stocking/non-stocking decisions for multi-item problems are doing this for single location problems. The papers that study multi-item, multi-location problems use Lagrangian-based heuristics and assume that demand is Poisson distributed (Archibald et al., 1997; Wong et al., 2005). Furthermore, these papers do not take into account warehouse capacity constraints. This thesis contributes to the literature because it proposes a stocking/non-stocking model for multi-item, multi-location problems with capacity constraints. The model used in this thesis uses empirical discrete demand distributions and the PACCAR Parts fill rate definition in case of an (R, s, nQ)-policy. However, with some minor adjustments in the service level and cost approximations, it can be used for other cases with other demand distributions or service level definitions.

- **Order fill rate.**
  PACCAR Parts uses the Order Fill Rate (OFR) as a definition for their service levels rather than the Volume Fill Rate (VFR). The OFR is less commonly used in practice, and less research has been performed on it compared to the VFR. Larsen and Thorstenson (2008) derived formulas for the OFR in case of discrete demand and when a base-stock policy is used to control the inventory. On the other hand, Donselaar, van and Broekmeulen (2014) derived formulas for the VFR in case of discrete demand when an (R, s, nQ)-policy is used to manage the inventory. This paper combined both studies by deriving an expression for the OFR in case of discrete demand and an (R, s, nQ)-policy to control the inventory. Additionally, a recursive expression was derived that enables an efficient calculation of the minimum required safety stock levels for the different minimum required OFR levels. Moreover, Wingerden, van et al. (2016) studied which classification criterion captures the trade-off between service level and costs the best when the VFR is used. In this thesis, the classification criterion that is proposed by Wingerden, van et al. (2016) is adjusted to the OFR case.

- **Real-Coded Genetic Algorithm with ordered chromosomes, problem-oriented crossovers, and fitness value calculation by simulation.**
  For the determination of safety stock levels in complex problems like the problem at PACCAR Parts, it is common in the literature to use RCGA to determine the optimal safety stock

levels (Nakandala et al., 2016; Yu et al., 2020; Feng et al., 2017; Gu et al., 2020; Hochmuth & Köchel, 2012). However, these studies assume known demand distributions and derive analytical formulas to calculate the fitness values of the chromosomes. In this thesis, simulation is used to calculate the fitness values of the chromosomes. This enables the RCGA to examine the fitness value of the chromosomes without making questionable assumptions related to seasonality, transshipments, or known demand and lead time distributions. In order to limit the computational time of an RCGA with simulation fitness evaluation, the number of iterations has to be minimized explicitly. Therefore, this thesis proposed ordered chromosomes in combination with linear crossover operators. Furthermore, a problem-oriented crossover operator is proposed that can be used to perform efficient crossovers operations. The combination of efficient crossover operators and the way how the chromosomes are created such that the solution space is limited to feasible and logical solutions enables one to use simulation as fitness value evaluation in safety stock level optimization.

9.4 Limitations & Future Research

This section describes the main limitations of this research. Based on these limitation, directions for future research are proposed.

- **The proposed IP model does not take into account the current situation.** The stocking/non-stocking decision that the IP model makes does not take into account the current allocation of the items across the warehouses. In section 9.2, an implementation method is explained that enables PACCAR Parts to implement the IP model gradually. A drawback of this method is that it takes time for items to get out of stock before new items can be stocked. In order to overcome this, a suggested direction for future research is to consider the current situation in the IP model. For example, this can be done by extending the IP model with additional penalty costs for stocking options that suggest a stocking/non-stocking decision per item per warehouse that deviates from the current situation. This way, stocking options that align with the current situation become more attractive. Accordingly, the IP model only selects stocking options that only yield significant cost reductions compared to the current situation.

- **The empirical distributions for some items rely on very few demand observations.** The expected PACCAR Parts fill rate and expected inventory costs for a certain reorder level are calculated using the empirical demand distributions from the last rolling year. The demand for the last rolling year is considered in order to take into account the newest sales trends. The disadvantage of this approach is that for some items, only a few demand observations can be made in one year. Therefore, the extent to which these empirical demand distributions are accurate is limited. Future research could investigate how the distributions of these demands can be described more accurately. For example, analyses can be performed on whether there have been many variations in the sales patterns of certain items over the years. If the demand for an item was relatively stable over the years, more accurate distributions could be found by extending the historical data horizon to more than one year.

- **The number of items that the RCGA can consider is relatively low.** The proposed RCGA uses simulation to calculate the fitness values. For every iteration in the algorithm, new simulations have to be run to calculate the fitness values of new offspring chromosomes. In order to limit the computational time of the algorithm, only a small set of items was used in this simulation in this research. If more items could be considered, the results would be slightly more accurate. Therefore, a proposed direction for future research is to find ways to decrease the computational time of the RCGA. This can be obtained by speeding up the simulation model or finding genetic operators that converge to the near-optimal solution faster.

- **The parameters of the RCGA are not fully optimized.**
  The parameters of the RCGA in this research are not fully optimized. Du and Swamy (2016) state that it is convenient to try out different RCGA parameters in order to optimize the obtained solution fully. In this research, the extent to which parameter tuning has been performed is limited due to the high computational time involved. A direction for future research comes with tuning the parameters in the RCGA. For example, Figure 8.4 suggests that the optimal solution can be improved if the termination criterion is set less strict. Nonetheless, this parameter tuning is expected only to improve the solution to a small extent. For PACCAR Parts, these minor improvements are not considered to outweigh the additional computational and research time. However, this direction for future research may be interesting from an academic point of view.

- **Proactive transshipments are not considered in this research.**
  In the literature on transshipment inventory models, emergency transshipments are also known as reactive transshipments. These transshipments are only allowed once demand arrives at a particular location that has no stock of the demanded item (Paterson et al., 2011). On the other hand, proactive transshipments are allowed at any moment in time. However, no proactive transshipments are facilitated by PACCAR Parts currently. For this reason, they are not considered in this research. Nevertheless, proactive transshipments can have a potential benefit for PACCAR Parts. The potential advantage for the warehouse that sends the transshipped items is that it can reduce its inventory costs by losing excess inventory. For the receiving warehouse, the proactive transshipments can reduce ordering costs and lead time. Hence, implementing proactive transshipments can be the subject of future research.

References

Aken van, J. (2005). Management research as a design science: Articulating the research products of mode 2 knowledge production in management. *British Journal of Management*, *16*(1), 19 - 36. https://doi.org/10.1111/j.1467-8551.2005.00437.x

Altiparmak, F., Gen, M., Lin, L. & Paksoy, T. (2006). A genetic algorithm approach for multi-objective optimization of supply chain networks. *Computers & industrial engineering*, *51*(1), 196–215. https://doi.org/10.1016/j.cie.2006.07.011

Archibald, T. W., Sassen, S. & Thomas, L. (1997). An optimal policy for a two depot inventory problem with stock transfer. *Management Science*, *43*(2), 173–183. https://doi.org/10.1287/mnsc.43.2.173

Boucherie, R. J., Houtum, van, G.-J., Timmer, J. & Ommeren, van, J.-K. (2018). A two-echelon spare parts network with lateral and emergency shipments: A product-form approximation. *Probability in the engineering and informational sciences*, *32*(4), 536–555. https://doi.org/10.1017/s0269964817000365

Boylan, J. E., Syntetos, A. A. & Karakostas, G. C. (2008). Classification for forecasting and stock control: a case study. *Journal of the operational research society*, *59*(4), 473–481. https://doi.org/10.1057/palgrave.jors.2602312

Cesarelli, G., Scala, A., Vecchione, D., Ponsiglione, A. & Guizzi, G. (2021). An innovative business model for a multi-echelon supply chain inventory management pattern. *Journal of Physics: Conference Series*, *1828*(1), 012082. https://doi.org/10.1088/1742-6596/1828/1/012082

Chen, J. & Lu, J. (2011). Modeling multilocation transshipment with application of stochastic programming approach. In (Vol. 7027, p. 157-167). https://doi.org/10.1007/978-3-642-24918-1_18

Deb, K. (2000). An efficient constraint handling method for genetic algorithms. *Computer methods in applied mechanics and engineering*, *186*(2-4), 311–338. https://doi.org/10.1016/s0045-7825(99)00389-8

Donselaar, van, K. & Broekmeulen, R. (2014). *Stochastic inventory models for a single item at a single location.* (BETA publicatie : working papers; Vol. 447). Technische Universiteit Eindhoven.

