MASTER

Understanding spare part fill rate misalignment between theory and practice
a data-driven case study

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Understanding spare part fill rate misalignment between theory and practice

A data-driven case study

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In partial fulfillment of the requirements for the degree of
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Abstract

In order to achieve spare part fill rate targets, capital good manufactures generally use optimization models to determine effective inventory policies. In practice, the optimized inventory policies often result in a different realized fill rate than predicted by the optimization model. This difference is defined as the *fill rate gap*. Recognizing model limitations and understanding what drives the fill rate gap is essential in managing its consequences and proposing solutions to bring theory closer to practice. In this master thesis a method is developed to understand and investigate the fill rate gap. A discrete-event simulation model is proposed capable of simulating part-level inventory trajectories. With these trajectories, resulting fill rates for a specific historical period of time can be calculated. Moreover, the model creates different what-if scenarios to test the impact of several potential factors affecting the fill rate gap. Analysis performed using this model at GKN Fokker Services shows that human interaction and lead time deviations positively influence realized fill rates, while demand forecasting has a negative impact on the achieved fill rate. For the first time, a holistic perspective is taken on inventory control models and their behavior in practice. The method helps to create a feedback loop between optimized model values and its realizations in practice, providing a way to learn from past results and assertively take actions to close the fill rate gap. This helps organizations to better do what they promise, manage their inventory more effectively and create a better process control.

Executive summary

Introduction

Manufacturers of capital goods are often tasked with the responsibility of maintaining the after-sales services. This entails replacing broken parts within a short, or agreed upon, lead time. To achieve minimal response time, it is essential to effectively manage the inventory of spare parts. To this end, a part replenishment model is used to optimize inventory policies, guiding the decisions on which parts to stock, how many parts to stock, when to order new units and how many units to order at once. Making these decisions helps in finding a trade-off between minimizing costs (i.e., inventory holding cost, backorder cost and ordering cost) and maximizing fill rate of spare part inventory. The part replenishment model optimizes the inventory policies using historical data, after which the policies are used in an operational process to make purchasing and stocking decisions in practice.

This research considers the inventory control process at GKN Fokker Services (addressed as *Fokker* for the remainder of this summary), an independent aerospace service provider. At Fokker, the perception exists that the model fill rate, as determined by the part replenishment model, deviates from the realized fill rate in practice. In other words, the optimized inventory policies do not result in a similar objective value (fill rate) when used in practice. This observation of fill rate mismatch is defined as the *fill rate gap* and is the main subject of interest in this thesis. The thesis aims to understand and investigate this gap, as narrowing it helps organizations to do what they promise, manage their inventory more effectively, create process control and it allows for a feedback loop between model output and its realization in practice. To achieve this aim, the first part of the thesis deals with creating a model capable of quantifying the impact of potential causes of the fill rate gap. The second part then uses this model in a case study at Fokker to measure the fill rate gap and measure and explain the impact of different fill rate gap causes.

Model

The goal of the first part of the thesis is to develop a model that is able to quantify and explain causes of a fill rate gap. To achieve this, the potential fill rate gap causes that the model should be able to test have to be identified. To achieve this, three steps are taken. First, a literature study is performed to create a longlist of potential causes based on theory. Second, the inventory control system of Fokker is described using a process model, illustrating that every theoretical aspect of the part replenishment model has a corresponding realization in practice (demand forecast versus actual demand, model lead times versus actual lead times, etc.). The differences between these aspects leads to a list of observed fill rate gap causes in practice. Thirdly, the longlist of theoretical causes is decreased to a shortlist based on the observed causes in practice and further discussion on relevance. The resulting shortlist of potential fill rate gap causes that the model should be able to test is presented in Table 1.

Next, a model is developed to quantify and explain the impact of the shortlist causes on the fill rate gap for a specific group of parts. Fokker performs a *stock-run* every half year, in which inventory policies are optimized based on two year of historical data. These policies could then be adjusted, after which they are entered into Fokker's ERP system so they can be used to make decisions. Consequently, different causes manifest themselves in some way over a period of six

#	Causes	Color
1	**Demand forecast**	
	a. Order moment	
	b. Order size	
2	**Lead times**	
	a. Supplier lead time	
3	**Human interaction**	
	a. Inventory policy changes	
	b. Order moment	
	c. Order size	
4	**Fill rate calculation**	
	a. Calculation method	
5	**Classification**	
	a. Grouping spare parts	

Table 1: Shortlist of fill rate gap causes

months, creating the actual fill rate gap. In order to quantify and explain the impact of a single cause on the fill rate gap, its effect has to be isolated. The model used for this purpose should be able to make a statement about what happens with the realized fill rate when a specific cause does, or does not, occur, without changing anything else. In essence, the model has to change what really happened in a period of six months, based on the occurrence, or non-occurrence, of a particular cause.

Simulation is a method often used to test the impact of changes in conditions and courses of action, and therefore forms the basis of the developed model in this thesis. More specifically, a discrete-event simulation (DES) is used to simulate the realized fill rate. This base model is then used to create what-if scenarios reflecting what would have happened if a specific shortlist cause did, or did not, occur, while keeping all other processes equal based on historical data. Detailed process models of the inventory control system at Fokker are constructed, forming the basis for identifying the required model entities, attributes, events, performance measures and simulation implementation. Moreover, an Access tool is developed to collect, transform and combine all necessary data to perform a validation of the model and run the actual simulation and scenarios.

Case study

In the second part of the thesis the discrete-event simulation model is used in practice at Fokker. The time period between the *stock-runs* of the 2$^{\text{nd}}$ of July 2018 and the 2$^{\text{nd}}$ of April 2019 is taken as the simulation period. All parts having an annual demand rate of two or more lines in the period between the 1$^{\text{st}}$ of July 2016 and the 1$^{\text{st}}$ of July 2018 are taken into account. The actual case study setup is illustrated in Figure 1.

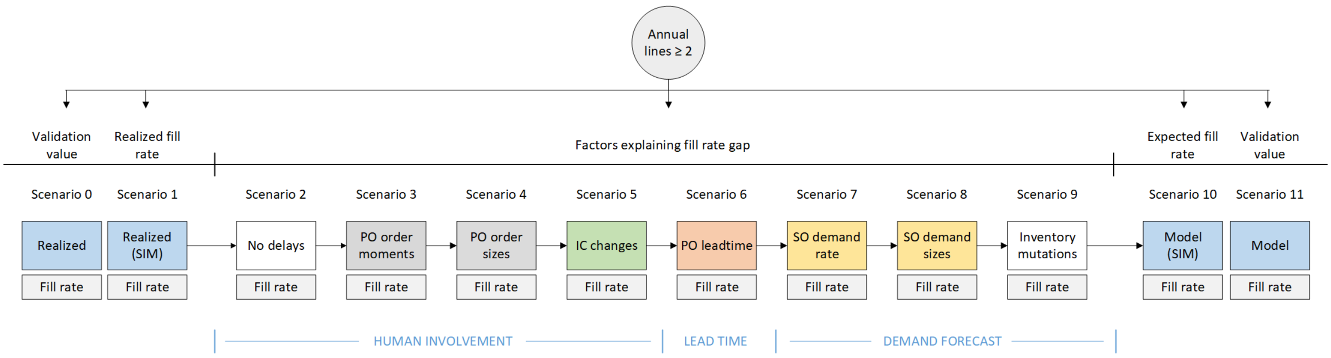

Figure 1: Setup of case study

The case study starts with simulating, and validating, the realized fill rate in the simulation period (blue box on the left). Next, the predicted fill rate of the part replenishment model is simulated and validated (blue box on the right). The difference between these fill rate values represents the actual size of the fill rate gap. To understand how the fill rate gap is composed, intermediate what-if scenarios are created based on the causes on the shortlist (human involvement, lead time and demand forecast). Note that the used colors in the figure correspond with the causes of Table 1. So, we start with a simulation of what really happened in the simulation period. Then, using four steps, a scenarios is created in which all human involvement is taken out. Note that scenario 2 deals with BO, SO and PO handling delays originating from humans postponing required actions. The resulting scenario fill rate provides insights into the impact of human involvement on the fill rate gap. Then, the realized lead times are taken out and replaced by the model lead times. This provides the impact of lead times on the fill rate gap. Finally, the same method is used to test the impact of demand forecasting by replacing the actual demand with a simulation of the forecasted demand. In this way, we move from a simulation of what really happened with the fill rate to a simulation of the part replenishment model, quantifying fill rate gap causes along the way.

Results

For every scenarios presented in Figure 1 an item- and line fill rate measurement is made, depicted in Figure 2 and 3. The results indicate that an item- and line fill rate gap is present, as the realized- and model fill rates of scenarios 1 and 10 (the black dots) are not horizontally aligned. The line fill rate gap is 3.56%, while the item fill rate gap is only 0.74%. Based on further analysis, it is shown that most scenarios differ significantly from each other based on fill rate and represent individual causes impacting the gap. Moreover, the total fill rate gap is composed of several positive- and negative fill rate impacts compensating each other to some extent. First, human involvement positively impacts the realized line- and item fill rate with 2.12% and 1.39% respectively. This is mainly caused by the knowledge and experience of the purchasers, resulting in an order frequency and average order size higher than the optimized inventory policies suggest, but lower than the suggestions of the adjusted policies entered into the ERP system. Second, the model lead times have a positive impact of 3.21% and 2.24%. This is due to the fact that actual lead times are on average 20 days faster then assumed in the part replenishment model. Third, the demand forecasting negatively impacts the realized fill rates with 8.89% and 4.37%. It predicts, on average, lower rates and lower demand sizes. The policies are therefore not fully calibrated for the actual demand.

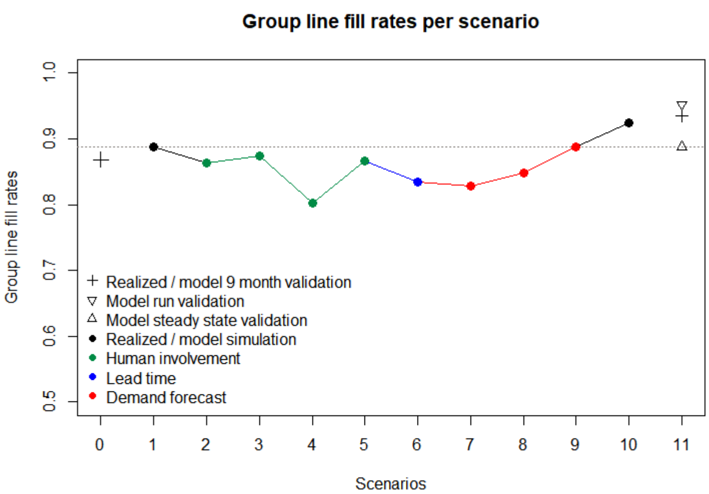

Figure 2: Results line fill rate

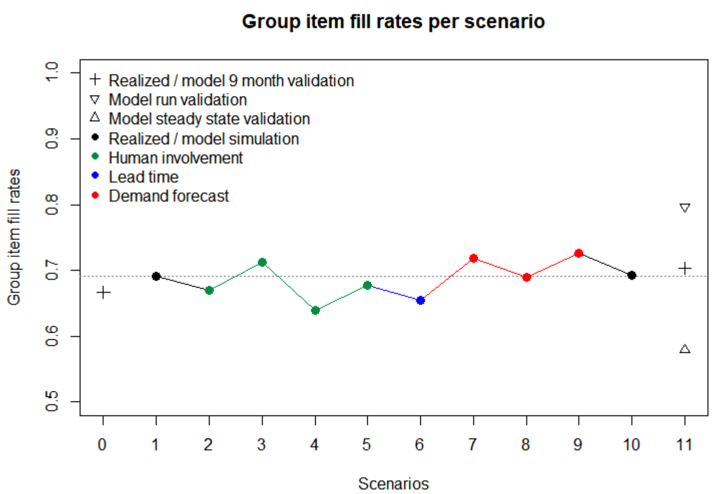

Figure 3: Results item fill rate

Conclusion

This thesis has created insights into the difference between realized- and model fill rates. Recognizing model limitations and understanding what drives the fill rate gap is essential in managing its consequences and proposing solutions to bring theory closer to practice. The thesis has shown that, by using the discrete-event simulation model, causes can be quantified and explained, creating a feedback loop between optimized model output and its realizations in reality. This research is the first to place inventory control models in a more holistic perspective, covering the relationships between modelled and realized values in more detail. Using the understanding of the reasons for the fill rate gap and the impact of every cause, a better control on the process is gained, potentially resulting in more effective inventory management. With this, the circle is closed.

It is recommended to Fokker to involve the purchasers in making changes to optimized inventory policies, to better align model lead times with their actual values, investigate other demand forecasting methods and use the simulation model before every *stock-run* to establish and monitor strategies to narrow the fill rate gap.

Future research may focus on generalizing the model to allow for different inventory policies, fill rate calculations and causes to be tested and to automatize simulation runs and output analysis. Moreover, research may be conducted on developing models that are better equipped to deal with non-steady-state behavior in practice, on taking a holistic perspective on inventory management and on standardizing feedback loops between optimized model values and their realizations in practice.

Preface

Back in September 2013, it never crossed my mind that I found myself on the verge of the best time of my life. This master thesis marks the end of this period. It started with my bachelor, primarily focused on getting the basics down of industrial engineering, exploring student life and getting to know myself better. With this experience, I had the opportunity to challenge myself with a board membership at UniPartners Eindhoven. A valuable and extremely instructive year. From there, I deepened my knowledge with a master program, partly conducted in the exiting student life at UPorto in Portugal. And now, after all those years, I could try and use all that I have learned in this master thesis. The past six years proved to be memorable, rewarding and entertaining. For this I want to thank a number of people I had the privilege of meet and work with.

First of all, I want to thank my family. My parents, sister and uncle and aunt. Without your help and understanding I would not have made the choices that brought me here. I am eternally grateful for the opportunities that you provided me with. I could not have done it without you. I also want thank my girlfriend for always listening and cheering me up when I needed it. Finally, I want to thank the friends I made along the way. The past six years would not have been this amazing without you. We can look back at an amazing time in which we created unforgettable memories.

Then, I would like to thank several people from the TU/e who have been involved in this project. Without a doubt, I want to express my gratitude to Willem van Jaarsveld, my mentor and first supervisor. Without your guidance I would not have been able to tackle the project the way I did. Whenever I doubted on the way to proceed, you could always clearly explain the roads I could take. The feedback you provided at every meeting helped me to focus on the most important aspects instead of wanting to do it all. Thank you for helping to structure my efforts for the better. I also want to thank you for the opportunity to present my work at the Fokker, Philips and NS collaboration on real-time data analysis. Furthermore, I want to thank my second supervisor, Rob Basten. Thank you for asking the right questions during our meetings and guiding me to a more clear thesis. Finally, I want to thank Alp Akçay for taking the effort to assess my thesis as third supervisor.

I also want to thank GKN Fokker Services for the opportunity to perform my master thesis project at your offices. In particular, I want to thank Charlotte Zohlandt for always taking the time to meet with me and provide me with valuable insights into Fokker and my project. Your feedback has helped me finalize the project in a way suitable for all parties involved. I also want to thank Kaveh Alizadeh for always challenging me and helping me out when I needed it. My time at Fokker has been very pleasant thanks to you two.

Stan van Klink

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List of Abbreviations

Abbreviation	Explanation
BO	Backorder
DES	Discrete-event simulation
ERP	Enterprise resource planning
FCFS	First Come First Serve
IC	Inventory Controller
IP	Inventory position
MC	Monte Carlo
MILP	Mixed Integer Linear Program
MOQ	Minimal order quantity
PO	Purchase order
(s,S)	Reorder level (s) and order up to level (S)
SA	Spares Analytics
SKU	Stock keeping unit
SL	Service level
SLA	Service level agreement
SO	Sales order
WRS	Wilcoxon rank-sum test

List of Definitions

Definition	**Explanation**
Adjusted inventory policy	Inventory control parameters entered into the ERP system.
Fill rate gap	Fill rate misalignment between model and realized fill rates.
Fill rate gap cause	A potential reason explaining why the realized fill rate differs from the model fill rate.
History period	Period of time that is used to optimize inventory policies in the part replenishment model (often two years).
Inventory control parameters	The parameters essential for controlling inventory based on a specific policy. In case of GKN Fokker Services, these are the reorder (s) and order up to level (S).
Inventory control system	The whole of processes and methods used to manage and control the inventory (part replenishment model, purchasing process, etc.).
Inventory policy	Method used to manage the inventory of a part, e.g. (s, S) policies.
Item fill rate	Percentage of ordered items filled immediately from stock.
Line fill rate	Percentage of complete order lines filled immediately from stock.
Model fill rate	The fill rate as predicted by a part replenishment model.
Optimized inventory policy	Inventory control parameters optimized by part replenishment model.
Part replenishment model	A method or model used to determine inventory control parameters.
Realized fill rate	The fill rate realized in practice, based on historical sales data.
Sample group	Group of spare parts selected for investigation.
Simulation period	Period for which the discrete-event simulation is ran (six months).
Stock-run	The term used at GKN Fokker Services to indicate the process of calculating new optimized inventory control parameters based on the part replenishment model.
Undershoot signal	The moment the inventory position of a part is equal to, or drops below, its corresponding reorder level, a notification is added to the report showing these occurrences. These notifications are called undershoot signals.
What-if scenario	Alternative reality in which a specific parameter of reality is adjusted to test what would have happened.

Chapter 1

Introduction

1.1 Problem context

The services delivered by the users of a capital good, such as a machine, train or airplane, heavily depend on the proper functioning of this good. Oftentimes, the task of maintaining the fleet of capital goods is the responsibility of the capital good producer or a specialized service provider (Kranenburg and van Houtum, 2015). This task is called after-sales service and ensures that broken parts are replaced within a short, or agreed upon, lead time. It aims to minimize capital good downtime and support maintenance endeavours, which are the largest cost components (two-thirds) during the exploitation phase of a capital good according to Kranenburg and van Houtum (2015). Superior after-sales service can, therefore, be used to create a sustainable competitive advantage (de Souza et al., 2011).

In order to achieve minimal response times, the management of spare part inventory is essential. The proportion of the total stock devoted to service parts is often considerable in an industrial context, ranging up to 60% of the total stock value (Vereecke and Verstraeten, 1994). A core question asked in capital good practice is therefore:

How to control our spare part inventory in order to balance cost and fill rate?

Regularly, the answer to this question involves using a part replenishment model that optimizes inventory policies to achieve a certain part availability target. Such systems provide guidance in answering four questions (Bošnjaković, 2010):

- Which parts to keep on stock?
- How many units to keep in stock of these parts?
- When to order new units?
- How many units to order at once?

