MASTER

Human decision making in a spare part replenishment environment

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Human decision making in a spare part replenishment environment

Master Thesis

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Abstract

VDL Nedcar is dealing with unnecessarily large spare parts inventories. To avoid this from happening again, VDL Nedcar requires better insight into how these unnecessarily large inventories were created. This research aims to gain insights into the way that inventory managers are influenced by spare parts attributed in their decision making concerning spare parts management. To identify the impact of inventory managers on spare parts inventory management at VDL Nedcar, two models are developed: the VDL Nedcar Model and the theory-based model. The VDL Nedcar model consists of the spare parts inventory model currently used by VDL Nedcar complemented with the inventory manager's influence. The goal of the theory-based model is to function as a benchmark model that imitates the situation at VDL Nedcar excluding human involvement. This is done by basing all model designing decisions on the normal course of business of VDL Nedcar. Both models are simulated with historic data to obtain an average on hand inventory. The deviations between the average on hand inventories can be assigned to human involvement since this is the main difference between the two models. So the human impact is identified and expressed as a deviation in average on hand inventory for each NPG. A multiple linear regression model is used to search for relations between the spare part attributes and the inventory deviations. The model revealed significant relations for the attributes "costs" and "reorder point". Thus, these two attributes are identified to have an impact on the decision making process of the inventory managers at VDL Nedcar. These results form a first insight into how behavioral operations management can be applied within a spare parts management setting creating an opening for future research in this area. Furthermore, it contributed to the prevention of excessive spare parts inventories in the future by obtaining a better understanding of how inventory managers at VDL Nedcar are influenced in their decision making.

Executive summary

Introduction

Nowadays, the trend among companies is to automate business processes as much as possible. Operating in a highly competitive and fast automating market, this also applies to VDL Nedcar. However, this seems to be a tremendous challenge in the field of spare parts management for capital goods. Despite the increasing complexity of the scientific theories in this area and the continuing advancement of spare part algorithms, in practice human involvement seems indispensable (Sanders and Manrodt, 2003). Almost all, if not, companies need humans to take responsibility for the spare part process (Flemisch et al., 2012).

Despite the dependency of humans within the spare parts management process, the existing research on the role humans play in spare parts management is very limited to none-existent. However, it is noticed that research on human influence in other business processes shows interesting results with wide implications. Especially in the field of forecasting and inventory management of production related goods, human behavior is well studied (Donohue et al., 2018).

The aim of this research is to create a better understanding of how humans are influenced in their decision making concerning spare parts management and consecutively implementing behavioral operations management in a spare parts management area. Furthermore, the research is executed in collaboration with VDL Nedcar. VDL Nedcar wants to obtain a better understanding of the human impact on their spare parts management and with it the human behavior.

Problem Definition

The contracting automotive market caused VDL Nedcar to cut back on their maintenance budget. By analyzing the maintenance department for possible cost reductions, it was concluded that the spare parts inventory is unnecessarily large. Several projects were executed to reduce the excessive spare parts inventories. However, none of these projects are concerned with preventing this from happening again in the future. To avoid excessive spare parts inventories in the future, Nedcar needs better insight into how these unnecessarily large inventories were created.

The spare parts inventory process at VDL Nedcar is controlled by inventory managers. However, humans can be influenced in various ways and thus can be compromised in their rational decision making (Donohue et al., 2018). Since VDL Nedcar has no insight in the decision making process of the inventory managers and these inventory managers play an important role in the spare parts process, it is reasonable to assume that the human involvement plays a significant part in the cause of excessive spare parts inventories. Therefore, identifying the human impact on spare parts management is important to avoid excessive spare parts inventories in the future. Furthermore, it is important to obtain a better understanding of how and why humans make the decisions that impact the spare parts inventories (positive and negative). The current research aims at identifying the human impact on spare parts inventory management to determine whether the decisions that caused the impact are influenced by spare part attributes. Spare part attributes are characteristics of individual spare parts, e.g. costs and leadtime (time it takes for a part to be delivered after the order is placed).

Research Questions and Methodology

The objective of this research is to clarify the impact of spare part attributes on human decision making to prevent excessive inventories in the future. This leads to the following main research question:

Which spare part attributes influence the inventory managers in controlling the spare parts inventories and how do these relations contribute to excessive inventories?

Three supporting research questions have been defined to establish an answer to the main research question. The first supporting research question is defined as follows:

RQ1 *How to identify the impact inventory managers have on spare parts inventory management at VDL Nedcar?*

In order to analyze how inventory managers are influenced by spare part attributes, it is necessary to identify the contribution of the inventory managers to spare parts management. Therefore, the first research question is generated. This research question aims to isolate human behavior from the spare parts inventory model at VDL Nedcar.

RQ2 *How to identify relations between spare part attributes and the impact inventory managers have on the spare parts management process of VDL Nedcar?*

RQ3 *What is the exact relation between the relevant attributes and the inventory manager's impact on spare parts inventory management?*

The objective of RQ2 is to construct a method that investigates whether there are spare part attributes that influence human decisions concerning spare parts inventory management. An example of such decisions is the determination of the reorder point for a specific Non Production Good (NPG). After constructing a method capable of identifying the attributes that influence the inventory managers, the exact relations between spare part attributes and the inventory manager's involvement can be determined by answering RQ3. An example of a finding could be: if an inventory manager notices a long leadtime for an NPG, the inventory manager sets a too high value for the reorder point (parameter).

Due to the lack of existing research, it is impossible to formulate well supported hypotheses. Therefore, the decision is made to perform an exploratory research to answer the research questions and satisfy the research objectives. The first part of the project concerns the identification of human impact on spare parts inventory management. Together with the corresponding spare part attributes this forms the input for the second part of the research. In the second part of the research the human impact is analyzed to find answers to the second and third research question.

Identifying The Impact of Human Involvement on Spare Parts Management

To identify the impact of inventory managers on spare parts inventory management at VDL Nedcar, two models are developed: the VDL Nedcar Model and the theory-based model. The VDL Nedcar model consists of the spare parts inventory model currently used by VDL Nedcar complemented with the inventory manager's influence. Simulating this model with the actual orders and demands gives a representation of the reality of VDL Nedcar. The goal of the theory-based model is to develop a model that can be used as a benchmark model to identify the human impact on spare parts inventory management. To achieve this, a model that represents the situation of VDL Nedcar as accurate as possible with an exception of the influences of the inventory managers is developed. This is done by basing all model designing decisions on the normal course of business of VDL Nedcar. From this a single-location, single-item inventory model with a (R,s,nQ) policy is obtained. Furthermore, the model performance is measured by the aggregate fill rate and backorders are placed in case of a shortage. With an exception of the exclusion of emergency shipments and obsolescence, this model represents the normal course of business at VDL Nedcar as accurate as possible.

The developed method for identifying the impact inventory managers have on spare parts management is simulated using a case study at VDL Nedcar. Within this case study, all spare parts of three production lines of VDL Nedcar are used. Comparing the average on hand inventories obtained from the models shows the impact of the inventory managers at VDL Nedcar. Observing the average inventory deviations, it is noticed that the involvement of inventory managers have both positive and negative impacts. An impact is considered negative when a higher average inventory on hand is obtained (for the same level of performance), and vice versa.

Now the human impact is identified, a list containing the deviations and average on hand inventories of the two models is compiled. This list is complemented with spare part attributes obtained from VDL Nedcar's ERP system (SAP). This constructs a dataset where each row contains the inventory on hand of both models, the deviation between them, and all obtained spare part attributes. Furthermore, each row represents several human decisions that caused the deviation, which can be analyzed in phase two of this research. This concludes the first phase of this research.

Inventory Deviation Analysis

Now the impact of the inventory managers is identified, it is possible to search for relations among the human impact and the corresponding spare part attributes. A multiple linear regression model is build to search for significant relations. This is a statistical technique that is common for situations with multiple explanatory variables and a single dependent variable. This research uses the identified inventory deviations as dependent variable and the spare part attributes as explanatory variables. The analysis technique is suited for this research to explain changes in the dependent variable by using the known explanatory variables. The model revealed significant relations for the variables "costs" and "reorder point". Thus, these two variables are identified to have an impact on the decision making process of the inventory managers at VDL Nedcar. The model results are displayed in Table 1.

Table 1: Multiple linear regression model output

DV= Relative Deviation				
Coefficients:	**Estimate**	**Std. Error**	**t value**	**Pr(>—t—)**
(Intercept)	18.79104	8.60949	2.183	0.02961 *
BatchSize	0.21489	0.14479	1.484	0.13851
lnCosts	-2.94379	1.02487	-2.872	0.00428 **
IfPresoecifiedVendor1	2.96770	5.45315	0.544	0.58658
costcenter	1.72412	8.36619	0.206	0.83683
lead	-0.14011	0.29915	-0.468	0.63976
lnreorderpoint	-12.74816	4.29866	-2.966	0.00319 **
AmountOfDemands	-0.05970	0.08047	-0.742	0.45859
IfBatching1	-5.25569	3.95352	-1.329	0.18444
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				

First, the multiple linear regression model shows the presence of a significant negative relation between costs and relative inventory deviations. This indicates that an increase in the cost of a NPG leads to a decrease of the relative inventory deviation. The decrease in the relative inventory deviation represents a deteriorating human impact on the spare parts management process. This contributes to the development of excessive spare parts inventories at VDL Nedcar.

Second, the multiple linear regression model shows the presence of a significant negative relation between reorder point and relative inventory deviation. This indicates that for a higher reorder point of VDL Nedcar, the human impact worsens. The worsening impact contributes to the development of excessive spare parts inventories at VDL Nedcar.

Conclusion and Recommendations

This exploratory research was conducted with the general objective of clarifying the impact of spare part attributes on human decision making to prevent excessive inventories in the future. The objective can be viewed from two different perspectives, a business perspective and a scientific perspective.

From a scientific perspective this research created a first insight into how behavioral operations management can be applied within a spare parts management setting. Relations between human impact on spare parts inventory control and spare part attributes have been identified creating an opening for future research:

- Broaden the explanatory variables with factors obtained from qualitative data, for example from interviews.
- Perform a field study so individual human decisions can be analyzed to confirm propositions.
- Implementing the methodology of this research at another company to compare the findings.

From a business perspective, this research created a better understanding of the human decision making process at VDL Nedcar which led to several recommendations to encounter the business problem that was identified at the beginning of this research

- Raising awareness of the presence of the found relations.
- Develop a method for inventory managers to practice so they can learn by doing.
- Provide training for the inventory managers to learn and test them on the content.
- Introduce a KPI that measures the pare parts management performance.

Preface

This research is executed to conclude the Master Operations, Management, and Logistics at the Technical University of Eindhoven. Over the past couple of years, I have gained a lot of knowledge and experience to come to this moment. However, it would not be possible to come this far without the support of the people surrounding me.

Firstly, I would like to thank my parents for their unconditional support throughout my whole academic career. Since primary school, they have been encouraging me to do my very best and get the most out of it. No matter what, I could always count on them being there for me.

Secondly, I would like to thank Philippe van de Calseyde. Thank you for the effort you put into the numerous brainstorm sessions we have had. Despite the research topic being somewhat out of your comfort zone, you provided me with valuable insights and positivity. Furthermore, I would like to thank my second supervisor Rob Basten who, despite his role as second supervisor, was very involved in the project.

Thirdly, I would like to thank my company supervisor Serge Hermans and all the other colleagues of the FAS maintenance department of VDL Nedcar. Besides providing me with information, you have made me feel welcome and given me a great time at VDL Nedcar.

Lastly, with the completion of this project, my time as a student comes to an end. In 2014 I moved to Eindhoven on my own to start this adventure and now in 2021 I am finishing it surrounded by an amazing group of friends. Thank you all for supporting me and giving me an amazing couple of years. In particular my roommates with whom I have spent much time during the corona lockdown. To conclude, I want to thank my girlfriend who has supported me during my semester abroad and listened to all my issues during this project.

Thank you all!

Luuk Jeurissen

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Chapter 1

Introduction

Nowadays, the trend among companies is to automate business processes as much as possible. Operating in a highly competitive and fastly automating market, this also applies to VDL Nedcar. However, this seems to be a tremendous challenge in the field of spare parts management for capital goods. These challenges are caused by several emerging trends of the last years. Systems are becoming larger and more complex, increasing the number of components. At the same time, these more advanced systems are more reliable. From a reliability perspective, this is favorable. However, from a spare parts management perspective, this complicates the process by causing a reduction in demand data. Statistical analysis become (almost) impossible because of this. These are merely some examples of reasons that can explain the complexity within spare parts management (Van Houtum and Kranenburg, 2015). Despite the increasing complexity of the scientific theories in this area and the continuous improvements of spare part algorithms, in practice human involvement seems indispensable (Sanders and Manrodt, 2003). Almost, if not all, companies need humans to take responsibility for the spare part process (Flemisch et al., 2012).

The field of behavioral operations management focuses on the creation of a better understanding of why and how individuals make decisions and how these decisions impact business processes (Loch and Wu, 2007). The vast majority of these studies are executed in supply chain related areas, e.g. forecasting (Donohue et al., 2018). However, (almost) no research is performed on behavioral operations management in spare parts management.

The aim of this research is to create a better understanding of how humans are influenced in their decision making concerning spare parts management and with it implementing behavioral operations management in a spare parts management area. Furthermore, the research is executed in collaboration with VDL Nedcar. VDL Nedcar wants to obtain a better understanding of the human impact on their spare parts management and with it the human behavior.

1.1 Company Description

VDL Nedcar is an independent car manufacturer, which is part of the VDL group since 2012. The company started in the ’60s with the production of DAF passenger cars and was called DAF car BV. In 1975, the company started producing Volvo cars. Subsequently, the name was changed to Volvo Car BV (in 1975 when Volvo obtained a majority interest). Later, the production had to be increased to ensure a profitable future. This led to a partnership with Mitsubishi Motors. This is when the name NedCar arose. Over time, the ownership of NedCar changed multiple times between different car brands e.g. Volvo, Mitsubishi, and DaimlerChrysler. The main competence of the company is the ability to produce different types of cars on the same production line. When the VDL Group bought NedCar from Mitsubishi in 2012 they changed the name to VDL Nedcar. After rebuilding the production lines, they started building the Mini commissioned for the BMW group. The company is divided into four departments;

- Press Shop: here the production process of the car starts with deep drawing, bending, and cutting processes to create the pressed parts.
- Body Shop: here 1,300 robots assemble various parts to create the unpainted body of the car.
- Paint Shop: here the body of the car is cleaned, degreased, and coated.
- Final Assembly: in this department the “cars” arrive as coated body shells and leave as personalized, tested, ready to sell cars.

The current research project took place in the final assembly department of VDL Nedcar. In this department, humans and robots work side by side to deliver high-quality products. This department has the largest human workforce of the four departments, due to the high variation in the production process. Furthermore, the spare parts stock of the final assembly makes up for approximately 16% of VDL Nedcar's spare parts stock (approximately 34 million Euro). As result, the maintenance department of the final assembly department is the most ideal place within VDL Nedcar to perform the research.

1.2 Problem Definition

In 2018 the vastly growing automotive industry stagnated. This stagnation turned out to be the start of a contraction of the market that caused worldwide car production to decline (Wagner, 2020). VDL Nedcar also became a victim of this and saw its production drop by approximately 18% from 2018 to 2019. Since the budget of VDL Nedcar is highly dependent on the production volume, significant savings are necessary. This also accounts for the maintenance department of which the size is also related to the production volume. By analyzing the maintenance department for possible cost reductions, it was concluded that the spare parts inventory is unnecessarily large. Therefore, a couple of projects were launched to reduce the excessive spare parts inventory. An example of such a project is the identification and elimination of dead stock. Dead stock is defined as inventory that has been unmoved for a long time due to a lack of demand. This is unfavorable to companies since this causes an unnecessary reduction in liquidity (Hakim et al., 2018). The vast majority of these projects is dealing with the reduction of the current surplus of spare parts. However, to avoid excess spare parts inventories in the future, measures must be taken. In order to determine which measures are necessary, it is crucial to obtain an understanding of how the excessive inventories are caused.

Almost, if not, all companies require humans to take responsibility for the spare parts process. This also applies to VDL Nedcar, where the spare parts inventory is mainly controlled by the inventory managers. However, humans can be influenced in various ways and thus can be compromised in their rational decision making (Donohue et al., 2018). Since VDL Nedcar has no insight in the decision making process of the inventory managers and these inventory managers play an important role in the spare parts process, it is reasonable to assume that the human involvement plays a significant part in the cause of excessive spare parts inventories. Therefore, identifying the human impact on spare parts management is important to avoid excessive spare parts inventories in the future. Furthermore, it is important to obtain a better understanding of how and why humans make the decisions that impact the spare parts inventories (positive and negative). This knowledge could be used in their advantage to avoid negative impacts (or stimulate positive impacts). The current research aims at identifying the human impact on spare parts inventory management to determine whether the decisions that caused the impact are influenced by spare part attributes. Spare part attributes are characteristics of individual spare parts, e.g. costs and leadtime (time it takes for a part to be delivered after the order is placed).

At VDL Nedcar inventory managers are actively involved in creating a judgmental forecast of products that are not related to production, known as NPG's. These judgmental forecasts are based on experience and knowledge of the inventory manager, suggestions of the planner and additional information provided by the supplier. Subsequently, the inventory managers use these forecasts to determine the inventory control parameters. These parameters are used within inventory models to make decisions (explained in more detail in Section 2.2). An example of such a parameter is the re-order point, which determines when a new order has to be generated (Syntetos et al., 2010). These inventory parameters are then used to control the inventory levels in accordance with the determined inventory policies. In case an engineer in operations notices a reoccurring shortage of a specific NPG, he reports this to the planner. This could result in a change of the suggested parameters, which can be seen in Figure 1.1.

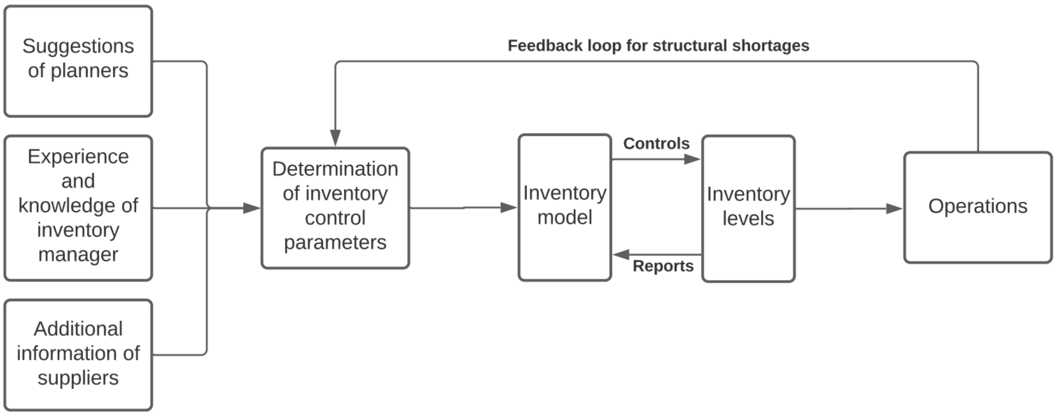

Figure 1.1: Overview process at Nedcar

Most companies have automated inventory models in place, which make decisions based on set parameters and a spare parts demand forecast. In the case of VDL Nedcar, this program is SAP. Besides the involvement in creating a spare parts demand forecast and setting the inventory parameters for SAP, inventory managers are necessary to make adjustments to the output of SAP. These adjustments are called judgmental adjustments and are based on past experiences. Furthermore, the inventory manager is able to take unique events into account while determining the necessity and magnitude of a judgmental adjustment (Goodwin, 2000). In the case of VDL Nedcar, the inventory manager is informed by the engineer or planner about upcoming unique events. Subsequently, the the inventory manager makes sure that the required actions are taken. This is an example of a manipulation of the SAP output by an inventory manager. So, VDL Nedcar has an inventory model that is influenced by human involvement by setting the model parameters and manipulating the output.

Above, the human influence on spare parts management is described and it is noted that inventory managers play a significant role in the spare parts process of VDL Nedcar. Despite this significant role, the knowledge about the impact of the human contribution is very limited to none. Furthermore, an understanding of how inventory managers are influenced by spare part attributes in their decision making is unknown. Without this knowledge, VDL Nedcar remains prone to the creation of excessive spare parts inventories in the future. For example, inventory managers could maintain too high inventory levels for spare parts with high leadtimes. This could indicate that inventory managers are negatively influenced by high leadtimes which causes excessive spare parts inventories. This leads to the following problem statement:

VDL Nedcar does not know which spare parts attributes influence the inventory managers that control the spare parts inventory model, and thus the influence of the spare part attributes on excessive inventories.

Obtaining knowledge of how inventory managers impact the spare parts inventory control and how they are influenced by spare part attributes, gives opportunities. Inventory managers can use this knowledge to their advantage in two ways. For spare part attributes that have a positive impact, inventory managers should be extra alert so that they do not miss their presence However, for characteristics that have a negative impact, the presence could evoke caution. Raising awareness among humans can lead to a decrease in inventory levels and with it tied up money.

1.3 Research Questions

As stated in the previous section, VDL Nedcar does not know which spare part attributes influence the inventory managers within spare parts inventory management. Consequently, the relations between the spare part attributes and the impact of the inventory managers is unknown. It is important for VDL Nedcar to obtain a better understanding of the human role within spare parts management to avoid excessive inventories in the future. Therefore, it is important to research the relations between spare part attributes that influence the inventory managers and the impact inventory managers have on spare parts management. This results in the following research question:

Which spare part attributes influence the inventory managers in controlling the spare parts inventories and how do these relations contribute to excessive inventories?

Three research questions are formulated to divide the research into manageable smaller parts. This aids in executing the research in a more structured and thorough manner. The answers of the three research questions serve as support to the main research question. RQ1 covers a relatively large part and is formulated as follows:

RQ1 *How to identify the impact inventory managers have on spare parts inventory management at VDL Nedcar?*

In order to analyze how inventory managers are influenced by spare part attributes, it is necessary to identify the contribution of the inventory managers on spare parts management. Therefore, the first research question is generated. This research question aims to isolate human behavior from the spare parts inventory model at VDL Nedcar.

RQ2 *How to identify relations between spare part attributes and the impact inventory managers have on the spare parts management process of VDL Nedcar?*

RQ3 *What is the exact relation between the relevant attributes and the inventory manager's impact on spare parts inventory management?*

The objective of RQ2 is to construct a method that investigates whether there are spare part attributes that influence human decisions concerning spare parts inventory management. An example of such decisions is the determination of the reorder point for a specific NPG. After constructing a method capable of identifying the attributes that influence the inventory managers, the exact relations between spare part attributes and the inventory manager's involvement can be determined by answering RQ3. An example of a finding could be: if an inventory manager notices a long leadtime for an NPG he sets a too high value for the reorder point (parameter).

1.4 Research Objective

The research objective can be separated into a business objective and scientific objective. This is done because there are two stakeholders to this project: VDL Nedcar and Technical University of Eindhoven (TU/e). The general objective is identifying the spare part attributes that influence the human decision making process within spare parts inventory control and clarifying the impact of these decisions on the excessive spare parts inventories.