Donselaar, van, K. & Broekmeulen, R. (2022). *Is your warehouse capacity tight? order more inventory!* Unpublished manuscript. Department of Industrial Engineering and Innovation Sciences, Eindhoven University of Technology.

Donselaar, van, K., Broekmeulen, R. & Kok, de, T. (2021). Heuristics for setting reorder levels in periodic review inventory systems with an aggregate service constraint. *International Journal of Production Economics*, *237*, 108137. https://doi.org/10.1016/j.ijpe.2021.108137

do Rego, J. R. & De Mesquita, M. A. (2015). Demand forecasting and inventory control: A simulation study on automotive spare parts. *International Journal of Production Economics*, *161*, 1–16. https://doi.org/10.1016/j.ijpe.2014.11.009

Du, K.-L. & Swamy, M. (2016). *Search and optimization by metaheuristics.* https://doi.org/10.1007/978-3-319-41192-7

Feng, X., Moon, I. & Ryu, K. (2017). Warehouse capacity sharing via transshipment for an integrated two-echelon supply chain. *Transportation Research Part E: Logistics and Transportation Review*, *104*, 17–35. https://doi.org/10.1016/j.tre.2017.04.014

García-Benito, J. & Martín-Peña, M. (2020). A redistribution model with minimum backorders of spare parts: A proposal for the defence sector. *European Journal of Operational Research*, *291*. https://doi.org/10.1016/j.ejor.2020.09.014

Gholamian, M. & Nasri, M. (2019). A multi echelon location-inventory model with lateral transshipment. *Operations and Supply Chain Management: An International Journal*, *12*(2), 88–99. https://doi.org/10.31387/oscm0370226

Gu, L., Zhou, Y. & Zhang, Z. (2020). Multi-echelon inventory optimization of spare parts considering cross-region transshipment and changing demand. In *2020 global reliability and prognostics and health management (phm-shanghai)* (pp. 1–6).

Hadley, G. W. & Whitten, T. (1963). *Analysis of inventory systems.* Englewood Cliffs, NJ.

Harris, F. W. (1913). How many parts to make at once. *Factory, The Magazine of Management*, *10*(2), 135–136. Retrieved from https://pubsonline.informs.org/doi/abs/10.1287/opre.38.6.947

Hochmuth, C. A. & Köchel, P. (2012). How to order and transship in multi-location inventory systems: The simulation optimization approach. *International Journal of Production Economics*, *140*(2), 646–654. https://doi.org/10.1016/j.ijpe.2011.09.021

Larsen, C. & Thorstenson, A. (2008). A comparison between the order and the volume fill rate for a base-stock inventory control system under a compound renewal demand process. *Journal of the Operational Research Society*, *59*, 798-804. https://doi.org/10.1057/palgrave.jors.2602407

Li, H. & Jiang, D. (2012). New model and heuristics for safety stock placement in general acyclic supply chain networks. *Computers & Operations Research*, *39*(7), 1333–1344. https://doi.org/10.1016/j.cor.2011.08.001

Li, Z., Li, H. & Xu, X. (2019). Efficient lateral transshipment policy for multi-retailer system. In *2019 ieee/sice international symposium on system integration (sii)* (p. 756-763). https://doi.org/10.1109/SII.2019.8700447

Meissner, J. & Senicheva, O. V. (2018). Approximate dynamic programming for lateral transshipment problems in multi-location inventory systems. *European Journal of Operational Research*, *265*(1), 49–64. https://doi.org/10.1016/j.ejor.2017.06.049

Mo, D. Y., Wang, Y., Ho, D. C. & Leung, K. (2022). Redeploying excess inventories with lateral and reverse transshipments. *International Journal of Production Research*, *60*(1), 3031-3046. https://doi.org/10.1080/00207543.2021.1910360

Nahmias, S. & Olsen, T. L. (2015). *Production and operations analysis.* McGraw-hill, New York.

Nakandala, D., Lau, H. & Ning, A. (2016). A hybrid approach for cost-optimized lateral transshipment in a supply chain environment. *Business Process Management Journal*, *22*(4), 860-878. https://doi.org/10.1108/BPMJ-08-2015-0122

Nakandala, D., Lau, H. & Zhang, J. (2017). Strategic hybrid lateral transshipment for cost-optimized inventory management. *Industrial Management & Data Systems*, *117*, 1632-1649. https://doi.org/10.1108/IMDS-08-2016-0325

Nakandala, D., Lau, H., Zhang, J. & Gunasekaran, A. (2018). A pragmatic decision model for inventory management with heterogeneous suppliers. *Enterprise Information Systems*, *12*(5), 603–619. https://doi.org/10.1080/17517575.2018.1432766

Paterson, C., Kiesmüller, G., Teunter, R. & Glazebrook, K. (2011). Inventory models with lateral transshipments: A review. *European Journal of Operational Research*, *210*(2), 125–136. https://doi.org/10.1016/j.ejor.2010.05.048

Paterson, C., Teunter, R. & Glazebrook, K. (2012). Enhanced lateral transshipments in a multi-location inventory system. *European Journal of Operational Research*, *221*(2), 317–327. https://doi.org/10.1016/j.ejor.2012.03.005

Patriarca, R., Costantino, F. & Di Gravio, G. (2016). Inventory model for a multi-echelon system with unidirectional lateral transshipment. *Expert Systems with Applications*, *65*, 372–382. https://doi.org/10.1016/j.eswa.2016.09.001

Purnomo, A. (2011). Multi-echelon inventory model for repairable items emergency with lateral transshipments in retail supply chain. *Australian Journal of Basic and Applied Sciences*, *5*(3), 462–474. Retrieved from https://www.researchgate.net/publication/

286157651_Multi-echelon_inventory_Model_for_Repairable_Items_emergency_with_lateral_transshipments_in_retail_supply_chain

Ray, T., Singh, H., Isaacs, A. & Smith, W. (2009). Infeasibility driven evolutionary algorithm for constrained optimization. In (Vol. 198, p. 145-165). https://doi.org/10.1007/978-3-642-00619-7_7

Ri-Hong, G., Peng-Cheng, Y., Jiang-Sheng, S. & Cheng-Ying, Y. (2012). Research on multi-echelon inventory model of repairable spare parts with lateral transshipments. In (p. 2014-2017). https://doi.org/10.1109/ICICEE.2012.535

Rosling, K. (2002). Inventory cost rate functions with nonlinear shortage costs. *Operations Research*, *50*, 1007-1017. https://doi.org/10.1287/opre.50.6.1007.346

Sherbrooke, C. C. (2006). *Optimal inventory modeling of systems: Multi-echelon techniques* (2nd ed.). Springer, New York.

Silver, E. A., Pyke, D. F. & Peterson, R. (1998). *Inventory management and production planning and scheduling* (Vol. 3). Wiley, New York.

Song, J.-S. (1998). On the order fill rate in a multi-item, base-stock inventory system. *Operations research*, *46*(6), 831–845. https://doi.org/10.1287/opre.46.6.831

Srinivas, M. & Patnaik, L. M. (1994). Adaptive probabilities of crossover and mutation in genetic algorithms. *IEEE Transactions on Systems, Man, and Cybernetics*, *24*(4), 656–667. https://doi.org/10.1109/21.286385

Syntetos, A. A., Babai, M. Z. & Altay, N. (2012). On the demand distributions of spare parts. *International Journal of Production Research*, *50*(8), 2101–2117. https://doi.org/10.1080/00207543.2011.562561

Syntetos, A. A., Boylan, J. E. & Croston, J. (2005). On the categorization of demand patterns. *Journal of the operational research society*, *56*(5), 495–503. https://doi.org/10.1057/palgrave.jors.2601841

Tempelmeier, H. (2000). Inventory service-levels in the customer supply chain. *OR Spectrum*, *22*, 361-380. https://doi.org/10.1007/s002910000044

Teunter, R., Babai, M. Z. & Syntetos, A. (2010). Abc classification: Service levels and inventory costs. *Production and Operations Management*, *19*, 343 - 352. https://doi.org/10.1111/j.1937-5956.2009.01098.x

Topan, E. & Heijden, van der, M. C. (2020). Operational level planning of a multi-item two-echelon spare parts inventory system with reactive and proactive interventions. *European journal of operational research*, *284*(1), 164–175. https://doi.org/10.1016/j.ejor.2019.12.022

Williams, T. (1984). Stock control with sporadic and slow-moving demand. *Journal of The Operational Research Society*, *35*(10), 939-948. https://doi.org/10.1057/jors.1984.185

Wingerden, van, E., Tan, T. & Houtum, van, G. (2016). *Design of a near-optimal generalized abc classification for a multi-item inventory control problem.* (BETA publicatie : working papers; Vol. 494). Technische Universiteit Eindhoven.