Making these decisions helps in finding a well-advised trade-off between minimizing costs (i.e., inventory holing cost, back order cost and ordering cost) and maximizing availability (fill rate) of inventory, resulting in a set of inventory policies best suited to achieve a certain stock availability. These values are then used in practice to make purchasing and stocking decisions. Figure 1.1 provides an overview of an example of such a process.

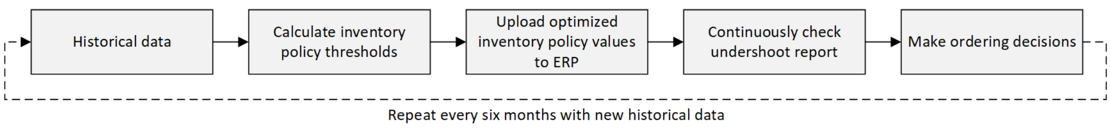


Figure 1.1: Current inventory control system

First of all, all required historical data is collected. With this data, a part replenishment model optimizes a set of inventory policies. The optimized policies are then uploaded to an ERP system, which generates undershoot signals when the inventory drops below a certain threshold. All signals are summarized in a report. Using the report and the inventory polices, purchasers make procurement and stocking decisions. The process of optimizing the inventory policies will be defined as a *stock-run* and is repeated after a specific period of time (six months).

In essence, this process is very general. Historical data is collected, which is used to optimize inventory policies. These optimized values are then used in an operational process. GKN Fokker Services, an independent service provider for aerospace, has the described process of Figure 1.1 in place. This research is performed in collaboration with them.

1.2 Company introduction

GKN Fokker Services is an independent aerospace service provider, located in Hoofddorp, The Netherlands. It is a business unit of GKN Fokker Technologies, which remained after the bankruptcy of Fokker Aircraft in 1996. In 2015 Fokker Technologies was acquired by the British engineering concern GKN.

As a whole, GKN Fokker Technologies is a leading global aerospace specialist. In 2018, they employed around 5,000 employees with locations in The Netherlands, Romania, Turkey, Canada, Mexico, USA, China, India and Singapore. Their primary capabilities focuses around four business units, namely Fokker Aerostructures, Fokker Landing Gear, Fokker Elmo (electronics) and Fokker Services. GKN Fokker Technologies do not build fully operational aircraft themselves, but rather produce parts and work together with other builders such as Lockheed Martin, Airbus, Boeing and Bombardier. Their mission it to support their customers word-wide in excellence in designing, building and operating smart, safe, sustainable and affordable aircraft, by offering distinctive integrator solutions, featuring sophisticated technologies.

GKN Fokker Services is responsible for the availability, maintenance and repair of parts of aircraft operators, while also maintaining the aircraft built by Fokker Aircraft. Four different products are offered to the commercial and defense market, namely

- Rotable trading.
- Standard parts total support.
- Part distribution.
- Part manufacturing.

With warehouses in Hoofddorp, the USA and Singapore, a total of 54,000 in- and 85,000 outbound transactions are realized yearly (2017). Using a total area of 12,000m2 warehouse space, more than 50,000 unique spare parts are stored, valued at 100 million euro.

Spare part availability, the main focus on the thesis, is the responsibility of the Parts Distribution team within the Product Management department. The team primarily focuses on continuous stock acquisition to achieve desired availability levels for their customers. Hence, effective spare part inventory management is an important aspect of operations for GKN Fokker Services.

1.3 Research design

1.3.1 Problem statement

Many companies, among which is GKN Fokker Services (addressed as *Fokker* for the remainder of this thesis), have a process in place that is similar to the one displayed in Figure 1.1. At Fokker, however, the perception exists that the model fill rate, as determined by the part replenishment model, deviates from the realized fill rate in practice. The main problem of interest for this thesis is therefore:

The model fill rate deviates from the realized fill rate.

This difference, or misalignment, is referred to as the *fill rate gap* for the remainder of this thesis. Investigating this gap is important for several reasons and has multiple benefits. These are discussed below.

Do what you promise to do. An inventory control system is most effective if the optimized decision variables (inventory policies) result in similar objective values (cost, fill rate) in practice. If not, a company is less able to do what they promise to do. This is especially relevant when service level agreements (SLA) are agreed upon with customers. For example, based on such an agreement *Company A* is required to meet a 90% availability of spare parts. To achieve this, *Company A* uses a part replenishment model that states to follow the set of inventory policies B. When a different availability is achieved when this set of policies B is used in practice, *Company A* can not do what it promises and fails to meet the service level agreement with all its consequences.

Effective inventory management. Not being able to do what you promise proves improvements can be achieved in effectively managing inventory. Consider the example of *Company A* again, which uses the set of inventory policies B to achieve an availability of 90%. Now assume the model states that this level of availability is possible with an investment of €100,000. In practice, three things could happen:

1. *Company A* achieves its target availability of 90% using policy set B with an investment of €100,000
2. *Company A* achieves a higher availability than 90% using policy set B with an investment of €100,000. This means unnecessary investments in stock are made.
3. *Company A* achieves a lower availability than 90% using policy set B with an investment of €100,000. This means a loss of customer base and other (in)direct costs.

The misalignment presented in points 2 and 3 prevent effective management of service stock, which is undesirable for capital intensive organizations and their customers (Cavalieri et al. (2008), Aronis et al. (2004)). Furthermore, both scenario 2 and 3 lead to a situation in which a decision maker is unable to fully trust the suggestions and corresponding objective outcomes of the model. This further decreases the potential to effectively manage the spare part inventory (Glasserman and Tayur, 1995).

Process control. A main benefit of narrowing the fill rate gap is an increased sense of process control. When more insight is gained into the spare part behavior and the factors influencing this behavior, a better understanding of the inventory management process is the result. With this increased process knowledge, better informed decisions can be made.

No feedback loop. Another benefit of identifying a fill rate gap and understanding its causes, is the opportunity to create a feedback loop. When we can learn from what happened, actions can be taken to bring model fill rates and realized fill rates closer to each other in the future. This also contributes to the trust in and sense of control over the model.

Measuring realized fill rates. A final, more Fokker specific, advantage is the fact that the current fill rate performance is not yet consistently measured in the same way the part replenishment model calculates its fill rate. This creates ambiguity as to which fill rates are actually achieved and makes a comparison with the model fill rate troublesome.

1.3.2 Aim

The aim of this thesis is to understand and investigate the difference between realized- and model fill rates. Recognizing the limitations of the model and understanding what drives the fill rate gap is essential to manage its consequences and propose solutions to narrow the gap. By identifying the fill rate gap and quantifying and explaining its causes a feedback loop can be put in place, ultimately closing the circle.

In order to achieve the aim of the thesis, three different aspects should be taken into account.

1. Develop a standardized and consistent measuring method to calculate realized fill rates, following the same calculation method used by the inventory optimization model.

2. Develop a method to identify and quantify causes of a fill rate gap and analyse inventory behavior. This system should be able to create insights into model and realized part fill rates. This will be the main part of the research.
3. Develop actionable insights to bring model and realized fill rates closer to each other. Here the methods of point 1 and 2 are applied at Fokker in the form of a case study.

Adding these steps to the current inventory control system illustrated in Figure 1.1, Figure 1.2 is created. Here the feedback loop (closing the circle) is clearly illustrated.

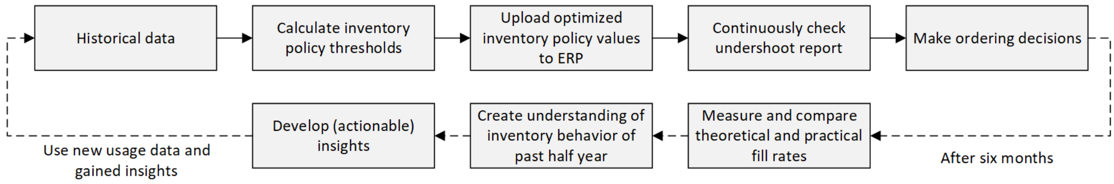


Figure 1.2: Improved inventory control system

1.3.3 Scope

As we aim to compare a modeled situation with its associated realization in practice, the restrictions imposed by the part replenishment model used at Fokker should be taken into account. The part replenishment model only deals with groups of non-repairable spare parts. This restriction is taken into account in order to be able to compare theory with practice. Besides this, only particular warehouses are taken into account when optimizing the inventory control parameters. These are the warehouses which fall within the scope of this research. Furthermore, a single echelon approach is taken to not impose more complexity to the research and follow the way the optimization model is currently used by Fokker. Moreover, the research will evolve around continuous review (s, S) inventory policies using a compound (bootstrap) Poisson demand process as forecast method (see Chapter 3 for more details). Finally, the most recent *stock-run* of July 2018 will be used as the basis for analysis (see Chapter 7), implying that all user settings and design choices are considered to be given. This assumption is reasonable as only minor changes have been made to these settings since the introduction of the part replenishment model at Fokker. Note, however, that we do aim to develop methods which could be repeated every time a new stock-run is scheduled.

1.3.4 Research questions

Based on discussions above, the main research question can now be formulated:

How to guarantee continuous insight into the difference between model and realized fill rates for groups of non-repairable spare parts?

To provide more structure to the main research question, three research questions (RQ) are formulated following the three research aspects mentioned in Section 1.3.2. Every research question is then further divided into sub-parts.

RQ 1 Develop a standardized and consistent measuring method to calculate realized fill rates, following the same calculation method used by the inventory optimization model.

1. *How can a fill rate gap and its potential causes be identified?*
   (a) *How can a realized fill rate be measured consistently in order to compare it with the model fill rate?*
   (b) *How can the existence of a statistical significant fill rate gap on group level be demonstrated?*

(c) *Which initial causes can be found that potentially explain a fill rate gap?*

RQ 2 Develop a method to identify and quantify causes of a fill rate gap and analyse inventory behavior. This system should be able to create insights into model and realized part fill rates. This will be the main part of the research.

2. *How can the causes of a fill rate gap be quantified?*
   (a) *How can a method be developed to simulate the actual occurred inventory trajectory of a spare part and measure a fill rate on group level?*
   (b) *How can a method be developed to quantify the effect of identified causes of a fill rate gap?*

RQ 3 Develop actionable insights to bring model and realized fill rates closer to each other. Here the methods of point 1 and 2 are applied at Fokker in the form of a case study.

3. *How can the devised methods be used in practice to identify and analyse a fill rate gap?*
   (a) *How can the devised methods be used to identify a fill rate gap and its potential causes?*
   (b) *How do the identified causes influence the fill rate gap and what is their isolated contribution?*
   (c) *How do the identified causes explain the realized fill rate?*
   (d) *How can the effects of the causes of the fill rate gap be mitigated?*

1.4 Outline

The remainder of the thesis is structured as follows. Chapter 2 provides a review of the existing literature concerning potential causes of a fill rate misalignment, ending with a longlist of theoretical causes. In Chapter 3 a deepening of the part replenishment model and operational replenishment process at Fokker is provided. It exists of a mathematical formulation of a part replenishment model and an elaboration on how this would be adopted in practice by inventory controllers.

Next, the focus is shifted to developing a model answering Research Questions 1 and 2. Chapter 4 defines the requirements of such a model by decreasing the longlist of theoretical causes to a shortlist. These causes should the model be able to test. Chapter 5 then conceptually describes the model that is developed in this thesis, by discussing the model goal, modeling method, validation method and model output. Finally, Chapter 6 dives deeper into the actual programming and data requirements of the model. This collection of chapters form the first part of the thesis.

The second part of the thesis focuses on performing a case study at Fokker to answer Research Question 3 using the developed method of the first part. First, Chapter 7 introduces the setup of the case study. The results of adopting the developed model are presented in an overview in Chapter 8, while Chapter 9 goes into more detail.

To conclude the thesis, Chapter 10 consists of a conclusion, providing a discussion on the literature gap, research limitations and the implications of the main findings for practice and inventory control research.

Chapter 2

Literature review

This chapter presents the relevant literature on causes for the existence of a fill rate gap in a spare part context. It is attempted to identify, describe and analyse these causes and structure them in an overview. This overview is structured as described in Figure 2.1.

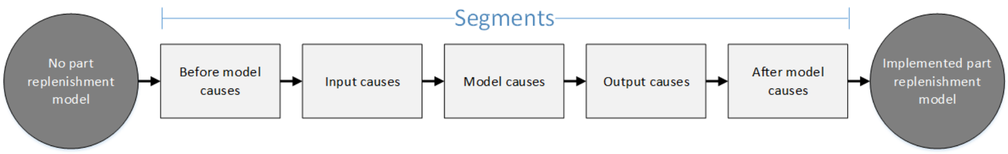


Figure 2.1: Setup of literature review

The situation where *no part replenishment model* is in place (left side of the figure) is used as starting point. At the far right side of the figure the situation of implementation is portrayed, indicating a formal part replenishment model is in place. Dividing these two situations are five segments, each indicating a specific set of potential fill rate gap causes. Every segment will be elaborated upon in a single section. The review will be concluded with a discussion of a literature gap and a *longlist* of potential causes for a fill rate gap. This list forms a valuable starting point for the purpose of model development and requirement identification.

2.1 Before model causes

Inherent to the introduction of a part replenishment model is the commodity they should deal with. Within the scope of this research, this commodity constitutes of spare parts. Investigating the characteristics of spare parts could, therefore, unveil important causes leading to a fill rate gap. This section discusses how spare part characteristics and using a part replenishment model could lead to a fill rate gap.

2.1.1 Spare part characteristics

Spare part replenishment models are often considered to be a special case of general inventory management. The main difference being that the former possess a set of special characteristics, making it increasingly difficult to determine the amount of inventory to stock (de Souza et al. (2011), Hu et al. (2018), Cohen et al. (2006), Adrodegari et al. (2011)). Depending on these characteristics the most suitable replenishment policy should be selected (Huiskonen (2001), Huang et al. (2006)). Not, or insufficiently, taking these characteristics into account could create a misalignment between model and realized fill rates. Hu et al. (2018) summarizes the four, in their eyes, most important characteristics as *demand pattern*, *maintenance*, *variety* and *obsolescence*. The influence of these factors on the fill rate gap will be discussed in this paragraph.

Demand pattern. Spare parts are often subject to intermittent demand patters (e.g., Hu et al. (2018), Kranenburg and van Houtum (2015), Mobarakeh et al. (2017), Teunter and Sani (2009)), defined as random demand with a large proportion of zero values (Altay et al. (2012), Boylan and Syntetos (2010)). When this type of demand occurs, it is often highly variable in size, creating erraticness. The combination of intermittent and erratic demand is also known as *lumpy* demand. The slow-moving and compounding nature of this demand patters makes forecasting very challenging. Altay et al. (2012) adds to this conclusion that the intermittent demand pattern is particularly prevalent in the aerospace, automotive, military and IT sectors.

Unsurprisingly, methods to forecast intermittent demand patterns are well studied, as shown by Teunter and Sani (2009) in an overview. Hasni et al. (2018) and Syntetos and Boylan (2018) illustrate more recent research on this subject. However, in most theoretical discussions on part replenishment models, the distribution of demand is assumed to be known or given, while these distributions may not fit as well as expected in practice. This results in deviations between expected and realized demand patterns. A more recent paper of Van Wingerden (2019) does, however, tries to model uncertain demand rates using a distribution instead of a point estimate. As optimized inventory control parameters heavily dependent on the forecast of demand, modeling future demand adequately is, therefore, essential in preventing fill rate gaps to occur.

Maintenance. Besides being intermittent in nature, spare part demand also heavily depends on maintenance. Instead of customer usage dictating part consumption, Hu et al. (2018) and Kennedy et al. (2002) argue that maintenance policies direct demand as parts are only needed when corresponding parts fail in the field. The preventive branch of maintenance policies allow for accurate spare part needs predictions upfront, potentially making any form of stock redundant (Kennedy et al., 2002). Corrective policies, however, are unplanned and employed after a part has failed (Fritzsche and Lasch, 2012). The unavailability of required spare parts then immediately cause loss in production, service and profitability (Hu et al., 2018).

Valuable insights in forecasting spare part demand can be gained by understanding the maintenance policies driving the actual demand. Consequently, forecast accuracy can be improved, positively influencing fill rate misalignment as discussed previously.

Variety. The number and variety of spare parts kept by service organizations are usually very large (Kranenburg and van Houtum (2015), Mobarakeh et al. (2017)), easily reaching numbers into the thousands. To manage overall inventory effectively, the large number and variety of parts, including different characteristics they possess, have to be taken into account. However, identifying appropriate replenishment policies for each part becomes very challenging, potentially resulting in sub-optimal or infeasible policies. Consequently, expected fill rates could prove to be impossible to achieve, causing fill rate gaps.

One way of gaining more control over the wide and varied assortment of spare parts is classification, where parts are grouped based on attribute similarities (Molenaers et al., 2012). Syntetos et al. (2009a) states that this method supports decision makers by focusing their attention to the most important parts and aiding in forecast and control decisions. Note that classification is especially useful if different forecast and/or replenishment policies can be used for each class of parts. While formal classification methods exist, such as ABC analysis (Molenaers et al., 2012) or artificial neural networks (Partovi and Anandarajan (2002), Chen et al. (2010)), Huang et al. (2010) argues that subjective judgement is still often used as means of classification in practice.

Classifying spare parts is a very important concept associated with setting more realistic service level targets (Huang et al. (2006), Huang et al. (2010)). Obviously, when the service level targets are misjudged and set too high or too low for certain parts, deviations are bound to occur in reality. Nonetheless, the impact of a classification method on the realizations of fill rate predictions in practice is seldom investigated in literature.

Obsolescence. Spare part inventories are prompt to obsolescence, especially when intermittent demand patterns are present (Porras and Dekker, 2008). 23% of parts become obsolete every year, according to Cohen et al. (2006), while companies often lack methods for dealing with this issue

(Adrodegari et al. (2011)). Cobbaert and Van Oudheusden (1996) even conclude that ignoring an obsolescence risk as small as 20% may result in an average cost increase as large as 15%.

To prevent parts from getting outdated, it is of particular importance to minimize inventories, while preventing equipment downtime due to small availability (Hu et al., 2018). However, deciding on stock levels for obsolescent machines is difficult as obsolescence is a problem for those parts which are rarely needed (Kennedy et al., 2002) and inventory tends to be relatively expensive as the part has to replace a specific element of equipment. Furthermore, parts sit in inventory as long as the part is not required, increasing the risk of obsolescence even more. Oddly, little research has been performed on stock obsolescence: Adrodegari et al. (2011) concludes that only 4% of the papers in their literature review on spare part inventory management addresses the issue of obsolescence, Kennedy et al. (2002) find that many inventory models do not explicitly consider the costs of obsolete inventory and the survey of maintenance models performed by Cho and Parlar (1991) do not even mention the term obsolescence or any models considering it. The two most recent contributions to the literature of obsolescence in inventories are van Jaarsveld and Dekker (2010) and Pinçe and Dekker (2011).