1.4.1 Business Objective

The objective of VDL Nedcar is focused on real-life implications. It is key to obtain a better understanding of the impact of spare part attributes on the decisions of inventory managers concerning the control of the spare parts inventory. Once the attributes that influence the inventory managers in their decisions become clear, impacts on the inventory levels can be linked to the presence of these attributes. As mentioned in Section 1.3, the presence of high leadtimes could influence the inventory manager causing an excessive inventory level. This information can be used to raise awareness of certain influences among the inventory managers. Due to awareness, the employees can actively ignore attributes that have negative outcomes and actively seek and act on attributes that have a positive influence. This should ultimately result in a better understanding of how inventory managers are influenced and avoid excessive inventories in the future.

1.4.2 Scientific Objective

The academic purpose of the TU/e is more focused on the scientific part of the project. As mentioned before, there is (almost) none existing literature on the role humans play in spare parts management. However, literature in a closely related field to human decision making on spare parts management exists, namely behavioral operations management in production related inventory management. This research field focuses on creating a better understanding of why and how individuals make decisions and how these decisions impact inventory management for production goods. Similar to the observation in the problem definition of the current research, these studies observed that most inventory models are subjected to human influences. An interesting finding within the field of behavioral operations management for inventory management was made by Schweitzer and Cachon (2000). They found out that humans tend to order the mean demand instead of the "optimal" order quantity from the newsvendor model. The newsvendor model is a mathematical model within operations management that focuses on optimizing the inventory levels and is characterized by fixed prices and uncertainty (Arrow et al., 1951). By discovering this behavior Schweitzer and Cachon (2000) identified the "pull-to-center" effect, whereas the decision-maker tends to order an amount that is equal to the mean demand instead of the ''optimal" order quantity. This proves that human-decision makers exhibit irrational behavior in their decisions concerning inventory management under uncertain demand (Donohue et al., 2020). Subsequently, the observed effect is explained using behavioral operation theories such as cognitive biases and social preferences (more on this in Chapter 5).

The field of behavioral operations management for inventory management shows interesting results when looking at the human impact on business processes (Loch and Wu, 2007). However, there are no studies that focus on spare parts management within the field behavioral operations management. The field of inventory management for production goods and the field of spare parts management are quite similar. For example, both fields have the objective of minimizing costs while satisfying demand to a certain target. However, they also differ from one another in several perspectives. The main difference is the demand pattern which is more predictable for regular parts in comparison with spare parts.

Since the field of inventory management for regular items obtained interesting findings and the different research fields are quite similar, it could be interesting to research spare parts management from a behavioral operational management perspective. In case the research comes up with interesting findings, it could set a precedent for further research. So, the scientific objective of this study is to obtain interesting findings to encourage further research into the topic.

1.5 Scope

Within this research project, the decisions made by humans within spare parts management are analyzed. Since this process is quite large, the research is focusing on the decisions concerning the controlling of the spare parts inventories. As stated before, the decisions concerning the determination of the parameters and manipulation of the model output are made (mainly) by the inventory managers. The decision of limiting the research to this aspect of inventory management is to ensure feasibility of the project with respect to time constraints. Furthermore, it is not feasible to analyze all different sorts of spare parts inventories within the time constraint of this research. Therefore, the research project is performed using a subset of spare parts. This subset is logically created and only contains spare parts of which stock is held (NPGS). Furthermore, only spare part attributes that can be extracted from the ERP system are taken into account as factors that could influence the process. This excludes individual and subjective factors from consideration, e.g. mood and hunger. The decision of excluding these factors from the research was made because of the difference in the method of data gathering. The used spare part attributes are extracted directly from the Enterprise Resource Planning (ERP) system (SAP for VDL Nedcar), however, this is not possible for the individual and subjective factors. These factors would require extensive interviews and/or surveys, which compromises the feasibility of the project. This could be an interesting topic for future research.

1.6 Methodology

This section describes how the research project was conducted in order to answer the research question and satisfy the research objectives. As described in Section 1.4.2, the existing literature on the subject is virtually non existent. Therefore, it becomes complicated to develop expectations of relations between spare part attributes and the inventory manager's impact. The lack of existing literature and expectations makes it impossible to formulate well supported hypotheses. Therefore, the decision is made to perform an exploratory research to answer the research questions and satisfy the research objectives. This type of research is common for new research topics due to flexibility (Babbie, 2020). Furthermore, exploratory researches are often used to obtain new insights and provoking further research. This is in line with the scientific objective of the current research. Besides this, it also solves the problem of being unable to specify hypotheses since exploratory researches do not use these.

The execution of the research is divided into two phases. Phase one focuses on identifying the impact of inventory managers on spare parts management at VDL Nedcar. This will answer the first research question. The identified impacts are then listed with the corresponding spare part attributes from SAP. This will form the output of the first phase and immediately serves as input for the second phase. In the second phase the obtained list is analyzed to find answers to the second and third research question (explained in Section 1.3). Figure 1.2 provides a representation of the methodology including an indication of when the different research questions are going to be answered. Furthermore, the representation also provides a distinction between actions and deliverables.

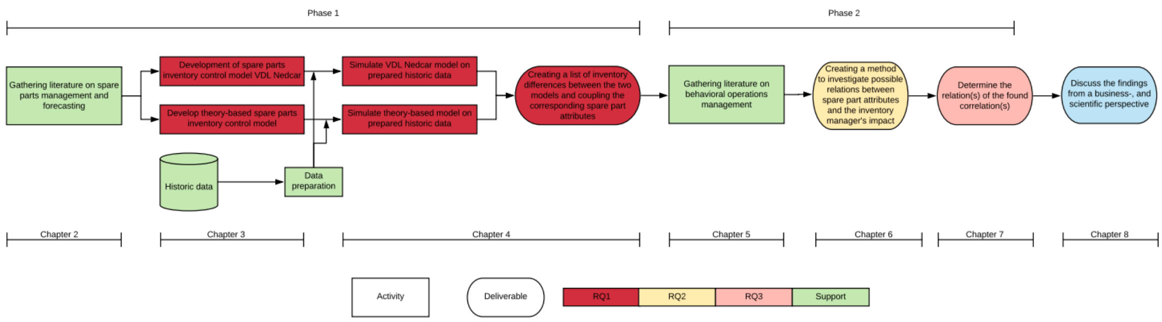

Figure 1.2: Methodology overview

1.6.1 Phase 1

The first phase focuses on identifying the impact of inventory managers on the spare parts management process of VDL Nedcar. As mentioned in Section 1.2, the inventory managers contribute to spare parts inventory control by determining the inventory parameters of the model and adjusting the output of the model (when deemed necessary). The impact of these human actions need to be isolated. In similar studies, this is done by logging the human actions and coupling them to the corresponding consequences. This is especially common within the field of behavioral operations management for forecasting processes. These type of studies often analyze the deviations from the forecasting algorithm caused by humans. This can be done by logging human adjustments and coupling them to the impact of the adjustment. However, within a spare parts management environment, this becomes more complicated. The impact of a human adjustment within forecasting is straightforward since the accuracy of the forecast can be assessed when the forecasted demand occurs. For spare parts management decisions this is more complex since it is impossible to assess whether decisions are correct. For example, the decision of stocking an expensive item with a leadtime of six months seems wrong if the decision is analyzed 2 years later and no demand has occurred. However, if one day later a breakdown occurs and the availability of that spare part avoids enormous downtime costs, the earlier deemed wrong decision seems good. Therefore, a different approach of identifying the human impact is necessary.

The identification of the inventory manager's impact in this research is also complicated due to the involvement in different parts of the spare parts management process. To cope with this complication, no distinction is made as to where humans have been involved in the process for certain impacts. All human impact on the inventory management for a NPG will be grouped as cause for a single impact. To identify the impact, two different models are generated. The first model, referred to as the VDL Nedcar model, represents the real situation at VDL Nedcar. This model consists of the spare parts inventory model currently used by VDL Nedcar complimented with the inventory manager's influence. The second model, referred to as the theory-based model, represents the situation at VDL Nedcar without the inventory manager's influence. This model replaces the human input by scientific theories that are applicable to VDL Nedcar. So, the difference between the two models is the human involvement. To make both models comparable, the theory-based model will be constrained. This constraint is going to assure that the theory-based model achieves the same level of performance as the model that displays the current situation of VDL Nedcar.

Phase 1 starts with collecting and preparing historic data, which will be used to run simulations of the different inventory models. The data will be extracted from the ERP system of VDL Nedcar: SAP. Before the extracted data can be used it has to be processed in a way that the data is meaningful for the research. For example, outliers within the extracted data have to be removed to obtain meaningful results in a later stage of the research project. Next, the average inventories of the two models will be compared to obtain deviations. These deviations represent the difference in inventories caused by the inventory managers. A higher average inventory level for the VDL Nedcar model indicates a surplus for the NPG since the same performance could be achieved with a lower average inventory level. So this would indicate a negative impact of the inventory manager's involvement. Conversely, a lower average inventory level of the VDL Nedcar model indicates a positive impact of the inventory manager's involvement. This approach enables the listing of all impacts caused by the inventory managers and answers the first research question.

1.6.2 Phase 2

Phase 2 starts with searching for relations between the spare part attributes that are available to the inventory managers and the deviations obtained in the first phase. More specific, a multiple linear regression model will be developed to investigate whether there are relations between the dependent and independent variables. The development of this model will answer the second research question. The relations indicate which spare part attributes influence the inventory managers in their decision making process. Next, the relations between the relevant attributes and the deviations of the first phase are researched to define the exact relation. These exact relations form the answer to the third research question.

Furthermore, the findings will be discussed from a business-, and scientific perspective in the last chapter. In the scientific implications, the obtained exact relations are coupled with behavioral operation theories to explain the found relations. The business implications discuss the managerial implications of the influenced inventory manager's decisions. This allows to connect the relevant attributes to a managerial impact and form recommendations to VDL Nedcar.

1.7 Thesis Outline

The research consists of two parts to find an answer to the research problem defined in this introduction. This first part is the subject of Chapter 2 till Chapter 4 and deals with the identification of the inventory manager's impact. Chapter 2 provides literature regarding spare parts inventory control and forecasting to support the decisions, assumptions, and conclusions for the next two Chapters. In Chapter 3, two conceptual models have been created: the VDL Nedcar model and the theory-based model. The literature from the previous chapter will be used as a basis for developing these models. The two conceptual models will then be used in Chapter 4 to identify the impact of the inventory managers in a case study at VDL Nedcar. This concludes the first part of the research. Subsequently, the identified impacts will be analyzed in the second part which is the subject of Chapter 5 till 8. Chapter 5 creates a base of literature that can be used to interpret and explain the relations that are displayed in Chapter 7. The methods for finding these relations are provided in Chapter 6. The research is concluded with a general discussion in Chapter 8 which addresses the implications, recommendations, and limitations of this research.

Part I

Identifying The Inventory Deviations

Chapter 2

Literature on Spare Parts Inventory Control and Forecasting

In this chapter, the relevant literature regarding spare parts management is provided. This is done to obtain a better understanding of spare parts management. Furthermore, the literature supports the decisions, assumptions and conclusions throughout the development of the two spare parts inventory models. The chapter covers literature on spare parts inventory control and forecasting that is directly applicable to VDL Nedcar.

Nowadays, companies are increasingly concerned with controlling their spare parts inventory to cut costs. However, this is a challenging task due to the intermittent and lumpy nature of the demand for these parts (Kourentzes, 2014). To tackle this challenge, companies and academics are developing all kinds of spare parts inventory models. These models have the goal to reduce inventory costs while maintaining a certain performance measurement target. The existing literature focuses on different aspects of inventory management; time bucket selection, demand forecasting models, lead time demand distribution, and inventory control models (do Rego and de Mesquita, 2015). In terms of time bucket selection, two approaches are considered; single demand approach (SDA) and period demand approach (PDA). The SDA considers individual order data in comparison to the traditional PDA which groups the order data into buckets of varying sizes (e.g. weekly, monthly, etc.). The demand buckets are used as input for forecasting models. These forecasting models, discussed in Section 2.1, create estimations for the parameters of the lead time distribution. In the case of individual order data, the lead time demand is modeled using a compound Poisson demand. The obtained lead time demand distributions are commonly used as input for inventory control models to make decisions (Willemain et al., 2004). Figure 2.1 gives an overview of how historic data is used to control the inventory of spare parts.

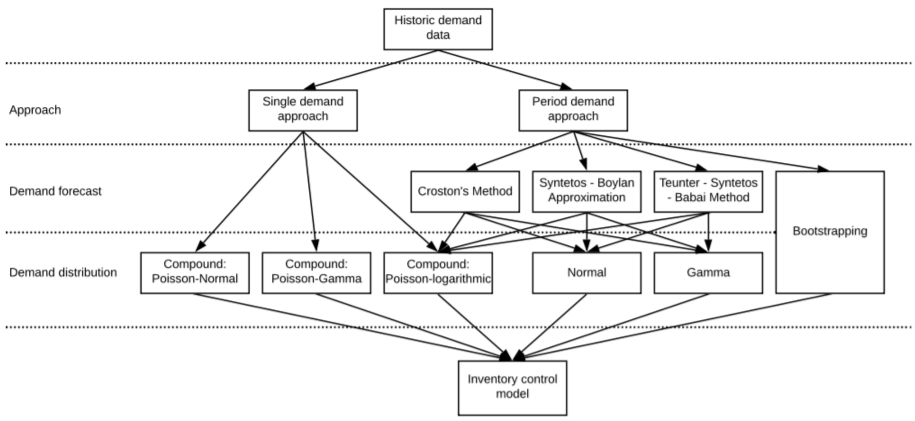

Figure 2.1: Spare parts management and forecasting overview

In the remainder of this chapter, the different aspects of spare parts inventory models are discussed that are applicable in the situation of VDL Nedcar. Furthermore, the lead time demand distribution and applicable forecasting methods are covered to create a deeper understanding in order to develop the theoretic model.

2.1 Spare Parts demand Forecasting

As mentioned before, spare parts demand has an intermittent and/or lumpy nature. Intermittent demand is highly infrequent and contains a lot of time periods without demand. Furthermore, if the intermittent demand is erratic, high variability of demand sizes, it is called lumpy (Turrini and Meissner, 2019). Due to the intermittent and/or lumpy demand, the results of standard forecasting methods become inaccurate (Van der Auweraer and Boute, 2019) (Kourentzes, 2014) (Mobarakeh et al., 2017). Therefore, new methods of forecasting were developed especially for intermittent and/or lumpy demand. According to the observed literature, these methods can be divided into two different types of methods; (1) parametric methods, (2) non-parametric methods.

Parametric forecasting methods estimate parameters e.g. the mean and variance to fit demand distributions (Boylan and Syntetos, 2010). These estimations are based on available data. Parametric methods are in comparison to non-parametric methods respectively simple, while still obtaining proper results (Syntetos et al., 2015). However, parametric methods have the disadvantage of being based on assumptions, which results in a bias if the assumptions do not hold (Zhu et al., 2017). Since the emphasis of this research is not on forecasting demand there is chosen to limit the literature to parametric methods.

According to Kourentzes (2014), the first systematic approach that addresses the intermittent demand of spare parts was developed by Croston (1972). Croston noted that the forecasts for intermittent demand performed with Single Exponential Smoothing (SES) (Brown and Meyer, 1961) overestimated the actual demand. This overestimation resulted in a lower degree of forecasting accuracy. Croston's method separates the data into two different series. This is done to make separate estimations of; (1) the probability of occurrence and (2) the size of the demand. These estimations are performed by separate SES, with smoothing parameter α. By doing this a more useful and flexible forecasting method is obtained (Croston, 1972). Croston's method assumed that both the spare parts demand (y_t) and the interdemand interval are stationary (Hellingrath and Cordes, 2013). The non-zero demand follows a Bernoulli distribution resulting in an independent and identically distributed geometric for the interdemand interval. Furthermore, Croston assumed that the size of the demand is independently identically distributed. Let p''_t be Croston's estimate of the mean interval between nonzero demands, and z''_t be Croston's estimate of the mean size of a nonzero demand. This gives

$$\text{if } y_t = 0, \text{ then,}$$
$$\begin{aligned} z''_t &= z''_{t-1} \\ p''_t &= p''_{t-1} \\ q &= q+1 \end{aligned}$$

$$\text{else,}$$

$$\begin{aligned} z''_t &= z''_{t-1} + \alpha\left(y_t - z''_{t-1}\right) \\ p''_t &= p''_{t-1} + \alpha\left(q - p''_{t-1}\right) \\ q &= 1 \end{aligned}$$

with q representing the number of periods since a demand occurred. After calculating the separate estimations of the average demand size and average interdemand interval, the estimation of the mean demand per period (y''_t) can be calculated with the following equation.

$$y''_t = \frac{z''_t}{p''_t}$$

According to Willemain et al. (1994), the superiority of Croston's method is proven, if the simplifying assumptions hold. To evaluate if the method performs better in accuracy in comparison to the traditional SES method, Willemain et al. (1994) performed a Monte Carlo comparison with artificial data and a comparison using real industrial data of four companies was performed. This is done to evaluate the performance of Croston's method in practice because this adds complexity and (possibly) violates assumptions. Both comparisons showed that Croston's method was superior in terms of accuracy in comparison with the SES method. Furthermore, Croston's method has a low computational overhead making it more applicable.

Syntetos and Boylan (2001) showed a bias in Croston's method, a tendency to overestimate demand. Croston's method claims that the estimated demand size and the estimated interdemand interval are independent. If this claim is true the following equation should hold.

$$E\left(\frac{z_t''}{p_t''}\right) = E\left(z_t''\right) * E\left(\frac{1}{p_t''}\right)$$

But converting this results in the following inequality, proving a bias within Croston's method.

$$E\left(\frac{1}{p_t''}\right) \neq \frac{1}{E\left(p_t''\right)}$$

After discovering the bias in Croston's method, they started researching the cause to eventually develop an improvement. It was found that the error was dependent of the smoothing value (α). Syntetos and Boylan (2005) showed that the bias can be approximated for all values of α with the following equation.

$$\text{Bias approximation } = \frac{\alpha}{2-\alpha} * \mu * \frac{(p-1)}{p^2}$$

With p being the average number of periods between consecutive demands. Incorporating the approximation into the existing Croston's method led to a new forecasting method, the Syntetos - Boylan Approximation (SBA) (Syntetos and Boylan, 2005). This resulted in the following new equation for $y_t^{''}$.

$$y_t'' = \left(1 - \frac{\alpha}{2}\right) * \frac{z_t''}{p_t''}$$

According to Xu et al. (2012) is SBA superior to Croston's method. This was tested using a simulation experiment with 3,000 real intermittent demand data series.

2.2 Spare Parts Inventory Models

Spare parts inventory models are developed to optimize stock levels, in order to reduce inventory costs while maintaining a predetermined performance measurement target. This is a difficult trade-off because lowering stock levels reduces inventory costs, but could lead to unplanned downtime due to a lack of required spare parts. Unplanned downtime often leads to high costs and sometimes to a shortfall in production (Van Houtum and Kranenburg, 2015). Spare parts inventory models have two approaches of controlling the inventory: the item approach and the system approach. The item approach optimizes individual spare part inventories in order to reach a certain performance target while complying with decomposed constraints. The system approach does not look at individual inventories but optimizes the spare parts inventory to reach a system performance objective. According to (Sherbrooke, 2006), the system approach (also referred to as the multi-item approach) is able to maintain high inventories for cheap parts and low inventories for expensive parts. This can lead to lower costs (50% lower) while obtaining the same performance as the item approach. At VDL Nedcar the inventory is controlled per item, therefore an item approach would be more applicable, moreover in Section 3.3.2.

Furthermore, a spare parts network generally can exist out of an install base, central warehouse(s), and local warehouse(s). The install base is the technical system that is in use, i.e. in the case of VDL Nedcar the machines that are used for production. In general, the immediate spare parts demand of the install base is satisfied by a specified local warehouse and the local warehouses are supplied by the central warehouse. If the demand for an install base cannot be satisfied by the stock of the specified local warehouse, the demand surplus could be satisfied by another local warehouse (this is called a lateral transshipment). In case a lateral transshipment is impossible or not allowed, the responsible local warehouse can either wait until the required spare part becomes available again (backorder) or request an emergency shipment from the central warehouse. The central warehouse holds the inventory for all the local warehouses and is supplied by external suppliers. In Figure 3 a clear overview of a general spare parts network is displayed.

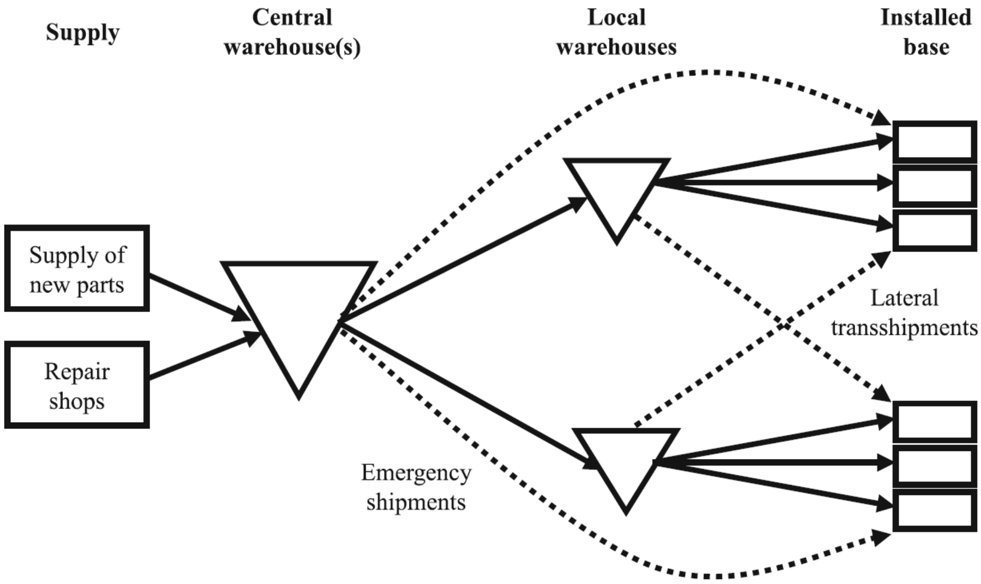

Figure 2.2: Overview of spare parts network (Van Houtum and Kranenburg, 2015)

However, the spare parts network of VDL Nedcar exists of a single local warehouse, from where the installed base is supplied. This local warehouse is supplied by external suppliers. Consequently, lateral transshipments are not possible. However, it is possible to order emergency shipments at the external supplier. Since the objective of this chapter is to obtain a more in depth understanding of inventory management applicable to VDL Nedcar, the remainder of the chapter is going to be restricted to single-item, single location inventory models.

Spare parts can be categorized into two groups; critical and non-critical parts. By definition, critical parts are essential to the working of the machine i.e. if a critical part breaks down the machine is unable to function normally. The models discussed in this literature study are meant for critical spare parts. Thus, only critical spare parts are discussed in the remainder of the research. Non-critical spare parts have no urgency, therefore, they can be planned with regular inventory methods (Van Houtum and Kranenburg, 2015).