Wong, H., Houtum, van, G.-J., Cattrysse, D. & Oudheusden, van den, D. (2005). Simple, efficient heuristics for multi-item multi-location spare parts systems with lateral transshipments and waiting time constraints. *Journal of the Operational Research Society*, *56*(12), 1419–1430. https://doi.org/10.1057/palgrave.jors.2601952

Yu, C., Zhou, Y. & Zhang, Z. (2020). Multi-agent reinforcement learning for dynamic spare parts inventory control. In *2020 global reliability and prognostics and health management (phm-shanghai)* (p. 1-6). https://doi.org/10.1109/PHM-Shanghai49105.2020.9280935

Zelibe, S. C. & Bassey, U. N. (2021). Two-echelon inventory model with service consideration and lateral transshipment. *WSEAS Transactions on Systems*, *20*, 108–123. https://doi.org/10.1287/mnsc.33.10.1302

Zipkin, P. H. (2000). *Foundations of inventory management.* McGraw-hill, New York.

Appendix A

Flowchart simulation model

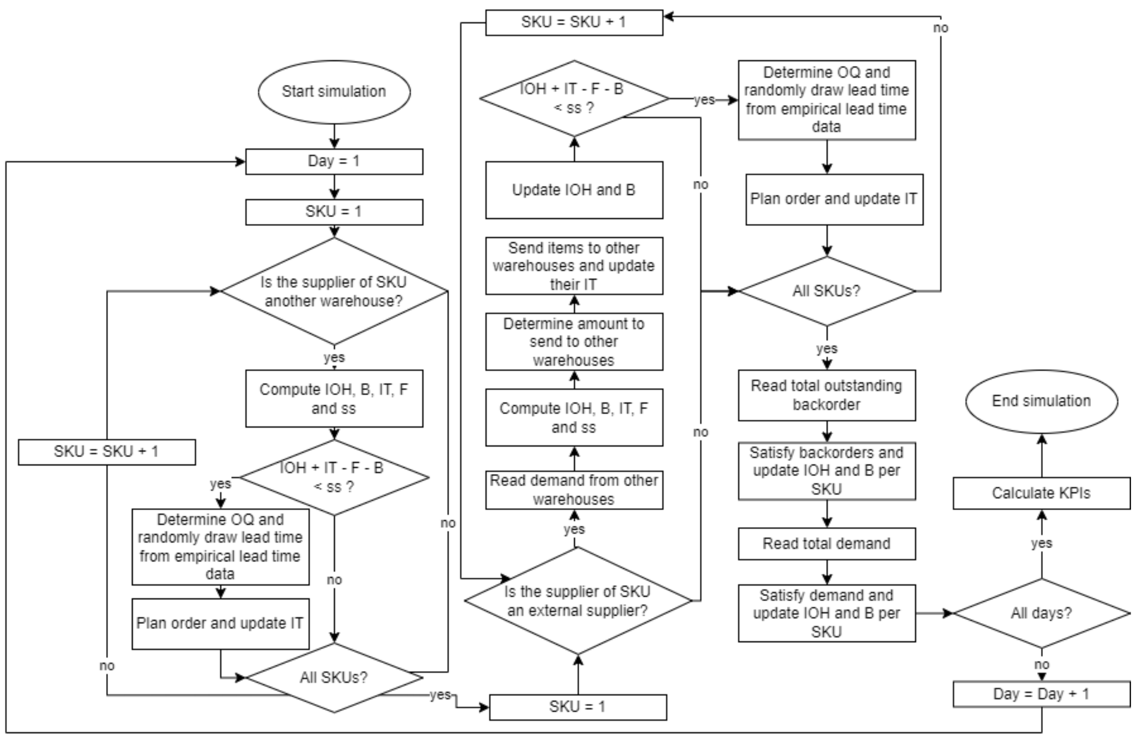


Figure A.1: Flowchart of the simulation

IOH: *Inventory On Hand at the beginning of the period*, B: *Outstanding backorders*, IT: *In Transit position*, F: *Forecasted demand during lead time + review period*, ss: *safety stock level*, OQ: *Order Quantity*

Appendix B

Simulation model validation

In order to reflect on the performance and reliability of the simulation model compared to the actual situation, a validation is performed. For this, the actual data on the obtained KPIs are retrieved from the PACCAR Parts database. The validation of the simulation model based on the PACCAR Parts fill rates and inventory values can be found in Tables B.1 and B.2 respectively. Note that for measurement of the actual performances, the same items are considered as have been considered in the simulation (i.e. not taking into account the parts that were removed as has been explained in section 3.1.1).

	2019			**2020**			**2021**		
	Actual	**Simulation**		**Actual**	**Simulation**		**Actual**	**Simulation**	
		Inc. T	*Exc. T*		*Inc. T*	*Exc. T*		*Inc. T*	*Exc. T*
European	0.987	0.973	0.966	0.985	0.972	0.962	0.962	0.964	0.949
Eindhoven	0.970	0.955	0.942	0.962	0.952	0.937	0.970	0.938	0.918
Madrid	0.940	0.936	0.915	0.932	0.934	0.908	0.935	0.924	0.894
Leyland	0.966	0.953	0.935	0.950	0.950	0.929	0.921	0.943	0.914
Budapest	0.944	0.958	0.943	0.943	0.953	0.933	0.905	0.939	0.916

Inc. T: including templates. Exc. T: excluding templates

Table B.1: PACCAR Parts fill rate validation

	2019			**2020**			**2021**		
	Actual	**Simulation**		**Actual**	**Simulation**		**Actual**	**Simulation**	
		Inc T	*Exc T*		*Inc T*	*Exc T*		*Inc T*	*Exc T*
European	55653	56014	46648	54278	67811	45736	60373	68371	56431
Eindhoven	34044	33206	28849	33907	46642	29485	38152	43792	37896
Madrid	1644	1843	1439	1669	1763	1351	2142	2272	1704
Leyland	10617	10878	8308	9940	10721	7978	10055	11843	8462
Budapest	9348	10086	8053	8762	8685	6922	10023	10464	8370

Inc. T: including templates. Exc. T: excluding templates

Table B.2: Average inventory value validation (in thousands of euros)

From the validation, it can be concluded that the simulation model yields somewhat worse performances compared to the actual situation regarding the PACCAR Parts fill rate. Nevertheless, the inventory values that are obtained by the simulation model without templates are significantly lower than the actual values. This can be declared by the templates that were added and the manual adjustments that were made by the inventory planners in that specific year. The simulation model with templates still yields worse PACCAR Parts fill rate results compared to the actual situation. On the other hand, the inventory is higher compared to the actual situation. Only for the data set of 2021, a slightly higher PACCAR Parts fill rate is obtained compared to the actual situation. As stated before, templates are applied to poorly performing products. Since the current templates are used, they likely are the most applicable to the relatively newest data set (i.e. 2021). Even though, the increase in PACCAR Parts fill rate is relatively low compared to the increase in average inventory value. Hence, it is concluded that the current templates are not representative and applicable to the older data sets. Therefore, the templates are not considered in the rest of this study.

Appendix C

Sensitivity analysis lead times

In section 2.3, it was concluded that assuming the inter-arrival times between the warehouses to be always equal to 14 days is inaccurate. In order to examine the effects of this assumption, the simulated performances of the current lead time assumption are compared with the situation in which the expected inter-warehouse lead times are equal to the average values that are displayed in Table 2.3. The results of these simulations are displayed in Table C.1. Note that the simulation model without templates is used for this comparison.