Spare parts are bound to get obsolete, increasing the importance of taking this characteristic into account when developing part replenishment policies. Not doing so results in excess or shortage of inventory, potentially causing fill rate gaps.

2.1.2 Model

Part replenishment models attempt to mimic inventory relationships in practice using structures, forecast and parameter values describing the system being simulated. However, as we can deduct now, the reality of spare parts is highly complex. Models are therefore always simplifications and abstractions of the real system we want to study. On top of this, it is simply impossible to forecast the future with absolute precision. Even if all assumptions, input data and parameter settings reflect the conditions believed to be true in practice, the model outputs of future conditions are at best uncertain. An inaccuracy to a certain extent is inevitable.

The very fact that a model is used to determine replenishment policies introduces a certain amount of uncertainty by itself. This implication has not yet been investigated in inventory management literature.

2.2 Input causes

Every model takes certain input, transforms it and presents the output. In each of these steps factors could be at play driving expected values further away from practice. The quality of input parameters, i.e., the extent to which they correctly mimic reality, influences the performance of the model output in practice.

The goal of this section is to investigate the relationship between the input side of the model and the fill rate gap. Section 2.3 then discusses the transformation itself, while Section 2.4 considers the model output. First, important inventory relationships are explained, forming the basis for further analysis. Next, a discussion on stochastics is provided. Finally, model parameters are considered causing fill rate gaps.

2.2.1 Inventory relationships

In order to understand why and how certain model input can cause a fill rate gap, an understanding of the inventory relationship at play is necessary. To be more specific, the distribution of the inventory level plays an important role in describing stock situations and calculating performance measures. Equation Equation 2.1 displays the mathematical expression of this distribution for a (s, S) inventory policy (Kranenburg and van Houtum (2015) and Axsäter (2006)). Here, D_L

presents the demand during lead time.

$$P(IL = j) = \sum_{k=max\{s+1,j\}}^{S} P(IP = k)P(D_L = k - j), \ j \leq S \tag{2.1}$$

2.2.2 Stochastics

Stochastic inventory models depend on stochastic variables, as the above discussion already suggested. Such variables are random, meaning their values are not certain or known (exactly) beforehand. However, to ensure minimal discrepancy between model output and its realization in practice, these random variables should coincide, to a certain extent, with actual observed values in reality. For the discussion on part replenishment models stochastic variables occur as unknown future demand and lead times.

2.2.2.1 Demand

In order to make inventory decisions for a particular time instance in the future, it is imperative to state something about the demand behavior for this time period. Logically, Gardner (1990) noticed that forecasting demand is a necessary prerequisite for making inventory decisions in practice, as inventory control models heavily depend on the forecast of future demand (Prak and Teunter, 2019). Based on this dependency, Gardner (1990) argues that making the right decision in forecasting method has significant effects on customer service levels and the reduction of inventory costs. His argument is strengthened by other papers, such as Croston (1972), Watson (1987), Eppen and Martin (1988) and Downing et al. (2011), that show forecasting errors actively disfigure predictions of customer service levels.

Following the reasoning presented above, two important deductions are made. First, modelling the demand process $D(t)$ adequately is critical to achieve inventory control parameters resulting in minimal cost and predicted customer service levels in practice (e.g., Kerkkänen et al. (2009), Zhao et al. (2002)). Being unable to meet this requirement will, without doubt, contribute to a fill rate (or a more general service level) gap. Second, theoretical inventory control models consider demand data to be an input, without explicitly recognizing that this data is the result of a forecasting system. Implicitly, the assumption is made that the stochastic demand process adequately follows the actual demand based on forecasting error measures such as MAD, MAPE, BIAS and TS (Watson (1987) and Tiacci and Saetta (2009)).

Combining both deductions, it can be stated that correct forecasting methods should be selected, while keeping in mind we are dealing with a forecast. Elaborating on this, Tiacci and Saetta (2009) show, by using a comparative simulation test of global system costs and service measures of a (s, S) policy, that the proper forecast method should be chosen on the basis of total cost and service level of the global inventory control system, instead of solely relying on forecast error measures. Watson (1987) complements the discussion by arguing that demand forecasting and re-order policy are not independent of each other for lumpy demand patterns. He states that these specific patterns can cause large fluctuations in the forecast demand parameters, resulting in increased ordering and holding costs, together with a discrepancy between the desired and realized customer service level.

Naturally, a large body of research exists on exploring and showing the relationship between forecast error and organizational performance measures (Kerkkänen et al., 2009) and generating forecast methods specifically designed to deal with intermittent demand patterns (Tavares and Almeida (1983), Willemain et al. (2004), Watson (1987)). However, the relationship between forecasting inaccuracies and a potential fill rate gap is fairly unfamiliar territory. Oftentimes, the demand is forecasted and assumed to sufficiently align with actual demand and no effort is made to check whether this was actually the case to assess its impact.

2.2.2.2 Lead time

Besides future demand introducing randomness, lead times could also be uncertain. Without assuming a certain demand distribution, it is possible to theoretically understand why uncertain lead times influence the occurrence possibility of a fill rate gap.

Investigate Equation 2.1 again, showing the distribution of the inventory level. Then, recall that the showed relationship is important in calculating any performance measure and it depends on the distribution of the inventory position and the demand during lead time (Section 2.2.1). The latter distribution depends on the length of the lead time. When the lead times tend to vary, i.e. experiences randomness, they should be modelled as stochastic variables instead of a static value. This, in turn, should be expressed in the demand during lead time distribution as well. When this distribution does not coincide with the realized demand during lead time, a fill rate gap will result. When, for example, the lead time is set to be 10 days, while the actual time is 30 days, it can easily be seen that fill rates will differ between the model and practice. Axsäter (2006) proposes methods to deal with this stochastic lead time.

2.2.3 Model input parameters

Internally, a part replenishment model should reflect the relationships found in reality to a significant extent. Often, the possibility exists to configure values which are used by these relationships at the input side of a model. These values are model parameters and should, as a collective, reflect the reality as accurately as possible. In the light of spare part replenishment models, input parameters could include information on part characteristics, install base information, costs and lead times. When the model parameters do not reflect reality, differences between model output and realized values in practice are bound to occur.

2.3 Model causes

For capital good service providers, keeping a spare part inventory facilitates in preventive and corrective maintenance (Kranenburg and van Houtum, 2015) and serves as protection against equipment downtime (Kennedy et al., 2002). In order to achieve a required level of customer service, decisions have to be made on which parts to stock, in which quantities to stock them, when to place new orders and how much to order at once (Bošnjaković, 2010). However, the minimization of inventory holding, back order and ordering costs have to be considered as well. Here, a very clear trade-off is demonstrated which dominates most of literature (Kennedy et al. (2002) and Hu et al. (2018)): maximize part availability, while minimizing costs. Finding the correct balance between these objectives is the main goal of a part replenishment model.

There is no shortage of mathematical models which have been developed in literature to deal with spare part replenishment, as summarized by Kennedy et al. (2002). Strikingly though, none of these models consider the accuracy of its realization in practice. Implicitly, the assumption is made that the optimised model output will result in the same service levels in practice. However, the existence of a fill rate gap proves the opposite.

This section clarifies fill rate gap causes erupting from the use of a part replenishment model. It is not intended to present a detailed mathematical explanation of how such an optimization model works. Instead, main relationships are demonstrated that aid in explaining how model output may differ from its realization in reality. Chapter 3 will introduce a mathematical model to optimize part replenishment decisions in more detail.

2.3.1 Model relationships

In line with Section 1.3.3, the remainder of this section will deal with continuous review (s, S) inventory policies for groups of spare parts using a compound (bootstrap) Poisson demand process as forecast method.

2.3.1.1 Continuous review (s, S) inventory policy

Inventory policies dealing with a reorder level s and order up to level S are argued to be the best theoretical fit for managing parts subject to low and intermittent demand (Sani and Kingsman, 1997). Additionally, this type of inventory policy provides the flexibility of offering a base-stock policy $(S-1, S)$ as a special case of the more general (s, S) policy. Based on the relationship between holding- and fixed ordering cost, either a one-for-one base-stock policy or a batching strategy is optimal (Kranenburg and van Houtum, 2015). A base-stock policy is used when demand is low and fixed ordering costs are negligible compared to individual item costs or non-existent at all (Fritzsche and Lasch (2012), Kranenburg and van Houtum (2015)). The batching strategy is more suitable when fixed ordering costs are high compared to the cost of a part. As a companies ability to meet a desired availability level depends on the inventory policies employed at the central and local warehouses (de Souza et al., 2011), the decision made by the model is especially relevant in achieving desired service levels in reality.

2.3.1.2 Compound Poisson

Without discussing a specific optimization model, it is clear from Section 2.2.1 that the distribution of the inventory level is essential in determining service level measures. Specifically, based on Equation 2.1 it is known that the distributions of the demand during lead time and inventory position are leading in calculating a service level.

Distribution of demand during leadtime. For a compound Poisson demand process, a single customer arrives after an exponentially distributed period of time with rate $\frac{1}{\lambda}$. The demand size of each arriving customer is also a stochastic variables, of which the distribution is denoted as the compounding distribution. Let $f_{j,q}^n$ be the probability that n customers give the total demand q for part j. The exact evaluation of this variable is not relevant at this point (see Chapter 3 for a detailed description). The distribution of compound Poisson demand during lead is presented in Equation 2.2, with j being a part taken from the total set of spare parts J.

$$P(D_{j,L} = q) = \sum_{n=0}^{\infty} \frac{(\lambda_j L_j)^n}{n!} e^{-\lambda_j L_j} f_{j,q}^n \tag{2.2}$$

From above equation, three important factors of uncertainty are identified: lead time L, demand rate λ and demand size distribution $f_{j,q}^n$. Additionally, the variable values can differ per part. Based on these variables, the demand process is estimated and taken as given from that point forward. However, if the expected values differ (significantly) from its realization in practice, the modeled demand distribution will not coincide with the observed distribution. This will, inevitably, result in a fill rate gap.

Distribution of the inventory position. As we are dealing with a compound Poisson demand distribution, the probability to visit a specific inventory position between $s+1$ and S is not uniformly distributed as it would be with pure Poisson demand Axsäter (2006). Instead, this distribution depends heavily on the distribution of the demand size $f_{j,q}^n$. Again, the exact evaluation of the distribution of the inventory position is not relevant at this point (see Chapter 3 for a detailed description). Nonetheless, the importance and potential impact of $f_{j,q}^n$ on a fill rate gap is seen immediately.

2.3.1.3 Conclusion

The fill rate for part j heavily depends on the chosen method to describe the demand process and the corresponding parameter estimates. In the case of a compound Poisson demand process, the used lead time (L), demand rate (λ) and the demand size distribution ($f_{j,q}^n$) together form the basis of all other estimated distributions (demand during lead time, inventory position, inventory level). If these estimates do not coincide to a significant extent with the corresponding realizations in practice, the proposed inventory control parameter values will not result in the fill rate promised by the model.

Surprisingly, understanding the relationship and deviations between expected values of stochastic part replenishment models and their realizations in practice has yet to be investigated structurally in research. Often, these parameters are treated as given when optimizing inventory models, without providing a notion of uncertainty and its impact on the results of the model.

2.4 Output causes

After the transformation process of a model is done, it presents its output. If a gap exists between modeled measures and realized, it will be made visible based on this output. This section investigates how the actual output could cause a fill rate gap.

First, the importance of the type of measurement is considered. Second, a discussion on service level as random variable is provided.

2.4.1 Service level measurements

Customer service, especially in a spare part context, is essential to maintain a customer base. When a service part is demanded, it should be delivered to the customer based on agreements made concerning time, cost and quality. In order to assess and control the level of customer service and understand model performance, service level measurements are drawn up. To structure these measurements, Zhaohui Zeng and Hayya (1999) states that, regardless of the type of firm, the management effectiveness of inventory decisions centers on three areas:

1. Cost: holding and ordering.
2. Service level: control the amount of inventory needed for satisfying customer demand.
3. Inventory turnover ratio: measures how effectively inventories are being used.

Part replenishment models minimize the relevant costs (1) by restricting the solution space to those inventory policies yielding a specified service level target (2). Measuring service levels can be achieved in different ways, using a specific measurement framework. It could be an event-based measure, indicating the probability of an event occurring (e.g., a stock-out) or a quantity-based measure which indicates the magnitude of the event. A combination of both event- and quantity measures is also possible. Besides this, measurements can be made from a supply point of view (per SKU) or based on demand. This latter option can be further divided into measures per customer, per order, per order line, etc. Finally, the time period used as reference is important as well. possibilities here are measurements per period, per replenishment cycle, per evaluation horizon, etc.

The framework and calculation method used for the model service level should be identical to the way in which the service level is determined in reality. If not, discrepancies are the logical consequence.

2.4.2 Service level as random variable

Another interesting point is the fact that the service level calculations determine the expected value of the part availability. The service level itself is a random variable, while the standard definitions only express the expected value (Minner, 2018). A service level accompanied by a measure of variability (standard deviation) could provide a more robust measure of achieved service. This has not yet been investigated in inventory control literature.

In this setting, a combination with statistical process control could be investigated. Providing the service level with tolerance or control limits increases the correctness of its interpretation. Besides this, introducing a probability θ of a realized service level reaching required level α would also give more control. This can be expressed as $P(SL \geq \alpha) \geq \theta$. Finally, providing a confidence interval will provide the same result.

2.5 After model causes

A part replenishment model suggests values for the inventory control parameters which, based on its internal relationships, will result in a certain fill rate. However, in the perspective of an inventory control system, these outputs are only a part of the system as a whole. Something has to be done with the outputs in order to actually use them. This section will introduce factors in this final step which could explain a fill rate gap.

Human interaction with optimization models is discussed first. Next, the influence of inventory accuracy on a potential fill rate gap is explained. Finally, supplier quality is mentioned.

2.5.1 Human interaction

A part replenishment model seldom operates purely on its own. Instead, human interaction is necessary to interpret, adjust or use the output of the model. As a consequence of humans interacting with the model, inaccuracies can arise based on a phenomenon called *algorithm aversion*.

Dietvorst et al. (2015) define algorithm aversion as the phenomenon where human forecasters are chosen in favor of statistical forecast algorithms. The same research shows that this behavior even holds when humans have evidence the statistical method outperforms human forecasting efforts. The reasoning behind this aversion is that people tend to lose confidence in algorithms more quickly as supposed to human forecasters after seeing them make the same mistakes. Previously conducted research also provides several causes as to why algorithm aversion may be experienced by humans:

1. Humans have a desire for perfect forecasts (e.g., Dawes (1979), Highhouse (2008)).
2. Algorithms are perceived as not being able to learn (Dawes, 1979).
3. The belief that human forecasters can learn through experience (Highhouse, 2008).
4. The perception that algorithms can not consider individual targets (Grove and Meehl, 1996).
5. Ethical concerns about relying on algorithms for important decisions (Dawes, 1979).
6. The perception that algorithms can not consider qualitative data (Grove and Meehl, 1996).
7. People are more willing to forgive a human forecaster for making the same mistake as an algorithm, even if the mistake is larger (Dietvorst et al., 2015).

Dietvorst et al. (2018) investigate how algorithm aversion can be mitigated. Summarizing, the researchers found that the willingness of humans to use an algorithm increases when they have the possibility to modify it. Here, the restrictiveness of these adoption capabilities is rather unimportant. In the context of intermittent demand, Syntetos et al. (2009b) even show that made adaptions to the forecast do not necessarily lead to worse forecasts. In fact, managerial judgemental adjustments can be effective for demand experiencing intermittent patterns (Syntetos et al., 2009b). Finally, the research of Dietvorst et al. (2018) suggests that providing users of an imperfect algorithm (some) control over the forecast will make them feel more satisfied with the forecasting process. Consequently, the users are more likely to believe that the algorithm is superior and choose to use an algorithm to make subsequent forecasts.

Remarkably, most, if not all, industrial engineering research on this subject has been performed in a retail context. However, this phenomenon could also occur in an inventory management situation in capital goods. In general, algorithm aversion could manifest itself using a part replenishment model in the following three ways:

- Adjusting the demand forecast used as input by the model.
- Changing the direct output of the model (i.e., optimized inventory control parameter values).
- Not following the models suggestions in reality (i.e., order moment, order size).

Based on above discussion, it is made clear that not addressing the occurrence of this phenomenon could result in humans altering the outputs of forecasts based on their judgements (Petropoulos et al., 2016). These alternations could very well result in realized fill rates deviating from the ones suggested by the model, especially when taking into account that algorithms are almost always better forecasters than humans (Dawes (1979), Grove et al. (2000)).

2.5.2 Inventory accuracy

When automated forecast- and replenishment systems are put in place, the accuracy of the inventory records used by these models is imperative. This *inventory accuracy* is a well researched area within the field of retail inventory management (e.g., Shteren and Avrahami (2017), Fleisch and Tellkamp (2005), Chuang and Oliva (2015), Atali et al. (2009), Avrahami et al. (2013)). With good reason, as the inventory records are used to determine order quantities in practice. According to DeHoratius and Ton (2015), inventory inaccuracies affect the future availability of parts in three ways:

1. When the actual part inventory level is lower than the system level due to inaccuracies, the actual service level will be lower as well.
2. The bias of inventory data may prevent an automated replenishment system from triggering an order when the systems inventory is greater than the actual level. Likewise, an unnecessary order could be triggered if actual inventory levels are larger than the system levels.
3. When a part that is out of stock is reported as in stock, the replenishment system may wrongly conclude that there is no demand. As the item is not available for customers, no sales is observed, even when there are customers willing to buy the product. This will lower the forecast for the next period, resulting in less stock of this item.

Despite the considerable amount of research, Raman et al. (2012) notices that inventory inaccuracies are often not taken into account in automated inventory decision systems in a retail context. This conclusion is striking as inventory inaccuracies are often experienced in practice (DeHoratius and Raman, 2008) and its link with supply chain performance is demonstrated repeatedly as well (e.g., Fleisch and Tellkamp (2005), Lee et al. (2003), Shteren and Avrahami (2017)).

Moreover, most research on inventory accuracy has been performed in a retail setting, dismissing the context of capital goods and spare parts in specific. This raises the question whether the accuracy of spare part inventories is as important as for stock held in retail. On the one hand, one could argue that in a capital good context, where the up-time of machines is essential, any discrepancy between system- and actual inventory can easily result in fill rate discrepancies. This is in particular true for costly parts which are stocked in small amounts. On the other hand, an argument can be made that spare parts are often dedicated to certain equipment in the installed base and are subject to a particular maintenance strategy. Therefore, demand frequencies are often low, while service levels are high. Combining inventory levels with a small level of safety stock could then buffer easily against inventory inaccuracy. This latter argument is most applicable to cheaper, more bulky spare parts.