As mentioned before, the objective is to minimize the inventory costs while maintaining a certain fill rate (or another performance measurement). Costs that are important to take into account are; costs of spare parts, downtime costs, and holding costs. Minimizing the costs of spare parts is a difficult trade-off for a lot of companies. Lowering the spare parts inventory saves initial investments and holding costs, but leads to a greater chance of downtime. This could affect the output of the company resulting in a direct loss of revenue and indirectly lead to a loss of reputation. Therefore, companies create high spare parts inventories to prevent this (Van Houtum and Kranenburg, 2015). To find a balance in this trade-off, most companies determine a performance objective that has to be met. This way the possibility of cutting costs is limited because a certain performance objective has to be met. The performance of the model can be measured in different ways. A common method is measuring the amount of demand that can be satisfied from stock immediately, this is called the fill rate. Alternative methods are measuring the machine availability and measuring the aggregate mean waiting time until demand is satisfied.

Furthermore, obsolescence complicates the spare parts inventory process even more. Due to the complexity of (some) spare parts and the possible low demand, spare parts could become obsolete (Hasni et al., 2019).

Spare parts inventory models use replenishment policies to determine the moment and size of an order. The existing literature shows six main spare parts inventory policies (Miranda et al., 2014). Within these six different policies a clear differentiation can be made between: discrete review (periodic review) and continuous review.

The first type of model are periodic review models. These models use a review period (R) which is the time between two consecutive moments on which the inventory level is checked (Silver et al., 1998). These models check the inventory levels once in each review period and determine at that time whether a replenishment is necessary. This means that these models only order once each period, e.g. once every two weeks. Below are the three most commonly used periodic review models in a spare parts environment displayed, containing the replenishment logic behind them (Miranda et al., 2014).

- (R, s, nQ) model contains a re-order point (s) and a fixed order quantity (Q). This model orders n times a fixed amount Q if the inventory level is below s at the moment of the periodic review.
- (R, S) model only contains an order-up-to level (S). This model orders if the inventory level is below S at the moment of a periodic review. The amount that is ordered is equal to the amount the inventory level is below S.
- (R, s, S) model is a combination of the two models above and uses both a re-order point and an order-up-to level. The decision of a replenishment order is made if the inventory level is below s at the moment of the periodic review and the order amount is equal to the amount the inventory level is below S.

The second type of models are continuous review models. These models monitor the inventory continuously, resulting in a review period of zero (Van Donselaar and Broekmeulen, 2014). This means that at every moment in time the inventory level is known and thus replenishment decisions can be made instantly. Below the three most commonly used continuous review models in a spare parts environment are displayed, containing the replenishment logic behind them (Miranda et al., 2014).

- (s, Q) model contains a fixed re-order point and a fixed order quantity. So at every moment in time the inventory level drops below s an order of the amount Q is placed.
- (s, S) model contains a re-order point and an order-up-to level. So at every moment in time the inventory level drops below s an order is placed. The order amount equals the difference between S and the inventory level at the moment of ordering.
- $(S - 1, S)$ model is a special type of (s, S) model called a one-for-one replenishment model. This is because every time the inventory lowers, a replenishment order is placed.

Chapter 3

Model Development

In this chapter, a method is designed to identify the human impact on spare parts management. With the development of this method, the first research question is immediately answered. During this chapter the design of the two conceptual models that are used in the identifying method are discussed. In this discussion the model goal, assumptions, and description are reported for the two spare parts inventory models. Furthermore, the simulation method for the two models is provided. These models are developed to enable the isolation of the human impact on inventory management (see Section 1.6).

3.1 General Model Assumptions

To realize models that represent the reality of VDL Nedcar as well as possible, a few assumptions have to be made. This is necessary to create models with regard to their respective model goals (see Sections 3.2.1 and 3.3.1), while managing an imperfect practical situation.

- The SAP data that is selected to use is assumed to be true and accurate. This assumption may not always hold in practice, but a thorough evaluation, selection, and cleaning process makes this a credible assumption (described in Section 4.1.3).
- All NPG's on stock are assumed to be new and without depreciation.
- VDL Nedcar has no Key Performance Indicator (KPI) that assesses the availability of spare parts when needed. Therefore, the average achieved uptime percentage of the production line is assumed as the performance objective.
- Products are non-perishable.
- Leadtimes are assumed to be deterministic and known. In practice, this assumption will not always be correct as multiple factors could cause variability in the leadtime. However, due to modeling purposes, it is assumed that the leadtime is deterministic (Van Houtum and Kranenburg, 2015).
- It is assumed that in case of a stock out, the shortage is backordered. However, within the field of spare parts management, it is common to use lateral transshipments and/or emergency shipments instead of backorders since this prevents long downtimes (as explained in Section 2.2). The spare parts network of VDL Nedcar consists of a single central warehouse, making lateral transhipments not applicable. VDL Nedcar does make use of emergency shipments, however, this is excluded from the model due to lack of necessary information (emergency leadtimes and costs) and model complexity.
- The demand rate is not sensitive to downtimes of machines because the time of machines being down is extremely small (by either short downtimes or rare occurrence).
- All NPG's are assumed to be critical since VDL Nedcar does not hold inventories for non-critical NPG's.
- The demand is assumed to follow a Poisson distribution, more on this in Section 3.3.2.

3.2 VDL Nedcar Model

3.2.1 Model Goal

The goal of this research is to identify whether specific spare part attributes have an impact on the way humans control the spare parts inventory. In order to examine this, the impact of humans on spare parts inventory control needs to be determined. This first model aims to represent the situation of VDL Nedcar. A key aspect is representing the human role within this process. At VDL Nedcar the vast majority of the decisions concerning inventory management are made by humans. Therefore, it can be assumed that the inventory level over time is determined by human decisions. Thus creating a model that mimics the inventory management at VDL Nedcar results in an inventory overview that represents a bundle of human decisions.

3.2.2 Model Description

The VDL Nedcar model calculates the actual inventory levels for all spare parts over time. Therefore, the order and demand data of the included NPG's are necessary. The set of NPG's is denoted by I and the number of NPG's is denoted by $|I|(\in \mathbb{N} := \{1, 2, \ldots\})$. Demand occurs when a part fails and needs to be replaced. The replacement part is obtained from the warehouse and the replaced part is either scrapped or repaired. The time of a repair or delivery of NPG $i \in I$ is the leadtime (L_i) and is assumed to be constant and known. At VDL Nedcar an (R,s,nQ) replenishment strategy is implemented, therefore, the inventory over time of NPG $i \in I$ can be generated using the inventory control parameters: reorder point (s_i), leadtime (L_i), and lot size (Q_i).

The remainder of this subsection is written according to the information of Van Donselaar and Broekmeulen (2014). The inventory on hand (OH_i) is the number of spare parts that are physically on stock. OH_i can be calculated using Equation 3.1. In this equation IP_i is the inventory position, which represents the sum of all inventories minus possible backorders (BO_i). To determine the order moments and quantities the inventory position is used instead of the inventory on hand. The inventory position is better suited because it takes unreceived orders into account. To determine the inventory on hand after a potential delivery ($\tau + L_i$) at a random moment in time (τ), the inventory position at τ and the demand (D_i) of the interval ($\tau, \tau + L_i$) is needed. By taking the inventory position at τ into account, all outstanding orders at τ will be included. Since it is logically impossible to have a negative inventory on hand, the $max(0, x)$ function is included in Equation 3.1.

$$OH_i(\tau + L) = \max(IP_i(\tau) - D_i(\tau, \tau + L_i), 0) = (IP_i(\tau) - D_i(\tau, \tau + L_i))^+ \tag{3.1}$$

If the demand in ($\tau, \tau + L_i$) exceeds the inventory position at (τ), backorders (BO_i) occur. The amount of backorders at ($\tau + L_i$) can be determined with Equation 3.2.

$$BO_i(\tau + L_i) = \max(D_i(\tau, \tau + L_i) - IP_i(\tau), 0) = (D_i(\tau, \tau + L_i) - IP_i(\tau))^+ \tag{3.2}$$

The sequence of events happening in a period (from review moment to review moment) are as follows: Demands come in during the day and seven days per week, while deliveries are received at the end of the day and only on weekdays. Furthermore, the review moment takes place at the end of every day, so after the occurrence of possible demands and/or deliveries. The inventory on hand and inventory position is measured when a review moment takes place together with all subsequent actions (e.g. placing an order).

Since the model will be compared to another model based on inventory on hand, it is important to have a certain performance measurement. This is necessary to ensure a meaningful and fair comparison. As mentioned in section 2.2, measuring a fill rate is a common performance measurement method for spare parts (Van Donselaar and Broekmeulen, 2014). Furthermore, VDL Nedcar has no implemented performance measurement method leaving this design decision open for interpretation. Since the performance measurement method must be the same for the theory-based model and the VDL Nedcar model, the decision is based on which method is preferred for designing the theory-based model. The reorder point of the theory-based model is not predetermined by VDL Nedcar but has to be computed. The fill rate is often useful to set reorder points. Therefore, the aggregate fill rate is used as performance measurement for both models. The fill rate is obtained by computing the fraction of demand that can be satisfied immediately from stock.

3.3 Theory-Based Model

3.3.1 Model Goal

In Section 3.2 a model is created to represent a humanly controlled spare parts inventory. However, to identify the human impact, a benchmark model that imitates the situation at VDL Nedcar excluding human involvement is necessary. This benchmark model (hereafter referred to as theory-based model) will control the spare parts inventory according to the literature discussed in Chapter 2. The theory-based model is designed to represent the situation at VDL Nedcar with the exception of human influence. The decisions made by the model are strictly based on the existing spare parts inventory theory.

3.3.2 Model Description

The objective of the theory-based inventory model is to function as a benchmark for the situation at VDL Nedcar. Therefore the theoretic model should be comparable with the situation at VDL Nedcar in terms of design. The design aspects concerning a spare parts inventory model are discussed in Section 2.2. At VDL Nedcar the installed base is supplied with NPG's from a single central warehouse. This central warehouse is supplied by several external suppliers. The set of NPG's is denoted by I and the number of NPG's is denoted by $|I|(\in \mathbb{N} := \{1, 2, \ldots\})$. Demand occurs when a part fails and needs to be replaced. The replacement part is obtained from the central warehouse and the replaced part is either scrapped or repaired. The time of a repair or delivery of a new part is the leadtime (L_i) and is assumed to be constant and known. In case of a shortage at the central warehouse, a backorder is placed for the required NPG. For these occasions, some of the external suppliers offer emergency shipments. However, due to a lack of insight into emergency costs and leadtimes, it has been decided to exclude the emergency shipment option from the theory-based model. In case the inventory position drops to or below the reorder point, a regular demand is generated. Batching is applied to NPG's where the external supplier predetermined a batch size. Furthermore, despite that VDL Nedcar has to cope with obsolescence of NPG's, the model does not take obsolescence into account. Obsolescence enhances the complexity of the model beyond the scope of this research project, making it a possibility for future research.

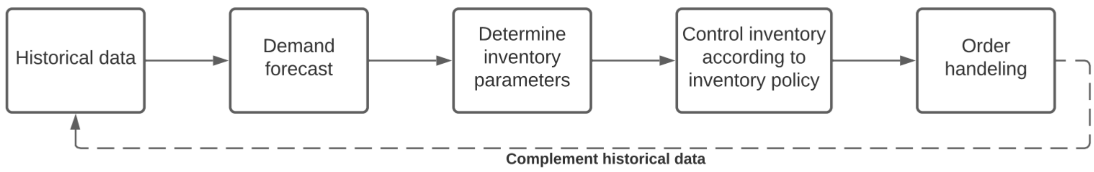

Figure 3.1: General process overview theory-based model

Figure 3.1 provides a general overview of the processes of the theory-based model. The model starts with generating a forecast based on the available historical data. The goal is to generate demand distribution parameters for each NPG $i \in I$. These parameters can then be used to determine the reorder points. As mentioned before, the batch sizes and leadtimes are known. Together with the reorder points they form the inventory control parameters. These are then computed in the inventory policy to maintain a sufficient inventory.

The forecasting process starts with implementing a time bucket selection approach (described in Section 2.2). This model uses the traditional PDA which groups the demand data into time buckets of size L_i days. Since the leadtime demand is useful for determining the reorder point, this time bucket has been chosen. Once the demand data is grouped into buckets, it can be used as input for the forecasting model. This forecasting model will be used to obtain parameters of the demand distribution. Due to the intermittent nature of the spare parts demand, it is recommended in literature to use Crostons's method to estimate the distribution parameters (as explained in Section 2.1). The literature on Croston's method confirmed the decision for the PDA approach to cope with the zero-demand periods. These parameters can then be used to model the Poisson distribution of the demand. In the case of spare parts demand it is common to use a Poisson distribution. Figure 3.2, gives an overview of the forecasting process.

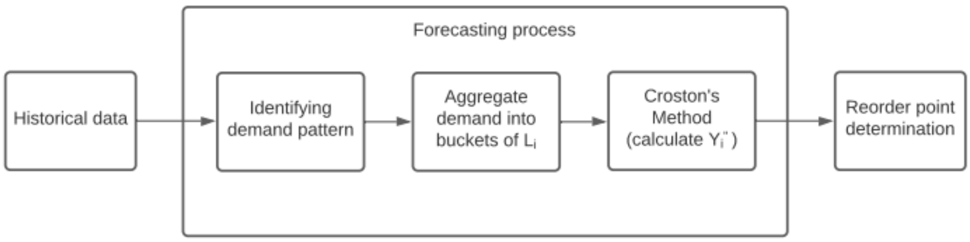

Figure 3.2: Forecasting process of theory-based model

Figure 3.3 shows that once the distribution parameters are obtained, the item approach is implemented to achieve the general objective of most inventory models: minimizing the inventory costs while adhering to a certain performance measurement. This results in the following problem (P):

$$\begin{array}{ll} \min & C(s, Q) \\ \text{subject to} & \beta(s, Q) \geq \beta^{obj}, \end{array}$$

In this model the aggregate fill rate is used to measure the performance. The aggregate fill rate represents the percentage of demand that immediately can be satisfied from stock for all NPG's $i \in I$ together and can be calculated with Equation 3.4. M represents the total demand rate (Equation 3.3) and $\beta_i(s_i, Q_i)$ the item fill rate.

$$M = \sum_{i \in I} m_i \tag{3.3}$$

$$\beta(s, Q) = \sum_{i \in I} \frac{m_i}{M} \beta_i\left(s_i, Q_i\right) \tag{3.4}$$

In order to fulfill a demand immediately, the on hand inventory has to be positive. Therefore, the probability of having a positive on hand inventory (P$\{OH_i > 0\}$) has to be determined. This probability is equal to the probability of having an inventory position smaller than the minimum stock level for each possible value of the inventory position. An equation for the item fill rate can be obtained from Van Houtum and Kranenburg (2015), however, this formula does not take batching into account. Transforming the range from $x = 0, .., s_i - 1$ to $x = 0, .., s_i - 1 + u_i$ and introducing the discrete uniform distributed random variable U_i with range $U_i = 1, .., Q_i$ makes the equation applicable for batching. This gives:

$$\beta_i\left(s_i, Q_i\right) = \sum_{u=1}^{Q_i} \sum_{y=0}^{s_i - 1 + u} P\left\{Y_i = y\right\} P\left\{U_i = u\right\} \tag{3.5}$$

Since U_i is uniformly distributed, the equation can be abbreviated to:

$$\beta_i\left(s_i, Q_i\right)=\frac{1}{Q_i} \sum_{u=1}^{Q_i} \sum_{x=0}^{s_i-1+u} P\left\{Y_i=y\right\} \tag{3.6}$$

In Section 2.2 two different approaches of controlling the spare parts inventory were discussed: the item approach and the system approach. Despite obtaining lower costs with similar performance for the system approach, this model uses the item approach. This decision is made because the item approach is a better representation of the current situation at VDL Nedcar. At VDL Nedcar the inventory managers monitor and control the inventories for individual NPG's. So, the item approach is implemented to find a solution for problem P. This heuristic makes locally optimal decisions at each stage to satisfy the fill rate objective for each individual NPG. The model starts with a set of efficient solutions, $s_i = 0$ for all NPG's. This solution achieves the lowest possible costs, namely $C(s_i) = 0$. However, this solution does not comply with the restriction of achieving a set target fill rate β^{obj}. For the item approach the target fill rate requires to be decoupled to specific target fill rates for each NPG $i \in I$ (β_i^{obj}). When using the fill rate as performance measurement, the decoupled target fill rates β_i^{obj} are equal to β^{obj}.

The item approach continues to increase the reorder point until $\beta_i(s_i, Q_i) > \beta_i^{\text{obj}}$. Once this happens the reorder point that obtains the lowest costs while achieving β_i^{obj} is selected as the reorder point for NPG i. In the final sub-process of the reorder determination process are the newly obtained reorder points communicated to the inventory control process so that they can be used from that moment on.

The equations concerning the fill rate and aggregate fill rate assume continuous review. This is in contrast to the rest of the model which assumes a periodic review (R=1). However, due to the relatively low value of the review period in contrast to the leadtimes, the continuous equations are allowed in the model (Axsäter, 2015). When implementing the conceptual model, this needs to be confirmed with a sensitivity analysis. In the sensitivity analysis the leadtime will be increased with the review period to assess the impact on the model performance.

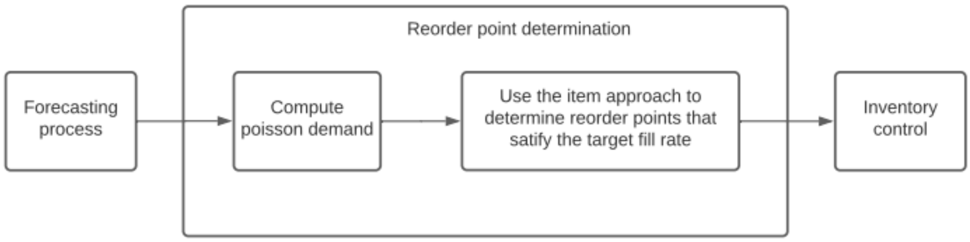

Figure 3.3: Order process of theory-based model

The inventory control process of the theory-based model monitors and manages the spare parts inventory. This is done according to an (R, s, nQ) replenishment policy. The model monitors the inventory position at the end of every day to determine whether an order is required. An order is deemed necessary if the inventory position drops to or below the reorder point. The inventory position is best suited for this because it takes the pipeline stock into account (Van Donselaar and Broekmeulen, 2014). A demand is fulfilled immediately if the inventory on hand is sufficient. In case of an insufficient inventory on hand, a backorder for the shortage is placed immediately. This entire process is visualized in Figure 3.4.

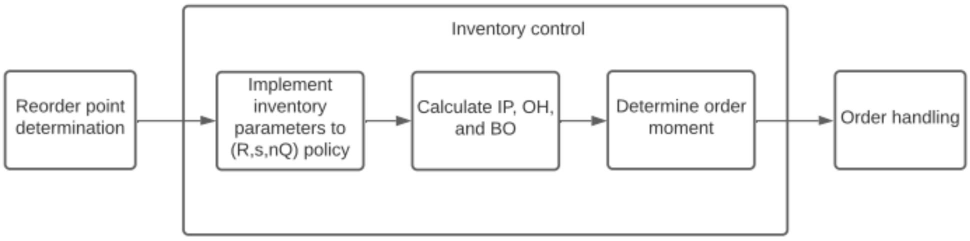

Figure 3.4: Inventory control process of theory-based model

The basic inventory model of Van Houtum and Kranenburg (2015) follows a basestock (S_i) policy with one-for-one replenishment. The basestock is the amount of inventory that is held as on hand inventory to fulfill demand and is regarded as a decision variable. Since the model adheres to a one-for-one replenishment and is monitored continuously, a single item is ordered when the inventory drops below the basestock. For the basestock policy it holds that:

$$OH_i(t) = (S_i - X_i(t))^+ \tag{3.7}$$

$$BO_i(t) = (X_i(t) - S_i)^+ \tag{3.8}$$

Combining Equation 3.7 and 3.8, results in the stock balance Equation of Sherbrooke (2006).

$$OH_i(t) - BO_i(t) = S_i - X_i(t) \tag{3.9}$$

However, to adhere to the model goal, the theory-based model follows an (R,s,nQ) instead of a basestock policy. Therefore, the model has to take batching into account. Furthermore, the model is not monitored continuously, since it is not realistic to assume that an inventory manager monitors continuously. So, the model contains a review period, which is set to one day (as mentioned in Section 3.1). The implementation of the (R,s,nQ) policy changes the range of values the inventory position can take. According to Axsäter (2015), the inventory position at an arbitrary point in time is distributed over $s_i + 1, s_i + 2, ..., s_i + Q_i$ when the time is deterministic and batching is applied. As mentioned in Section 3.1, the demand during the leadtime plus review time is assumed to be Poisson distributed with the demand rate over $L_i + R$ as mean. Therefore, it holds that:

$$OH_i(t) - BO_i(t) = s_i - U_i - X_i \tag{3.10}$$

U_i is a deterministic uniformly distributed random variable over a range from 1 till Q_i. Using Equation 3.10 the steady state equation for the on hand stock and backorder can be derived.

$$OH_i = (s_i + U_i - X_i)^+ \tag{3.11}$$

$$BO_i = (X_i - (s_i + U_i))^+ \tag{3.12}$$

For a batch size of one, the model policy is equal to the basestock policy. Since $S_i = s_i + 1$ is obtained if $Q_i = 1$.

When the inventory position drops to or below the current reorder point in the warehouse process, the order process is activated. The first step in this process is determining the amount that is needed. This amount can be determined with the inventory position and the applicable reorder point.

$$Q_i(t) = \text{Max}\,(1, (R_i(t) - IP_i(t)) \tag{3.13}$$

If the amount is determined, it has to be checked whether the amount is a multiple of the batch size. When this is the case, the specified quantity can be ordered. However, if the required amount is not a multiple of the batch size, it is rounded up to the closest multiple of the batch size before ordering. For example, if the required amount is three and there is a batch size of two, an order of four will be generated. This process is visualized in Figure 3.5.

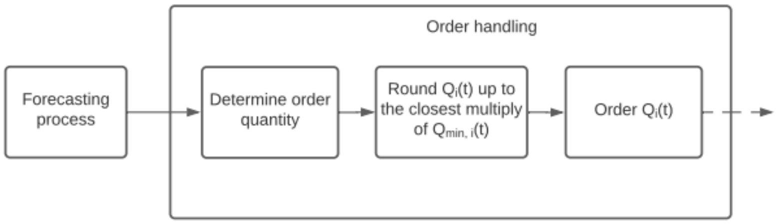

Figure 3.5: Order handling process of theory-based model

To conclude the model description, a clear overview of all model design decisions is provided in table 3.1

Design parameters	**VDL Nedcar**	**Theoretic model design decisions**
Inventory controlling approach	Inventory managers monitor and control NPG's individualistic	Item approach
Performance measurement	Machine availability instead of availability of spare parts. So no clear measurement of inventory control performance	Fill rate
Spare parts network	Central warehouse and install base	Single-location
Criticality	VDL Nedcar only keeps stock of critical spare parts, so it can be concluded that all spare parts of which they keep stock are critical	Strictly critical parts
Obsolescence	Applicable	Not included
Replenishment Policy	The inventory is periodically (daily) reviewed, with the use of a reorder point. With ordering they have to adhere to batching for some NPG's predetermined by the supplier	(R,s,nQ) model

Table 3.1: Theory-based model decisions

3.4 Simulation

To obtain an overview of the inventory on hand of both models, two separate deterministic simulations are created. These types of simulations are used to capture natural processes or underlying mechanisms and report to management. This makes a deterministic simulation suited for the model goals (see Sections 3.2.1 and 3.3.1). Furthermore, deterministic simulations are not subjected to randomness due to the usage of known input. This enables deterministic simulations to create a more accurate representation of a process, the inventory control process of VDL Nedcar with and without human involvement, in this case. The simulation output will be the inventory on hand for every t on the timeline. This can be used to calculate an average on hand inventory, which is the model goal.