		2019		**2020**		**2021**	
		Current	*Proposed*	*Current*	*Proposed*	*Current*	*Proposed*
PACCAR Parts fill rate	*European*	0.966	0.965	0.962	0.962	0.949	0.948
	Eindhoven	0.942	0.941	0.937	0.937	0.918	0.917
	Madrid	0.915	0.906	0.908	0.899	0.894	0.884
	Leyland	0.935	0.933	0.929	0.927	0.914	0.912
	Budapest	0.943	0.940	0.933	0.931	0.916	0.911
Average inventory value (×1000€)	*European*	46648	45900	45736	45177	56431	55697
	Eindhoven	28849	28642	29485	29312	37896	37737
	Madrid	1439	1299	1351	1258	1704	1624
	Leyland	8308	8143	7978	7840	8462	8267
	Budapest	8053	7816	6922	6767	8370	8069

Table C.1: Performances for current and proposed inter-warehouse lead time assumption

From Table C.1, it can be concluded that the average inventory value decreases when the proposed lead time assumption is adopted. Recall from section 2.3 that the warehouse in Eindhoven is the biggest supplier for the other warehouses. Also, recall that the actual lead time between Eindhoven and the other warehouses is on average smaller than 14 days. This explains that the warehouses in Madrid, Leyland, and Budapest have less inventory using the proposed lead time assumption. This results in lower inventory costs. On the other hand, the PACCAR Parts fill rates in these warehouses is somewhat lower. This holds since the extra inventory that was ordered in the current situation due to the overestimation of the lead time served as extra safety stock. For the remaining part of this thesis, the proposed lead time assumption is followed (i.e. use the expected actual lead time to forecast the demand during the lead time plus review period). In this way, more accurate decisions on the safety stock levels per product can be made.

Appendix D

Stocking opportunities

	Stocking warehouse			
	EHV	**MAD**	**LEY**	**BUD**
1				
2	EHV			
3	EHV	MAD		
4	EHV		LEY	
5	EHV			BUD
6	EHV	MAD	LEY	
7	EHV	MAD		BUD
8	EHV		LEY	BUD
9	EHV	MAD	LEY	BUD
10		MAD		
11		MAD	LEY	
12		MAD		BUD
13		MAD	LEY	BUD
14			LEY	
15			LEY	BUD
16				BUD
17	EHV-MAD			
18	EHV-MAD		LEY	
19	EHV-MAD			BUD
20	EHV-MAD		LEY-BUD	
21	EHV-MAD			BUD-LEY
22	EHV-LEY			
23	EHV-LEY	MAD		
24	EHV-LEY			BUD
25	EHV-LEY	MAD-BUD		
26	EHV-LEY			BUD-MAD
27	EHV-BUD			
28	EHV-BUD	MAD		
29	EHV-BUD		LEY	
30	EHV-BUD	MAD-LEY		
31	EHV-BUD		LEY-MAD	
32		MAD-EHV		
33		MAD-EHV	LEY	
34		MAD-EHV		BUD
35		MAD-EHV	LEY-BUD	
36		MAD-EHV		BUD-LEY
37		MAD-LEY		
38	EHV	MAD-LEY		
39		MAD-LEY		BUD
40		MAD-LEY		BUD-EHV
41		MAD-BUD		
42	EHV	MAD-BUD		
43		MAD-BUD	LEY	
44		MAD-BUD	LEY-EHV	
45			LEY-EHV	
46		MAD	LEY-EHV	
47			LEY-EHV	BUD
48			LEY-EHV	BUD-MAD
49			LEY-MAD	
50	EHV		LEY-MAD	
51			LEY-MAD	BUD
52			LEY-MAD	BUD-EHV
53			LEY-BUD	
54	EHV		LEY-BUD	
55		MAD	LEY-BUD	
56				BUD-EHV
57		MAD		BUD-EHV
58			LEY	BUD-EHV
59				BUD-MAD
60	EHV			BUD-MAD
61			LEY	BUD-MAD
62				BUD-LEY
63	EHV			BUD-LEY
64		MAD		BUD-LEY
65	EHV-MAD-LEY			
66	EHV-MAD-LEY			BUD
67	EHV-LEY-BUD			
68	EHV-LEY-BUD	MAD		
69	EHV-BUD-MAD			
70	EHV-BUD-MAD		LEY	
71		MAD-LEY-BUD		
72	EHV	MAD-LEY-BUD		
73		MAD-BUD-EHV		
74		MAD-BUD-EHV	LEY	
75		MAD-EHV-LEY		
76		MAD-EHV-LEY		BUD
77			LEY-BUD-EHV	
78		MAD	LEY-BUD-EHV	
79			LEY-EHV-MAD	
80			LEY-EHV-MAD	BUD
81			LEY-MAD-BUD	
82	EHV		LEY-MAD-BUD	
83				BUD-EHV-MAD
84			LEY	BUD-EHV-MAD
85				BUD-MAD-LEY
86	EHV			BUD-MAD-LEY
87				BUD-LEY-EHV
88		MAD		BUD-LEY-EHV
89	EHV-MAD-LEY-BUD			
90		MAD-LEY-BUD-EHV		
91			LEY-BUD-EHV-MAD	
92				BUD-EHV-MAD-LEY

Every row in this table displays one of the stocking opportunities for a specific item. Per warehouse, it is displayed for which warehouses the demand is stocked. Note that white space in a cell indicates that the item is non-stocking for this warehouse. For example, consider option 42. The interpretation of this stocking option is as follows: Eindhoven stocks to own demand, Madrid stocks it own demand plus the demand of Budapest, and the demand of Leyland is not stocked.

Table D.1: Stocking opportunities

Appendix E

Recursive equations

As has been stated in section 4.2.1, costs given a minimum individual PACCAR Parts fill rate per stocking option per part have to be estimated. This can be done by using Equations 4.7 and 4.9. In order to speed up the computational time for finding the minimum s level that satisfied a certain PACCAR Parts fill rate, a recursive expression for equation 4.7 has been derived:

$$\begin{aligned}
\text{PACCAR Parts fill rate}(s+1) &= \frac{1}{Q}\sum_{k=s+1}^{s+Q}\sum_{n=0}^{k-1} P(J \leq k-n)P(D_{L+Z}=n) \\
&= \frac{1}{Q}\sum_{k=s}^{s+Q-1}\sum_{n=0}^{k-1} P(J \leq k-n)P(D_{L+Z}=n) - \frac{1}{Q}\sum_{n=0}^{s-1} P(J \leq k-n)P(D_{L+Z}=n) \\
&+ \frac{1}{Q}\sum_{n=0}^{s+Q-1} P(J \leq k-n)P(D_{L+Z}=n) \\
&= \text{PACCAR Parts fill rate}(s) + \frac{1}{Q}\sum_{n=s}^{s+Q-1} P(J \leq k-n)P(D_{L+Z}=n)
\end{aligned} \tag{E.1}$$

The same has been done for Equation 4.9:

$$\begin{aligned}
E[I^{OH}(s+1)] &= \frac{1}{Q}\sum_{i=0}^{Q-1}\sum_{d=0}^{s+i}(s+i-d+1)P(D_t=d) \\
&= \frac{1}{Q}\sum_{i=0}^{Q-1}\Big(\sum_{d=0}^{s+i-1}(s+i-d+1)P(D_t=d) + P(D_t=s+i)\Big) \\
&= \frac{1}{Q}\sum_{i=0}^{Q-1}\Big(\sum_{d=0}^{s+i-1}(s+i-d)P(D_t=d) + P(D_t=d)\Big) + \frac{1}{Q}\sum_{i=0}^{Q-1} P(D_t=s+i) \\
&= \frac{1}{Q}\sum_{i=0}^{Q-1}\Big(\sum_{d=0}^{s+i-1}(s+i-d)P(D_t=d) + \sum_{d=0}^{s+i-1} P(D_t=d)\Big) + \frac{1}{Q}\sum_{i=0}^{Q-1} P(D_t=s+i) \\
&= \frac{1}{Q}\sum_{i=0}^{Q-1}\sum_{d=0}^{s+i-1}(s+i-d)P(D_t=d) + \frac{1}{Q}\sum_{i=0}^{Q-1}\Big(\sum_{d=0}^{s+i+1} P(D_t=d) + P(D_t=s+i)\Big) \\
&= E[I^{OH}(s+1)] + \frac{1}{Q}\sum_{i=0}^{Q-1}\sum_{d=0}^{s+i} P(D_t=d)
\end{aligned} \tag{E.2}$$