2.5.3 Supplier quality

Forecasts of demand during leadtime are essential in optimizing inventory control parameters, as discussed in Section 2.2.1 and Equation 2.1. Service providing companies in a capital good context are often dependent on (external) suppliers to maintain inventory levels. Consequently, the lead times used to optimize the parameters are usually based on expected- or observed supplier lead times. However, in reality, suppliers can make mistakes and deal with uncertainties as well, causing actual lead times to differ from the values used in the optimization model. Think of shipping the wrong product, insufficient part quality or transportation delays. This results in fill rate gaps, as explained in Section 2.2.2.

2.6 Conclusion

This section discusses an identified literature gap and provides a longlist of potential fill rate gap causes based on previously conducted research.

2.6.1 Research gap

Previous research mainly focuses on optimizing the output of part replenishment models, which covers only one section of the field of service part logistics. Moreover, the used parameter values and demand process are often treated as given. Very little attention is given to the impact of deviations between actual and model in- and output processes. The discussed literature demonstrated that failing to investigate and understand this, a misalignment emerges between model- and realized service levels.

Consequently, a need arises to place inventory control models in a more holistic perspective, covering the relationships between modelled and realized values in more detail. A mismatch between model output and its realization in practice is bound to happen (see Section 2.1.2). However, recognizing model limitations and understanding what drives this mismatch is essential in managing its consequences and proposing solutions to bring theory closer to practice. Gaining insight into the relationship between model output and their realizations in practice could also aid in creating a feedback loop, providing a way to learn from past results and assertively take actions to close a service level gap in the future. Such an endeavour potentially yields large financial, customer and operational benefits.

2.6.2 Longlist

Based on the literature review performed for this thesis, it is possible to deduct a *longlist* of potential causes for the existence of a fill rate gap. This list will act as a starting point for identifying design requirements for developing a method to investigate part replenishment models in a more holistic perspective. The list summarizes the causes discussed in the previous sections.

Before model causes

- Spare part characteristics
  - Demand pattern
  - Maintenance dependency
  - Large variety
  - Obsolescence risk
- A model is per definition an abstraction of reality.

Input causes

- Stochastics introduce uncertainty.
  - Demand
  - Lead time
- Model input parameters are incorrect or have too much influence on output.

Model causes

- Continuous review (s, S) inventory policy
- Compound Poisson demand process
  - Distribution of demand during leadtime
  - Distribution of the inventory position

Output causes

- Different framework and calculation method used for model and reality.
- Service level is a random variable in itself.

After model causes

- Human interactions.
- Inventory inaccuracies.
- Poor supplier quality.

Chapter 3

Current inventory control system

Figure 1.1 clearly shows the interplay between an inventory replenishment model and the operational process it is being used for. Based on historical data, the model optimizes decision variables, that are then used in an operational process to make decisions. Ultimately, using the optimized decision variables in practice should result in the same objective value as determined by the part replenishment model. In order to better understand the relationship between the part replenishment model and the replenishment process in practice, this chapter will elaborate on both in more detail. This understanding is also required to place the longlist of potential fill rate gap causes of Chapter 2 in perspective.

First, Section 3.1 provides an overview of the part replenishment model used by Fokker. The use of the optimized decision variables in practice is then illustrated in Section 3.2. The combination of the part replenishment model and the operational replenishment process will be referred to as the inventory control system.

3.1 Part replenishment model

In this section, an overview of the part replenishment model is provided. Besides this, a discussion on transients model behavior is added. A mathematical evaluation of the model, as well as a description of the optimization problem, is provided in Appendix B.

3.1.1 Replenishment model overview

The part replenishment model used at Fokker is internally known as *Spares Analytics (SA)*. It uses a variable period of historical demand data to optimize (s, S) inventory policies for non-repairable spare parts. The model is ran every six months, usually taking two years of historical data to perform the optimization.

The key principle of the model is the idea of creating groups of all spare parts considered in the model. These groups are created based on the parts similarities on specific characteristics, depicted in Table 3.1. Note that one part may be present in multiple groups, based on its characteristics. However, an individual part only receives one optimized (s, S) inventory policy.

Next, every group can be provided with an individual fill rate target, that will act as restriction in the optimization model. Either a target on the required percentage of items filled immediately from stock (item fill rate) or the required percentage of complete lines filled immediately from stock (line fill rate) can be selected (Axsäter, 2006). The provided fill rate target is group specific and calculated as a weighted average of the individual part fill rates of that group. This means that not all the parts in this group have to meet the target, as long as the weighted average of all part fill rates meets the target. When an item fill rate is selected, the group average is weighted based on expected annual revenue per part, while the line fill rate average is weighted on expected

Characteristic	**Option**
Price	*Cheap* | *Expensive*
NHI-part	*Yes* | *No*
Platform	12 options
Product group	5 options
RNLAF	*Yes* | *No*
Historical demand lines	*Minimum* | *Maximum*

Table 3.1: Part characteristics available for grouping parts

annual demand rate per part. The mathematical formulation for this weighted average fill rate restriction on group level is provided in Section B.2.

Additionally, the part replenishment model used by Fokker allows the user to set values for a selection of model parameters. Table 3.2 summarizes these parameters. In reality, these values hardly change between *stock-runs* and are fairly constant. They have been set when the program went live several years ago and have not been altered significantly since.

Parameter	**Description**
Obsolescence cost fraction	Fraction of part value allocated to obsolescence (€/ €)
Annual holding cost fraction	Fraction of part value allocated to holding cost (€/ €/ year)
Marginal ordering cost	Cost for placing an order (€)
Ordering + shipping lead time	Additional time (days)
Forecast multipliers	Multiplier of demand rate of part to mimic increasing or decreasing demand
Warehouse transfer times	Transfer time from main warehouse to local warehouse (days)

Table 3.2: Model parameters of part replenishment model

Finally, the model is ran in order to optimize the decision variables in the form of (s, S) policies for all parts in every group. Note that groups that do not receive a fill rate target are left open. The optimization model calculates the resulting fill rate based on the optimized decision variables of the parts through targets set for these parts in other groups. Appendix B provides a mathematical evaluation of the model and a description of the optimization problem.

Continuing on the above model overview, several important assumptions are made in the part replenishment model of Fokker. These are summarized below.

1. Review is continuous
2. Part supplier lead times are deterministic
3. Demand for each part follows a compound Poisson process
4. Part inventory policies take the form of (s, S)
5. Fill rate objectives are weighted averages of groups of parts
6. Performance is measured using an item- or line fill rate

For the remainder of this thesis, the made assumptions are considered to be given. It is beyond the scope of the research to discuss the correctness of the assumptions.

3.1.2 Transient model behavior

By solving the mathematical optimization model as presented in Appendix B, the resulting fill rates are steady state values. However, in practice, after the implementation of new inventory control parameters a transient state is entered. In this state, the system has not yet reached steady state due to the changes made in the process variables. The steady state situation is only achieved after a period of time, the transient time.

In theory, the implemented inventory policy changes immediately cause the placement of purchase orders to raise the inventory position of the parts that are below the recommend reorder level to the order up to level. Parts with an inventory position larger than the reorder level will not be ordered yet. Moreover, excess inventory has to be reduced as well. This can only be achieved by the occurrence of demand, which takes time. Then, ideally, all excess inventory is sold and orders are placed based on the new inventory policy parameters. At this moment the steady state is achieved, corresponding to the recommended average inventory positions (RAIP), i.e., the theoretical steady state distribution of the recommended (s, S) inventory policies.

It is difficult to capture transient behavior of a system in simple rules that always work. However, the part replenishment model does propose several rules to come up with a course estimate of the fill rates for different moments in the transient time. These are summarized in Table 3.3.

Moment	**Demand**	**Current IP (CIP)**	**Adjustments to current IP**	
			$CIP < RAIP$	$CIP > RAIP$
Run	No demand	IP	RAIP*	CIP
X months	Extrapolate history	IP − demand X months	RAIP*	CIP
Ideal	No excess inventory	IP (= RAIP*)	-	-

Table 3.3: Transient behavior rules
*: RAIP = Recommended average inventory position (steady state)

The **Run** moment represents the situation directly after the implementation of the new inventory policies. It is modeled by raising the inventory positions of all parts that are below the recommended average inventory position to that average inventory position. Parts with a larger current inventory position than the average are left unchanged.

Next, the part replenishment model provides a method to estimate the effect demand has on the reduction of inventories (**X months**). Based on a user entered value of X months, the model extrapolates the historical demand data X months into the future. The result is then subtracted from the current inventory positions. If the value of the subtraction is below the recommended average inventory position, the average is used as current IP. Otherwise, the current IP is used.

Finally, the **Ideal** situation represents the steady state behavior of the model where the current inventory positions are equal to the recommended average IP and no excess demand exists.

Section 5.3 discusses the way used to deal with these different fill rate values.

3.2 Replenishment process

The optimized decision variables (policies $c = (s, S)$ for every part j) are used in an operational process. To achieve this, first, the optimized policies are extracted from the model and transferred to an Excel sheet. In this sheet, the reorder and order up to levels for every part j are present. Now, the opportunity exists to manually adjust several policies, something that is often done. Adjustments are made based on business knowledge, investment costs or external factors. Next, the Excel sheet is used to upload the new policies to Fokkers ERP system.

Once uploaded, the policy parameters are accessible by the operational buyers. They can make purchasing decisions based on these levels for the parts they are responsible for. To reinforce this process, the ERP system keeps track of undershoot signals and collects them in a report. An undershoot signal is created when the inventory position (= stock on hand + outstanding orders - backorders) of a specific spare part drops to, or below, its reorder point s. The report containing the undershoot signals is checked once or twice a week. Note that there is no formal need for the operational buyers to follow the exact policy. Their experience and knowledge is an important factor in ordering parts. Every placed order is then received at Fokker after a specific lead time.

As stated before, the combination of the part replenishment model and the operational replenishment process will be referred to as the inventory control system.

Part I

Model development

Chapter 4

Deduce requirements on cause measurement from longlist

As explained in Chapter 1, the aim of this thesis is to understand and investigate the difference between realized- and model fill rates. To achieve this aim, a model will be developed. However, before designing a model, it should be clear which requirements it should meet. In Chapter 2, a longlist of potential theoretical causes of a fill rate gap is created. Then, in Chapter 3, a better understanding of the part replenishment model and the replenishment process is provided. This chapter uses this knowledge to narrow down the longlist of causes to a shortlist. These causes then form the requirements of the model, as the model should be able to test the impact of these specific causes on the fill rate gap. This methodology is illustrated in Figure 4.1.

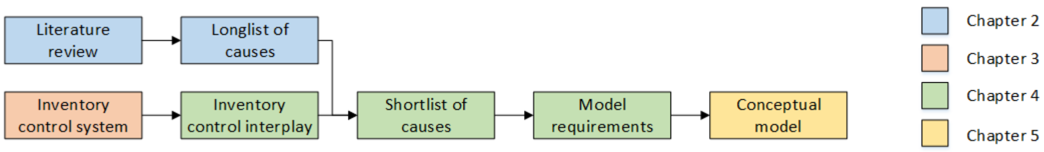


Figure 4.1: Methodology for creating shortlist

In Section 4.1 a process model of the part replenishment model and replenishment process is created, based on the information provided in Chapter 3. It is shown that by investigating the interplay between the model and the operational process it is being used in, several potential causes of a fill rate gap can be observed. Then, in Section 4.2, the longlist of potential fill rate gap causes of Chapter 2 is reduced to a shortlist of causes. This is achieved by using the observed fill rate gap causes of Section 4.1 and an additional, more theoretical, discussion on cause relevance. Finally, the chapter is ended with an overview of the shortlist of potential fill rate gap causes that the model should be able to test in Section 4.3. These form the final model requirements on cause measurement.

Note that, for the remainder of this thesis, the term *fill rate gap cause* will be used to define a potential reason explaining why the realized fill rate differs from the model fill rate.

4.1 Observed fill rate gap causes

This section aims to identify fill rate gap causes occurring at Fokker by creating a process model of its inventory control system. For this purpose, Chapter 3 is used, as well as additional interviews with Fokker employees and managers. The resulting process model is provided in Figure 4.2.

The process model depicts all steps taken to go from historical data to an actual realized fill rate in practice. Moreover, the moment the optimized decision variables of the part replenishment

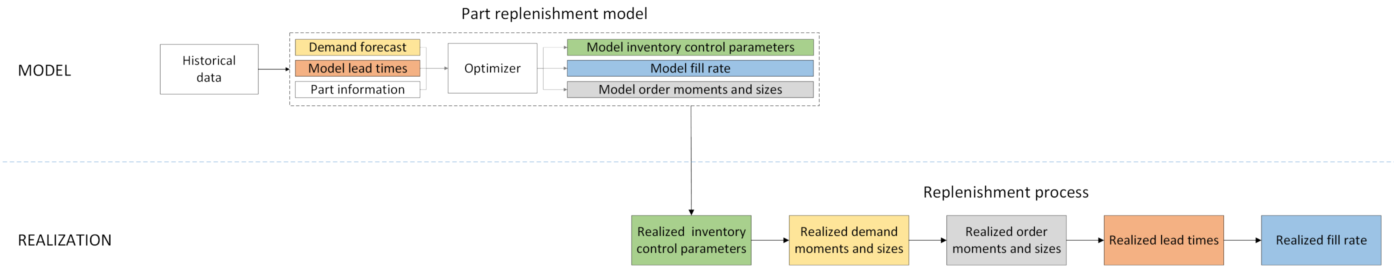


Figure 4.2: Interplay part replenishment model and operational replenishment process

model (inventory policies) transit to reality is visualized as well. Based on this process, it is seen that every theoretical aspect of the part replenishment model (top part) has a corresponding realization in practice (bottom part). For example, the demand forecast versus the actual demand and the model lead times versus the actual achieved lead times. To reinforce this concept, the same colors are used for every theoretical aspect and its practical counterpart. These aspects clearly indicate reasons why a model fill rate can deviate from a realized fill rate. The remainder of this section discusses the process steps of the part replenishment model and the operational purchasing process, and finally identifies several observed fill rate gap causes based on the process model.

4.1.1 Model

The top part of Figure 4.2 depicts the steps taken in the part replenishment model based on Section 3.1. First, two years of historical demand data is collected, together with ERP supplier lead times. This combination of demand and lead time data is used to create a forecast of demand in the form of a compound Poisson process. Lastly, part information data is required to create groups of parts having similarities on specific characteristics.

Next, the replenishment model uses the demand forecast, model lead times and part information to optimize (s, S) inventory policies for all parts considered. As a result, the optimized inventory control parameters for every part j are calculated, as well as the model fill rates for every group created in the model. The latter value is divided into the steady state fill rates and the fill rate measurements in the transient time. Note that the fill rate is the weighted average over all parts present in the group, weighted on either expected annual revenue (item) or expected annual demand rate (line). Finally, the optimized inventory policies could be seen as a theoretical order moment and size. Every time the inventory position IP of part j drops below, or is equal to, the parts reorder level s an order is placed (order moment) of size $S - IP$.

4.1.2 Realization

The bottom part of Figure 4.2 illustrates the operational replenishment process in which the optimized decision variables are used. The arrow visualizes the transition of the optimized inventory policies from the part replenishment model to practice. In case of Fokker, the arrow symbolizes the Excel sheet used to import policies to the ERP system. During this transition step, adjustments can be made to the optimized inventory policies as discussed in Section 3.2. For this reason, the model inventory control parameters can differ from their realizations in practice, as indicated with the green boxes in Figure 4.2. This is the first observed fill rate gap cause.

Next, the actual demand takes place, which could differ from the forecast (yellow boxes). This, again, could be a cause for a fill rate gap. Then, the operational buyers place purchase orders at particular times and of particular sizes. These could diverge from the theoretical moments and sizes (grey boxes). The orders arrive after a specific lead time that could be different from the model lead time (orange boxes), potentially causing a fill rate gap. Finally, the realized fill rate is calculated, which has to be done in the same way as the model to prevent a fill rate gap to arise (blue boxes).

4.1.3 Fill rate gap cause identification

Based on the difference that can arise between the theoretical aspects of the part replenishment model and their counterparts in practice, a summary of observed fill rate gap causes is made in Table 4.1.

Color	Model aspect	Counterpart in practice	Origin of difference (cause)
	Demand forecast	Real demand moments and sizes	Observations in reality
	Theoretical inventory policy	Actual inventory policy	Altered by management
	Theoretical order moments and sizes	Real order moments and sizes	Decisions of operational buyers
	Model lead times	Real lead times	Dependent on supplier
	Model fill rate	Realized fill rate	Measuring method

Table 4.1: Observed fill rate gap causes based on process model of inventory control system

4.2 Reducing the longlist

In this section, the longlist of potential fill rate gap causes of Section 2.6.2 is reduced to a shortlist. Every segment of potential fill rate gap causes is sequentially discussed, following the same structure as the literature review of Chapter 2. For every segment, every individual potential cause is discussed separately. The results of this section are summarized in Table C.1. This table indicates how the observed fill rate gap causes relate to the theoretical causes from the longlist and provides a list of final included causes.

4.2.1 Before model causes longlist

The before model fill rate gap causes identified in Chapter 2 exist of spare part characteristics (demand pattern, maintenance dependency, large variety and obsolescence risk) and the fact that a model is an abstraction of reality.

Spare part characteristics - demand pattern *(included)*: Based on the observed causes of Table 4.1, the demand pattern characteristic is identified. The part replenishment model assumes the distribution of demand to be known in the form of a compound Poisson process. However, in practice, this distributions may not fit as well as expected. The model then optimizes the inventory policies using a demand process different from reality, leaving the policies poorly resistant against actual demand in practice. This could be a potential fill rate gap cause.

Spare part characteristics - maintenance dependency *(excluded)*: Understanding the maintenance policies driving the spare part demand can provide valuable insights for forecasting demand. However, Fokker has no insight into the maintenance methods employed by their customers for the non-repairable items. For this reason, the maintenance dependency cause is excluded from further research.

Spare part characteristics - large variety *(included)*: As discussed in Section 2.1, one way of gaining more control over the large variety of spare parts is classification. The part replenishment model employed at Fokker uses a classification method based on subjective judgement, which is often the case in practice according to Huang et al. (2010). However, every group adopts the same forecasting method, while the control policy could differ per group (base-stock and (s, S)). This offers limited flexibility. Nonetheless, the impact of the classification on the fill rate gap should be taken into consideration.

Spare part characteristics - obsolescence risk *(excluded)*: Fokker's replenishment model does take an obsolescence factor into account, making it less likely this factor adds to the gap.