Chapter 4

Case Study at VDL Nedcar

In this chapter the VDL Nedcar model and theory-based model are used to identify the impact of inventory managers in a case study at VDL Nedcar. Before being able to obtain results from the models, a selection of the gathered data is made and the obtained selection is cleaned. Next, the implementation of both models is discussed. In this discussion the occurred challenges and corresponding solutions of the implementation are covered. Thereafter, the models are validated to ensure meaningful results. Lastly, the model results are presented and the output of the first research phase is constructed and discussed. This will conclude the first part of this research as described in section1.6.

4.1 Data

4.1.1 Initial dataset

The objective of the first part of this research is to map the deviations in spare parts inventory of VDL Nedcar with a benchmark of the past five and a half years. Furthermore, it is also needed to connect relevant spare part attributes to these deviations. To achieve this, historic data is necessary. The dataset which is gathered from the ERP system of VDL Nedcar, SAP Enterprise, contains all movements of all spare parts within the final assembly department. The dataset contains 557,646 lines, all representing a single inbound or outbound movement. Besides the spare part unique NPG number, each line exists of eight variables which are introduced in Section 6.1. Furthermore, all changes that have been made to the leadtime, reorder point, lot size and Material Status (MS) are extracted. This is important for both the inventory parameters (batch size, leadtime, and reorder point) and the spare parts attributes since changes could have far reaching implications. For example, an increase in reorder point should be taken into account otherwise the VDL Nedcar model will generate different inventory levels than the actual situation.

4.1.2 Data Selection

To ensure that the research remains tangible, the decision is made to create a subset of the data presented in section 4.1.1. This subset consists of all spare parts that are assigned to three different sub-lines. This ensures that people have more affinity with the research causing greater support throughout the organisation. The subset consists of the following sub-lines:

- Front suspension, on this line the front suspension of the car is assembled
- Rear suspension, on this line the rear suspension of the car is assembled
- Marriage, on this line the undercarriage is joined to the body

The decision for these specific sub-lines are based on their building year. All three lines were built in 2015, making them relatively new. Due to their newness, the employees were more familiar with the SAP system when the introduction of the spare parts took place. This resulted in a more thorough and complete registration of the new spare parts leading to qualitatively better and complete data. Looking at the data of spare parts that were introduced earlier, we notice that multiple fields, e.g. lot size, costs, etc were filled blank or incorrectly. The decision of focussing on the relatively new sub-lines reduced the time window in which the inventory movements took place to approximately five and a half years (from 5-1-2015 till 28-9-2020). This is a significant reduction of the time window in comparison with the total dataset that contained all inventory movements from 4-1-2013 till 28-9-2020. This reduction is also observed in the amount of movements and unique NPG's, respectively from 557,646 to 7,203 and 46,575 to 909. In table 4.1 the impact of choosing for a subset is visualized for all data.

Data	Entire dataset	Subset
Inventory movements	557646	7203
NPG's	46575	909
Variables	20	20
Changes in lead time	7340	39
Changes in lot size	10793	42
Changes in NPG status	25533	91
Time window	4-1-2013 till 28-9-2020	5-1-2015 till 28-9-2020

Table 4.1: Changes in the size of the data through selection

The reduction in amount of changes seems tremendous, but this gives a distorted image. The vast majority of changes for NPG's outside the subset are adjustments to compensate for fields that were left blank when introducing the NPG's to the SAP system. So, the changes are not relevant because the old value has no meaning.

4.1.3 Data Cleaning

The selected data subset, hereafter referred to as dataset, needs to be cleaned due to the occurrence of missing and inaccurate data. Missing data is defined as the absence of a value for certain variables of an observation. Observations with one or more missing values for one of the variables are deleted. Furthermore, if too many values of the same variables are missing, the variable is deleted from the dataset. However, examining the extent of the missing values for each variable, it is concluded that no variables have to be deleted.

While exploring the dataset, it was also observed that some observations maintained values for certain variables that are not (realistically) possible. These values were modified if possible, otherwise deleted. The variable lot size maintained a value of zero for multiple NPG's, however, it impossible to order in batches of zero. Through discussion with inventory managers of VDL Nedcar, the decision is made to modify all observations with a lot size of zero to a lot size of one. Furthermore, the dataset included some meaningless inventory movements. In collaboration with one of the inventory managers of VDL Nedcar, all movement types were categorized as either meaningful or not-meaningful. Thereafter, all observations that represented a not-meaningful movement were deleted. Besides meaningless inventory movements, the data analysis also showed NPG's without any form of demand within the time window. Since deviation in inventory level are highly unlikely for these NPG's, it was decided to remove these NPG's from the dataset.

It was also observed that a couple NPG's maintained a price of 0.01, which seemed unlikely after examining the NPG's individually. According to the inventory managers, these prices are inaccurate due to a lack of knowledge at the moment of registering the NPG. Lastly, the NPG's with a NPG status of 05, which represents "flagged for deletion", were individually observed. In case the specific NPG was flagged for deletion in the last two years of the five and a half years of historic data and had enough movements the NPG was maintained. Otherwise all observations of the specific NPG were deleted. The data cleaning actions resulted in a reduction of the dataset, but ensured an increased level of data quality. The extensiveness of the reduction can be observed in table 4.2

Data	Dataset before cleaning	Dataset after cleaning
Inventory movements	7203	6460
NPG's	909	467
Variables	20	20
Changes in lead time	39	39
Changes in lot size	42	42
Changes in NPG status	91	91
Time window	5-1-2015 till 28-9-2020	5-1-2015 till 28-9-2020

Table 4.2: Changes in the size of the data through cleaning

4.2 VDL Nedcar Model

Now that we have selected and cleaned the dataset, a case study is conducted. In this case study the dataset that is selected and prepared in Section 4.1.3 will be implemented in the conceptual model of VDL Nedcar. This will lead to an overview of the on hand inventory situation of the specified production lines.

In order to initialize the VDL Nedcar model, the inventory parameters need to be set. Since the goal is to represent the past of VDL Nedcar, the inventory parameters should be set to the actual parameters. However, analyzing the order data shows that a majority of the orders did not adhere to the settings extracted from SAP. For example, orders were constantly placed before the inventory dropped to or below the reorder point. So, using the inventory parameters extracted from SAP would not provide an accurate representation of the past situation of VDL Nedcar. Therefore, the SAP inventory control parameters were deemed insufficient. To deal with this, both the actual historical demand and actual historical orders are used in the model. This decision causes the best representation of the human decisions that have been made in the past concerning inventory control.

Due to the decision of taking the actual historical orders and demands from SAP it is impossible to calculate a performance measurement over the used timeline. This is because SAP does not allow negative inventories and VDL Nedcar does not properly register the requirement date of a specific spare part. This results in the inability of assessing whether the stock was zero or backorders occurred. Besides the lack of backorder information, it is also not possible to determine an average waiting time for the spare parts since the requirement date is not registered properly. Furthermore, VDL Nedcar has no KPI that assesses the availability of spare parts when needed. So, besides being unable to calculate a performance measurement, there is also no historic performance information available on spare parts management. However, VDL Nedcar maintains a target plant uptime. This is measured according to experts from VDL Nedcar as the percentage of time that the production line is adding value to the goods for the customer. The target plant uptime is internally set to 96%. Figure 4.1 gives a display of the achieved plant uptime from 2015 up to and including 2019 which shows a deviation from the set target. Unfortunately, the actual achieved plant uptime cannot be publicly displayed, due to confidentiality. Nevertheless, it may be assumed that this value is known by the researcher for carrying out the research. The weeks that indicate a plant uptime of zero (visible in figure 4.1) were not incorporated in calculating the average plant uptime. During these weeks the plant was closed due to holidays, therefore, those weeks are not meaningful.

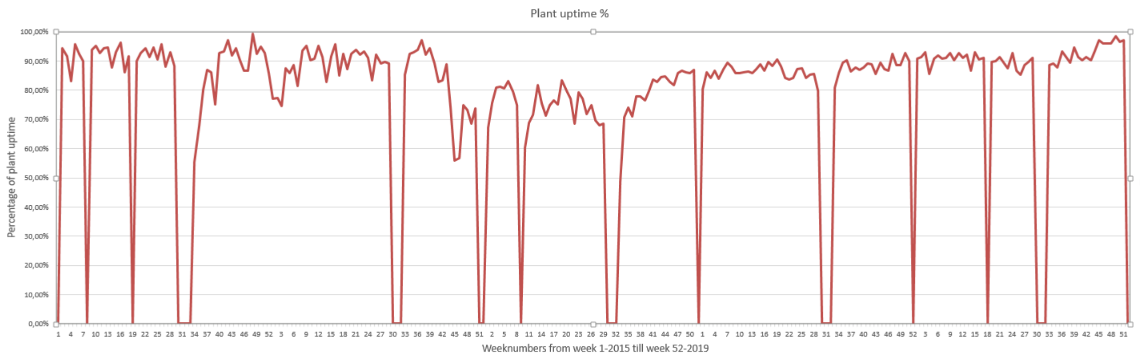

Figure 4.1: Overview achieved plant uptime

Plant downtime is not solely caused by shortages of spare parts. In fact, according to the responsible maintenance engineer, the part of downtime caused by insufficient spare parts inventory is minimal. Therefore, it is assumed that the inventory management performance measurement has to be higher than the realized average plant uptime.

Now the stock parameters are determined, the simulation can be executed. The time of the simulation is run from 1-1-2015 till 28-9-2020 with increments of one (day). The input of the simulation consists of the demand and orders of VDL Nedcar of the set timeline. Deterministic simulations consist (mostly) out of equations. For the simulation of the VDL Nedcar model Equations 3.1 and 3.2 are used. The simulation is initialized based on the on hand inventory of VDL Nedcar at 1-1-2015 and it is assumed that there were no backorders or pipeline stock (X_i) at t=0 (1-1-2015). This is necessary since the formulas require input from before the specified timeline. The simulation output will be the inventory on hand for every t on the timeline. This can be used to calculate an average on hand inventory, which is the objective.

4.3 Theory-Based Model

Next, a case study is conducted using the theory-based model developed in Section 3.3. In this case study the dataset that is selected and prepared in Section 4.1.3 will be implemented in the theory-based conceptual model and simulated. This will lead to an overview of the on hand inventory that would have been achieved for the specified production lines at VDL Nedcar without human interference.

The simulation is run from 1-1-2015 till 28-9-2020 with increments of 1 (day). The input of the simulation consists of the demand of VDL Nedcar of the set timeline. In comparison to the simulation input of the VDL Nedcar model, this simulation excludes the order data. This input is not necessary since the theory-based model generates orders using the inventory control parameters.

While analyzing the data, it was noticed that the demand size is highly infrequent and contains a lot of zero-demands. As described in Section 3.3.2, it is common to group the demand data into time buckets of a size equal to the leadtime. The grouped demand of two NPG's with the same leadtime (L_i = 14) is displayed in figure 4.2. Observing the time buckets confirms the belief of intermittent demand which is common for spare parts (Mobarakeh et al., 2017) (Syntetos et al., 2010).

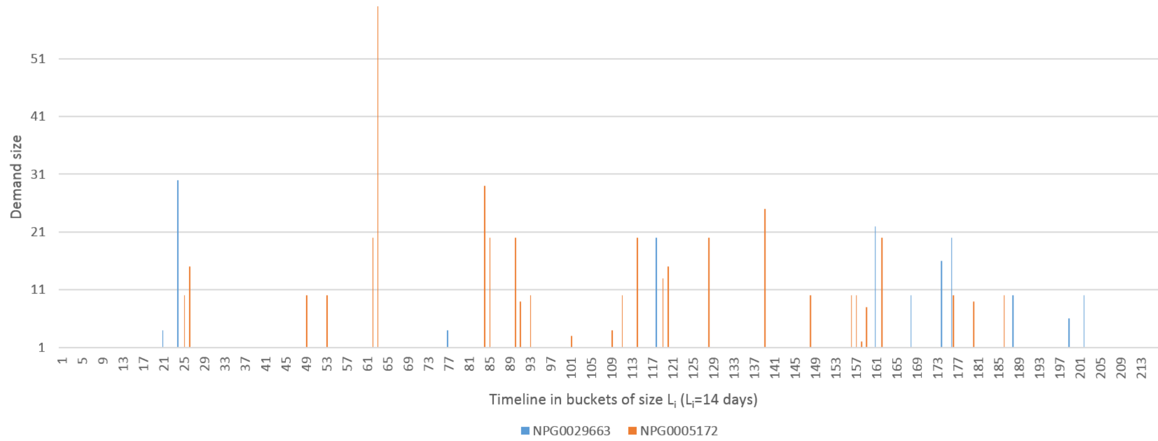

Figure 4.2: Preview demand grouped in time buckets

These time buckets are then used as input for the forecasting method. This model makes use of Croston's method to create a forecast and obtain the demand distribution parameters. Croston's method (as explained in Section 2.1) is recursive, meaning that it takes previous forecasts into account. However, there is no previous forecast at t=0. Therefore the interval to the first demand (q_f) and the size of the first demand (y_f) are used:

$$y_0'' = y_f/q_f$$

$$z_0'' = y_f$$

$$p_0'' = q_f$$

Furthermore, α is set to 0.2, this value works well in practice (Willemain et al., 1994).

To implement the inventory control policy for the specified case study, the demand parameters are determined. The batch size and the leadtimes are obtained from the data and remain constant during the entire timeline. The reorder point functions as a decision variable and is determined by implementing the item approach. This approach looks at all NPG's individually and increases the reorder point until the individual NPG achieves a fill rate that satisfies the fill rate objective. Since VDL Nedcar has no performance measurement for spare parts that can be used as a reference point, there is no one correct setting for the target fill rate. However, as mentioned before, the target plant uptime and achieved plant uptime are known. Since the target fill rate is a variable in the theory-based model it is possible to run the deterministic simulation for multiple target fill rates. Thus, the simulation will be run for the target and achieved fill rate.

The reorder point determination process is executed at the start of the model to generate initial reorder points for the inventory policy. However, this is a data intensive process as it requires a leadtime demand rate. Since the production lines that are being investigated in this research are relatively new, there is no demand data from before the timeline over which the simulation runs. That is why it was decided to use the first three of the five and a half years to determine a leadtime demand rate. These three years of demand data is complemented with older demand data for a couple of NPG's. So, the first three years of the data will function as a warm up period. Thereafter, the reorder points will be revised annually, starting from 1-1-2018. By revising the reorder point annually it is ensured that recent demand data is included in the reorder point determination. This will give the forecasting process more (relevant) historical data which will result in a better forecast in general. The complementation of the historical data is visually represented by the dotted line in Figure 3.1.

Now the inventory control parameters are determined, the inventory control process can be executed. However, this process also needs input from before the timeline. It is assumed that there were no backorders or pipeline stock (X_i) at t=0 (1-1-2015). Furthermore, The simulation is initialized based on the on hand inventory of VDL Nedcar at 1-1-2015

The simulation output will be the inventory on hand for every t on the timeline. This can be used to calculate an average on hand inventory, which is the model goal. However, the average on hand inventory output of the simulation will be limited to the last two years of the timeline. This decision is made based on two reasons: first, at t=0 the theory-based model used data of the upcoming three years which causes an unfair advantage. Second, the difference in the average on hand stock between the two models will be minimal at the beginning of the simulation since both models start with the same initial inventory and the NPG's are subjected to low demand.

4.4 Validation

To ensure that the models are developed and working properly, the models are validated. The VDL Nedcar model simulates the situation of VDL Nedcar over the last five and a half years. To validate whether the model simulates the inventory on hand properly it is compared with the actual on hand inventory of VDL Nedcar at the cut-off time of the timeline. It is possible to subtract a snapshot of the actual on hand inventory of the specified set of NPG's for the cut-off time of the timeline. Comparing the on hand inventory of the model at t = 2894 (9-9-2020) confirmed as expected an exact resemblance to the snapshot. This ensures the working of the VDL Nedcar model.

Validating the working of the theory-based model is a bit more complicated because it can not be compared to an existing situation. However, firstly the separate model processes are checked on the logic behind them and secondly the python code is controlled, by evaluating the output of the separate processes for certain input. Furthermore, both the on hand inventories and inventory positions are evaluated with experts from VDL Nedcar to check whether no unusual values occur. This was done by studying the inventory position and inventory on hand graphs of different NPG's. However, studying these graphs gives only insights into the correctness of the ordering and warehouse process.

To validate the reorder determination process of the theory-based model, a single NPG was selected to calculate the initial reorder point by hand. Since the revised reorder points later on are calculated using the same method it is not necessary to calculate more than the initial reorder point. Croston's method is also calculated by hand to ensure the validity of the entire reorder determination process. All values that have been recalculated by hand correspond to the values that are extracted from the model. The calculations are displayed in appendix A. To conclude, all validation processes have shown that the models work properly.

4.5 Results

4.5.1 Results VDL Nedcar Model

The VDL Nedcar model produced an inventory on hand overview for each item over the specified timeline. The results of this model are graphically displayed in Figure 4.3 till 4.6. It visualizes the difference between four NPG's in terms of demand size and interval. Furthermore, it is also visible that there is no NPG that obtains a positive value for the number of backorders, as explained in Section 3.2.2. Analyzing the graphs with the corresponding inventory parameters from table 4.3, it is possible to assess whether the inventory adheres to the set inventory policy. The NPG in figure 4.3 seems to adhere to the reorder point and the batch size with some exceptions. In particular, at the end of the graph, it is noticed that the inventory stays zero for a longer period and then rises to (approximately) ten. This could be explained by the occurrence of a backorder or a deviation of the order size. Furthermore, between 2015 and 2016 the inventory on hand stays unchanged for a longer period and is above the reorder point. Despite there being no demand, the first movement is an increase in inventory on hand. This could indicate a human intervention, e.g. to prepare for an upcoming event.

Observing the on hand inventory behavior of the NPG in figure 4.4, it can be concluded that the NPG follows the inventory policy according to the parameters from table 4.3 to a reasonable extend. Some remarkable peaks occur which could indicate human interventions. Furthermore, it is noticed that the inventory on hand occasionally remains zero for a long time which could be an indication of backorders.

The evolution of the inventory on hand of the NPG in figure 4.5 does not adhere to the inventory policy and settings at all. This can be seen at the beginning of the graph where an amount of three is ordered while the reorder point is not reached yet.

The last NPG that is displayed in figure 4.6 appears to ignore the inventory policy and settings for the first six and a half years but then appears to adhere to the settings. The introduction date and possible parameter setting changes have been checked for this item but could not clarify the phenomenon. A possible explanation is a human intervention based on extra maintenance information.

	Leadtime (in days)	Reorder point VDL Nedcar	Batch size
NPG0005172	14	8	20
NPG0072046	9	0	1
NPG0067050	2	1	1
NPG0063625	17	0	1

Table 4.3: Inventory control parameters

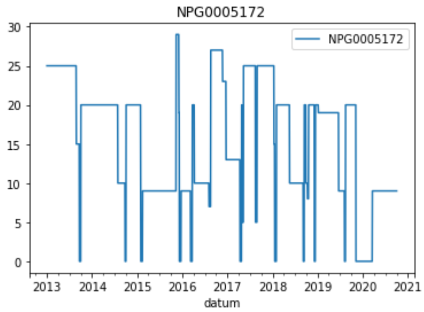

Figure 4.3: Inventory overview NPG0005172

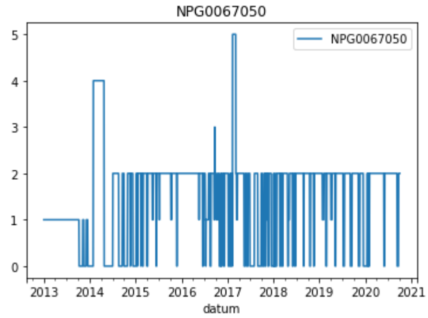

Figure 4.4: Inventory overview NPG0067050

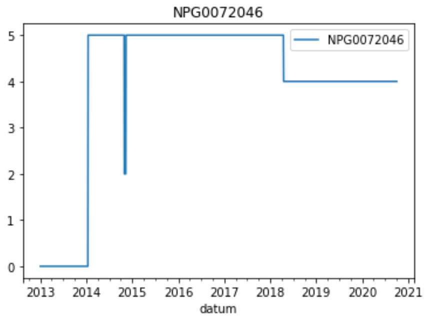

Figure 4.5: Inventory overview NPG0072046

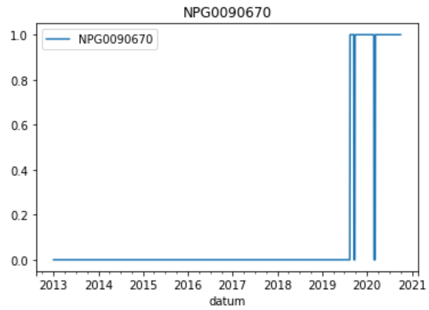

Figure 4.6: Inventory overview NPG0090670

The analysis of the four different inventories over time confirms the statement made in Section 4.2. The SAP inventory parameters are deemed insufficient to represent the actual situation at VDL Nedcar. This supports the decision of using both the actual demand and order data.

The main goal of the VDL Nedcar model is to obtain the average on hand inventory of all NPG's for the actual situation at VDL Nedcar. With Figure 4.3 till 4.6 a couple of examples were given of the evolution of the inventory on hand of these NPG's. The evolution of the inventories provides the possibility of determining an average on hand inventory of the last two years of the timeline. These average on hand inventories satisfies the main goal of the VDL Nedcar model.

4.5.2 Results Theory-Based Model

The theory-based model starts with generating initial reorder points. As described in section 3.3.2, leadtime demand rates are required. The leadtime demand rates are calculated with three different historic demand intervals, namely, [5-1-2015, 1-1-2018], [5-1-2015, 1-1-2019] and [5-1-2015, 1-1-2020]. Respectively, these will generate the initial leadtime demand, the leadtime demand after the first revision, and the leadtime demand after the second revision. As mentioned before, for some NPG's there is historic demand available from before the specified timeline, for these NPG's the lower bound of the interval is changed as follows:

- If there is demand in the interval [13-7-2012, 1-1-2013] the lower bound of the interval will be 13-7-2012
- If there is demand in the interval [2-1-2013, 1-1-2014] the lower bound of the interval will be 2-1-2013
- If there is demand in the interval [2-1-2014, 1-1-2015] the lower bound of the interval will be 2-1-2014

The lower bounds of the intervals are adjusted because Croston's method is initialized by the first demand (amount of periods till the first demand and demand size). Therefore, it is not appropriate to generalize the adjusted lower bound for all NPG's. In table 4.4 the maximum, minimum, and average of all leadtime demand rates are displayed. Analyzing the values shows that the leadtime demand rates vary strongly with a minimum of 0.0054 and a maximum of 51.16898. Furthermore, the average leadtime demand rate is quite low which indicates that the leadtime demand rates of most NPG's are closer to the minimum. This is also confirmed by the boxplot in figure 4.8. This supports the statement of dealing with intermittent demand which has a high variability and low demand rates. Observing the average leadtime demand rates show that the demand increases over time, especially since an alpha of 0.2 means that the historic forecasts weights in quite heavy.