Appendix F

Parameter settings

	2019			2020			2021		
	s 1	**s 2**	**s 3**	**s 1**	**s 2**	**s 3**	**s 1**	**s 2**	**s 3**
European (F_A^{EUR})	0.990	0.991	0.992	0.988	0.989	0.990	0.979	0.980	0.981
Eindhoven (F_A^{EHV})	0.967	0.968	0.969	0.965	0.966	0.967	0.943	0.944	0.945
Madrid (F_A^{MAD})	0.935	0.936	0.937	0.929	0.930	0.931	0.919	0.920	0.921
Leyland (F_A^{LEY})	0.965	0.966	0.967	0.961	0.962	0.963	0.945	0.946	0.947
Budapest (F_A^{BUD})	0.963	0.964	0.965	0.955	0.956	0.957	0.945	0.946	0.947

Table F.1: Settings for PACCAR Parts fill rates of items in Group A per scenario in IP model

	s 1	**s 2**	**s 3**	**s 4**	**s 5**
2019	0.965	0.970	0.975	0.980	0.985
2020	0.965	0.970	0.975	0.980	0.985
2021	0.945	0.950	0.955	0.960	0.965

Table F.2: Target PACCAR Parts European fill rates for safety stock heuristic per scenario

Appendix G

Validation IP model for 2020 and 2021

		Scenario								
		1			**2**			**3**		
		Target	*IP*	*Sim*	*Target*	*IP*	*Sim*	*Target*	*IP*	*Sim*
PACCAR Parts fill rates for B items	*European*	0.866	0.866	0.851	0.859	0.859	0.844	0.853	0.853	0.840
	Eindhoven	0.829	0.896	0.813	0.823	0.890	0.802	0.816	0.887	0.797
	Madrid	0.783	0.843	0.747	0.776	0.840	0.746	0.770	0.833	0.744
	Leyland	0.785	0.830	0.777	0.778	0.826	0.774	0.772	0.817	0.772
	Budapest	0.850	0.910	0.821	0.844	0.906	0.820	0.837	0.900	0.817
Total costs per year for part B items (×1000€)			2576	2947		2514	2827		2472	2754

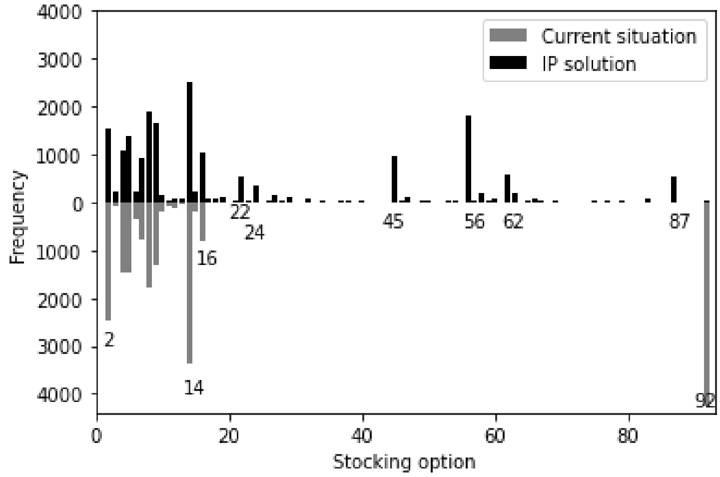
Table G.1: Validation of IP model for data of 2020

		Scenario								
		1			**2**			**3**		
		Target	*IP*	*Sim*	*Target*	*IP*	*Sim*	*Target*	*IP*	*Sim*
PACCAR Parts fill rates for B items	*European*	0.820	0.820	0.811	0.813	0.813	0.807	0.807	0.807	0.801
	Eindhoven	0.823	0.897	0.764	0.816	0.834	0.758	0.810	0.823	0.753
	Madrid	0.730	0.845	0.721	0.723	0.822	0.720	0.717	0.815	0.712
	Leyland	0.771	0.859	0.757	0.765	0.778	0.755	0.758	0.767	0.751
	Budapest	0.763	0.891	0.744	0.757	0.824	0.742	0.750	0.813	0.725
Total costs per year for part B items (×1000€)			2710	3038		2645	2869		2606	2785

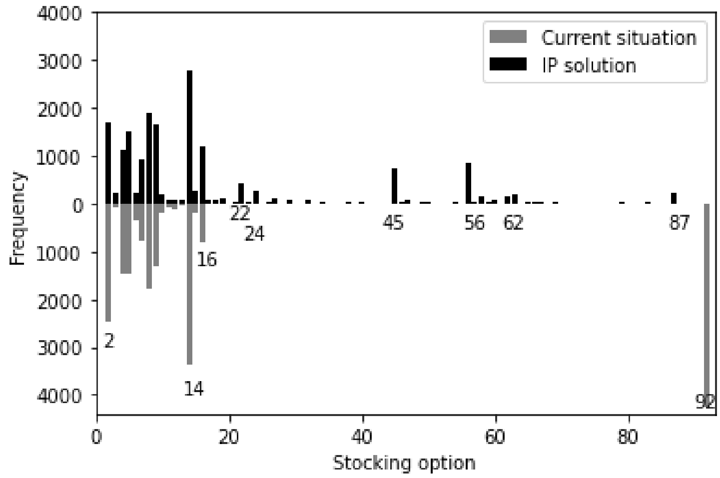
Table G.2: Validation of IP model for data of 2021