Model is an abstraction of reality *(included)*: Even if all assumptions, input data and parameter settings reflect the conditions believed to be true, we know there will be inaccuracies to a certain extent. The key idea of this research, however, is to understand where these inaccuracies come from, quantifying them and ultimately distinguishing between causes that originate inherently from using a model and causes that can be controlled. This provides a better understanding of the process and contributes to enhanced process control, resulting in actionable insights to narrow the fill rate gap where possible.

4.2.2 Input causes longlist

The literature study suggests demand- and lead time stochastics and incorrect model parameter to be potential fill rate gap causes.

Stochastics - demand *(included)*: The discussions in Chapter 3, as well as the observed fill rate gap causes of Table 4.1, confirm that this cause does occur. As discussed, demand patterns play an important role in explaining the fill rate gap.

Stochastics - lead time *(included)*: The part replenishment model assumes lead times to be deterministic and known beforehand. As long as supplier lead times are always the same, this solution is appropriate. However, when lead times differ, the optimized inventory policies could prove to result in a different fill rate. Therefore, investigating the difference between the realized and model lead times could prove to be fundamental in explaining a fill rate gap.

Model parameters *(partly included)*: Model parameters being incorrect or having too much impact on the output is not observed immediately. The part replenishment model used at Fokker uses different parameters, summarized in Table 3.2, and discussed below.

As the model takes an obsolescence cost fraction into account, this factor is excluded.

The costs for holding and ordering inventory should correspond with the values in practice. The model will make a trade-off between both types of costs when deciding how to minimize the total inventory investment by setting the re-order and order-up-to levels. The impact on the fill rate, however, is only minimal as the fill rates form the restrictions of the model. When the cost parameters change, the targets should still be met, only the allocation of the inventory over the different parts change. Therefore, the cost parameters are not taken into account explicitly.

The model lead time only encompasses the time between the moment the supplier accepts the order and the moment the order is ready to be shipped. To account for the ordering- and shipping time, an additional lead time parameter value can be used in the part replenishment model. This value is then used for all parts. Therefore, it is likely that for some items this added lead time component is useful, while for others parts it is not. They are taken into account when developing the model as a part of the model lead time.

Warehouse transfer times are not taken into account as we will focus on a single-echelon problem.

Finally, forecast multipliers are input parameters of the model in which the expected demand per year can be altered. This will directly influence λ_j for part j subject to the multiplier. The resulting adjustments are rather small, especially for slow moving parts. On the other hand, when the same, or larger, forecast multipliers are used during multiple and successive runs of the model, the impact could increase. Therefore, the forecast multipliers are taken into account as part of the demand forecast method.

4.2.3 Model causes longlist

The model causes on the longlist of theoretical fill rate gap causes have to do with the continuous review inventory policies and the compound Poisson process.

Continuous review *(included)*: The part replenishment model assumes continuous review (s, S) inventory policies. In practice, however, the continuity assumption can not be achieved at all times. The report containing undershoots is only checked once or twice a week. This discrepancy potentially results in a fill rate gap and should, thus, be taken into account.

Compound Poisson demand process *(included)*: The fill rate for part j for a given base-stock policy (Equation B.8 and B.10), and thus the fill rate for a specific group, heavily depends on the chosen method to describe the demand and the corresponding parameter estimates. In the case of a compound Poisson demand process, the used lead time (L_j), demand rate (λ_j) and the expected order quantities ($f_{j,q}$) together form the basis for all other estimated distributions (demand during lead time, inventory position, inventory level). These values are determined based on historical demand data. However, if these estimates do not coincide with the corresponding realizations in practice to a significant extent, the optimized inventory policies will not result in the fill rate suggested by the part replenishment model.

4.2.4 Output causes longlist

The output causes on the longlist have to do with the calculation method of the fill rates and the variability of the service level measure itself.

Fill rate calculation method *(included)*: When comparing the model fill rate, as determined by the part replenishment model, with the realized fill rate, it is imperative that the same measuring method is used. If not, both situations cannot be compared to each other. This should be considered when developing the model.

Variability of service level measure *(included)*: In this research, this potential cause is taken into account. The part-level fill rates are highly variable as a result of the lumpy demand pattern. Filling a specific order can have a large impact on the achieved part fill rate. However, the fill rate measure used in this thesis is a weighed average over the parts in a specific group. With this, the variability in fill rate is decreased. Moreover, statistics are used to test the significance of fill rate differences. Section 5.3.3 elaborates on the use of these methods in more detail and explains their workings.

4.2.5 After model causes longlist

The theoretical after model causes are summarized as human interaction, inventory inaccuracies and poor supplier quality.

Human interactions *(included)*: Human interactions play a very important role in potentially explaining why a fill rate gap exists. Figure 4.3 summarizes three different possibilities for humans to interact with the inventory control system at Fokker (**A**, **B** and **C**).

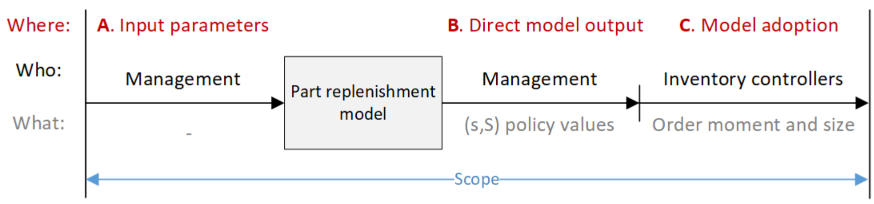


Figure 4.3: Interfaces of human interaction with inventory control system

Point **A** illustrates the adjustments humans can make to the input parameters of the part replenishment model in the form of forecast multipliers. At **B**, management has the opportunity to adjust the optimized inventory policy parameters ((s, S) levels for all parts j) before they are entered into the ERP system. Finally, position **C** describes the model adoption by the inventory controllers. They should make purchasing decisions based on the inventory control parameters, but they are allowed to purchase items at times and of sizes that, to them, seem appropriate.

At every position a form of human interaction takes place. As stated in Chapter 2, allowing the users of a model to impact, to some extent, the model in- and output could either in- or decrease the quality of the results. At Fokker, it is not clear whether the forecast is adequate enough and to what extent the model is adopted by the inventory controllers. Therefore, these are very likely causes of a fill rate gap and should be taken into account.

Inventory inaccuracies *(included)*: Based on the discussion in Section 2.5.2, the issue of inventory accuracy seems to be a less relevant factor for explaining fill rate discrepancies in a capital good context. However, if data is available on this subject, it could be taken into consideration.

Poor supplier quality *(included)*: Poor supplier quality is an external factor influencing the size and quality of ordered goods, as well as the lead time to a certain extent. However, due to lack of data, only the lead time aspect will be taken into account.

4.3 Shortlist of causes

Based on similarities of the identified fill rate gap causes in the previous section, the following main fill rate gap causes are identified: demand forecast, lead times, human interaction on policy adjustments, human interaction on policy follow-up, fill rate calculation method and classification as a consequence of large part variety.

The demand forecast cause can be further broken down into the actual moment an order is received at Fokker and the size of that order. To elaborate, the forecast method could predict the order rate correctly, while deviating from the actual order size, or vice versa. The same holds for the human interaction on policy follow-up. In a similar manner, this cause is broken down into the actual moment of placing an order and the size placed by the inventory controller. To illustrate, when the policy suggests to order due to the inventory position dropping below the reorder point of a part, the inventory controller could comply by placing an order. However, the order could be of a different size than the model advises ($S - IP$). The other way around is also possible, in which the inventory controller places an order of recommended size, but at a different moment.

Table 4.2 summarizes the discussed causes, forming the final shortlist of potential fill rate gap causes that the model should be able to test. Notice the same color scheme is used again.

#	Causes	Color
1	**Demand forecast**	
	a. Order moment	
	b. Order size	
2	**Lead times**	
	a. Supplier lead time	
3	**Human interaction**	
	a. Inventory policy changes	
	b. Order moment	
	c. Order size	
4	**Fill rate calculation**	
	a. Calculation method	
5	**Classification**	
	a. Grouping spare parts	

Table 4.2: Shortlist of fill rate gap causes

Chapter 5

Model overview

In the previous chapter, a shortlist of potential fill rate gap causes is created. This chapter elaborates on the type of model that is developed to quantify and explain these causes, as well as the key functionalities of the model. It acts as a conceptual overview, while the next chapter explains the exact modeling choices and inner workings in more detail.

Section 5.1 states the goal of the model and what is aimed to achieve. In Section 5.2 the method used to develop the model is explained. Then, in Section 5.3, the model validation method is discussed. Finally, an overview of the output of the model is provided in Section 5.4.

5.1 Goal of model

The inventory control system for spare parts used by Fokker is a complex system, characterized by a high involvement of decision makers and stochastic processes. Such systems are challenging to control or improve as a result of the high exposure to variability and subjective factors influencing decision making. Consequently, misalignment between model and realized fill rates are experienced.

Chapter 4 identified a shortlist of potential causes for this misalignment. The main goal of the model to be developed is to quantify and explain these causes for a specific group of parts. In the first place, the model should be able to show that a difference exists between the fill rate predicted by the part replenishment model and the fill rate observed in reality. With this, the actual existence of a fill rate gap is proved. Secondly, the model should be able to quantify the causes presented in the shortlist of Section 4.3. Moreover, insights have to be created on part level to explain in a more detailed way how the identified causes manifest itself. In other words, insights into the way inventory moves through the company is necessary to understand the impact of the causes. Finally, the analysis performed with the model should be repeatable for every *stock-run*.

5.2 Modeling method

To achieve the goal of quantifying and explaining fill rate gap causes, a model is developed. This section introduces the modelling challenge, the type of model created to solve this challenge and its high-level workings.

5.2.1 Modeling challenge

Fokker uses their part replenishment model to determine the optimal inventory policy parameters for all parts, as mentioned in Chapter 3. This process, known as a *stock-run*, is repeated every six months. In other words, every six months the model states which inventory policies to maintain to achieve a certain fill rate. The optimized policies are then possibly adjusted, after which they are entered into Fokkers ERP system so purchasers can use them to make decisions. Then, after six months of using the policies, the realized fill rate differs from what the model predicted. Consequently, different shortlist causes have manifested themselves in some way over this period of six months, creating the actual fill rate gap. The main modeling challenge is that in order to quantify and explain the impact of a single cause on the fill rate gap, its effect has to be isolated. The model used for this purpose should be able to make a statement about what happens with the realized fill rate when a specific cause does, or does not, occur, without changing anything else. However, there is no observational data on all the ways in which a cause can manifest itself, as only one manifestation of causes occurred in the six months between stock-runs. So, in essence, the model has to change what really happened in a period of six months of history (create alternative realities), based on a specific cause occurring, or not, in a particular way.

To illustrate, the model should be able to state what would have happened with the realized fill rate if the operational buyers made different purchasing decisions. Or what the impact is of the realized supplier lead times on the achieved fill rate.

5.2.2 Discrete event simulation

One method used to test the impact of changes in conditions and courses of action is simulation. This approach focuses on analysing real-world processes or systems by imitating its operations over time (Boon et al., 2017). Using simulations allows for mathematically analysing complex systems, even if stochastic (random) processes are the foundation of such systems.

Therefore, to solve the modeling challenge of the previous section, a simulation approach is used. More specifically, a discrete-event simulation (DES) model is developed. Boon et al. (2017) describe a DES as being completely regulated by handling a sequence of events, all taking place at random times. With every event taking place, the state of the system changes. So, in a discrete-event simulation model, the system jumps from one event time to the next, making calculations based on the new model state. The event times, and thus the scheduling of the different events, often happens based on a specific event time distribution. Using this modeling technique to analyse a fill rate gap is advantageous due to several reasons, summarized below.

Applicable to context. Discrete-event simulations are often used in queuing theory and are capable of imitating an inventory control system. As this thesis analyses such an inventory control system, DES is very applicable to the situation.

Deterministic and stochastic processes. A DES is based on scheduling and handling events. Often, the event times are based on a distribution and, thus, occur randomly. However, this thesis focuses on learning about the fill rate gap using six months of historical data at the time. It is known beforehand which events took place and at what times. Depending on the cause that is being tested, randomness may be absent. By making some simple adjustments however, it is possible to schedule events based on already known times. In this way, deterministic processes can be analysed as well. Moreover, when stochastics are introduced, the model can easily deal with that as well, making DES a very versatile way of modeling the inventory control system.

What-if scenarios. With DES it is possible to create a simulation of the real inventory control process. However, by changing the rules used to schedule events, this system can easily be adjusted to reflect what would have happened if a specific cause occurred or was absent. This idea helps in creating what-if scenarios based on the causes presented in the shortlist (Section 4.3), creating an alternative reality reflecting what would have happened if a specific cause did, or did not, occur, while keeping all other processes equal based on historical data (Jacobson et al., 2006).

5.2.3 Modeling concept

In order to quantify and explain the shortlist causes of the fill rate gap, we propose to use a discrete-event simulation model. This model is capable of making what-if scenarios to test the impact on the fill rate of a specific cause occurring or not. Then, the question remains, how does this work in practice.

The conceptual idea is as follows. The base model exists of a simulation of the inventory trajectories of a selected group of parts based on six months of historical data. With this simulation, the realized fill rate for this group of parts is calculated. The base model, thus, determines the achieved fill rate on group-level and shows what happened on part level based on the inventory trajectories. Next, the rules of the base model are changed. Alternative realities are created in which a specific fill rate gap cause did, or did not, occur, while keeping all other processes unchanged based on historical data. With this, the impact of the changes on the fill rate gap is tested. A specific group of parts is used for this analysis, in order to take the classification into account. Using this idea as a building block, Figure 5.1 illustrates the key analysis concept.

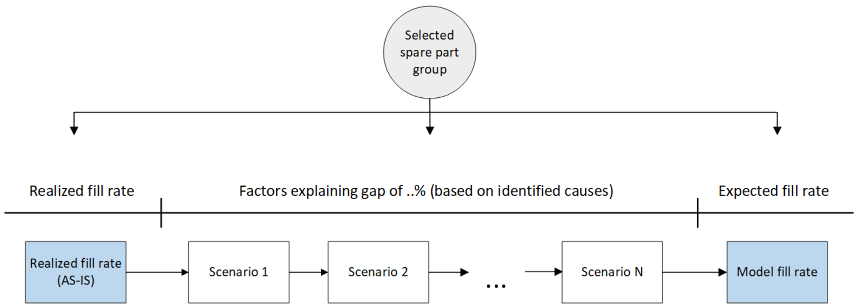


Figure 5.1: Basic simulation model setup

First, the group of spare parts is selected that will be analysed. Next, the base simulation is created, simulating the realized fill rate over six month of history by creating the inventory trajectories of all parts in the group. Then, the rules of the base model are adjusted to create a simulation of the part replenishment model, stating the model fill rate. The difference in fill rate between the base model, simulating the realized fill rate, and the simulation of the model fill rate is the actual fill rate gap. Finally, a set of scenarios is created based on the shortlist causes to *connect* the two simulations, calculating the impact of the changes on the fill rate along the way.

Due to the nature of the shortlist causes (Section 4.3), it is possible to adjust the simulation of the realized fill rate sequentially and end up with the simulation of the part replenishment model. Starting with the simulation of reality, the *human involvement* cause can be tested by creating a scenario in which no human involvement is present. In other words, a scenario in which the inventory policies as optimized by the part replenishment model are exactly followed. This scenario has now moved the simulation one step further from reality to a simulation of the part replenishment model. Next. the actual supplier lead times can be replaced by the model lead times, approaching the model simulation even more. Finally, the real demand can be replaced by a simulation of the theoretical demand. The result is a full replenishment model simulation.

These changes sequentially adjust the simulation of the realized fill rate to create a simulation of the part replenishment model. With this, both simulations are now *connected*. With every new scenario a fill rate gap cause is tested and its impact on the fill rate is determined. With it, it is not only possible to measure group fill rates of fictitious scenarios, but also part-level insights are obtained as simulating part inventory trajectories are key to this method.

5.2.4 What-if scenarios

Following previous subsection, this subsection aims to elaborate on the key principle of creating the intermediate what-if scenarios to connect the simulation of the realized fill rate with the model fill rate. Chapter 6 goes into detail on all possibilities, while this subsection explains the conceptual idea using an example.

Consider the simulation of the realized fill rate achieved in a historical period of six months. In order to simulate the corresponding part inventory trajectories, data is required on all inventory movements. An example is purchase order data, stating the time and size of an increase in inventory due to a purchase made by an inventory controller. When simulating what really happened, these moments and sizes are scheduled based on their actual occurred values. However, it would also be possible to not use this historical data to schedule purchase orders, but instead schedule them based on the optimized inventory policies. In this way, the impact of exactly following the policy as compared to what really happened can be tested.

This idea, of either using historical data to schedule events or schedule events based on different rules, forms the basis for creating the what-if scenarios.

5.3 Validation method

In order to make sure the discrete-event simulation model performs as expected, a validation strategy is developed. This strategy exists of a group- and part-level validation, explained in this section. Additionally, a statistical method is explained to test the significance of differences between group fill rates between scenarios.

5.3.1 Group-level validation

Based on Figure 5.1, it can be concluded that there are two points at which a group-level validation can take place. First of all, the simulation set-up states that the realized fill rate is simulated. To validate whether the found group fill rate coincides with reality, the actual achieved fill rate should be determined. However, currently at Fokker, the realized fill rates are not yet measured in the same way the part replenishment model does. So, in order to validate the simulation at this point, data should be collected to achieve this. Chapter 6 elaborates on this in more detail.

Secondly, the model fill rate is simulated as well. In order to validate if the simulated model fill rate corresponds with the part replenishment model predictions, the fill rate output of the replenishment model is used. However, as discussed in Section 3.1.2, the optimization model provides several fill rate values based on different transient times and the final steady state situation. The most obvious choice would be to use the *X month* calculations. The simulation is ran for a period of six months, meaning the *6 month* fill rate estimate can be used as validation point. However, this is a very course approximation of the real fill rate value after six months. For this reason, the *run* and *ideal* fill rate calculations made by the part replenishment model are also taken into account. The *run* moment provides a fill rate value directly after implementing the new inventory policies, while the ideal moment represents the steady state situation. The six month moment lies in between these moments. These three fill rate values together provide a range in which the simulated model fill rate should fall.

5.3.2 Part-level validation

A second validation can be performed on part-level. Fokker services maintains a database of *inventory snapshots*, containing inventory levels of all parts measured once a month. As the simulation model evolves around creating inventory trajectories of all parts, these trajectories can be compared with the snapshots at certain moments in time. When the trajectories follow the known inventory levels correctly, an indication is given of the correctness of the simulation. Notice, however, that this validation method is only possible for the simulation of the realized fill rate. When what-if scenarios are created, the inventory trajectories no longer match the actual inventory levels measured in history.