	Initial demand rate	**First revision demand rate**	**Second revision demand rate**
Maximum	27.13634	49	51.16898
Average	0.402586	0.635346	0.618317
Minimum	0.005464	0.005691	0.005285

Table 4.4: Characteristics leadtime demand rates

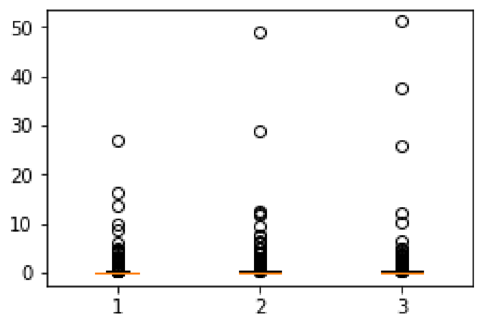

Figure 4.7: Box-plots of leadtime demand rates for different intervals

The increase in leadtime demand rate is also slightly noticed in the corresponding reorder points. The average reorder points are respectively, 2.28, 2.75, and 2.69. This reflects the relatively large increase between the first and second interval and the relatively small decrease between the second and third interval. However, the batch size does also play a significant role in determining the reorder points. Therefore, the increase in leadtime demand rate is not fully reflected in the reorder points.

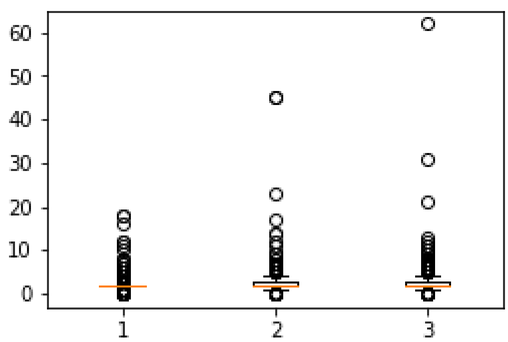

Figure 4.8: Box-plots of reorder points for different intervals

Implementing the obtained reorder points into the (R,s,nQ) policy of the theory-based model results in an actual achieved fill rate. This fill rate represents the performance of the used inventory policy and corresponding parameters for the demand of VDL Nedcar. It is noticed that the achieved fill rates in the simulation are significantly lower than the set objectives. Furthermore, it is also noticed that a number of NPG's achieve an individual fill rate of zero, which is exceptionally low. Studying these NPG's more in-depth, it is noticed that these NPG's have difficult to forecast demand i.e. interarrival times of multiple years and highly varying demand sizes in combination with little data. An example is NPG0081117 which has two non-zero demands within five and a half years, with a demand size of one and ten. These underperforming NPG's are one of perhaps several causes of the significant fill rate gap. Figure 4.9 displays box plots of the individual fill rates of the different scenario's. The box plots confirm that the vast majority of the NPG's perform acceptable, especially scenario three and four where more than half of all NPG's achieve a fill rate of 100% (since the median is 100%). It also could be that the assumed demand distribution does not fit as well in practice as taught or at least for the demand of some NPG's. van Wingerden (2019) does not use point estimates but models uncertain demand rates using a distribution to decrease (prevent) a fill rate gap.

The theory-based model goal is to function as a meaningful benchmark to the VDL Nedcar model. As explained in section 3.2.2, the theory-based model performance should be equal to the situation at VDL Nedcar to make a meaningful comparison. Unfortunately, due to confidentiality, it is not possible to display the actual achieved fill rates. Observing the two different scenario's it is noticed that both actual achieved fill rates are quite low. Therefore, it is investigated whether a higher actual fill rate can be obtained with an increased fill rate target of either 98% or 99.5%. Analyzing all obtained results it is decided to choose the third scenario with a target fill rate of 98%. This scenario is accepted because the individual fill rate of the vast majority of the NPG's is above the aggregated fill rate. Furthermore, comparing the average inventory on hand of the theory-based model with the VDL Nedcar model shows a great level of resemblance or tolerable differences.

Besides the execution of the model for different fill rate objectives, the model is also executed with an enhanced leadtime for the sensitivity analysis. This is done to evaluate the impact of the continuous equations in the periodic review model. The actual achieved fill rate increased 0.15% so it is confirmed that the impact of the continuous equations is small

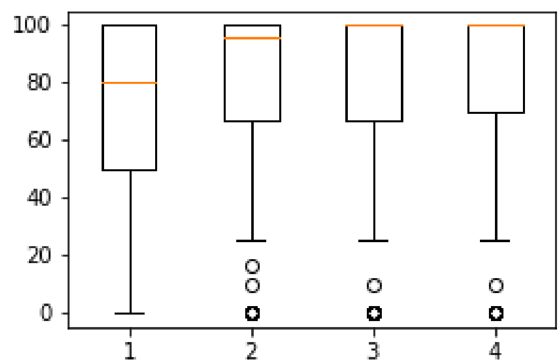

Figure 4.9: Box-plots of individual fill rates for different scenario's

Now that a scenario is selected, the inventory on hand and inventory position can be analyzed for the fourth scenario. The inventory control parameters are provided in table 4.5 and are required to analyze the inventory overview in figure 4.10 and 4.11. In figure 4.10 the reorder level is low due to the relatively large batch size in comparison to the lead time demand rate. It is observed that when one part is ordered, the inventory position immediately increases to nine. The inventory on hand, however, decreases to minus one. Due to the demand for five parts before the ordered items are delivered, the inventory on hand decreases even more before it increases. Also notice that the second demand does not trigger a new order since the order decision is based on the inventory position. The remaining demand can be covered with the on hand stock. Furthermore, this NPG has an relatively low fill rate ($\beta_i\left(S_i, Q_i\right) = 50.0\%$). This can be explained due to the low reorder point and the hard to forecast (relatively) large demand immediately after the previous demand. During the observation of figure 4.11 it is immediately apparent that there is no occurrence of demand in the first part of the graph. This is an example of a NPG without demand before 1-1-2015. As explained before, this part of the timeline is not incorporated during the initialization of Croston's method. Analyzing the part of the graph with demand, it is noticed that the inventory position is constant. This is caused by the moment of measuring the inventory position and the batch size. The inventory position is distributed over $\{s_i + 1, ..., s_i + Q_i\}$ because it is measured after the orders are placed (mentioned in Section 3.1). Since the batch size of this NPG is equal to one, the inventory position seems constant. However, if the inventory position would be measured after the demand but before the orders are placed it displays a decrease to or below the reorder point. Lastly, it is noticed that an unusually large demand occurs after approximately 1800 days. This demand size is three times as great as all the other demand sizes and therefore impossible large to account for. Despite this one backorder, the fill rate still obtained a value slightly above average (($\beta_i\left(S_i, Q_i\right) = 87.50\%$).

Table 4.5: Inventory control parameters

	Initial reorder point	First revision reorder point	Second revision reorder point	Batch size	Leadtime (in days)
NPG0057620	-1	-1	-1	10	17
NPG0068569	2	2	2	1	17

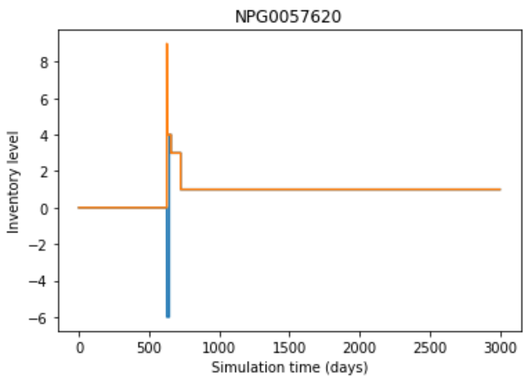

Figure 4.10: Inventory overview a

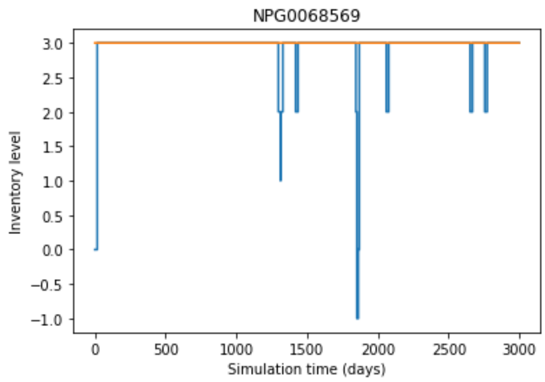

Figure 4.11: Inventory overview b

Furthermore, the evolution of the inventory on hand of all NPG's over the timeline offered the possibility of determining an average on hand inventory of the last two years of the timeline. This is the main output of the VDL Nedcar model and will be used to create the final output of the first phase of this research.

4.5.3 Output First Phase

As stated in section 1.6, phase 1 focuses on identifying the impact of inventory managers on the spare parts management process of VDL Nedcar. To achieve this, two models were created. The first model, the VDL Nedcar model, obtained the average on hand inventories for each NPG $i \in I$. These average on hand inventories are obtained by simulating how inventories are actually managed at Nedcar, thus including human involvement. The second model, the theory-based model, also obtained the average on hand inventories by simulating how inventories are actually managed at VDL Nedcar. However, the theory-based model replaced human involvement with theories from literature. Comparing the average on hand inventories for each NPG $i \in I$ results in a list of deviations. These deviations indicate the human influence on the spare parts management process of VDL Nedcar since the incorporation of human influence is the major difference between the two models.

Analyzing the deviations, it is noticed that they can be negative as well as positive, but also zero. These three different outcomes all have different meanings. If the deviation is negative, this indicates that the inventory manager obtained the same degree of performance as the theory-based model but with a lower average on hand inventory. In this case, the involvement of the inventory manager has a positive impact on the spare parts management process. Conversely, if the deviation has a positive value, the inventory manager maintains a too high inventory level creating excessive inventories. A deviation value equal to zero indicates that human involvement has no impact on the spare parts management process over time.

Now the human impact is identified, a list containing the deviations and average on hand inventories of the two models is compiled. This list is complemented with spare part attributes obtained from SAP. This constructs a dataset where each row contains the inventory on hand of both models, the deviation between them, and all obtained spare part attributes. Furthermore, each row represents several human decisions that caused the deviation, which can be analyzed in phase two of this research. A snapshot of the constructed dataset is displayed in appendix B. This concludes the first phase of this research.

Part II

Analyzing the Average Inventory On Hand Deviations

Chapter 5

Literature on Behavioral Operations Management

In this chapter, the relevant literature regarding behavioral operations management is provided. This is done to obtain a better understanding of the theories behind human decision making within business processes. As mentioned before in Section 1.6, this research follows an exploratory research method. This causes the inability to formulate hypotheses. Therefore, a broad spectrum of literature is necessary to support the findings. The different behavioral operation theories are discussed in the remainder of this chapter.

Humans are essential within business processes to make operational decisions (Arrow et al., 1951). As stated before, planners and inventory managers play a crucial role in managing spare parts inventories. However, humans can be influenced in various ways and thus can be compromised in their (rational) decision making. These humans can vary from inventory managers and planners to workers performing a repetitive task in a fulfillment center (Donohue et al., 2018). The behavioral operations studies focus on creating a better understanding of why and how these individuals make decisions and how these decision impact business processes. This could be used to improve operational decision making, resulting in higher operational performance. The existing literature covers the behavioral implications within different areas of operation management (OM). A review of this literature generated a couple of main areas within operation management:

- Supply chain management (SCM)
- Inventory management
- Procurement and auctions
- Forecasting

Despite supply chain management being an overarching area over the other three areas, they are dealt with separately. This decision was made due to the considerable amount of existing behavioral operations literature that focusses on the separate area's. Within operations management, it is generally assumed that decision-makers use rational thinking to maximize profit. However, in practice it is observed that this is not always the case (Donohue et al., 2018). People tend to deviate from the normative decision theory, caused by cognitive biases. This is an umbrella term for systematic patterns that influence the rationality of the human decision making process (Buss, 2005). Cognitive biases often occur due to the use of short cuts within the human mind. These shortcuts allow people to make fast decisions in situations with limited time, but it also causes decisions that did not take all relevant information into account (Tversky and Kahneman, 1974). There are a lot of different cognitive biases that influence the human decision making process, through an extensive literature review a list of important ones is composed in Table 5.1

Bias	Explanation
Ambiguity effect	The decision-maker chooses an option of which the outcome and the corresponding probability are known, without considering options of which the probabilities are unknown (Donohue et al., 2018).
Anchoring bias	The decision-maker uses the initial piece of information (the anchor) as a reference point to judge new information and sticks to this anchor. These judgments can be worthless because it is unknown whether the initial information is meaningful/relevant (Zhang et al., 2007) (Tversky and Kahneman, 1974).
Availability bias	The decision-maker's mind uses a shortcut that relies on recent experiences for assessing decision options. For example, someone who recently experienced a car accident will estimate the probability of a car accident higher than someone who does not have this experience (Donohue et al., 2018).
Confirmation bias	The decision-maker tends to interpret information in a way that confirms his/her beliefs and then uses the information as he/she interpreted it (Nickerson, 1998).
Overconfidence effect	The decision-maker overestimates his/her competence in creating a judgment. The overconfidence effect is mainly observed for moderate or difficult tasks (Donohue et al., 2018) (Pohl, 2004).
Hot-hand fallacy	The decision-maker has an unfairly increased belief of achieving a ''successful" outcome, due to earlier achieved success. This cognitive bias is often observed during sports, for example, people believe that a basketball player has a higher chance of scoring if he did hit the previous shots (Donohue et al., 2018).
Loss aversion	The decision-maker tends to avoid losses because he/she estimates a bigger loss then the potential gain (Donohue et al., 2018) (Tversky and Kahneman, 1992)
Risk aversion	The decision-maker tends to choose for a (slightly) lesser outcome, but with a higher certainty. In comparison to loss aversion, the decision-maker is more concerned with the uncertainty, than with the outcome (Donohue et al., 2018).

Table 5.1: Overview of cognitive biases

Besides the influence of cognitive biases, the decision making process can also be influenced by social preferences. Similar to cognitive biases, these influences can cause non-rational decision making. Social preferences are studied within social psychology and behavioral and experimental economics and are defined as non-selfish preferences. In this case, the decision-maker does not only take his/her payoff into account but is also concerned with the payoff of others (Charness and Rabin, 2002) (Loch and Wu, 2007). People value status, respect, fairness, group identification, and relationships, therefore, social preferences are used to intuitively navigate complex social interactions. The preference for reciprocity or reciprocal fairness is an important and well-studied type of social preference (Fehr and Fischbacher, 2002). Within this type of preference, the decision-maker is not motivated by a possible material benefit but responds the same way to an action as he/she perceives it, i.e. in case the decision-maker perceives an action as kind he/she will react in a kind manner. Another important type of social preference is the inequity aversion which was defined by Fehr and Schmidt (1999). They stated that a decision-maker subjected to the inequality aversion preference always tries to minimize inequality in the outcome. The decision-maker creates a payoff ‘’benchmark” which he/she assumes to be fair. In case the payoff for the other person is higher than this benchmark, the decision-maker will feel envy and alter the decision in a way to lower that payoff. On the other hand, the decision-maker will alter the decision to obtain a higher payoff for the other person if the payoff is (too) low. The inequality aversion and the reciprocity preference are quite similar in some situations, however, the reciprocity preference is observed as the more influential preference. A completely different type of social preference is the pure altruism preference. This preference is characterized by unconditional kindness. The decision-maker always tries to improve the payoff for the other person. An example of an action subjected to the altruism preference is giving money to charity (Fehr and Schmidt, 2006). The last type of social preferences are spiteful or envious preferences. A decision-maker that is subjected to a spiteful or envious preference perceives a positive payoff for the other person always as a negative outcome of the decision. This goes even so far that the decision-maker is willing to sacrifice a decrease in his/her payoff to decrease the payoff of the other person (Loch and Wu, 2007). Lastly, culture can also affect the decision making process (Loch and Wu, 2007). Culture exists out of the ideas, customs, knowledge, skills, and social behavior that is transmitted to an individual by a certain population. Within the decision making process assumptions that come from a specific cultural background can have a great impact. Especially because people are unaware of these cultural influences comparable with a fish being unaware of living in water. The three areas discussed above are seen by the existing literature on behavioral operations management as the three main areas that influence human decision making: 1, cognitive biases 2, social preferences 3, cultural norms (Fahimnia et al., 2019). Combining these main areas with the broad scope the research direction applies, the following definition for behavioral operations can be generated: ‘’Behavioral Operations Management is a multi-disciplinary branch of OM that explicitly considers the effects of human behavior in process performance, influenced by cognitive biases, social preferences, and cultural norms.” (Loch and Wu, 2007, 13)

Chapter 6

Inventory Deviation Analysis

This chapter addresses the second research question by developing a method for analyzing the relations between spare part attributes and the impact inventory managers have on the spare parts management process of VDL Nedcar. The output of the first phase consists of a list containing all inventory deviations caused by human influence. The deviations on this list are accompanied with NPG specific spare part attributes. So, the list contains for each NPG a (possible) average inventory deviation and corresponding spare part attributes. In this chapter, the spare part attributes will be discussed to obtain a better understanding. This is important in order to understand possible relations among the attributes and the measured inventory deviation later on. Next, it is describes how the dataset is prepared so that it can be analyzed properly. Finally, the analysis procedure is thoroughly explained and substantiated.

6.1 Variables

The list of average inventory deviations is complemented with all spare part attributes obtained from SAP. As described in Section 1.5, the research is limited to spare part attributes from SAP. Among all the possible available data, nine variables are obtained to use in this research. The variables that are selected meet the criteria of being known by the inventory manager, and being inventory management related. Furthermore, the selected variables are checked for missing and inaccurate data in Section 4.1.3. Below, the nine selected variables are discussed in-depth to create a better understanding.

The relative inventory deviation represents the impact of the inventory managers on the spare parts management process. In the first phase of this research, the inventory manager's involvement is identified. The identified involvement is expressed as a deviation in average on hand inventory (explained in Sections 4.5.3). In case the human involvement caused a lower average inventory the direction was positive and vice versa. However, the magnitudes of the deviations have no comparable meaning since the impact of a certain deviation could differ among NPG's. A deviation of one item has a different impact on fast moving NPG's with relatively high inventories than for slow moving NPG's with relatively low inventories. Therefore, the relative inventory deviation variable is derived. The deviation in average on hand inventory is divided by the average demand rate expressed in days, see Equation 6.1. By dividing the average on hand inventory deviation with the average demand rate, the magnitude of the deviation becomes comparable for different NPG's.

$$RelativeDeviation_i = \frac{AverageInventoryDeviation_i}{DemandRate_i} \tag{6.1}$$

So, now a variable is created with a meaningful distance and zero, classifying the variable as ratio. This classification is preferred for multiple analysis methods (Hair et al., 2009)

The reorder point is created by inventory managers of VDL Nedcar. These inventory managers obtain information from the supplier concerning the machine to determine which parts are critical and need to be stocked. When a part is classified as critical, the inventory manager gathers information of the part and generates the reorder point based on his or her experience. Therefore, the reorder point of VDL Nedcar (from this moment on referred to as reorder point) represents a judgemental forecast. So, it could be interesting to explore whether certain demand expectations of the planners and inventory managers have relations to the observed inventory deviations.

The leadtime indicates the amount of time the SAP system of VDL Nedcar assumes is between delivery and the moment of ordering (expressed in days). The leadtimes are set by the supplier and remain constant over the timeline of this research. If the leadtime is zero, the NPG is instantly delivered. Furthermore, the leadtime variable has equal distances to neighboring points. So, the variable has a ratio scale since it has a meaningful zero and equal intervals. Leadtime plays a significant role as an inventory parameter within inventory management and could influence inventory managers in their decision making. This makes leadtime a suitable candidate for the analysis.

The IfVendor variable indicates whether a supplier is specified for handling the orders. This variable is dichotomous and holds a value of one if there is a specified vendor and a value of zero if there is no specified vendor. For NPG's without a prespecified vendor the inventory manager has to find and contact a vendor before being able to order.

The batch size is the specified order size, determined by the supplier. For NPG's where the supplier prescribes a batch size, it is only possible to order multiples of this amount. Similar to leadtime, the batch size plays a significant role as an inventory parameter within inventory management and could influence inventory managers in their decision making.

The Cost of an NPG is also assessed as a possible valuable and meaningful variable. Including this variable gives the opportunity of assessing whether the costs of an NPG influence the decision process of the inventory manager. In the literature it is observed that costs influence human impact in other business area's (for example forecasting of production goods).

The amount of demands that occur for an NPG within the timeline is displayed in this variable. This provides the opportunity to assess whether there is a distinction in human influence for relatively fast moving and slow moving NPG's.

The IfBatching variable indicates whether the inventory manager is making use of a batching strategy. This enables the opportunity of analyzing inventory managers within different inventory strategies. This variable is dichotomous and holds a value of one if the inventory manager uses a batching strategy, and a value of zero if he does not. The decision of applying a batching strategy is in almost all cases determined by the supplier by prescribing a batch size.

The IfCostCenter variable indicates whether a costcenter is specified for demand. The costcenter is a defined unit within a company that deals with accounting and controlling. Costs and performances can be allocated to a costcenter. This enables a company to trace expenses and ensures that all costs are accounted for. The variable is dichotomous and holds a value of one if there is a specified costcenter, and a value of zero if there is no specified costcenter. Analyzing the data shows that for all items either always or never a costcenter is specified.

6.2 Data Preparation

Now that the variables are familiarized, the data needs to be prepared for analysis. The first phase generated a list consisting of 467 observations. Each observation represents an NPG and contains the corresponding spare part attributes and a possible relative deviation. In Section 4.1.3, the data was already analyzed and treated for missing data. However, before the dataset can be used to identify relations, the dataset needs to be checked for outliers. An outlier is defined as an observation with a unique combination of characteristics identifiable as distinctly different from other observations (Hair et al., 2009). These different observations have the potential to cause model misspecification and incorrect analysis results. Therefore, it is important to identify outliers and appropriately deal with them. The outlier detection method is applied to the relative inventory deviation.