Appendix H

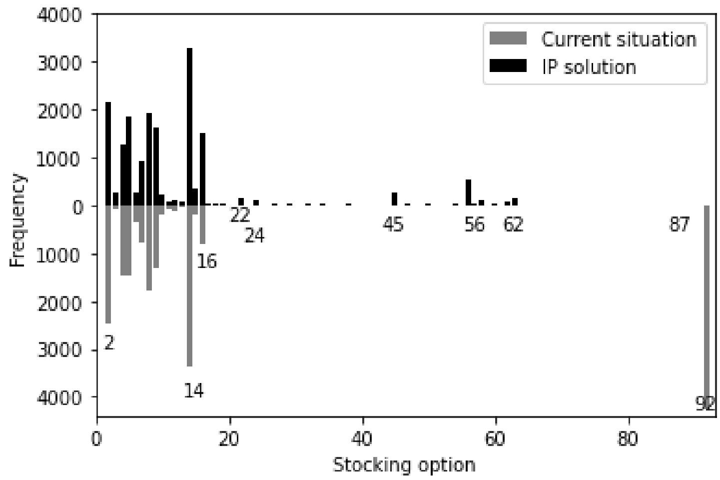
Analysis of IP model



(a) Scenario 1

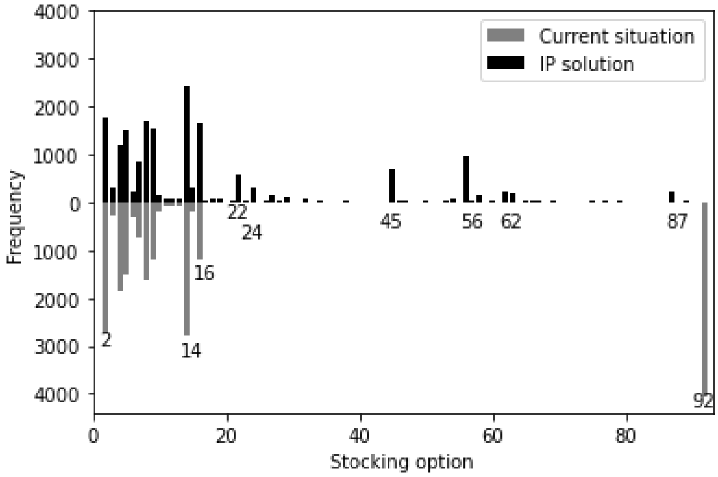


(b) Scenario 2

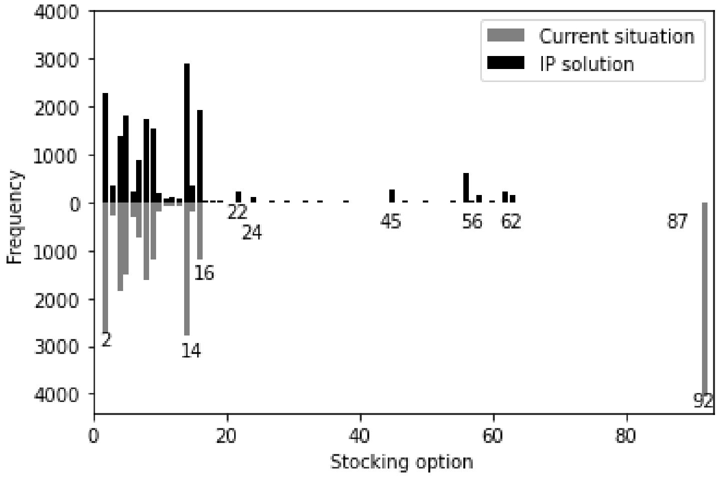


(c) Scenario 3

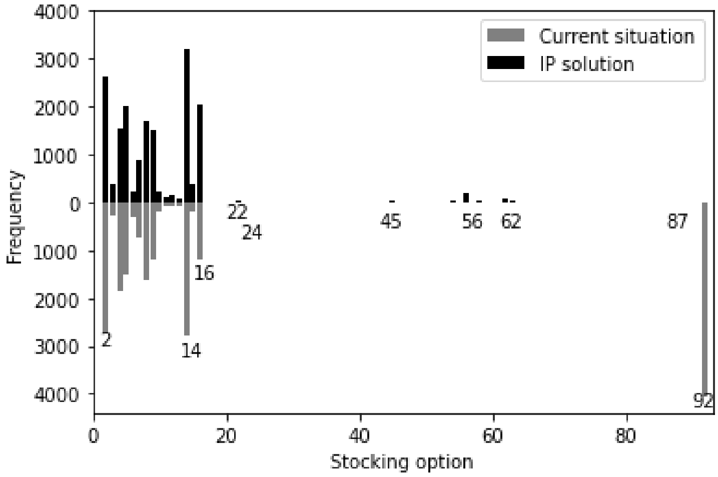
Figure H.1: Frequency of stocking options for different scenarios of the PACCAR Parts fill rate of items in group A for 2020



(a) Scenario 1



(b) Scenario 2



(c) Scenario 35

Figure H.2: Frequency of stocking options for different scenarios of the PACCAR Parts fill rate of items in group A for 2021

Appendix I

Results of IP model

		Current	IP scenario			Heuristic
			1	*2*	*3*	
PACCAR Parts fill rates	*European*	0.870	0.878	0.873	0.868	0.870
	Eindhoven	0.832	0.839	0.831	0.828	0.826
	Madrid	0.781	0.790	0.784	0.779	0.781
	Leyland	0.793	0.795	0.793	0.788	0.790
	Budapest	0.844	0.856	0.853	0.850	0.840
Average inventory values (×1000€)	*European*	17001	16506	16011	15756	17015
	Eindhoven	12136	11852	11396	11209	12139
	Madrid	335	384	364	366	344
	Leyland	2700	2177	2118	2124	2550
	Budapest	1831	2092	2133	2058	1982
Costs per year (×1000€)	*Rush transshipments*	694	629	630	637	670
	Regular transshipments	175	119	115	114	150
	Total transshipments	869	748	745	751	819
	Inventory	2040	1981	1921	1891	2042
	Total	2909	2729	2667	2642	2861

Table I.1: Performances of items in group B in 2019

		Current	IP scenario			Heuristic
			1	*2*	*3*	
PACCAR Parts fill rates	*European*	0.847	0.851	0.844	0.840	0.846
	Eindhoven	0.815	0.813	0.802	0.797	0.808
	Madrid	0.729	0.747	0.746	0.744	0.730
	Leyland	0.771	0.777	0.774	0.772	0.764
	Budapest	0.831	0.821	0.820	0.817	0.829
Average inventory values (×1000€)	*European*	17241	17163	16634	16279	17355
	Eindhoven	12390	12351	11871	11529	12264
	Madrid	333	390	379	374	344
	Leyland	2690	2252	2191	2204	2653
	Budapest	1828	2171	2193	2172	2094
Costs per year (×1000€)	*Rush transshipments*	702	643	643	659	664
	Regular transshipments	177	124	114	114	142
	Total transshipments	878	767	758	774	805
	Inventory	2069	2060	1996	1953	2083
	Total	2947	2827	2754	2727	2888

Table I.2: Performances of items in group B in 2020

		Current	IP scenario			Heuristic
			1	*2*	*3*	
PACCAR Parts fill rates	*European*	0.807	0.811	0.807	0.801	0.808
	Eindhoven	0.764	0.764	0.758	0.753	0.758
	Madrid	0.709	0.721	0.720	0.712	0.707
	Leyland	0.752	0.757	0.755	0.751	0.787
	Budapest	0.745	0.744	0.742	0.725	0.743
Average inventory values (×1000€)	*European*	18939	18446	17600	17665	18876
	Eindhoven	14152	13875	13113	13164	14027
	Madrid	327	380	361	355	331
	Leyland	2666	2143	2046	2056	2688
	Budapest	1795	2049	2081	2089	1830
Costs per year (×1000€)	*Rush transshipments*	611	550	573	547	586
	Regular transshipments	154	106	100	95	127
	Total transshipments	765	656	673	641	712
	Inventory	2273	2214	2112	2120	2265
	Total	3038	2869	2785	2761	2977

Table I.3: Performances of items in group B in 2021

Appendix J

Pseudo code of SnoS heuristic

Algorithm 1 Stocking/non-stocking (SnoS) heuristic

1: **for** Every stocking location (small, medium, and large) **do**
2: Free up space in warehouse LEY and EHV ▷ Step 1
3: Set number of items to stock (I) ▷ Step 2
4: Set number of free locations in BUD, LEY and EHV (x_{BUD}, x_{LEY}, x_{EHV}) ▷ Step 2
5: Set stocking options (S) to BUD, LEY, EHV, LEY+EHV ▷ Step 3
6: **while** I $\neq$ 0 **do**
7: **for** Every item $i \in$ I **do**
8: Calculate $E_{i,s}^{TransshipmentCosts}$ for $s \in S$ ▷ Step 4
9: Calculate $B_{i,s} = E_{i,s}^{TransshipmentCosts} - E_{i,BUD}^{TransshipmentCosts}$ for $s \in$ S ▷ Step 5
10: **end for**
11: Set $B_{i,s}$ with the highest value for $i \in$ I, $s \in$ S ▷ Step 6
12: Consider p as corresponding i and q as corresponding s
13: **if** q = LEY+EHV & I+1 < $x_{BUD} + x_{LEY} + x_{EHV}$ **then** ▷ Step 7
14: Allocate item p to LEY+EHV ▷ Step 6
15: Update x_{LEY}, x_{EHV} and remove i from I ▷ Step 6
16: **else**
17: Remove $B_{p,q}$ and start in line 11 ▷ Step 7
18: **end if**
19: **end while**
20: **end for**

Appendix K

Performances of items in group A

		2019	2020	2021
PACCAR Parts fill rates	*European*	0.981	0.979	0.970
	Eindhoven	0.958	0.956	0.934
	Madrid	0.926	0.920	0.910
	Leyland	0.956	0.952	0.936
	Budapest	0.954	0.946	0.936
Average inventory values (×1000€)	*European*	30116	28298	38460
	Eindhoven	16763	17197	25626
	Madrid	1054	924	1278
	Leyland	5764	5305	5614
	Budapest	6535	4872	5942
Costs per year (×1000€)	*Rush transshipments*	1149	899	1946
	Regular transshipments	481	483	711
	Total transshipments	1630	1383	2657
	Inventory	3614	3396	4615
	Total	5244	4778	7272