5.3.3 Between scenarios

Determining the statistical differences between two group-level fill rates is useful in two ways. First of all, it is a form of validation. When no statistical difference can be identified between the simulations of the realized- and model fill rate and their respective validation values, more evidence is gathered to ensure the correctness of the simulation model. Secondly, statistical differences on group-level fill rate between scenarios indicate significant changes between these scenarios. This helps to establish an idea on the significance of the impact certain causes have on the fill rate gap. For these two reasons, a statistical method is explained in this section that is capable of measuring statistical differences between group-level fill rates.

Every individual part fill rate is a realization of the actual fill rate, creating a sample of fill rates. When the samples are normally distributed, a *two sample t-test* can be used to determine if two sample means are statistically different from each other. To test this assumption, Figure 5.2 displays the item- and line part fill rate histograms based on the output of the part replenishment model. It is clearly seen that normality cannot be assumed, as is also proved using a *Kolmogorov-Smirnov test*. For both fill rate types the null hypothesis stating that the sample follows a normal distribution is rejected with a p-value smaller than 2.2×10^{-16}. To overcome the issue of non-normality, the *Wilcoxon rank-sum test (WRS)* is used. This is a non-parametric variant of the two sample t-test, meaning the normality of sample values is not required.

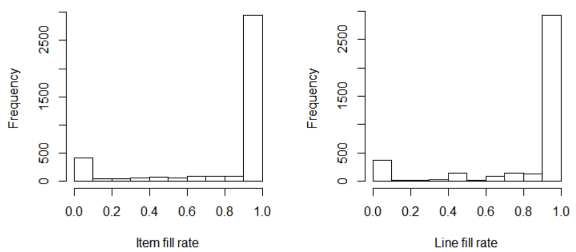


Figure 5.2: Histograms of model item- and line part fill rates

Furthermore, comparing the group-level fill rates of two scenarios with each other can be seen as testing a specific treatment. This treatment is the specific fill rate gap cause that is being tested. The first scenario represents the situation in which the cause does not occur, while the cause is present in the second scenario. Moreover, every part in the first scenario is also present in the second one. This interpretation of treatments and the stability of part occurrence per scenario results in the use of a *paired* Wilcoxon rank-sum test.

Another challenge has to be solved before the paired WRS can be used. The statistical test is used to establish whether two sample means differ significantly from each other. However, the mean of the sample of part fill rates does not result in the group-level fill rate. The group-level fill rate is a *weighted* average of these sample values. To adjust for this, the following transformation is applied to every individual part fill rate in the sample before using the statistical test.

$$\frac{w_j \ F_j(c)}{\sum_{j \in J_g} w_j} \ g_{size} \tag{5.1}$$

The item- or line fill rate for policy c, $F_j(c)$, is multiplied with its corresponding weight w_j. This value is divided by the sum of all sample weights and then multiplied with the size of the sample group g_{size}. Taking the average of these adjusted values results in the group-level fill rate.

Finally, the actual *Wilcoxon rank-sum test for matched pairs* is then applied as follows. Let X be the set of adjusted part fill rate values based on Equation 5.1 for every part j in a specific group g and a specific scenario. Then, $(x_1, ..., x_{g_{size}})$ is a sample of population X, with x_1 indicating the fill rate of part 1. Next, let Y be the set of adjusted part fill rates for every part j in the same group g for a different scenario. Then, $(y_1, ..., y_{g_{size}})$ is a sample of population Y. As we are dealing with matched pairs, consider random variable $D = X - Y$ with sample values $D_j = X_j - Y_j$ for

$j = 1, ..., g_{size}$. D_j then indicates the difference in adjusted part fill rate values for part j. When D has a mean value of zero, the means of population X and Y are equal. Otherwise, they are not. The hypothesis used by the *Wilcoxon rank-sum test for matched pairs* are provided below.

$$H_0 : \mu^X = \mu^Y \rightarrow \ H_0 : \mu^D = 0 \tag{5.2}$$
$$H_1 : \mu^X \neq \mu^Y \rightarrow \ H_0 : \mu^D \neq 0 \tag{5.3}$$

Using this statistical method, all scenarios can be compared with each other and statistical differences in group-level fill rates can be identified.

5.4 Output analysis

In order to conduct analysis using the discrete-event simulation model, its output should be considered. This section discusses the models group- and part-level output.

5.4.1 Group-level output

On group level, either a sensitivity- or sequential analysis can be performed.

Sensitivity analysis. Using the capability of the discrete-event simulation model to create what-if scenarios, a sensitivity analysis can be performed. Here, every model parameter is adjusted individually and compared to the simulation of the realized fill rate. Figure 5.3 illustrates this output analysis method. First, a group of parts is selected, after which the realized fill rate is simulated and validated using the methods described in the previous section. Then, every model parameter is changed one at the time to test its impact on the realized fill rate. The statistical method explained in previous section can be used to state the significance of the impacts.

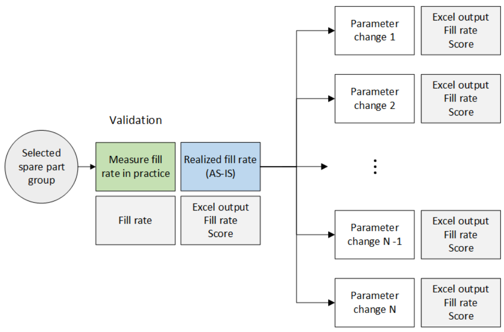


Figure 5.3: Extended simulation model setup with sensitivity analysis

Sequential analysis. A second group-level output analysis method is a sequential variant. The key concept is to create a chain of what-if scenarios, all building on top of each other. The changes made to a parameter in one scenario will still be present when another parameter is changed in the next scenario. In this way, the interaction effects between changes can be taken into account. This idea is also used in Section 5.2.3. Figure 5.1 schematically shows this output analysis method for a group of spare parts. Note the two validation points, one at the realized side and one at the model side of the simulation. The statistical method explained in previous section can be used as validation tool, but also to state the significance of the changes between scenarios.

5.4.2 Part-level output

On part-level, the discrete-event simulation model provides two sources of output.

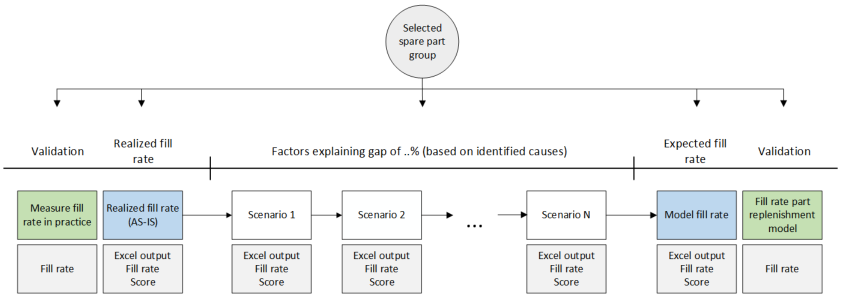


Figure 5.4: Extended simulation model setup with sequential analysis

Inventory trajectories. For every part being simulated, its inventory trajectory can be visualized. Figure 5.5 depicts an example of such an inventory trajectory. It illustrates the height of the on-hand inventory, the level of backorders and the inventory position per simulation time-interval. Using these graphs, differences between scenarios can be investigated on part-level. Moreover, insight is created into the inventory movements based on certain decisions.

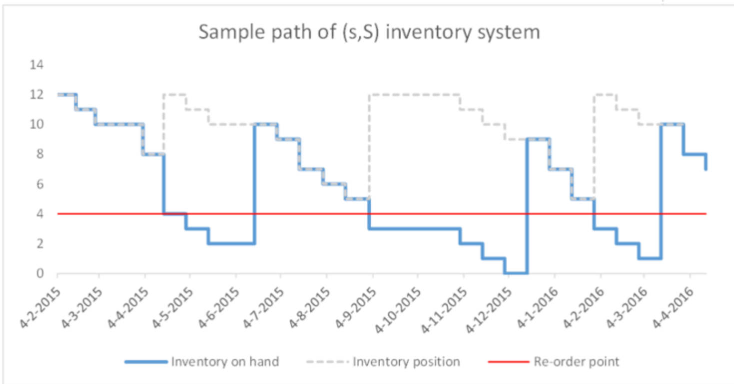


Figure 5.5: Sample path of theoretical (s, S) inventory policy

Performance output. The second part-level output is a collection of Excel files containing performance data. With this data, separate analyses can be performed to gain even more insight into the inventory behavior and impact of specific fill rate gap cause. For every what-if scenario, the model creates a computer folder to store the Excel sheets. The folder is named *Scenario-X*, where X is a user entered scenario number. Appendix D provides an overview of all Excel output on part-level.

Chapter 6

Model design

Chapter 5 introduced the discrete-event simulation model used to analyse the fill rate gap conceptually. To create and use the actual model, the methodology illustrated in Figure 6.1 is used (Duguay and Chetouane, 2007). This chapter covers the development of the actual model, finishing the first part of the thesis. The second part of the thesis, Part II, focuses on using the model in practice at Fokker. In this part, Chapter 7 introduces the case study and validates the simulation model. The model output is analysed in Chapter 8 and 9.

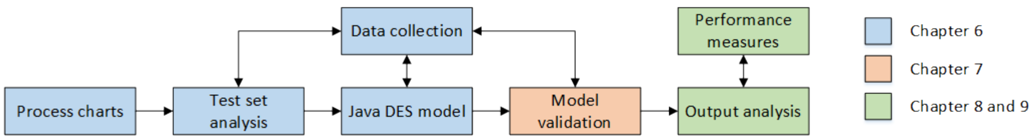


Figure 6.1: Main steps of methodology

In this chapter, Section 6.1 develops process charts of the inventory control system at Fokker, forming the basis for the programming of the simulation model. Then, in Section 6.2, a five step process is followed to create the actual model. Section 6.3 finalizes this chapter by discussing the data requirements and collection.

6.1 Process charts of conceptual model

This section aims to create a thorough understanding of the inventory control process that has to be simulated by developing process charts. Section 6.1.1 provides a description of the inventory control system. Then, in Section 6.1.2, the actual process charts are created. Finally, Section 6.1.3 elaborates on a few concepts requiring more attention before the actual simulation model is programmed.

6.1.1 Process description

A general overview of the inventory control process was already provided in Figure 4.2. However, the simulation model evolves around the bottom part this figure, illustrating the replenishment process in practice. In this process, the optimized inventory polices for every part are considered given. Based on these policies, the inventory controllers make operational purchasing and stocking decisions based on actual demand. Consequently, the inventory levels of the spare parts can in- or decrease, resulting in a particular process performance. Therefore, to fully understand the replenishment process, the reasons why inventory increases or decrease is discussed in the remainder of this section.

Increase inventory. The main mechanism to increase the physical inventory is placing purchase orders for specific parts at suppliers. After a particular lead time the parts arrive at Fokker, where they are inspected and booked to the inventory. Other possibilities for inventory to increase are arrivals of parts from internal suppliers (warehouse transfers, work orders) or stock updates (e.g., parts found).

Decrease inventory. Decreasing part inventory is mainly achieved by reacting to sales orders placed by customers. Customers require parts, which are picked, packed and made ready for transportation. At the moment the parts are picked, they are no longer available for other orders, decreasing the available inventory. Other inventory mutations could also result in a decrease of stock. Examples are warehouse transfers, work orders, stock updates (e.g., parts missing, parts stolen).

6.1.2 Process charts

Based on the process description, it is concluded that the replenishment process exists of four sub-processes: handling of sales orders, placing purchase orders, receiving purchase orders and dealing with other inventory mutations (stock updates, work orders, warehouse transfers). For each of these sub-processes a process charts is created in Figure 6.2. The remainder of this subsection discusses all four processes.

Handle sales orders (SO). When a customer places a sales order at Fokker, the on-hand inventory is checked in the warehouse. Based on its level, compared to the size of the order, three different flows can occur.

1. The on-hand inventory is zero → Sales order becomes a backorder
2. The on-hand inventory is larger than zero, but the sales order size is larger than the on-hand inventory → Split the sales order: deliver remaining on-hand inventory and backorder the remaining parts.
3. The on-hand inventory is larger than the sales order size → Deliver the sales order in total.

Finally, the the inventory position is updated automatically.

Place purchase order (PO). The placement of a purchase order can be initiated by two causes. First, the inventory position of a part may decrease to a level that is equal to, or lower than, its reorder level. If this is the case, an undershoot signal is created by the ERP system, resulting in an inventory controller placing a purchase order. Second, an inventory controller may decide to place a purchase order based on its own insights. In both cases a PO is placed and the inventory on order and inventory position are increased automatically.

Receive purchase order (PO). Incoming purchase orders undergo an inspection, after which the parts are stored in the warehouse. This will decrease the amount of inventory on order of this part, while simultaneously increasing the on-hand inventory. Next, it is checked if backorders are present for the received parts. If this is not the case, the inventory position is updated, after which the sub-process is done. However, when there are backorders, these are first delivered before the inventory position is updated.

Handle inventory mutations. Dealing with other inventory mutations mainly concerns in- or decreasing the on-hand inventory based on the type of mutation and updating the inventory position.

Finally, note that this process description is stylized. In theory, this is the way in which the processes are executed. However, in reality, it could turn out that in specific cases different decisions are made.

6.1.3 Supplier lead time and delays

In order to start programming the actual simulation model, two concepts have to be discussed, namely the supplier lead time and delays.

Supplier lead time. From the part replenishment model perspective, the supplier lead time is the time between the moment a parts inventory position drop to, or below, its reorder point and the actual arrival of the order. In reality, this time exists of several parts, together forming the total supplier lead time.

1. Ordering lead time → Time between an undershoot signal and the operational buyer placing the order at the supplier.
2. Internal supplier lead time → Time between the supplier receiving the order from GKN Fokker Services and the order being ready for transport.
3. Transport lead time → Time between the start of transport from the supplier until the order is received at the warehouse of Fokker.
4. Internal lead time → Time between receipt of order until the part is available in stock (quality control and storage operations).
5. Transfer lead time → Transport parts from a central warehouse to a secondary warehouse.

For the purpose of this thesis, the supplier lead time is defined as the period of time between the placement of a purchase order at a supplier and the moment the part is available in the inventory. This translates to combining the internal supplier lead time (2), transport lead time (3) and internal lead time (4). Transfer lead times (5) are not taking into account, as we are dealing with a single echelon inventory system (see Section 1.3.3). The ordering lead time (1), however, is better interpreted as a delay instead of a lead time. This is further explained in the next sub-section.

Ordering delay. Instead of interpreting the time between an undershoot signal and the placement of the actual order as a lead time, this time is better viewed as a delay. Optimally, at the very moment an undershoot takes place, a purchase order is placed. This is also assumed by the part replenishment model (continuous review). In practice, however, it is often the case that a delay exists between the undershoot signal and the inventory controllers reacting to it. This delay can be caused by the undershoot report only being checked once or twice a week, a need for more information before ordering or other external factors. In order to test the impact of this ordering delay on the performance of the inventory control system, it is necessary to decouple it from the overall supplier lead time. Only then its individual impact can be investigated.

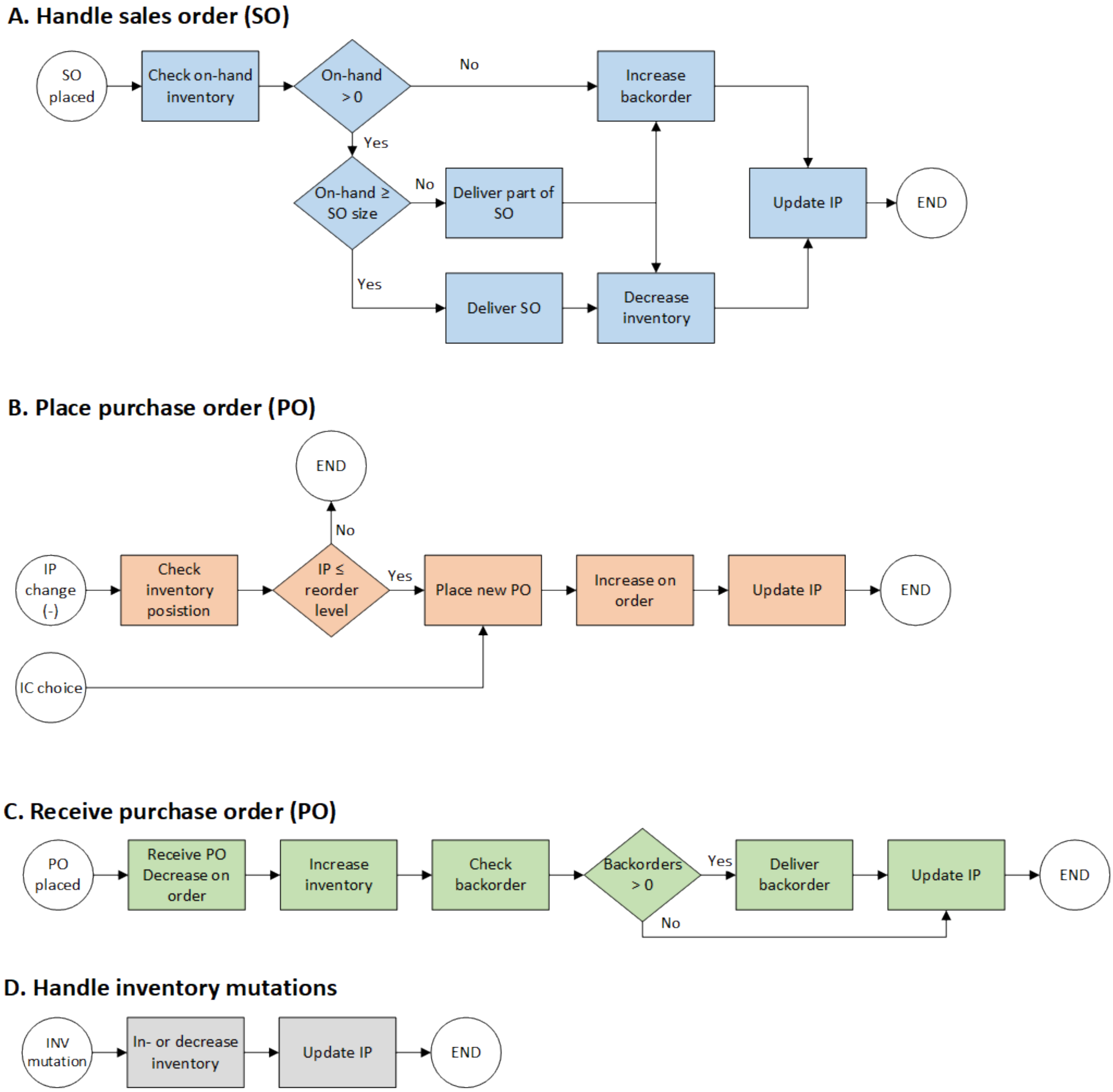


Figure 6.2: Inventory control system sub-processes

6.2 Model creation

Boon et al. (2017) proposes a five-step structure to create a discrete-event simulation model. In this section these steps are followed and discussed. The first step is to identify all relevant entities, or objects, that play a role in the model. Second, the attributes of these entities are determined. Third, the relevant events are identified. These are the time epochs at which the state of the system changes. Fourth, the performance measures that the model should simulate are determined as well as any additional properties that are needed to achieve this. The fifth step aims to specify the actual implementation of the simulation. This involves describing, in detail, when every event should be scheduled, and how it should be handled. Using the conceptual model of Section 6.1 as guideline, the remainder of this section discusses every step separately.