The Hampel identifier is a common method for outlier detection and is described as one of the most efficient and robust outlier identifiers according to Liu et al. (2004). The Hampel identifier calculates the standard deviation based on the median absolute deviation (MAD). The MAD is a method for measuring the variability of a sample. The method creates a window in which the observations must be. The bounds of this window are created by deducting or adding three times the MAD to the median. The observations with a relative deviation value outside the window are classified as outliers. Implementing the Hampel identifier to the dataset results in the classification of 99 observations as outliers. Removing these outliers from the dataset would mean a dataset reduction of 21.20%. This would cause a enormous loss of valuable information. Therefore, the more sophisticated and sensitive generalized ESD (Extreme Studentized Deviate) test for outlier identification is also implemented. In order to use this outlier detection method, the univariate dataset needs to follow an approximately normal distribution (Rosner, 1983). The generalized ESD requires an upper bound (r) which determines the amount of separate outlier tests that are executed. In the first test, a single outlier is searched for, then this is incremented by one each time until it searches for r outliers. For each test, a test statistic and a critical value is calculated. Subsequently, the amount of outliers is equal to i for the highest i where the test statistic is larger than the critical value ($i = 1, 2, ..., r$). Since the Hampel identifier found 99 outliers in the case dataset, the upper bound of the standardized ESD test is set to 99. As described, the univariate data needs to be approximately normally distributed, therefore a quantile-quantile plot (Q-Q plot) is generated. The graph indicates an approximately normal distribution, however, this will be discussed more in depth in the next Section. Analyzing the output of the standardized ESD test, it is observed that the highest i for which the test statistic is larger than the critical value is equal to 33. So, the standardized ESD test identified 33 outliers (7.07% of the dataset). This is a significant difference in comparison with the Hampel identifier. This difference can be explained by the robustness of the Hampel identifier. To decide which method is preferred, the identified outliers of both methods are extensively analyzed. In this analysis, the outliers were individually observed and a judgemental assessment was made concerning the validity of the observation. After this analysis, the conclusion is drawn that the robustness of the Hampel method causes the removal of too many observations. Therefore it is decided to remove the outliers identified by the standardized ESD test. This decision is also reinforced by the belief that the deletion of data is never desirable, as this leads to a loss of information. Lastly, box plots of the univariate dataset from before and after the deletion are created. This is done to ensure that the right decisions were made concerning the identification and deletion of outliers.

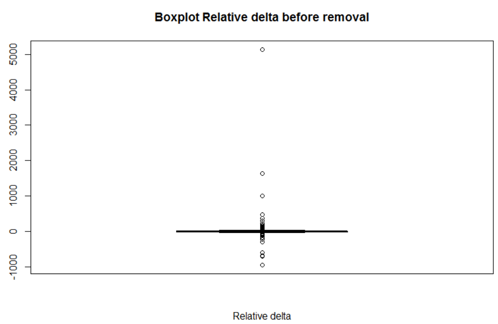

Figure 6.1: Box plot of relative delta before removal

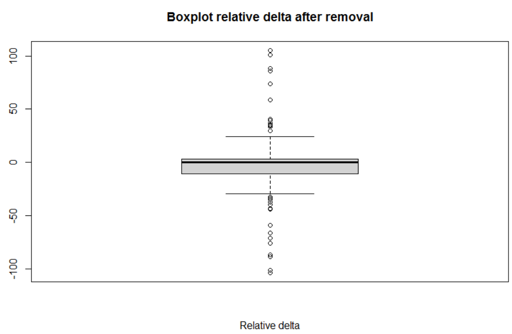

Figure 6.2: Box plot of relative delta after removal

As can be seen in Figure 6.1, the box plot contains observations with significant distance to the body of the box plot. This indicates the presence of outliers. In Figure 6.2, there are no observations with distances similar to Figure 6.1. Furthermore, looking at the observations with the largest distance in Figure 6.2, it is confirmed that all the outliers are removed.

6.3 Methods for Analysis

Now that we have a better understanding of the variables and prepared the data, the remaining 434 observations can be analyzed. The objective of the second phase of this research is to search for relations between the defined spare part attributes and the human influence on inventory management. To search for these relations a multiple linear regression model is implemented. This is a statistical technique that is common for situations with multiple explanatory variables and a single dependent variable. This analysis technique is suited to predict changes in the dependent variable by using the known explanatory variables. Besides a predictive objective, a multiple linear regression can also have an explanatory objective. In the case of an explanatory objective, the multiple linear regression analysis develops an understanding of the degree and character of the relations between the dependent and explanatory variables. In this research the relative inventory deviation is the dependent variable and the other variables that are explained in Section 6.2 are the exploratory variables. Thus, the model will use the exploratory variables to explain changes in the relative inventory deviation. Hair et al. (2009) describes a six stages process for developing a multiple linear regression model, this is depicted in Figure 6.3. This process will be followed to create a suitable multiple linear regression for this research.

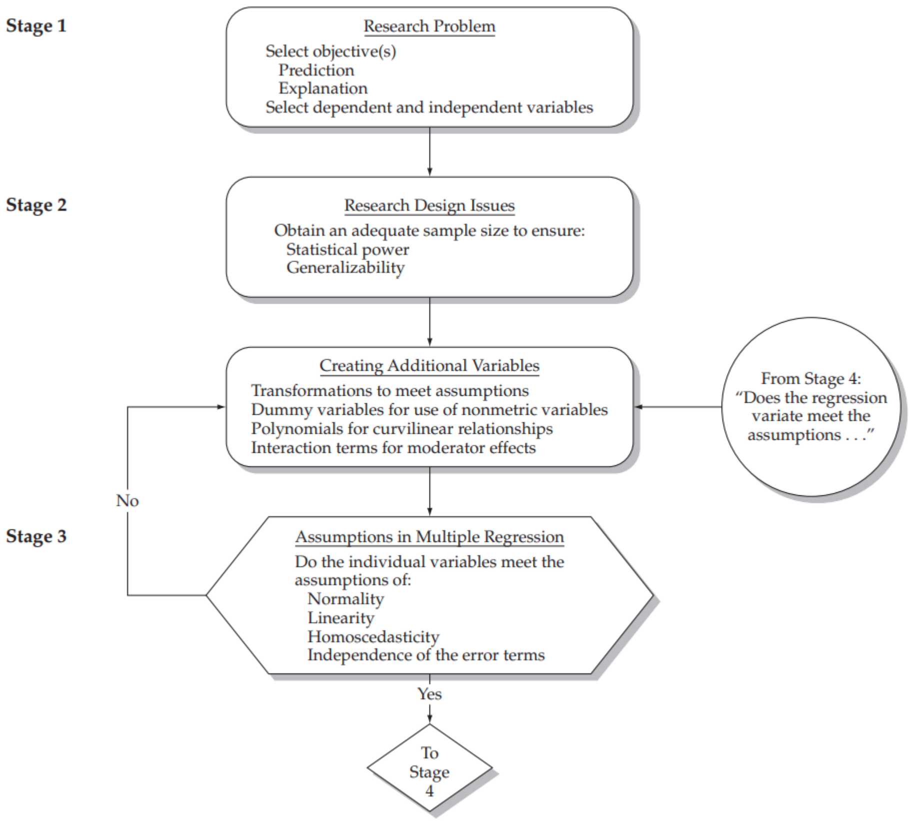

Figure 6.3: Phase 1-3 of the six-stage multiple linear regression creation framework (Hair et al., 2009)

In the first step of the process, the objective of the linear regression model is specified. The objective is based on the research problem. This exploratory research aims to identify possible relations between spare part attributes and humans influence on spare parts inventory management (at VDL Nedcar). Therefore, an explanatory objective is best suited for this research. The relative deviation is the dependent variable, and the other variables described in Section 6.2 are the explanatory variables. The decision is made to include all variables that have the slightest possibility of explaining the dependent variable since adding irrelevant variables does not create a bias in contrast to omitting relevant variables. This concludes the first step of the six-stage framework.

Next, the research design issues are evaluated and remedied. The sample size is considered as one of the most defining aspects of the designing process. The size plays an important role in the statistical power of the significance testing and generalizing the results (Hair et al., 2009). It is crucial that the sample size is not too large or too small since this can have serious implications on the appropriateness and statistical power of the multiple linear regression model. Since it is unknown what kind of relations to expect, the model must be able to identify weak relations. This ability is directly influenced by the sample size, the significance level, and the number of explanatory variables. In the book of Hair et al. (2009) a table is specified that indicates the minimum R^2 that can be obtained for specific settings of the significance level, sample size, and the number of explanatory variables. The R^2 indicates the percentage of total variation of the dependent variable that is explained by the regression model. Computing the setting of this case indicates a minimum achievable R^2 value of 0.05. This indicates that the model is able to detect significant values of R^2 for weaker relations. Furthermore, to ensure generalizability, there should be a ratio of at least five to one in terms of observations to variables. Since the sample set in this research contains 434 observations and only nine variables, the model exceeds the minimum required ratio and therefore does not have to worry about generalizability.

Then, the data is studied to determine whether it adheres to the requirements of a multiple linear regression model. This type of model solely accepts metric data. Therefore, non-metric data should be transformed into dichotomous variables (also known as dummy variables). This is already done for the variables IfBatching, IfVendors, and IfCostcenter in Section 6.1. Furthermore, it has to be determined whether transformations in the model specifications are needed. This can be done in two ways:

- Content-driven: Appropriateness is based on the nature of the data.
- Data-driven: Using a added variable plot and/or histograms to assess whether a log transformation has the desired effect.

Observing the dataset from a data perspective, the variables costs and reorder points are identified for possible transformations. Both variables indicate being positively skewed, this can be observed in the added variable plots in Figure 6.4 and 6.5. The observations are all clustered on a point, while a distribution over the line is preferred. Furthermore, in Appendix D the corresponding histograms are displayed. The histograms of both costs and reorder points indicate that the distribution is positively skewed. So, from a data perspective, it is verified that the variable costs and reorder points have to be logarithmically transformed. This is supported from a content perspective for the costs variable since costs are expressed in a monetary value. Logarithmic transformations are common for monetary variables due to diminishing returns.

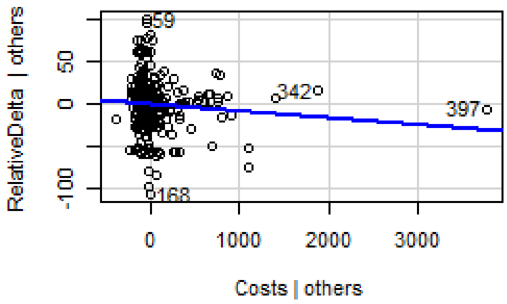

Figure 6.4: Box plot of relative delta before removal

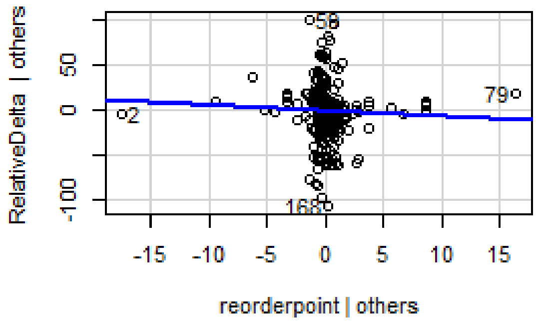

Figure 6.5: Box plot of relative delta after removal

In the added variable plots of the two transformed variables, it is noticed that both are distributed more across the line. However, for reorder point, there is still a concentration around zero. This can be explained by the significant amount of one's in the data. Observing the histograms of the logarithmically transformed variables, the distributions seem improved (displayed in Appendix D). Especially the distribution of the logarithmic costs shows a normal distribution. The spike in the histogram of logarithmically transformed reorder points can be explained by the significant amount of zero's. When ignoring the spike, the histogram shows an approximately normal distribution. These transformations will contribute to the confirmation of the first assumption which is discussed next.

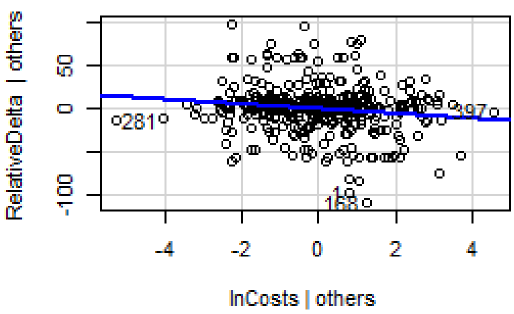

Figure 6.6: Box plot of relative delta before removal

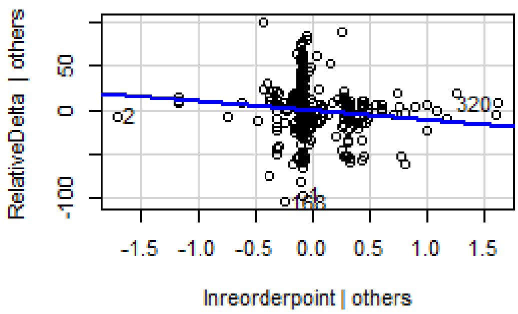

Figure 6.7: Box plot of relative delta after removal

Now that the design issues have been addressed, the assumptions underlying the multiple linear regression model are evaluated for the variate. Starting by assessing the assumption of linearity between the variate and the dependent variable. This is an important assumption since the concept of correlation is based upon this. This assumption can be tested by creating and evaluating added variable plots. This is already done in the previous step to identify if certain data transformations were necessary. There, it was already determined that the variables cost and reorder point had to be logarithmically transformed in order to satisfy the linearity assumption. The remaining added variable plots can be found in appendix C.

The second assumption, homoskedasticity, is checked with an analysis of the error term. Homoskedasticity means that variance is constant in the error term for all values of x. Firstly, the residuals are plotted against the fitted values in a diagnostic plot, which is displayed in Figure 6.8.

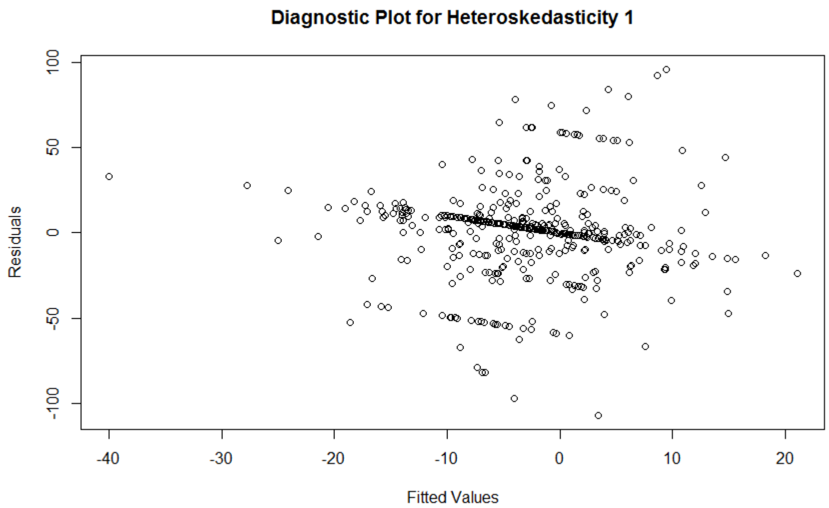

Figure 6.8: Diagnostic plot

The plot is evaluated by searching for patterns. A pattern in the diagnostic plot indicates the presence of heteroskedasticity which means that the variance increases for larger values of the independent variables. This would violate the model assumption and cause invalid standard errors. When analyzing the plot no clear pattern is visible. However, to confirm, a statistical test is executed. A common test for heteroskedasticity is the Breusch-Pagan test. This test obtained a value of 9.7308 with a p-value of 0.2844, which confirms the assumption of homoskedasticity.

The third assumption assumes that the error term is independent of the explanatory variables. This means that the predicted values are not related to each other. Therefore, the predictions are not sequenced. The error term consists out of everything that affects the dependent variable but is not included in the model. So, a dependent error term could be an indication of omitted variables. The assumption can be tested with the Dubin-Watson test. This test is also known as the lag-1 autocorrelation test and measures all correlation between a residual and the previous residual. Executing the Dubin-Watson test, a value of 1.705567 is obtained which is within the preferred window of 1.5 and 2.5 to confirm an independent error term.

The last assumption states that the error term is normally distributed. A histogram is a common method of assessing whether the error term is normally distributed. The histogram, displayed in Figure 6.9, shows an approximate normal distribution. However, the normally distributed error term does not need to be checked further since the sample size is larger than 30. A large sample size reduces the effects of non-normality, which becomes neglectable in a sample larger than 30 (central limit theory).

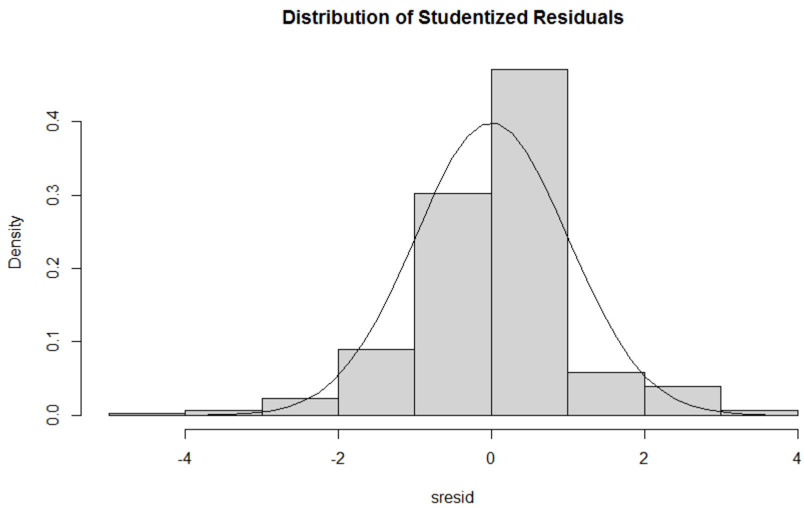

Figure 6.9: Histogram of error term distribution

This concludes the assessment of the multiple linear regression model assumptions and thus step three of the framework. This gives the following regression formula:

$$\begin{aligned} RelativeDelta_i = \alpha + \beta_1 log(Costs_i) + \beta_2 leadtime_i + \beta_3 Ifvendor_i \\ + \beta_4 BatchSize_i + \beta_5 log(ReorderPoint_i) + \beta_6 AmountOfDemands_i + \beta_7 IfBatchingi \\ + \beta_8 IfCostCenteri + \epsilon_i \end{aligned} \quad (6.2)$$

The first three steps of the model have now been completed and with it the construction of the multiple linear regression model. Now it is possible to implement the model and estimate values for β_0 and β_i using the least-squares method. This standard method in regression analysis minimizes the sum of the squared errors of the prediction. The obtained estimates indicate the extent to which the explanatory variables are related to the dependent variable. The decision for the least-squares method covers the first part of the fourth step of the framework. The second part of the fourth, fifth, and sixth steps focusses on assessing the model fit, interpretation of the model results, and validating the model. However, the results are necessary for these actions. Thus, these steps will be covered in the results as these are required.

Chapter 7

Results

The multiple linear regression model developed in Section 6 is implemented using the prepared case study data. This chapter gives an overview of the results of this implementation. The implementation completes the last three steps of the framework of Hair et al. (2009) and provides an answer to the third research question. Furthermore, additional statistics are presented that can be used to support the interpretation of the results.

7.1 Model Results

The multiple linear regression model developed in Section 6.3 is executed to search for relations. In Table 7.1, the output of the model is presented. As mentioned in Section 6.3, the estimates are determined using the least-squares method. The selection of the estimation method forms the first part of step four of the framework (Hair et al., 2009). The second part is concerned with the model fit. The overall significance of the multiple linear regression model is tested by the f-statistic. The null hypothesis of this statistical test states that the current model does not explain more variation than a model without explanatory variables. So, this test proves that R_2 is significantly different from zero for the developed model when rejecting the null hypothesis. The null hypothesis of the f-statistic is rejected, confirming the statistical significance of the model. Furthermore, R^2 is significantly different from zero with a value of 0.04339 which means that the explanatory variables of the model explain 4.34% of the variance in the dependent variable.

Next, the significance of the regression coefficients is tested. In Table 7.1 the levels of significance are presented for each regression coefficient. Here it is visible that both log(costs) and log(reorderpoint) are statistically significant under a significance level of 0.05 which is common to use (Hair et al., 2009). Decreasing the required significance level reduces the possibility of being wrong, however, because of the exploratory nature of this research a significance level of 0.05 is acceptable.

Table 7.1: Multiple linear regression model output

DV= Relative Deviation				
Coefficients:	**Estimate**	**Std. Error**	**t value**	**Pr(>—t—)**
(Intercept)	18.79104	8.60949	2.183	0.02961 *
BatchSize	0.21489	0.14479	1.484	0.13851
lnCosts	-2.94379	1.02487	-2.872	0.00428 **
IfPresoecifiedVendor1	2.96770	5.45315	0.544	0.58658
costcenter	1.72412	8.36619	0.206	0.83683
lead	-0.14011	0.29915	-0.468	0.63976
lnreorderpoint	-12.74816	4.29866	-2.966	0.00319 **
AmountOfDemands	-0.05970	0.08047	-0.742	0.45859
IfBatching1	-5.25569	3.95352	-1.329	0.18444
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1				

Now model significance is determined, the regression coefficients can be interpreted in step five. When interpreting the regression coefficients, the significance, direction and magnitude is evaluated. It is only possible to explain significant regression parameters. So, it is only possible to make meaningful interpretation of the variables reorder point and costs. These variables can be interpreted as follows:

- The negative estimate coefficient of -2.94 indicates a negative direction with magnitude 2.94. Given that the variable is significant and the other independent variables are kept constant, a decrease of 1% in costs will cause a decrease of 0.0294% of the dependent variable relative deviation.
- The negative estimate coefficient of -12.75 indicates a negative direction with magnitude 12.75. Given that the variable is significant and the other independent variables are kept constant, a decrease of 1% in reorderpoint will cause a decrease of 0.13% of the dependent variable relative deviation.

A common issue with interpreting the regression variate is multicollinearity. This is the degree of correlation among the explanatory variables in the regression variate. However, this problem is not caused by an inadequate model but by the data. Preferred are explanatory variables that do not correlate with each other but only with the dependent variable. Multicollinearity can be measured with the variance inflation factor (VIF) which is calculated with the following Equation:

$$VIF\left(x_1\right) = \frac{1}{1 - R_1^2} \tag{7.1}$$

The values of the VIF can be assessed using a rule of thumb which states the following:

- VIF greater than 2 = Consider respecifying the model.
- VIF greater than 10 = Drop variable from the model.

Observing the VIF's in Table 7.2, it is noticed that all values are below two, except for the variables reorderpoint and batchsize. However, the values are just slightly above two and it is merely a rule of thumb. Therefore we decide to keep the variables in the model (Hair et al., 2009).

The last step in the framework is validating the model. This is generally done by testing the developed model on a new sample from the population. However, due to the explanatory objective of this research and the amount of available data, this is not possible. Since there is no larger population for this research to draw a new sample set from it is not possible to validate the model with this method.

Explanatory variable	**VIF**
BatchSize	2.24
lnCosts	1.50
IfPresoecifiedVendor1	1.66
costcenter1	1.63
lead	1.11
lnreorderpoint	2.25
AmountOfDemands	1.05
IfBatching1	1.52

Table 7.2: VIF values of multiple linear regression model

7.2 Additional Statistics

In the previous chapter the output of the multiple linear regression model was discussed to obtain insights into the relations. To expand this, some additional statistics are obtained to create a better understanding of the data itself. The dataset consists of 434 observations which can be divided into three groups. The first group represents observations where human influence has a positive effect (greater than zero) and makes up 31.55% of the the whole. The second group makes up 39.91% of all observations an represents a negative human influence (less than zero). The last group represents the observations where human influence had no impact (equal to zero). The distribution of the human influence is visualized in Figure 7.1 with a histogram and in Figure 7.2 with a density plot.