Table K.1: Performances of items in group A

Appendix L

Results of safety stock heuristic

		Target PACCAR Parts European fill rate					Current
		0.965	*0.970*	*0.975*	*0.980*	*0.985*	
PACCAR Parts fill rates	*European*	0.958	0.962	0.966	0.971	0.975	0.965
	Eindhoven	0.940	0.949	0.952	0.957	0.961	0.941
	Madrid	0.880	0.886	0.892	0.899	0.901	0.906
	Leyland	0.930	0.937	0.941	0.946	0.950	0.933
	Budapest	0.929	0.936	0.941	0.944	0.951	0.94
Average inventory values (×1000€)	*European*	35440	39757	43277	50296	54794	44892
	Eindhoven	23995	26029	27649	30741	32464	28642
	Madrid	826	1070	1166	1340	1444	1351
	Leyland	5790	6652	7690	9064	9513	7978
	Budapest	4829	6005	6773	9151	11373	6922
Costs per year (×1000€)	*Rush transshipments*	2437	2166	1933	1611	1388	1854
	Regular transshipments	878	776	689	567	482	662
	Total transshipments	3315	2942	2622	2178	1870	2582
	Inventory	4253	4771	5193	6036	6575	5387
	Total	7568	7713	7815	8214	8445	7969

Table L.1: Results safety stock heuristic for 2019

		Target PACCAR Parts European fill rate					Current
		0.965	*0.970*	*0.975*	*0.980*	*0.985*	
PACCAR Parts fill rates	*European*	0.953	0.957	0.961	0.967	0.970	0.962
	Eindhoven	0.926	0.934	0.937	0.943	0.949	0.937
	Madrid	0.857	0.864	0.869	0.873	0.880	0.899
	Leyland	0.917	0.923	0.927	0.932	0.936	0.927
	Budapest	0.913	0.916	0.922	0.925	0.934	0.931
Average inventory values (×1000€)	*European*	36246	39567	42379	46626	50803	45177
	Eindhoven	25341	26577	27816	30274	31311	29312
	Madrid	869	925	946	1010	1056	1258
	Leyland	4560	6114	7317	8497	10124	7840
	Budapest	5476	5950	6299	6846	8312	6767
Costs per year (×1000€)	*Rush transshipments*	1984	1862	1736	1571	1485	1651
	Regular transshipments	788	736	683	616	578	670
	Total transshipments	2771	2597	2418	2187	2063	2321
	Inventory	4350	4748	5085	5595	6096	5421
	Total	7568	7713	7815	8214	8445	7742

Table L.2: Results safety stock heuristic for 2020

		Target PACCAR Parts European fill rate					Current
		0.945	*0.950*	*0.955*	*0.960*	*0.965*	
PACCAR Parts fill rates	*European*	0.937	0.941	0.946	0.952	0.955	0.948
	Eindhoven	0.910	0.916	0.919	0.923	0.925	0.917
	Madrid	0.808	0.812	0.817	0.823	0.826	0.884
	Leyland	0.905	0.909	0.913	0.915	0.922	0.912
	Budapest	0.895	0.899	0.904	0.907	0.912	0.911
Average inventory values (×1000€)	*European*	45905	48552	51409	55880	58454	55696
	Eindhoven	30035	32154	34270	37578	39292	37737
	Madrid	1159	1258	1327	1436	1491	1624
	Leyland	6910	7309	7916	8744	9155	8267
	Budapest	7801	7830	7897	8122	8516	8069
Costs per year (×1000€)	*Rush transshipments*	3233	3004	2790	2530	2380	2548
	Regular transshipments	1114	984	887	762	740	873
	Total transshipments	4346	3988	3676	3291	3121	3443
	Inventory	5509	5826	6169	6706	7015	6684
	Total	7568	7713	7815	8214	8445	10126

Table L.3: Results safety stock heuristic for 2021

Appendix M

Results of Real-Coded Genetic Algorithm

Class	2019	2020	2021
1	20.23	20.37	18.90
2	15.45	15.35	16.57
3	1.89	2.19	2.48
4	11.75	11.78	11.17
5	12.28	12.38	12.56
6	1.20	1.19	1.50
7	6.64	6.58	6.25
8	8.72	8.46	8.55
9	0.86	0.77	0.98
10	3.52	3.57	3.36
11	5.83	5.76	5.88
12	0.66	0.69	0.76
13	2.30	2.20	2.10
14	4.12	4.13	4.24
15	0.57	0.60	0.69
16	0.95	0.98	0.84
17	2.53	2.48	2.57
18	0.50	0.51	0.63

Table M.1: Percentage of SKUs per class

		Target PACCAR Parts European fill rates as percentage of current PACCAR Parts fill rates								**Current**
		99.50	*99.75*	*100.00*	*100.25*	*100.50*	100.75	101.00	101.25	
PACCAR Parts fill rates	*European*	0.964	0.965	0.965	0.966	0.968	0.969	0.970	0.972	0.965
	Eindhoven	0.940	0.941	0.942	0.944	0.946	0.947	0.949	0.952	0.941
	Madrid	0.909	0.910	0.911	0.914	0.915	0.913	0.913	0.915	0.906
	Leyland	0.933	0.935	0.936	0.939	0.942	0.944	0.947	0.950	0.933
	Budapest	0.942	0.943	0.944	0.946	0.950	0.951	0.954	0.957	0.940
Average inventory values (×1000€)	*European*	41250	41589	42415	43793	45103	46045	47859	49940	44892
	Eindhoven	25657	25757	26242	26952	27539	27997	28847	29928	28642
	Madrid	1195	1292	1288	1350	1412	1450	1538	1614	1351
	Leyland	7466	7553	7756	8080	8471	8693	9100	9601	7978
	Budapest	6931	6987	7130	7412	7681	7905	8374	8798	6922
Costs per year (×1000€)	*Rush transshipments*	1938	1933	1832	1779	1779	1706	1610	1570	1854
	Regular transshipments	651	634	614	584	550	538	517	483	662
	Total transshipments	2589	2567	2446	2364	2329	2244	2127	2053	2582
	Inventory	4950	4991	5090	5255	5412	5525	5743	5993	5387
	Total	7539	7557	7535	7619	7741	7769	7870	8046	7969

Table M.2: Results RCGA for 2019

		Target PACCAR Parts European fill rates as percentage of current PACCAR Parts fill rates								Current
		99.50	*99.75*	*100.00*	*100.25*	*100.50*	100.75	101.00	101.25	
PACCAR Parts fill rates	*European*	0.960	0.962	0.961	0.963	0.965	0.965	0.967	0.970	0.962
	Eindhoven	0.934	0.938	0.937	0.939	0.942	0.943	0.945	0.949	0.937
	Madrid	0.899	0.904	0.903	0.906	0.909	0.903	0.907	0.909	0.899
	Leyland	0.926	0.929	0.930	0.932	0.937	0.937	0.940	0.947	0.927
	Budapest	0.932	0.934	0.935	0.936	0.941	0.937	0.944	0.954	0.931
Average inventory values (×1000€)	*European*	42171	43292	43321	44185	46517	46932	48835	50516	45177
	Eindhoven	27207	27829	27767	28336	29619	29958	30834	30448	29312
	Madrid	1269	1306	1309	1330	1427	1430	1507	1624	1258
	Leyland	7460	7717	7760	7972	8464	8480	8985	9606	7840
	Budapest	6235	6440	6485	6547	7006	7064	7509	8839	6767
Costs per year (×1000€)	*Rush transshipments*	1572	1572	1572	1558	1449	1383	1320	1267	1651
	Regular transshipments	672	635	589	552	555	550	502	478	670
	Total transshipments	2244	2207	2160	2110	2004	1933	1822	1745	2321
	Inventory	5060	5195	5199	5302	5582	5632	5860	6062	5421
	Total	7305	7402	7359	7412	7586	7565	7683	7807	7742

Table M.3: Results RCGA for 2020

		Target PACCAR Parts European fill rates as percentage of current PACCAR Parts fill rates								Current
		99.50	*99.75*	*100.00*	*100.25*	*100.50*	100.75	101.00	101.25	
PACCAR Parts fill rates	*European*	0.947	0.948	0.949	0.950	0.951	0.953	0.955	0.955	0.948
	Eindhoven	0.917	0.918	0.919	0.921	0.922	0.925	0.927	0.928	0.917
	Madrid	0.887	0.886	0.888	0.891	0.890	0.891	0.892	0.889	0.884
	Leyland	0.912	0.912	0.914	0.918	0.920	0.923	0.926	0.927	0.912
	Budapest	0.913	0.914	0.916	0.919	0.920	0.923	0.927	0.927	0.911
Average inventory values (×1000€)	*European*	52148	52818	53743	54448	55900	57184	58475	58905	55696
	Eindhoven	35132	35557	36059	36328	37327	37996	38623	38876	37737
	Madrid	1580	1589	1635	1657	1708	1754	1838	1864	1624
	Leyland	8044	8165	8319	8600	8835	9108	9489	9543	8267
	Budapest	7391	7507	7730	7863	8030	8327	8524	8623	8069
Costs per year (×1000€)	*Rush transshipments*	2492	2483	2507	2426	2482	2365	2326	2318	2548
	Regular transshipments	846	852	817	798	758	739	725	707	873
	Total transshipments	3338	3335	3324	3224	3240	3104	3051	3025	3443
	Inventory	6258	6338	6449	6534	6708	6862	7017	7069	6684
	Total	9595	9673	9773	9758	9948	9966	10068	10093	10126