6.2.1 Entities

The entities are the main objects that play a role in the simulation of the inventory control system. Every entity is therefore programmed as an individual object, the main benefit being ease of tracking. Every entity, in combination with its attribute values, describes the state of the system. With this, it is convenient to deduct performance measures. The most important objects are discussed in this section.

Part. The foundation of the DES model is the simulation of inventory trajectories of spare parts. The description of these inventory movements is used to calculate performance measures. The entity responsible for changing the inventory levels are *parts*. They flow through the system and are affected by sales- and purchasing orders.

Inventory changes. As stated in previous section, three entities cause the inventory of a part to in- or decrease. A *purchase order (PO)* results in an increased on-hand inventory, while a *sales order (SO)* causes the inventory to decrease due to customer demand. Finally, an *inventory mutation* could either in- or decrease inventory, depending on the type of mutation. Each of these entities are translated to an object in the simulation model. Moreover, the inventory mutations are separated into in- and decrease entities.

Backorder. As Figure 6.2, image A, shows, incoming sales orders cannot always be (fully) fulfilled from stock. When this happens, the sales order is fully, or partly, backordered. In order to keep track of the current level of backorders and the parts they belong to, a *backorder (BO)* is also considered to be an entity in the simulation model.

Convenience entities. In order to easily track the current inventory status of a part, an *inventory tracker* entity is created. This object is initialized for every individual part and, among other things, keeps track of the on-hand inventory, inventory position and the number of parts on order. Furthermore, a *size selector* entity is created, which is able to select the correct PO and SO moments and sizes based on the scenario being ran, as well as the corresponding lead time size. A more detailed discussion is provided in Section 6.2.5.

This discussion brings the total number of entities to eight, together forming the basis of the simulation model. They either flow through the system being simulated, affect the inventory levels of the parts or are created for tracking and result calculation purposes.

6.2.2 Attributes

Is a discrete-event simulation, the collection of attribute values of every entity describe the state of the system. In this section, the most important attributes are discussed. In Appendix E, Section E.1, a more detailed overview is provided.

Part entity. The part entity is the object flowing through the inventory control system. This entity is described by an *ID* value, uniquely identifying the part. It is a number between one and the count value of the last part in the simulation. Furthermore, the optimized *reorder* and *order up to* levels are also required to make decisions in the simulation. Next, in order to calculate the item- and line fill rates, the parts *cost* and forecast *multiplier* are required. Finally, every part has its own *inventory tracker* and *size selector* attributes.

Inventory change and backorder entities. The sales order, purchase order, inventory mutation and backorder entities have several attributes in common. For starters, each entity is linked to a certain *part* object and have a certain *size*. Moreover, all these entities have a creation time and a time at which the object is closed. The former are *occurrence times*, such as order time (SO) or placement time (PO, mutation), while the latter are *mutation times*, such as a final delivery time (SO, BO) or receiving time (PO) (also see Section 6.3.2 on inventory movements).

Furthermore, several attributes are unique to the entity. For the sales orders, information is maintained on the current size delivered to the customer, while the backorder entity uses a boolean to record whether it is fully resolved or not. Figure E.1 provides a complete overview of all other attributes that are maintained in order to keep track of the object, its state and to facilitate performance measurements.

Convenience entities. The inventory tracker entity keeps track of the current status of a parts inventory. For this purpose, attributes are maintained on the *partID*, *start inventory*, *current on-hand inventory*, *available inventory* (current inventory minus any reservations), parts that are *on order*, the total amount of *backorders* and the *inventory position*. These values are also recorded per simulation time instance in order to visualize the inventory trajectories of every part after the simulation (see Figure 5.5).

The size selector entity is used to select different SO and PO sizes and moments, as well as lead time sizes. As we are simulating the inventory control process based on six months of historical time (see Section 5.2), the actual timing and sizes of the occurred sales- and purchase orders are known, as well as the realized lead times. This information is stored in the size selector object. Using this data, calculations are performed to determine the average, minimum and maximum value of the PO, SO and lead time sizes. These can then be used for different what-if scenarios. Moreover, the actual sizes are placed in a list and used in a sequence one at the time. Every time a value is used, it is placed at the end of the list again, so the list is never empty.

Besides this, simulation rules are added to the size selector entity to determine the PO size based on the parts reorder level, order up to level and inventory position. Also, historical demand rates and the parts demand size probability mass function (see Algorithm 2) are maintained in order to simulate the compound Poisson demand process used by the part replenishment model. E.2 provides a complete overview of the attributes of these entities.

6.2.3 Events

According to Boon et al. (2017), an event is the time epoch in which the state of the system changes. In order to identify these moments, two steps are performed. First, all events that are relevant for the discussed entities are determined. In the second step compound events are identified. These are events taking place simultaneously. The final set of events should not contain any compound events, as this is irrelevant for the implementation of the simulation model.

First of all, for the part and size selector entities, no relevant events exist. The part objects are initialized at the start of the simulation and flow through the system. Decisions are made based on its attributes and the object is linked to other objects, but its state will never change. The same holds for the size selector. This object simply stores information on sizes and occurrence moments of other objects. It state never changes, it is only used by other objects.

The inventory tracker entity, however, is a very valuable object to which events can be linked. It keeps track of all the inventory types of the parts and is, thus, affected when these levels change.

Important events here are the *inventory mutations increasing inventory*, *inventory mutations decreasing inventory*, *placing a PO*, *receiving a PO*, *receiving a SO*, *delivering a SO* and *fulfilling a BO*. The same events are also relevant for the PO, SO, inventory mutation and BO entities.

Finally, two other relevant events exist. The simulation model creates what-if scenarios based on six month of historical time. This period of time will be defined as the *simulation period*. The inventory policies being simulated in this period of time are optimized using a set of historical usage data of (usually) two years. This period of time will be defined as the *history period*. Based on these new definitions, it could be the case that some purchase orders are placed in the history period, but arrive in the simulation period. The same holds for some sales orders. These could be placed by customers in the history period, but Fokker fulfills them in the simulation period. For this reason, the events concerning the placement of a purchase order and sales order are divided into the ones placed in the history period and the ones placed in the simulation period.

This brings the total number of events to nine. The second step is to check whether some of these events occur at similar times. Theoretically, every time the inventory increases it should be checked if backorders are present, and if so, they should be delivered. This means that *inventory mutations increasing inventory* and *receiving a PO* should occur at the same time as *fulfilling a BO*. The same reasoning holds for every time the inventory decreases. When this happens, theoretically, the inventory position should be checked against the parts reorder level and a purchase order can be placed. In other words, *inventory mutations decreasing inventory*, *delivering a SO* and *fulfilling a BO* should all occur at the same time as *placing a PO*. The same holds for *receiving a SO* and *delivering a SO*. When a sales order is received by Fokker, theoretically, it should be picked and made ready for transport at the same time.

However, it is decided to keep all the individual events. The reason for this is twofold. First of all, when simulating reality, things do not always happen as they should theoretically. In essence, this is exactly what this thesis aims to show. For example, at the moment the inventory position decreases to a point below the reorder point, inventory controllers do not have to react immediately. Due to these kinds of relationships, the events are viewed as separate. Secondly, the model should test the impact of different fill rate gap causes by isolating them. In order to achieve this, the different events have to be isolated as well. For example, if we want to test the impact of an ordering delay (see Section 6.1.3), we should be able to schedule a *placement of a PO* a few time instances after an *inventory decrease* event. When they happen automatically after each other, as suggested theoretically, such causes cannot be tested.

To conclude, no compounding events exists in the current formulation of the events. Table Table E.1 in Appendix E provides an overview of all identified events. Notice that every event has a type and category. This is especially important in order to distinguish between different types of inventory mutations. The types taken into consideration are also presented in the same table.

6.2.4 Performance measures

The performance measures calculated by the model are already discussed in Appendix D. It mainly concerns information to visualize inventory trajectories, fill rate information and overall performance. The results are used for further analysis in Excel and R studio.

6.2.5 Simulation implementation

In this section the actual implementation of the simulation model is discussed. First the assumptions of the model, as well as some general guidelines, are explained. Then the initialization of the model is detailed, after which the main body of the model is described using pseudo-code. Next, more insight is provided into the creation of the what-if scenarios and the implementation of a Monte Carlo simulation. Finally, the actual event handling is described.

6.2.5.1 Assumptions and guidelines

As most inventory decisions are made on a daily basis, the time instances used for the simulation are also days. Moreover, the simulation is performed for a specific group of parts in order to test the impact of different part characteristics on the fill rate gap. Finally, several assumptions are made to facilitate the development of the model.

1. Ordering decisions can be made on a daily basis.
2. If the inventory position of a part is lower than, or equal to, the associated reorder point at the start of the simulation, a new order is placed immediately.
3. If there are no purchase orders placed in the history period that arrive in the simulation period, it is assumed the amount of on order parts and backorders are zero at the start of the simulation.
4. When multiple sales orders arrive for the same part at a single day, the largest sales order is handled first.
5. Sales orders of the same customer, placed at the same day but a different time, are consolidated to a single order.
6. Inventory mutations (stock updates, work orders, warehouse transfers) only happen in practice when inventory is available (100 percent fill rate). Therefore, they cannot cause backorders when used in a what-if scenario.
7. The model lead time is used for purchase orders placed in the simulation period of parts that have not been ordered in the history period.
8. A purchase order placed at the supplier will always be delivered and have the same size as the ordered quantity.
9. Splitting backorders is not possible, they are always delivered to the customer at once.

6.2.5.2 Initialization

Before actual scenarios can be simulated, the discrete-event simulation model has to be initialized. The steps involved in this process are illustrated in pseudo-code in Algorithm 1. First, the data required to perform the simulation and its scenarios is loaded from Excel sheets (see Section 6.3 for a detailed description on data requirements and collection). Next, the *getRunSetting* method is called, allowing the user to select the output analysis method to be used and to create individual what-if scenarios. Based on this user input, the *createPartList* method initializes the part entities and the *selectEvents* method initialization the event queue. The event queue is a list of scheduled future events, sorted by occurrence time. Depending on the scenario that has to be ran, the *selectEvents* method fills the queue with events that are already known based on historical data. The events that are scheduled based on simulation rules during the simulation itself are added at their creation time. Finally, a computer folder is created to store the output files of the simulation.

Algorithm 1 InitializeSimulation

```
Read all input files from Excel
Call getRunSetting to take user input to create scenario
Call createPartList to create part objects
Call selectEvents to select the events used for the scenario created
Place selected events in event queue 𝓕
Create folder on PC to store simulation output
```

6.2.5.3 Main body of simulation

With the simulation model initialized, the actual scenario handling can be performed. Algorithm 3 in Section E.3 illustrates the main body of the simulation model, from which all other methods are called.

After calling the *initializeSimulation* method, the current simulation *time* is set to zero and the *final timing* is set to the last day of the simulation period in order to end the simulation on time. Then, the inventory positions of all parts are initialized based on the events scheduled during initialization. These are primarily purchase orders that are placed in the history period, increasing the amount of parts on order. Based on the inventory positions and the parts reorder levels, purchase orders are placed when required.

From there, a while loop is entered to deal with the events from the event queue. With every loop instance, the first event from the event queue is taken and used to set the *part* variable and update the simulation *time* variable. Depending on the type of event taken from the queue, the switch statement dictates the case that should be entered to deal with it. When no event is found, the user is notified by a printed statement to the console.

When the event queue is empty, or the simulation *time* is larger than the *final timing*, the while loop is terminated. The *performAfterSimulationCalculations* method is called, initializing the calculation of different performance measures based on the data gathered using the simulation. The results of these calculations are stored in Excel and exported to the folder created in Algorithm 1. Finally, the *askForRepeat* method asks the user if a new scenario should be ran. If so, the simulation is started again from line two of Algorithm 1. If not, the simulation is terminated.

6.2.5.4 What-if scenarios

The switch statement of Algorithm 3 illustrates that for every event type a specific handling method is called. The way these methods deal with a specific event depends on the scenario that is being ran. For this reason, the creation of what-if scenarios is discussed first in this section. The remaining sub-sections discuss the Monte Carlo simulation addition and the actual event handling.

In Section 5.2 the concept of creating what-if scenarios to quantify and explain the impact of every shortlist cause (see Section 4.3) on the fill rate gap is explained. These scenarios are created based on the idea of either using historical data to schedule events or schedule events based on different simulation rules. In order create scenarios to test a specific cause based on this principle, Table 6.1 depicts all simulation parameters and their range of possible values.

The first column of Table 6.1 illustrates the actual simulation parameters that are used to create scenarios corresponding with the shortlist causes. For this purpose, mainly the colored parameters are used, which correspond with the causes displayed in Table 4.2. The remaining parameters add additional design freedom to the model.

In accordance with Section 6.1.3 and Section 6.2.3, the *PO ordering delay*, *inventory mutations* and *SO and PO placed in the history period* parameters are added in order to test their impact. Furthermore, the first three parameters are added to simplify the creation of scenarios by forcing a *First Come, First Serve* backorder handling logic, and no delays in reacting to sales- and backorders. The reason for this design choice is the fact that simulating any other possibility would be troublesome to program without adding much practical value to the model. Note, however, that the simulation of the realized fill rate does take the actual values of these parameters into account. Finally, the last seven parameters allow the user to multiply several model base values with a fraction. A fractional value of one corresponds with the original base value, while a value of 1.1 increases the base value with 10% and 0.8 decreases it with 20%. This could prove to be very useful for a sensitivity analysis.

The remaining three columns of Table 6.1 represent the total range of parameter values, starting from the simulation of the realized fill rate, to all possibilities for creating the scenarios and ending with the parameter values of the model fill rate simulation. The realized fill rate simulation uses historical data to schedule all events in the same way as they occurred in reality. For the scenarios, however, the *size selector* entity allows using different values and rules to schedule events. The PO lead time can be set using actual historical sizes, the historical average, -minimum or -maximum or the model lead times are used. The same holds for the PO and SO sizes. The only difference is that the model values are determined based on the inventory policy or compound demand distribution, respectively. For the PO and SO moments, actual historical data can be used or the inventory

Parameters	Values for different scenarios		
	Realized	Options for other scenarios	Model
BO logic	Actual	FCFS	FCFS
SO handling delay	Actual	No	No
BO handling delay	Actual	No	No
PO ordering delay	Actual	Uniform[x,y] ‖ No	No
PO lead time	Actual	Actual (sequence) ‖ Average ‖ Min ‖ Max ‖ Model*	Model
PO moments	Actual	Actual (import) ‖ Policy	Policy
PO sizes	Actual	Actual (sequence) ‖ Average ‖ Min ‖ Max ‖ Model**	Model
(s,S) policy parameters	After IC changes	Model ‖ After IC changes	Model
SO moments	Actual	Actual (import) ‖ Poisson rate	Poisson rate
SO sizes	Actual	Actual (sequence) ‖ Average ‖ Min ‖ Max ‖ Model***	Model
Import inventory mutations	Yes	Yes ‖ No	No
Import PO history	Yes	Yes ‖ No	No
Import SO history	Yes	Yes ‖ No	No
Reorder level factor	1	Fraction	1
Order up to level factor	1	Fraction	1
PO lead time factor	1	Fraction	1
Start inventory factor	1	Fraction	1
PO size factor	1	Fraction	1
SO size factor	1	Fraction	1
SO demand rate factor	1	Fraction	1

Table 6.1: Overview of scenario parameters
*: Part replenishment model, **: Policy (order up to - IP), ***: Compound distribution (Algorithm 2)

policy ($IP \leq reorder$) and Poisson demand rate are used, respectively. For the inventory policies, the user is allowed to either select the optimized inventory policies or the adjusted policies from the ERP system. Moreover, only the PO ordering delay can be tested using a uniform distribution, while the SO- and BO handling delay are always set to zero when creating a scenario. Finally, the inventory mutations and PO- and SO history can either be imported or not.

For the simulation of the model fill rate, the the assumptions and mathematical choices of the part replenishment model should be followed. Therefore, the backorders are fulfilled on a *FCFS* basis, no form of delay is allowed and no inventory mutations and PO and SO placed in the history period are assumed. The demand moments are simulated using a Poisson rate and every SO size follows the compounding distribution. PO lead times are assumed to coincide with the model lead times used in the optimization model. The moments of placing purchase orders are based on the policy ($IP \leq reorder$), as well as every PO size (order up to - IP). Finally, the optimized inventory policies are used.

Lastly, note that no explicit parameters are taken into account for the classification cause. The reason for this is that by selecting a spare part group to investigate, this cause can be quantified. If the same simulations were to be performed with a different group, with different characteristics, the influence of the classification can be found.

Chapter 7 explains the exact parameter settings used to test the shortlist causes and Table E.2 presents the translation of the conceptual parameters to code. Note that the user is allowed to build its own scenarios using the simulation model, creating a total set of around 16000 possible scenarios (without counting the fractions).

6.2.5.5 Monte Carlo simulation

Based on Table 6.1, it can be seen that most of the parameters have deterministic values, either based on historical data or simple calculations. Therefore, the same simulation results are achieved independent of the number of times a specific scenario is ran. However, some parameter values do result in scenarios experiencing uncertainty as a consequence of introducing probability distributions. In case of using the uniform distribution for PO ordering delay, scheduling SO moments using the Poisson rate and determining SO sizes based on the compounding distribution, difference arise between the results of multiple runs of the same scenario.

To deal with this outcome uncertainty, the DES model allows the use of Monte Carlo (MC) simulation when these specific parameter values are used in a scenario. The mathematical description of such a simulation approach are described in Appendix F. Besides this, Boon et al. (2017) proposes to use Equation 6.1 to determine the number of required simulation runs n to reach a desired level of accuracy ε of the simulated estimate (fill rate). For this, an estimate of the variance σ is required, as well as a value for $z_{\alpha/2}$.

$$z_{\alpha/2} \cdot \frac{\sigma}{\sqrt{n}} < \varepsilon \iff n > \left(\frac{z_{\alpha/2} \cdot \sigma}{\varepsilon}\right)^2 \tag{6.1}$$

If no estimate of σ is available, the following two-step approach can be used.