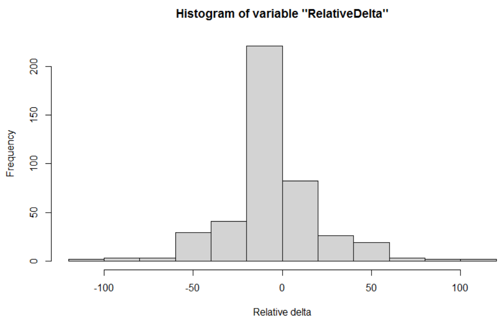

Figure 7.1: Histogram of relative delta

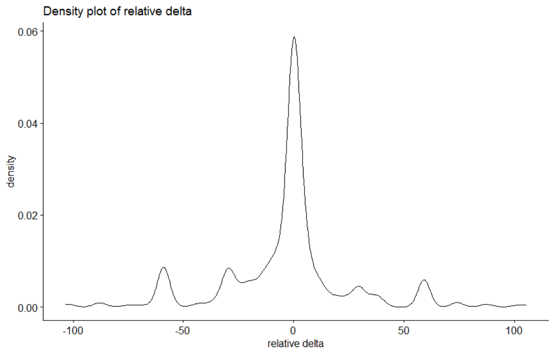

Figure 7.2: Density plot of relative delta

In the previous section a negative significant relation was identified between costs and relative deviation. To further research this, the NPG's are divided into two groups based on the costs: low cost NPG's and high cost NPG's. A NPG is categorized as a low cost NPG when it costs less than the average costs of all NPG's and the other way around for high cost NPG's. By performing a two sample t-test it is identified that the average inventories of the low cost NPG's differ statistically significant from the high cost NPG's (results are displayed in Table 7.3). A two sample t-test identifies statistical differences between the means of two groups. The test has a null hypothesis that states that the means of two groups are equal. In case of a p-value that is smaller than 0.05, the null hypothesis is rejected and it is statistically confirmed that the means of two groups are different. Table 7.3 shows that the inventories of low cost NPG's are significantly higher than for high cost NPG's. This seems normal since relative cheap products have higher demand rates in general. This is also confirmed in the two sample t-test that examined the statistical difference among average demand rate of NPG's (displayed in Table 7.6).

Two Sample T-Test	
Test Statistics	t = 5.4456,
	df = 327.94,
	p-value = 1.014e-07
mean of x	6.709779
mean of y	1.810345

Table 7.3: Two Sample T-Test output for inventory levels of VDL Nedcar (costs)

Two Sample T-Test	
	t = 2.7435
Test Statistics	df = 171.02
	p-value = 0.006726
mean of x	-0.6990401
mean of y	-9.5143839

Table 7.4: Two Sample T-Test output for relative deviation (costs)

As mentioned in Section 6.1, the reorder point is a representation of the forecast created by inventory managers. Since the average demand rate for low cost NPG's is larger on average then for high cost NPG's, it could be interesting to investigate whether the reorder points of low cost NPG's are also larger on average. The results of the two sample t-test are displayed in Table 7.5.

Two Sample T-Test	
Test Statistics	t = 4.5013
	df = 353.15
	p-value = 9.184e-06
mean of x	2.239748
mean of y	1.224138

Table 7.5: Two Sample T-Test output for reorder points of VDL Nedcar (costs)

Two Sample T-Test	
Test Statistics	t = 4.6147
	df = 328.66
	p-value = 5.653e-06
mean of x	0.7198969
mean of y	0.1060163

Table 7.6: Two Sample T-Test output for average demand rate (costs)

The belief of low cost NPG's having higher reorder points on average is confirmed by the results of the two sample t-test. However it is noticed that the relative difference between the average reorder points and average demand rates is larger for high cost NPG's. This could be an indication of overestimation of the expected demand for high cost NPG's.

The multiple linear regression model also identified a negative significant relation between the reorder points and relative deviation. To obtain a more in-depth understanding of this relation, several additional statistical tests are performed. A two paired t-test is used to identify if the average human impact statistically different for relatively low and high reorder points. The reorder points are divided into two groups, similar to the costs. Table 7.7 shows that the null hypothesis is rejected and a significant difference between the relative deviation of the two groups is confirmed. Looking further into the statics, no remarkable or notable discoveries are done. A two sample t-test is performed for relatively high and low reorder points to identify a difference in leadtime. However, the test confirmed the null hypothesis and indicated that there is no significant difference in average leadtime between relatively low and high reorder points (displayed in Table 7.8). A significant difference was found for the average batch size, however, this is not surprising. It is more common for items with high demand rates to use a batching strategy (displayed in Table 7.9).

Two Sample T-Test	
	t = 3.5017
Test Statistics	df = 262.01
	p-value = 0.0005434
mean of x	-1.225823
mean of y	-7.314871

Table 7.7: Two Sample T-Test output for relative deviation (reorder point)

Two Sample T-Test	
	t = 1.4881
Test Statistics	df = 157.18
	p-value = 0.1387
mean of x	11.78526
mean of y	10.86777

Table 7.8: Two Sample T-Test output for leadtime (reorder point)

Two Sample T-Test	
Test Statistics	t = -4.9141, df = 120.57, p-value = 2.84e-06
mean of x	1.403846
mean of y	12.330579

Table 7.9: Two Sample T-Test output for batch size (reorder point)

Chapter 8

General Discussion

In this chapter the findings of this research are discussed in-depth. First a conclusion of this research is provided by answering the research questions in a structured manner. Next, the research implications are discussed from a business and scientific perspective. Lastly, the limitations of this research are provided plus opportunities for future research.

8.1 Conclusion

This exploratory research was conducted with the general objective of clarifying the impact of spare part attributes on human decision making to prevent excessive inventories in the future. To execute this research, several research questions where developed. These research questions serve as support to the main research question. In this section the research questions will be answered in a structured manner to find an answer to the main question of this research:

Which spare part attributes influence the inventory managers in controlling the spare parts inventories and how do these relations contribute to excessive inventories?

This research has identified the human impact on inventory management to some extent. The human impact on inventory management was identified by comparing the situation of VDL Nedcar with a benchmark model. This benchmark model represented the situation of VDL Nedcar with the exclusion of human interference. So, the difference between the two models represents the human impact. Next, it was analyzed whether these impacts could be explained by several spare part attributes. Relations between human impact on spare parts inventory control and spare part attributes have been identified. This analysis forms a first insight into how behavioral operations management can be applied within a spare parts management setting creating an opening for future research in this area. Furthermore, this research created a better understanding of the human decision making process at VDL Nedcar which can contribute to the prevention of excessive inventories in the future.

8.1.1 Research Questions

RQ1 *How to identify the impact inventory managers have on spare parts inventory management at VDL Nedcar?*

To identify the impact of inventory managers on spare parts inventory management at VDL Nedcar two models are developed: the VDL Nedcar Model and the theory-based model. The VDL Nedcar model consists of the spare parts inventory model currently used by VDL Nedcar complimented with the inventory manager's influence. Simulating this model with the actual orders and demands gives a representation of the reality of VDL Nedcar. The goal of the theory-based model is to develop a model that can be used as a benchmark model to identify the human impact on spare parts inventory management. To achieve this, a model that represents the situation of VDL Nedcar as accurate as possible with an exception of the influences of the inventory managers is developed. This is done by basing all model designing decisions on the normal course of business of VDL Nedcar. From this a single-location, single-item inventory model with a (R,s,nQ) policy is obtained. Furthermore, the model performance is measured by the aggregate fill rate and backorders are placed in case of a shortage. With an exception of the exclusion of emergency shipments and obsolescence, this model represents the normal course of business at VDL Nedcar as accurate as possible. Comparing the average on hand inventories obtained from the models shows the impact of the inventory managers at VDL Nedcar. Observing the average inventory deviations, it is noticed that the involvement of inventory managers have both positive and negative impacts. An impact is considered negative when a higher average inventory on hand is obtained (for the same level of performance), and vice versa.

RQ2 *How to identify relations between spare part attributes and the impact inventory managers have on the spare parts management process of VDL Nedcar?*

The first phase of the research identified the relative inventory deviation in average inventory on hand caused by human influence. These relative inventory deviations are coupled with corresponding spare part attributes. A multiple linear regression model was built to search for significant relations between the spare part attributes and the inventory manager's impact. This is a statistical technique that is common for situations with multiple explanatory variables and a single dependent variable. This research uses the relative inventory deviation as dependent variable and the spare part attributes as explanatory variables. The analysis technique is suited for this research to explain changes in the dependent variable by using the known explanatory variables. The model is developed according to the framework of Hair et al. (2009).

RQ3 *What is the exact relation between the relevant attributes and the inventory manager's impact on spare parts inventory management?*

The model revealed significant relations for the variables costs and reorder point. Thus, these two variables are identified to have an impact on the decision making process of the inventory managers at VDL Nedcar.

First, the multiple linear regression model shows the presence of a significant negative relation between costs and relative inventory deviations. This indicates that an increase in the cost of a NPG leads to a decrease of the relative inventory deviation. The decrease in the relative inventory deviation represents a deteriorating human impact on the spare parts management process. This contributes to the development of excessive spare parts inventories at VDL Nedcar.

Second, the multiple linear regression model shows the presence of a significant negative relation between reorder point and relative inventory deviation. This indicates that for a higher reorder point of VDL Nedcar, the human impact worsens. The worsening impact contributes to the development of excessive spare parts inventories at VDL Nedcar.

8.2 Business Implications

The contracting automotive market caused VDL Nedcar to cut back on their maintenance budget. By analyzing the maintenance department for possible cost reductions, it was concluded that the spare parts inventory is unnecessarily large. This is unfavorable since it causes a reduction of liquidity. Several projects were executed to reduce the excessive spare parts inventories. However, none of these projects are concerned with preventing this from happening again in the future. To avoid excessive spare parts inventories in the future, Nedcar needs better insight into how these unnecessarily large inventories were created. The spare parts inventory process at VDL Nedcar is controlled by humans, as mentioned in Section 1.2. Since humans play an important role in this process, it is reasonable to assume that the human involvement plays a significant part in the cause of excessive spare parts inventories. Despite the role humans play in the spare parts management process and the belief that they could contribute to the problem of creating excessive inventories, the impact of human involvement is unknown to VDL Nedcar. The business objective of this research is focused on obtaining a better understanding of how humans can be influenced in their decision making concerning spare parts management and how this enables them to use the obtained knowledge to their advantage. Humans can use this knowledge to their advantage in two ways. People should be more alert for spare part attributes that cause a positive impact so that they do not miss their presence. This also applies for attributes that have a negative impact, the presence could evoke caution. Raising awareness among humans can lead to preventing future excessive spare parts inventories.

In this research it is found that an increasing reorder point causes a negative human impact. Furthermore, it was observed that inventory managers struggle more with NPG's of which they expect a higher demand rate. So, inventory managers tend to overestimate demand rates resulting in excessive spare parts inventories. Therefore, it is recommended that inventory managers should be more cautious with assigning higher reorder points to NPG's of which they expect a larger demand rate at first hand. A second recommendation could be to re-evaluate the reorder points of NPG's with a relatively high reorder point. However, it must be noted that this should be executed with caution since not all NPG's with a high reorder point cause a negative deviation. A second finding of this research is the negative relation of costs with relative inventory deviation. The impact of inventory managers becomes worse for an increase of the NPG's costs. This results in excessive inventories for more expensive NPG's. As stated in Section 1.2, VDL Nedcar struggles with having too much value tied up in excessive inventories. Therefore, it is an interesting finding that human impact on inventory management cause excessive inventories for relatively expensive NPG's. This is supported by the finding that inventory managers tend to overestimate the demand rate more for relatively expensive NPG's. Therefore, it is recommended to VDL Nedcar to take this information into account when setting reorder points for more expensive NPG's. This could lead to significant spare parts inventory value reductions because these are relatively expensive parts that have an impact on the total inventory value.

The findings of inventory managers being negatively influenced by an increasing cost and/or reorder point could be explained by the presence of cognitive biases. As mentioned before, it is recommended to inventory managers to use this knowledge to be more cautious in the future. However, this is difficult since people are blind to their own cognitive biases. Therefore, it recommended that VDL Nedcar supports their inventory managers to overcome these biases. In the scientific implications, the literature from Chapter 5 is used to discuss how the found relations could be explained. In this section, it is not important which biases explain the relations. It is merely important to know that biases are present to discuss how we can deal with them from a business perspective. Earlier it was stated that it is required to raise awareness among the inventory managers to cope with the found influences. Besides raising awareness, it is also possible to actively support the inventory managers to cope with the found influences.

Experimental studies on the human decision making process within inventory management for production related goods show improvements from learning by doing and feedback. In this experiment it was studied whether humans estimate the order quantity more accurate after multiple rounds. An improvement in the mean order quantities was observed after a hundred rounds (Bolton and Katok, 2008). Furthermore, Lurie and Swaminathan (2009) tested performance under different frequencies in which feedback is received e.g. after each realized demand. This study showed that a better performance was obtained when feedback is provided less frequently for items with highly variable demand. Since the spare parts demand is also highly variable, it could be beneficial for VDL Nedcar to ensure that inventory managers are not overloaded with feedback after each decision. Besides, it is recommended to VDL Nedcar to let their inventory managers gain experience by doing.Another substantial improvement can be gained by training the inventory manager. In an experiment of Bolton et al. (2012) it was observed that trained subjects scored significantly better, 89.2% efficient in comparison with 83.5%. Bolton et al. (2012) trained the participants by providing a video of one hour explaining how the profit maximizing order quantity can be computed. After watching the video, the subjects had to take a test concerning the content of the video to validate their understanding of the provided theories. This could be an accessible option for VDL Nedcar to improve the decision making process of the inventory managers. The improved decisions consequently contribute to the prevention of future excessive inventory.

Lastly, it is recommended to implement a spare parts management performance measurement as KPI. This could function as a balancing mechanism for dealing with a culture in which inventory managers are afraid of causing shortages to the extent of creating excessive spare parts inventories. Furthermore, assuming that the vast majority of excessive spare parts inventories are not caused deliberately, a KPI can also provide feedback to inventory managers about the impact of their decisions.

8.3 Scientific Implications

The scientific objective of this research (as described in Section 1.4.2) is to obtain interesting findings to encourage further research into the topic. There is (almost) no existing research on the role humans play within spare parts management. However, it is noticed that research on human influence in other business processes shows interesting results with wide implications (see Appendices E and F). Especially in the field of forecasting and inventory management of production related goods, human behavior is well studied.

This research started by identifying the human impact on spare parts management. This is done by comparing the average on hand inventory of a model that represents the actual situation at VDL Nedcar including human involvement with a benchmark model that imitates the situation at VDL Nedcar excluding human involvement. The comparison shows the human influence on the average on hand inventories. Observing the average inventory deviations, it is noticed that the involvement of inventory managers have both positive and negative impacts. An impact is considered negative when a higher average inventory on hand is obtained (for the same level of performance), and vice versa. A limitation of this research is that it does not measures the impact of individual human decisions. The deviations measured in this research are caused by a series of decisions over the past five and a half year.

The impacts caused by the involvement of inventory managers are analyzed to search for relations between spare part attributes and the impacts. These relations indicate how inventory managers are influenced by spare part attributes and impact the inventory management process. In general, operations management theories assume that humans make rational decisions. However, it is proven in behavioral operations management literature that this assumption does not always hold (Donohue et al., 2018). As mentioned in Section 5, cognitive biases, social preferences, and culture can cause humans to deviate from the normative decision. In this research the influence of spare part attributes on the decision making process of inventory managers is analyzed. The analysis found two meaningful relations which can be discussed using existing literature on behavioral operations management (see Chapter 5 and Appendices E and F).

8.3.1 Reorder Point

First, the multiple linear regression model shows the presence of a significant negative relation between reorder point and relative inventory deviation. This indicates that for a higher reorder point of VDL Nedcar, the human impact worsens and with it excessive inventories are created. The reorder point, which is determined by the inventory managers of VDL Nedcar, represents a judgemental forecast (explained in Section 6.1). Therefore, the found relation could be explained using behavioral operations theories on forecasting. A theory that could explain the observed relation is the nonbelief in the law of large numbers bias (Benjamin et al., 2016). This bias states that an individual is under-confident in the accuracy of the point forecast in the long run. In general, spare parts forecasts are created for a longer period of time. An example of the nonbelief is given by the experiment of Kahneman and Tversky (1972). In this experiment, humans predict the probability that out of a thousand coin flips, the number of heads will be between 450 and 550. The participants estimated a probability of 0.21, while the true probability is greater than 0.99. This indicates that people falsely believe that characteristics of large random samples still deviate from the true characteristics of the population. In the field of forecasting, this results in a tendency of overestimating due to under-confidence in the accuracy of the individual's forecast. This bias could explain the found relation between the reorder point and the human impact. The overestimation of the demand rate increases for larger values of the reorder point since the inventory managers misinterpret the confidence of larger sample sets (more fail data for higher demand rate) (Kahneman and Tversky, 1972).

Another proposition that could explain the overestimation of the demand rate is the availability bias. This cognitive bias states that humans tend to overestimate the probability of an event if they have experienced it themselves (recently) (Donohue et al., 2018). The negative human impact for relatively high reorder points could be explained by an overestimation of the probability of a failure. This overestimation could be caused by an earlier experience of shortages of similar NPG's by the inventory manager. This experience could be an incentive for inventory managers to increase reorder points and create excessive inventories. Donohue et al. (2018) state that negative events, i.e. shortages, have a larger influence on the decision-maker than positive events. However, this bias in combination with the findings of this research can merely explain the negative human impact and does not explain the negative relation. Additional data is necessary to be able to confirm whether this bias could explain the obtained relation but due to the limitation of this study to solely focus on quantitative data from SAP, this is not feasible in this research (discussed in Section 8.2).

Furthermore, to search for an explanation for the found relation outside the literature some additional statistical tests were performed. A two sample t-test confirms that on average the relative inventory deviation is greater for relative high reorder points. This suggests that inventory managers struggle more with controlling the inventory for NPG's of which they expect a higher demand rate. More specific, for NPG's of which the inventory manager expects a higher demand rate, the inventory levels are unnecessarily large. Due to the setting of identifying the human impact, negative human impacts always indicate excessive inventory levels. Observing the statistics of the NPG's with a relatively low and high reorder point, nothing remarkable is noticed. There is no statistical significant difference between the mean of the leadtimes between NPG's with a relatively low and high reorder point. However, a statistically significant difference between the batching strategy is found but this is expected since batching is more common for NPG's with relative demand rates.

Studies show that culture can affect the decision making process (Loch and Wu, 2007). At VDL Nedcar there is a strong culture that shortages of spare parts are condemned. These shortages stand out since they cause line stops. However, due to a lack of performance measurement, excessive spare part stocks go unnoticed. This sets a business culture in which excessive stocks are less condemned upon than shortages. This could explain that inventory managers are more inclined to overestimate the demand rate and therefore implement too high reorder points.

8.3.2 Costs

Second, the multiple linear regression model shows the presence of a significant negative relation between costs and relative inventory deviation. This indicates that an increase in costs of the NPG, the human impact worsens. The worsening human influence on inventory management results in an increase in excessive inventories at VDL Nedcar. Despite the lack of expectations or hypotheses of the output due to the exploratory design of the research, this relationship is somewhat contradictory. In general, low cost items have lower demand rates and thus lower reorder points. Going back to the negative relation between reorder point and human impact, the cost relation seems contradictory. By using additional statistical tests it is confirmed that the reorder point for relatively low cost NPG's is larger. Therefore, it is unexpected to some extent that the high cost NPG's with lower reorder points perform worse since this is conflicting with the other found relation. Furthermore, the negative relation concerning the reorder point is slightly more significant and has a greater impact. Despite the seemingly conflicting perception of the relation, we still try to explain the found relation since it is merely a perception that needs to be noted.

The determination of the reorder point of the theory-based model does not cause this relation. If a system approach was used, the found relation would be unexpected since this approach maintains low inventories for expensive parts. However, in this research the item approach was applied because it is more applicable to VDL Nedcar than the system approach. This approach does not take costs into account in making decisions concerning reorder points. So, evaluating the reorder point determination strategy seems not to contribute to the explanation of this relation.

In general high-cost spare parts have relatively low demand rates (Kennedy et al., 2002). This is confirmed in Section 7.2 where a two sample t-test statistically proved that the demand rate of high-cost NPG's is significantly lower. Observing the relative difference between the reorder point of VDL Nedcar and the actual demand rate for high- and low-cost NPG's, it is also noticed that inventory managers overestimate the demand for high-cost NPG's in comparison with low-cost NPG's. This overestimation could be caused by underweighting the majority of a small sample by a unique event, i.e. a shortage (Tong and Feiler, 2017). Since more expensive NPG's have a lower demand rate, less fail data is available causing a smaller information source for the inventory managers. The lesser amount of available information makes it more difficult for the inventory manager to make an accurate forecast. If the inventory manager has recently experienced a shortage of a similar NPG, the probability of demand could be overestimated. This proposition is in line with the availability bias (Donohue et al., 2018). However, due to the limitation of only using quantitative data and the lack of information on shortages, this proposition can not be proved.

Furthermore, in Section 7.2, a paired t-test shows that the average inventory on hand is significantly higher for relatively low-cost NPG's than for high-costs NPG's. This seems reasonable, as the demand rate for this type of NPG's is generally higher. The is also confirmed by a two-sample t-test in Section 7.2. The lower average inventory could explain the negative human influence with behavioral operations theory. At VDL Nedcar there is a strong culture that shortages of spare parts are condemned. These shortages stand out since they cause line stops. However, due to a lack of performance measurement, excessive spare part stocks go unnoticed. This sets a business culture in which excessive stocks are less condemned upon than shortages. For high-cost parts, it is more frightening to lower the stock since this brings the stock closer to zero. This behavior could be categorized as loss aversion. This is a common cognitive bias where the decision-maker avoids losses because he/she estimates the loss larger than the potential gain. In this case, the inventory manager is afraid of causing a shortage by lowering the average inventory. So, a combination of the reigning business culture at VDL Nedcar and the loss aversion bias can be used as a proposition that explains the negative relation between costs and human influence.

For the other variables, no meaningful relations are identified since they are statistically non significant. It is also not possible to conclude that these variables have no effect on the human impact in spare parts management because insignificance can be caused by various reasons. For example, not enough observations of the concerning variable to detect a significant relation.

8.4 Limitations and Future Research

This research is subject to several limitations. Limitations are shortcomings caused by the research's decisions concerning the methodology. These limitations form opportunities for future research.

Firstly, a limitation of this research is that it only uses quantitative data from an ERP system to find relations that explain the human behavior within spare parts management. This limits the amount of factors that can be included in the model. Furthermore, valuable insights could have been obtained from gathering qualitative data by conducting interviews. As explained in Section 1.5, these limitations are caused by the time constraint of this research. For future studies, it could be interesting to include more factors that could explain the human behavior. Furthermore, interviews could contribute to a better understanding of the identified relations.

Secondly, the method for identifying the human impact on the spare parts management process is limited. The method is merely able to identify the impact of an aggregation of all human decisions over time for a specific spare part. This causes that decisions cannot be analyzed separately, making it more difficult to substantiate propositions that explain the identified relations. Future research should perform a field study in which individual human decisions can be coupled to certain outcomes. This allows individual human choices to be analyzed to confirm propositions. Combining this with the first recommendation of conducting interviews to obtain qualitative information, will provide a better insight into the human decision making process concerning spare parts management. Furthermore, a field study gives the opportunity to make clausal relations.