Table M.4: Results RCGA for 2021

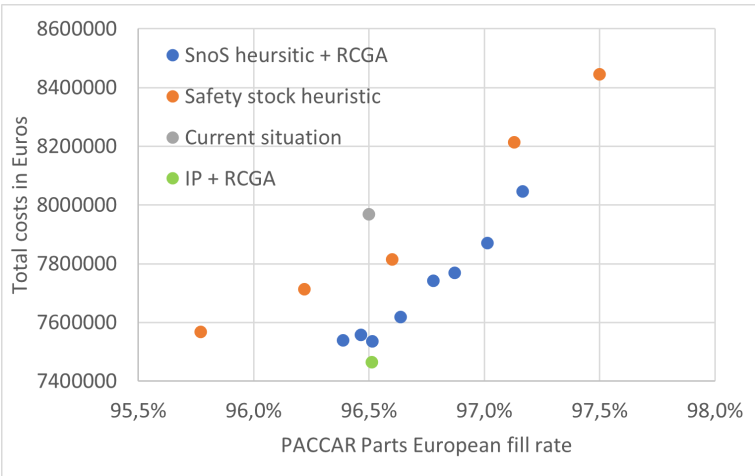


Figure M.1: PACCAR Parts European fill rate versus total costs for current situation, safety stock heuristic, and RCGA

		SnoS heuristic and RCGA	IP and RCGA	Current situation
PACCAR Parts fill rates	*European*	0.965	0.965	0.965
	Eindhoven	0.942	0.941	0.941
	Madrid	0.911	0.913	0.906
	Leyland	0.936	0.936	0.933
	Budapest	0.944	0.943	0.940
Average inventory values (×1000€)	*European*	42415	42451	44892
	Eindhoven	26242	26358	28642
	Madrid	1288	1324	1351
	Leyland	7756	7626	7978
	Budapest	7130	7144	6922
Costs per year (×1000€)	*Rush transshipments*	1832	1793	1854
	Regular transshipments	614	576	662
	Total transshipments	2446	2370	2582
	Inventory	5090	5094	5387
	Total	7535	7464	7969

Table M.5: Sensitivity analysis stocking/non-decision for 2019

Appendix N

Safety stock coverage levels per class

Class	Target PACCAR Parts fill rates as percentage of current PACCAR Parts fill rates							
	99.50	*99.75*	*100.00*	*100.25*	*100.50*	*100.75*	*101.00*	*101.25*
1	11.45	12.16	12.37	12.18	14.83	17.62	19.95	23.14
2	17.17	16.62	18.49	19.03	22.17	23.19	26.13	29.67
3	20.38	20.63	21.18	22.02	24.83	27.70	29.31	32.80
4	17.17	19.45	22.04	22.50	22.45	25.14	26.64	27.63
5	22.84	25.10	28.18	28.68	29.17	30.03	31.82	33.25
6	27.13	29.04	33.97	33.64	32.72	35.80	38.02	37.49
7	24.22	24.47	25.74	26.85	27.86	30.64	30.30	33.35
8	29.78	31.15	30.96	33.24	35.27	37.38	36.83	38.50
9	34.62	36.28	36.52	39.34	40.64	41.31	41.48	45.45
10	27.34	28.50	30.94	31.64	32.16	35.98	35.87	39.12
11	33.05	34.00	36.48	37.20	36.70	41.13	40.59	45.86
12	38.70	39.38	41.99	44.20	45.64	46.65	46.98	50.41
13	32.81	33.46	35.34	36.16	37.88	40.41	42.04	43.17
14	39.04	39.22	40.61	40.88	43.68	45.67	47.84	48.66
15	43.61	43.81	47.17	48.35	47.66	51.32	53.48	53.76
16	38.05	40.01	40.34	40.46	42.04	43.64	45.16	47.00
17	43.93	44.85	45.84	46.53	46.02	49.82	50.83	53.88
18	47.69	51.79	51.04	51.69	54.00	55.86	55.81	57.92

Table N.1: Safety stock coverage levels per class proposed by the RCGA for 2019

Class	**Target PACCAR Parts fill rates as percentage of current PACCAR Parts fill rates**							
	99.50	*99.75*	*100.00*	*100.25*	*100.50*	*100.75*	*101.00*	*101.25*
1	14.09	14.93	14.32	17.14	20.74	21.01	23.42	25.63
2	17.10	18.18	18.49	18.41	22.77	22.76	25.28	26.74
3	18.73	19.48	19.85	20.24	23.45	23.17	27.45	28.04
4	20.63	22.80	22.80	24.30	25.50	25.87	28.24	30.51
5	22.51	24.12	24.40	26.38	27.08	27.47	29.36	31.99
6	23.37	25.20	25.98	27.49	28.44	29.05	31.11	32.87
7	24.98	27.87	27.45	29.01	31.31	31.80	32.24	34.84
8	28.15	29.69	30.12	30.09	33.00	33.21	32.82	36.30
9	29.30	30.89	31.36	32.20	33.48	33.61	34.34	37.25
10	31.30	32.21	32.21	33.67	35.96	37.12	36.46	39.65
11	33.35	34.32	34.04	34.67	37.07	38.31	38.12	42.27
12	34.95	35.67	35.36	35.84	38.48	39.36	39.79	43.77
13	37.07	37.65	37.53	37.19	39.72	40.12	40.64	44.88
14	38.35	40.33	40.38	39.79	40.54	41.69	41.42	45.84
15	39.61	42.68	42.63	41.96	41.46	42.82	42.58	48.14
16	41.44	44.01	43.96	43.51	42.71	44.30	44.30	49.68
17	43.99	45.11	45.37	44.37	44.18	46.02	45.65	52.61
18	44.85	47.15	47.32	45.17	46.33	47.26	47.50	55.62

Table N.2: Safety stock coverage levels per class proposed by the RCGA for 2020

Class	**Target PACCAR Parts fill rates as percentage of current PACCAR Parts fill rates**							
	99.50	*99.75*	*100.00*	*100.25*	*100.50*	*100.75*	*101.00*	*101.25*
1	12.89	14.21	15.17	14.75	16.68	18.41	18.53	18.45
2	16.20	16.59	18.02	17.94	18.84	19.89	21.55	21.65
3	17.83	17.78	18.86	19.50	20.47	21.50	23.57	23.84
4	20.85	19.29	20.50	20.66	23.28	24.51	25.97	26.25
5	23.48	24.00	23.13	25.06	25.79	25.99	27.43	28.34
6	24.03	24.67	24.72	27.51	28.54	29.03	30.17	30.72
7	25.03	25.77	26.05	28.77	30.63	31.27	32.14	32.33
8	26.28	26.77	27.18	29.70	31.87	33.13	33.33	33.31
9	28.36	28.45	29.10	31.98	33.30	34.50	35.24	35.49
10	30.31	30.95	32.29	33.17	34.02	35.63	36.65	37.15
11	31.42	32.52	34.15	34.52	36.31	37.68	38.28	38.69
12	33.15	34.44	35.05	35.82	38.15	39.18	40.67	41.35
13	35.15	35.80	35.98	37.30	38.64	40.34	41.75	42.50
14	36.83	37.80	37.51	38.07	39.96	41.51	43.69	44.77
15	38.49	38.81	38.86	40.11	41.06	41.99	44.47	45.84
16	39.98	40.34	41.23	42.66	43.13	44.26	45.85	47.28
17	41.79	41.95	42.19	43.99	44.69	46.64	47.66	48.99
18	42.82	42.84	43.84	45.32	45.80	47.89	49.80	51.49

Table N.3: Safety stock coverage levels per class proposed by the RCGA for 2021