Thirdly, the conceptual inventory models are designed to serve the goal of representing the situation at VDL Nedcar. This makes it not possible to use the same conceptual model for companies that differ from these settings. However, the methodology of this research provides the ability to conduct similar research for different settings. For future research, it could be interesting to execute similar research at a different company to compare the findings and possibly identify company or sector specific behavior.

Fourthly, two concessions were made in the development of the conceptual inventory models. Emergency shipments and obsolescence are excluded from the conceptual models despite being applicable to VDL Nedcar. This decision was made in order to prevent the model from becoming too complex for this research scope. Future research could extend the current model with these aspects to obtain more factors for the analysis phase. This could bring new interesting insight into which factors influence human decision making. For example, it could well be that people are more willing to lower inventories when emergency orders are possible. Another example could be that human impact worsens for parts that are viable of becoming obsolete due to the uncertainty that comes with it. So, extending the conceptual inventory models with emergency shipments and obsolescence could be interesting for future research.

Lastly, a few limitations occurred due to a lack of (accurate) data. This resulted in sub-optimal designing decisions and assumptions. An analysis of the order data showed that the majority of the orders did not adhere to the inventory control parameters subtracted from SAP. This lead to the decision of using the actual order and demand data of VDL Nedcar which resulted in a loss of information and possibilities. This made it impossible to calculate a performance measurement since SAP does not allow negative inventories. Furthermore, VDL Nedcar does not properly register the requirement date of a specific spare part. This results in the inability of assessing whether the stock was zero or backorders occurred. This data-driven limitation results in a reduced insight of the human impact on spare parts inventory management. Therefore, as already stated in Section 8.1.1, it is recommended to VDL Nedcar to implement a spare parts management performance measurement that provides insights into backorders, among other things.

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Appendix A

Reorder determination process calculated by hand for single NPG

To start the demand has to be grouped into buckets from fourteen days ($L_i = 14$). This results in 138 buckets of which eighteen have non-zero demand. Using the formulas from section 4.3 to initialize, provided the values for the first row of table A.1. The other lines were calculated with equations for croston's method as described in section 2.1. Furthermore, as explained earlier, a alpha of 0.2 is used.

t	Demand	y"t	p"t	z"t
25	10.0000	0.4000	25.0000	10.0000
26	15.0000	0.4000	25.0000	10.0000
49	10.0000	0.5446	20.2000	11.0000
53	10.0000	0.5202	20.7600	10.8000
62	20.0000	0.6112	17.4080	10.6400
63	250.0000	0.7956	15.7264	12.5120
84	29.0000	4.6952	12.7811	60.0096
85	20.0000	3.7302	14.4249	53.8077
90	20.0000	4.0074	11.7399	47.0461
91	9.0000	4.0067	10.3919	41.6369
93	10.0000	4.1240	8.5135	35.1095
101	3.0000	4.1726	7.2108	30.0876
109	4.0000	3.3480	7.3687	24.6701
111	10.0000	2.7400	7.4949	20.5361
114	20.0000	2.8813	6.3959	18.4289
119	13.0000	3.2786	5.7168	18.7431
120	15.0000	3.1569	5.5734	17.5945
128	20.0000	3.6653	4.6587	17.0756

Table A.1: Values of Croston's method for NPG0005172

The leadtime demand rate that is obtaind following Croston's method for NPG0005172 is 3.6653, which is high in respect to the demand rates of the other NPG's. Now, the reorder point is going to be determined. The following values are applicable for NPG0005172: $Q_i = 20$, $\beta_i(s_i)^{obj} = 0.95$ and U_i with $\{1, ..., 20\}$. The $\beta_i(s_i)$ can be calculated for the geedy heuristic by inserting these values in equation 3.4 and starting with $s_i = 0$ and i=NPG0005172:

$\beta_i\left(0, 20\right) = \sum_{u=1}^{20} \sum_{x=0}^{-1+u} P\left\{Y_i = x\right\} P\left\{U_i = u\right\}$
$\beta_i\left(0, 20\right) = 1/20{*}(P\left\{Y_i \leq 0\right\}{+}P\left\{Y_i \leq 1\right\}{+}P\left\{Y_i \leq 2\right\}{+}...{+}P\left\{Y_i \leq 19\right\}) = 0.8167350000251912$

This does not adheres to the constraint of $\beta_i(s_i) \leq \beta_i(S_i)^{obj}$ for $s_i = 0$. So, the reorder point is increased by one. This keeps on going till the constraint is satisfied. So;

$\beta_i\left(1, 20\right) = 1/20{*}(P\left\{Y_i \leq 1\right\}{+}P\left\{Y_i \leq 2\right\}{+}P\left\{Y_i \leq 3\right\}{+}...{+}P\left\{Y_i \leq 20\right\}) = 0.8654551754449078$

$\beta_i\left(2, 20\right) = 1/20{*}(P\left\{Y_i \leq 2\right\}{+}P\left\{Y_i \leq 3\right\}{+}P\left\{Y_i \leq 4\right\}{+}...{+}P\left\{Y_i \leq 21\right\}) = 0.9094844099252989$
$\beta_i\left(3, 20\right) = 1/20{*}(P\left\{Y_i \leq 3\right\}{+}P\left\{Y_i \leq 4\right\}{+}P\left\{Y_i \leq 5\right\}{+}...{+}P\left\{Y_i \leq 22\right\}) = 0.94491679146394$
$\beta_i\left(4, 20\right) = 1/20{*}(P\left\{Y_i \leq 4\right\}{+}P\left\{Y_i \leq 5\right\}{+}P\left\{Y_i \leq 6\right\}{+}...{+}P\left\{Y_i \leq 23\right\}) = 0.9698458246370036$
$\beta_i\left(5, 20\right) = 1/20{*}(P\left\{Y_i \leq 5\right\}{+}P\left\{Y_i \leq 6\right\}{+}P\left\{Y_i \leq 7\right\}{+}...{+}P\left\{Y_i \leq 24\right\}) = 0.9851503771186227$
$\beta_i\left(6, 20\right) = 1/20{*}(P\left\{Y_i \leq 6\right\}{+}P\left\{Y_i \leq 7\right\}{+}P\left\{Y_i \leq 8\right\}{+}...{+}P\left\{Y_i \leq 25\right\}) = 0.9933996077845301$
So a reorder point of 6 is obtained since $\beta_i\left(6, 20\right)$ is the lowest fillrate that achieves the constraint.

Appendix B

Snapshot of output phase 1

Index	dcar invent	theory bas	delta	Quantity.1	Cost Ctr	eorder Poir	Ain. Lot Sz	TRLT	Vendor	mount in L	MRPC	PGr	vendors	flag	lead	reorder
NPG0028914	6	2	4	EA	nan	1	1	0	nan	129.3	703	703	0	nan	12	1
NPG0029663	50	46	4	EA	52300	3	100	0	nan	1.48	707	707	0	nan	10	3
NPG0030320	8	9	-1	EA	53850	3	10	0	nan	0.56	707	707	0	nan	10	3
NPG0034666	18	15	3	EA	53830	2	1	0	nan	3.5	702	702	0	nan	10	2
NPG0035870	4	83	-79	EA	nan	1	2	0	nan	119.73	702	702	0	nan	10	1
NPG0036176	5	3	2	EA	53850	1	1	0	nan	0.73	702	702	0	nan	10	1
NPG0038629	1	2	-1	EA	nan	1	1	0	nan	37.61	706	706	0	nan	10	1
NPG0038656	2	1	1	EA	nan	1	1	0	nan	15.08	706	706	0	nan	6	1
NPG0043995	8	2	6	EA	nan	1	1	0	nan	4.14	706	706	0	nan	10	1
NPG0056747	2	1	1	EA	nan	1	1	0	nan	34.94	703	703	0	nan	7	1
NPG0060401	1	2	-1	EA	nan	2	1	0	nan	81.99	703	703	0	nan	12	2
NPG0060466	2	1	1	EA	nan	1	1	0	47220	41.01	706	706	1	nan	12	1
NPG0062842	3	2	1	EA	nan	1	2	0	nan	41.17	702	702	0	nan	10	1
NPG0064612	2	2	0	EA	53850	1	1	0	nan	11.18	703	703	0	nan	12	1
NPG0064757	2	1	1	EA	nan	1	1	0	nan	13.9	706	706	0	nan	12	1
NPG0065092	1	1	0	EA	nan	1	1	0	nan	110.5	703	703	0	nan	12	1
NPG0069291	2	2	0	EA	53530	1	2	0	nan	187.4	706	706	0	nan	6	1
NPG0070295	3	1	2	EA	nan	1	1	0	nan	21.99	706	706	0	nan	6	1
NPG0034709	1	2	-1	EA	nan	1	1	0	nan	6.3	702	702	0	nan	10	1
NPG0026837	2	3	-1	EA	53850	2	1	0	nan	10.35	703	703	0	nan	10	2
NPG0027750	2	5	-3	EA	nan	2	1	0	nan	124.13	703	703	0	nan	10	2
NPG0056710	11	5	6	EA	nan	1	1	0	nan	41.8	703	703	0	nan	7	1

Figure B.1: Snapshot of output phase 1

Appendix C

Added variable plots

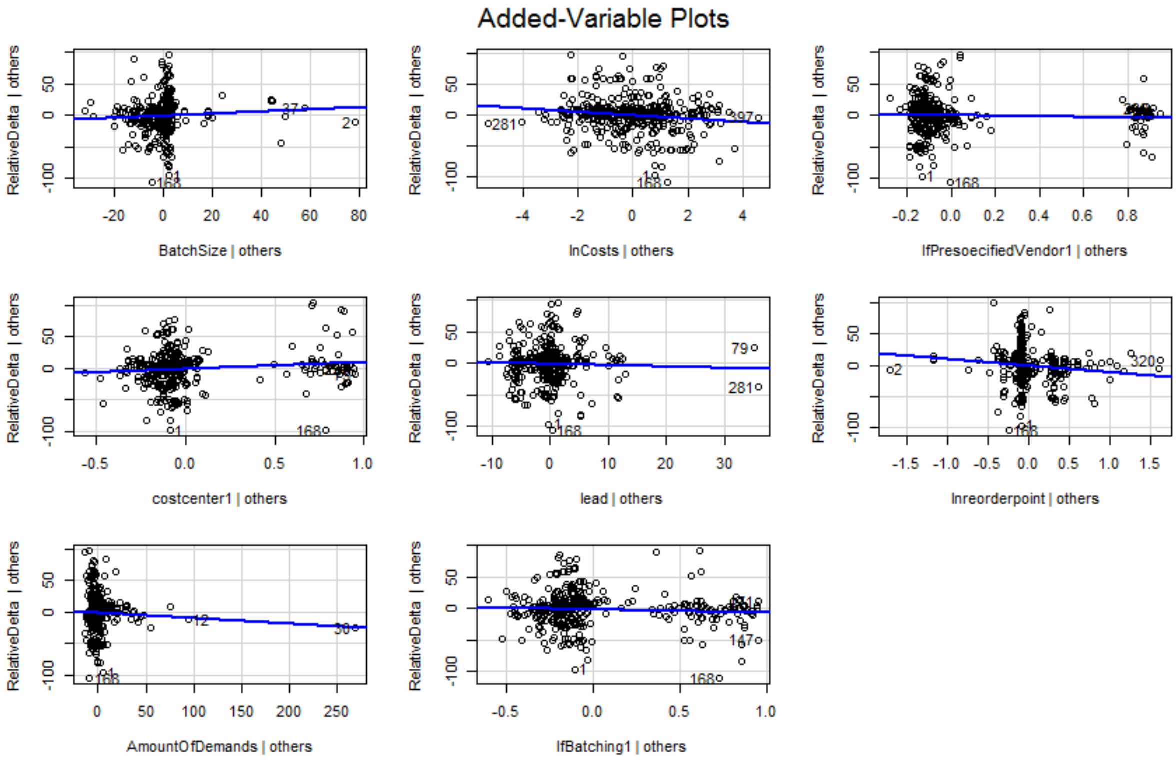

Figure C.1: Overview of all added variable plots

Appendix D

Histograms

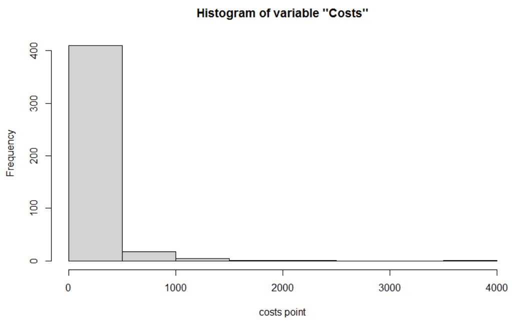

Figure D.1: Histogram of costs before transformation

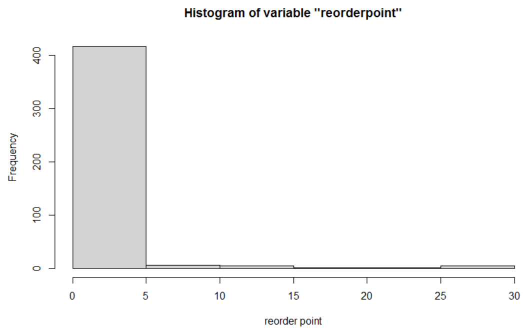

Figure D.2: Histogram of reorder point before transformation

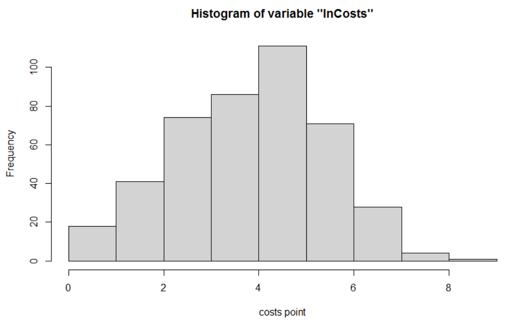

Figure D.3: Histogram of costs after transformation

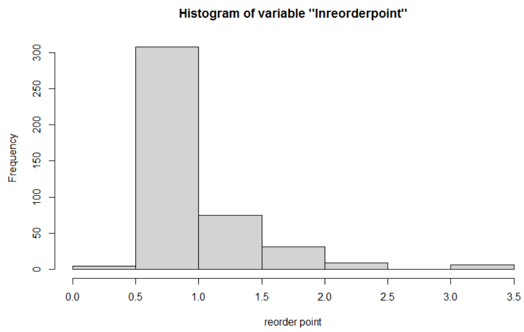

Figure D.4: Histogram of reorder point after transformation

Appendix E

Additional Literature on Behavioral Inventory Decisions

In general, inventory models assume that decision-makers use rational thinking to maximize profit. However, in practice, it is observed that this is not always the case (Donohue et al., 2018). This appendix is going to provide some insights into the existing literature on behavioral operations management for inventory management, in specific for the newsvendor model. The newsvendor model is a mathematical model within operations management that focusses on optimizing the inventory levels and is characterized by fixed prices and uncertainty (Arrow et al., 1951). Due to the amount of existing literature on the model and because it is one of the fundamental inventory models within operation management, the decision was made to use this model to explore human behavior within inventory management. The newsvendor model calculates an "optimal" order quantity (q*) that balances the costs of keeping inventory (holding costs) and the costs of missing demand (lost sales, backorder costs, emergency shipment). However, in practice it is seen that this model is mainly used as a suggestion, meaning that an inventory manager has to make the final decision concerning the order quantity. Schweitzer and Cachon (2000) researched the behavior of inventory managers concerning this decision. They found out that humans tend to order the mean demand (µ) instead of the "optimal" order quantity from the newsvendor model. By discovering this behavior they identified the "pull-to-center" effect, whereas the decision-maker tends to order an amount that is equal to the mean demand instead of the "optimal" order quantity. This confirms that human-decision makers exhibit irrational behavior in their decisions concerning inventory management under uncertain demand (Donohue et al., 2020). The Anchoring bias is often used in literature to explain the pull-to-center effect. This can be modeled by the mean anchoring heuristic using as the weight placed on the anchor, which is the mean demand in this heuristic:

$$\text{Order quantity } (q) = \alpha * \mu + (1 - \alpha) * q^* \quad \text{with } 0 < \alpha \leq 1$$

Bostian et al. (2008) performed a regression analysis and came up with an average value for α of 0.47. However, the value for α can vary from 0.20 (Bolton, Ockenfels, Thonemann, 2012) to 0.79 (Schweitzer and Cachon, 2000). The mean anchoring heuristic is easy to apply and is not dependent on historic data, which allows the heuristic to be applicable for modeling first-period decisions (no historic data available yet) and single-shot decisions. However, Lau et al. (2014) analyzed the order quantities on an individual basis, whereas other studies used aggregated data and discovered that order quantities are not strictly between the mean and optimal value. This discovery showed that the mean anchoring heuristic is unable to explain the variability, due to the restriction on α.

A heuristic that also models the anchoring bias, but takes the variability into account is the demand chasing heuristic. Within this heuristic, the decision-maker sets an anchor value based on the previous order and adjusts the anchor to the preceding actual demand (Bolton et al., 2012). It is often seen that in case the preceding actual demand turned out to be high, the decision-maker tends to increase the order quantity and vice versa (Donohue et al., 2018). There are four approaches for analyzing demand chasing within the existing literature, these are described in Table 1.

Approach	Description	Reference
Change Frequency	Measures the times that the order is adjusted towards or away from the preceding demand, providing an indication of demand chasing behavior.	(Schweitzer and Cachon, 2000) (Donohue et al., 2018)
Adjustment Score	Measures the adjustment of the order relative to the gap of the preceding period (gap = difference between order quantity and actual demand)	citepschweitzer2000decision (Donohue et al., 2018)
Regression	This approach uses the preceding order quantity as an anchor and adjusts the anchor with the preceding gap multiplied with the demand chasing factor. This factor gives a weight to ''the chasing" and is estimated using linear regression.	(Bostian et al., 2008)
Correlation	This approach searches for a correlation between the current order and preceding demand to indicate demand chasing.	(Bolton and Katok, 2008)

Table E.1: Demand chasing approaches

The performance of the different approaches was determined by analyzing the approaches in a simulation of demand consisting out of demand with and without chasing behavior. To assess the approaches, the number of false positives and negatives were measured for each approach. A false positive is when an approach identifies demand chasing behavior when it is not present. In case demand chasing behavior is exhibited without being identified by the approach a false negative occurs. After analyzing the four approaches, the correlation approach proved to be the best choice with this performance measurement (Lau et al., 2014).

Another bias that is being used in the existing literature to explain the pull-to-center effect is the overconfidence bias. Ren and Croson (2013) researched the overconfidence bias within the newsvendor model and found out that an underestimation of the demand variance can lead to the pull-to-center effect. They confirmed their findings by applying overconfidence reduction techniques to some of the participants, whereafter they noticed a decrease of the pull-to-center effect for those participants. Later, research by Lee and Siemsen (2017) also confirmed that the overconfidence bias is an explaination (among others) for the pull-to-center effect.

Culture can also influence the decision making process. In order to research the cultural factor, Feng et al. (2011) repeated the experiment of Bolton and Katok (2008) to identify cultural influences. However, Feng et al. (2011) executed the experience with Chinese students instead of Americans (as Bolton and Katok (2008) did). This enabled them to identify differences between the two cultural groups. Eventually, it was observed that the Chinese students exhibit the pull-to-center effect more heavily than the American students.

Appendix F

Additional Literature on Behavioral Forecasting

Within the field of behavioral operations, demand forecasting is observed as a key competence. Since planning is the art of coordinating an organization for the future, it is important to have an idea of how that future looks like. To achieve this, an indication of the timing and magnitude of future customer demand is crucial. The obtained forecast can be used as input for decisions concerning production planning, work schedule, resource allocation, and inventory parameters. There exist numerous statistical methods to predict demand, however, in practice it is observed that these algorithms are either not used or the outcome is adjusted based on human judgment (Donohue et al., 2018). This was confirmed by Boulaksil and Franses (2009), who conducted a case study. Within this case study, it was discovered that only 50% of the forecasters rely on forecasting algorithms. Therefore it is important to study human behavior within forecasting and whether behavioral aspects can explain forecast deviations. For example, the presence of a cognitive bias within the behavioral forecasting process causing an increased inaccuracy.

In practice, point forecasting is the most common method of forecasting. This type of forecasting uses a single point for the future that depicts the expected demand, which is often equal to the mean demand. Furthermore, point forecasting leaves room for human involvement which makes it the ideal forecasting method for analyzing human behavior. An important cognitive bias that is often experienced by forecasters within point forecasting is the anchoring bias. Several studies concluded that the initial anchoring is often inaccurate and not adjusted properly. A key discovery from Epley and Gilovich (2006) was that forecasters who use relevant information to set an anchor tend to stick to this anchor. This phenomenon can be explained due to a premature sense of satisfaction among the forecasters, which leads to insufficient adjusting. A heuristic that explains the observed behavior is the demand chasing heuristic. In these cases, the forecaster attaches too much value to the preceding demand. However, it was demonstrated by Lawrence and O'connor (1995) that in case the latest demand is informative, the forecaster should rely more on the anchor. An opposite heuristic states that the forecaster uses a long term average as the anchor, causing insensitivity toward recent demand.

A key competence of forecasting, which is often neglected, is filtering out the variability that is observed within the demand. Forecasters often have the misconception that the point forecast should resemble the actual demand, however, the goal of a forecast is to create a stable sequence of demand forecasts. This observation can be explained by representativeness heuristic (Kahneman and Tversky, 1972). Another challenge for a forecaster is to determine whether observed variations in the demand is random noise or a relevant factor. In case that the variation is merely caused by noise, the variation can be ignored. However, if the variation is caused by a relevant factor, the forecaster must incorporate this. This challenge is vastly researched end resulted in the system neglect hypothesis. This states that the forecaster tends to overreact in a stable environment while underreacting in an unstable environment (Donohue et al., 2018).

A key bias that is often observed in the forecasting process of non-stationary demand is trend dampening. This bias is caused by a premature belief of the forecaster that the trend that is noticed will diminish. In case of a positive linear trend, this will result in an inadequate point forecast of the demand. This is especially damaging in the short-term, due to a lack of responsiveness to the current situation. This observation can be explained by a combination of the anchor and adjust heuristic and the representativeness heuristic. The point forecast is anchored on the latest demand and insufficiently adjusted, causing an underestimation for a positive trend (lagging behind the trend). The insufficient adjustment could be explained by the representativeness heuristic, due to a belief derived from the natural environment. This belief is derived from the forecaster's personal life were trends are often short-lived.

On the other hand, human involvement within the forecasting process can also bring improvements. The addition of domain-specific knowledge to the forecasting process is the main contribution of human involvement (Lawrence et al., 2000). With this specific knowledge, humans can complement algorithms for specific settings. This knowledge often exists out of specific market characteristics or unquantifiable information. Furthermore, humans are more skilled in identifying interactions between variables (Seifert et al., 2015). Whether the contributions of human judgment are overall beneficial to the forecasting process is researched by Fildes and Goodwin (2007). In this research, the performance difference between a forecast subjected to human judgment was compared with the initial algorithmic forecast. It was observed that the adjusted forecast performed better on average, caused by a handful of big adjustments. These few big adjustmenst can be explained a due to unique event, e.g. promotion. Algorithmic forecasting models have difficulties with predicting these unique events because they operate using statistical logic and historic data.