1. Run the simulation model for a small value of n. Estimate σ from the simulation results.
2. Use this estimate in Equation 6.1 to compute the number of runs to get accuracy ε.

The above method will be used in the case study to establish the number of runs required to get a specific level of accuracy for the scenarios subject to stochastics.

6.2.5.6 Event handling

With the model parameters known, the attention can be brought back to the event handling methods present in Algorithm 3. As stated before, these methods deal differently with the same event depending on the model parameter values. For example, when the PO are scheduled based on historical data, there is no need check the inventory policy to schedule new purchase orders when the inventory decreases. Section E.5 illustrated how the event handling methods work using pseudo-code. Within these methods, more general, self-explanatory, methods are used to summarize steps that are repeated between event handling methods.

6.3 Data requirements and collection

In order to validate and run the simulation model, data is required. Section 6.3.1 discusses the data requirements for model validation. In Section 6.3.2 the data requirements to run the model are elaborated. Finally, the data collection method is explained in Section 6.3.3.

6.3.1 Validation

As discussed in Section 5.3, data is required to perform a group- and part-level validation of the simulation model. Both are discussed in this sub-section. Note that the results of the validation methods are discussed in Chapter 7.

Group-level. The group-level validation is performed for the realized fill rate simulation, as well as the simulation of the model fill rate. For the latter validation, only limited data is required. The simulated fill rate is compared to the *steady-state*, *run* and *X month* fill rates of the part replenishment model. Moreover, the part-level fill rates are required to perform the Wilcoxon rank-sum test for matched pairs.

In order to validate the simulation of the realized fill rate on group-level, its resulting fill rate has to be compared with the actual achieved fill rate in practice. However, no measurements are in place yet at Fokker that calculate the achieved fill rate in the same way the part replenishment model does. To determine the data required to achieve this, Equation 6.2 illustrates the expression of the group fill rate for a given group and given inventory policies c for all parts j (based on

Chapter 3).

$$\sum_{j \in J_g} \frac{w_j F_j(c)}{\sum_{j \in J_g} w_j} \tag{6.2}$$

Here, $F_j(c)$ is the fill rate for part j with given inventory policy $c = (s, S)$ and w_j indicates the weight used for every part fill rate (item: annual revenue, line: annual demand rate). The weights are determined before the simulation, based on the history period. This group-level fill rate expression can be applied to the *WCP SPARES* table in Fokkers database, containing a row for every sales order and specifying the SO size and whether this size was delivered from stock or not. Combining this data with information on the prices of every part, the realized item- and line fill rates can be calculated for a group of parts in a specific time period. For this purpose, a set of formulas are required, illustrated below.

$$ADR_j = L_{j,hist} \cdot m_j \cdot \frac{365}{d_{hist}} \tag{6.3}$$

$$AD_j = Q_{j,hist} \cdot m_j \cdot \frac{365}{d_{hist}} \tag{6.4}$$

$$w_{j,item} = AD_j \cdot c_j \tag{6.5}$$

$$w_{j,line} = ADR_j \tag{6.6}$$

$$F_{j,item}(c) = \frac{items\ from\ stock\ part\ j}{total\ items\ ordered\ part\ j} \tag{6.7}$$

$$F_{j,line}(c) = \frac{lines\ from\ stock\ part\ j}{total\ lines\ ordered\ part\ j} \tag{6.8}$$

First, the data in the *WCP SPARES* table is divided into the correct history- and simulation periods and filtered using the selected group of spare parts. Then, using Equation 6.3, the annual demand rate for part j is calculated by multiplying the total amount of order lines of part j in the history period ($L_{j,hist}$) with its forecast multiplier (m_j), and scaling it to an annual measure by multiplying with the ratio between 365 and the history period length in days (d_{hist}). Similarly, Equation 6.4 is used to calculate the annual demand of part j, only using the total amount of ordered items of part j in the history period ($Q_{j,hist}$) instead of the total number of order lines. Equation 6.5 and 6.6 are used to calculate the weights for every part j, with c_j being the cost of part j. Then, the ratio between the items tagged as delivered from stock in the simulation period and the total amount of items ordered in the same period represents the item fill rate (Equation 6.7). The line fill rate, presented in Equation 6.8, takes the ratio of only the lines delivered from stock and the total lines ordered. With all these values calculated, Equation 6.2 can be filled in to determine the realized item- and line fill rate in the simulation period. This value can then be used to perform a validation of the simulation of the realized fill rate.

Part-level. On part-level, a validation of the realized fill rate is performed by comparing the simulated inventory trajectories with the database of monthly inventory level snapshots. If a trajectory passes through the snapshot point, more evidence is gathered ensuring the correctness of the simulation model. The snapshot data is collected in a database table, containing a part identifier, a record day and the actual inventory level at that moment in time. Using this data, the simulation model returns the number of times the trajectory misses the snapshot value as percentage of the total number of used snapshot values. This percentage is also separated per part and a total count of parts missing the snapshot at least once is provided by the model.

6.3.2 Simulation

For the simulation model to run, data has to be collected concerning different parts of the model. This section elaborates on these data requirements.

Group selection. A specific group of parts has to be selected in order to take the classification shortlist cause into consideration. This can be achieved by multiple means, such as historic demand rate, price or any other characteristic presented in Table 3.1. The rest of all data is then filtered to this scope of parts. Note that the sample group is selected based on a characteristic value determined from the history period, which could be different in the simulation period. For example, parts having an annual historical demand rate of two, may have had no demand in the simulation period. The number of parts based on the history period can therefore differ from the parts in the simulation period. The same holds for other characteristics.

Time period. The simulation is performed for a period of time between two *stock-runs*. This simulation period has to be determined beforehand, so all data can be filtered based on this period. The two years before the simulation period then form the history period.

Part information. Information on the parts has to be collected in accordance with the attributes of the part entity. Every part receives an unique identifier, its optimized and adjusted reorder and order up to levels, a base price and forecast multiplier for fill rate calculations and a start inventory. The latter value is deducted from the monthly inventory snapshot table.

Inventory movements. The entities changing the inventory are purchase orders, sales orders and inventory mutations. Data is required in order to schedule the events corresponding to these entities. This data is used to create a list of events that the model can use when mandated by the scenario. First of all, every inventory movement event is combined with a part identifier, a type and category as illustrated in Table E.1 and an inventory movement size. Finally, every inventory movement has an occurrence- and mutation time. The former is the moment at which a PO, SO or inventory mutation is placed. The mutation time is the moment at which the actual inventory movement takes place, namely a SO delivery, a PO receipt and an inventory mutation taking effect on the inventory. For the inventory mutations, the occurrence and mutation time are the same. For the sales- and purchase orders, however, both times often differ and are used to divide the inventory movement event into a placement- and mutation event: PO / SO placed and PO received / SO delivered. With this distinction, different what-if scenarios can be created by only using specific historical data and schedule the other events based on different rules.

Monthly inventory snapshots. The monthly inventory snapshots are collected from the snapshot database of Fokker. For the parts in the group under investigation the record day and actual inventory level are used.

Demand distribution. In order to simulate the customer demand, instead of using the actual demand moments and sizes, information is required on the compound Poisson process. The part replenishment model uses the history period to determine a Poisson rate and compound demand size distribution (Algorithm 2) per part. In order to simulate this demand process, the part identifier is required, as well as the determined Poisson demand rate. Besides this, every demand size that occurred in the history period is recorded and accompanied with a probability of occurrence. The simulation model then schedules SO arrivals using the Poisson rate and determines the SO size using the compound distribution.

Data for size selector. As discussed, the size selector supports the selection of PO and SO sizes and moments, as well as lead time sizes. In order to initialize this entity, the part identifiers are collected, together with the realized lead time, PO and SO sizes in the simulation period. With this information, the simulation model calculates the remaining attributes of the size selector entity.

Interchangeability. A concept that has not been introduced yet is the interchangeability between parts. For specific parts, a preferred alternative part exists which Fokker aims use in the future. The part replenishment model therefore transfers all demand of the non-preferred part to the preferred variant. This has implications for the calculated item- and line fill rates on group level. For this reason, data on the interchangeability of parts is collected and used in the simulation model to calculate the fill rates. The collected data for the interchangeability has a part identifier and the associated part identifier of the preferred part.

6.3.3 Data collection tool

In order to automate the process of collecting the required data and allow the user to easily repeat the process every half year, a data collection method is developed. The method also deals with missing values.

The required data does not exists in the form needed for the simulation model. Therefore, an Access tool is developed to collect, transform and combine the available data from Fokkers databases to perform a model validation and run the actual simulation and its scenarios. The tool prompts the user to enter information on the sample group of parts and on the history and simulation period dates. Based on this, a set of 100 queries is ran, summarized in three macros.

1. Create sample group
2. Determine line- and item fill rate of simulation period
3. Get required simulation data

After the Access tool for data collection is done, three main output components are created.

1. SimulationData Excel file
2. FillrateCompare Excel file
3. Item- and line fill rate value table

The *SimulationData* Excel file contains all data required to run the simulation model. Data is available to simulate the realized fill rate, the model fill rate and all kinds of intermediate what-if scenarios. The *FillrateCompare* Excel file contains part-level fill rate and weight information on the realized fill rate and the model fill rate. This file is created to easily examine the size of the fill rate gap and perform the Wilcoxon rank-sum test for validation purposes. Finally, a table is created in the Access tool itself containing the item- and line fill rate values for the simulation period. A more detailed overview of the Access tool is provided in Appendix G.

Part II

Case study

Chapter 7

Case study introduction

With the creation of the simulation model, the first part of this thesis is finished. In the second part, this model is used in a case study at Fokker to identify and analyze a fill rate gap. This chapter starts off this part by introducing the case study. Section 7.1 first discusses the case study setup by elaborating on the chosen time periods and sample group of spare parts. In Section 7.2, the simulation model is validated. Then, in Section 7.3, the actual sequencing of what-if scenarios is explained in order to quantify the shortlist causes.

7.1 Setup

7.1.1 Time periods

The simulation model analyses a period of time between two consecutive *stock-runs*. This period of time is defined as the simulation period, while the preceding history period of the two years is used by the part replenishment model to optimize the inventory polices. In order to reflect the current situation at Fokker as good as possible and assure the optimized inventory policies are used for at least six months, the most recent historical simulation period is used as basis for analysis. This results in the history- and simulation period as summarized in Table 7.1.

Period	**From**	**To**	**Total length**
History	1st of July 2016	1st of July 2018	24 months
Simulation	2nd of July 2018	2nd of April 2019	9 months

Table 7.1: History and simulation period used in case study

The decision to focus on the most recent historical simulation period also implies that the grouping of the spare parts in the part replenishment model, the model parameter settings and the fill rate constraints of this run are considered to be given. This assumption is defensible, as these values have not been changed significantly over the course of time. They have been set when the program went live several years ago and have not been altered much since.

7.1.2 Sample group

Selecting a specific group of parts for analysis aids in testing the classification shortlist cause. Two alternative strategies are possible in selecting a sample group.

On the one hand, a particular characteristic can be taken and its values can be tested separately in the simulation model to test its impact. For example, only parts with an *expensive* classification on price could be included. Comparing these results with an analysis of only *cheap* parts helps in understanding the impact of this characteristic. With this approach, quick and specific conclusions can be drawn. However, a small amount of data points may be available and simulation results are very focused on the specific characteristic. This reduces the number of analysis possibilities with the simulation results. On the other hand, a more general group can be taken containing parts with all kinds of characteristic values. With this approach, more data points are available, but the simulation results are more general as well. However, the general results can be further analysed using Excel or R studio to make statements on specific part characteristics as well.

For the purpose of this thesis, the second approach is taken. All parts having an annual number of order lines of two or more in the history period are selected, eliminating extremely slow movers. This group is more general as it contains parts with all different kind of characteristics. Moreover, sufficient data is available on these parts and the simulation outcomes can be further interpreted to make statements on different part characteristics. Table 7.2 summarizes the number of parts in this sample group.

Group	**History**	**Simulation**
Sample	5983	3667
≥ 2	5983	2916
Generators	6395	3890

Table 7.2: Sample group overview

Using the Access tool, the parts contained in the selected group are tagged before entered into the part replenishment model. In this model, a separate group is created only containing the tagged parts. This is the sample group in the above table. Next, a group is created for all parts having an annual number of order lines of two or more based on the history period. As this is the same group as we selected for analysis, the number of parts in this group is equal to the parts in the sample group for the history period. Finally, by using the interchangeability table, the parts generating the demand are found. The size of this group is larger, as the model transfers demand from one part to another part, while this group considers both parts separately.

Besides looking at the amount of parts based on the history period, the parts are also counted in the simulation period. As already mentioned in Section 6.3.2, the number of parts can differ between the history- and simulation period due to characteristic values. In case of the selected sample group, it is seen that for $6395 - 3890 = 2505$ parts no demand has occurred in the simulation period. Besides this, $3667 - 2916 = 751$ sample parts are classified as having two or more order lines annually in the history period, but seem to have less in the simulation period. The actual simulation is performed with the 3890 parts in the simulation period and 6395 parts in the history period.

Appendix H provides a more detailed overview of the sample group compared to the total population of parts, based on the characteristics of Table 3.1. The total population of 18850 parts has been sampled based on the requirement of 2 or more order lines per year. This has resulted in a sample of 5983 parts, meaning that a large section of the population parts are very slow movers. Moreover, using the tables presented in the appendix, it is concluded that the average annual demand rate of the sample is 3.74. This is an increase of 1.16 compared to the population annual demand rate of 1.58. This increase makes sense as only slow movers are ignored in the sample group. Furthermore, the average demand size of the sample group is 181.28, while the population demand has an average size of 69.85. Thus, the ignored large portion of slow movers had a very small size as well.

In addition, the distribution of the number of parts over a characteristic values can be investigated. The ignored group of slow movers are expensive parts, as the proportion of these type of parts decreases from 11% in the population to 5% in the sample. In the same way it is concluded that the slow movers are often not *NHI*- and *RNLAF parts*, they originate from the *Fokker only* platform and they are often *vendor parts*.

7.2 Simulation model validation

Model validation can be done on group- and part-level, as discussed in Section 5.3. This section elaborates on both methods and provides the validation results.

7.2.1 Part-level validation

On part-level, the simulation of the realized fill rate is validated using the monthly inventory level snapshot data maintained by Fokker. By comparing the simulated inventory trajectories of the parts with these known inventory levels, the simulation can be validated based on the number of similarities. Table 7.3 and Figure 7.1 provide a summary of this validation.

Measure	Best	Removed
% snapshot difference	1.69%	0%
Total parts	3890	3645
Total parts with difference	245	0
% parts with difference	6%	0%
Item fill rate	69.11%	72.04%
Item fill rate validation	66.68%	69.92%
Line fill rate	88.83%	89.64%
Line fill rate validation	86.84%	87.69%

Table 7.3: Summary of part-level validation

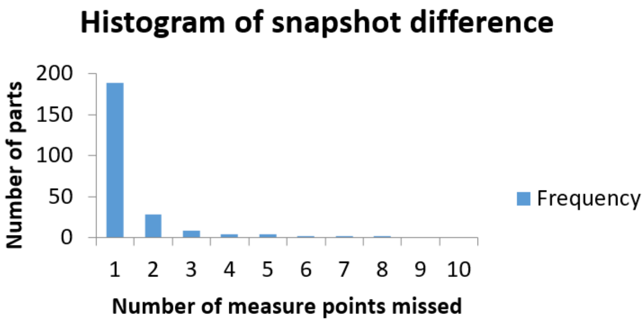


Figure 7.1: Histogram of snapshot difference

First, focus on the **best** column of the above table. This column displays the best achieved values after several iterations of data collection and simulation fine-tuning. The total percentage of snapshot difference is 1.69%. In total 3890 part trajectories are simulated over the course of 9 months. Including the start inventory, every part has therefore 10 inventory snapshot measuring points. This means that of the $10 * 3890 = 38900$ measuring points, $1.69\% * 38900 = 658$ points are not met exactly. This deviation is realized by 245 parts in total. Both the simulated as well as the validation values of the item- and line fill rates are also presented in the table.

In order to determine how to deal with the percentage of snapshot difference, the **removed** column is added to Table 7.3 and a frequency table of the number of missed snapshot points for the 245 parts is created in Figure 7.1. The frequency table shows that 80% of these parts only miss one snapshot value and 16% only miss two values. A reason for this could be a specific human-driven handling pattern that is not taken into consideration in the simulation rules or data is missing in the used data set. To test the impact of these misses, all 245 parts are removed from the data set and the new item- and line fill rate validation and simulated values are determined. The results are presented in the removed column and show that the fill rates increase, but the gap between the simulated value and validation value remains almost the same. In fact, the gap between the simulated and validated item fill rate decreased with 0.31%, while the gap for the line fill rate decreases with 0.04%. These results strengthen the argumentation that the simulation is not able to take some human handling pattern into account, rather than missing data being the cause of the validation gap. Adding to this the fact that most parts only miss one snapshot measuring point, the decision is made to keep the 245 parts into the simulation. Their impact on the fill rates is small and does not outweigh the loss of data by removing them.

7.2.2 Group-level validation

On group-level a validation is performed of the realized- and model fill rate simulations. For the former simulation, the Access tool calculates the actual achieved item- and line fill rates on group- and part-level. These values are then used as validation values. The model fill rate simulation is validated using the part replenishment optimization model. This model also provides output on the group- and part-level item- and line fill rates of the sample group. Moreover, to prevent a situation in which the group-level fill rates of the validation and simulation are the same, while the part-level fill rates deviate from each other, a correlation coefficient is used. This measure tests the strength of the linear relationship between the part-level fill rates of the simulated and validation values. When these part fill rates are exactly the same, a perfect linearity would be expected in the form of a correlation coefficient of one. Finally, to strengthen the results based on the correlation coefficient, the *Wilcoxon rank-sum test for matched pairs* (WRS) is used to assess the statistical difference between the simulated- and validation values using the *p-value*.

Validation of realized fill rate. Table 7.4 provides a summary of the validation of the realized fill rate simulation. The simulation seems to approach the validation values quite well. For both the item- and the line fill rate, the simulation is off target by around 2%. A reason for this small deviation could be the fact that the simulation tries to reproduce complex real world patterns with limited data, as mentioned in the previous section as well. However, the correlation is sufficiently high to state that the simulation model performs well. Also, the *p-value* of the Wilcoxon test, presented in the *WRS* column, is much larger than 0.05 percent. This indicates that for a significance level of 5% there is insufficient evidence to reject the null hypothesis stating that the validation- and simulation mean are equal.

Furthermore, when creating a scenario in which the PO, SO and BO delays are taken out and a *FCFS* backorder handling system is used, the item- and line fill rates become 67.01% and 86.37%, respectively. This is presented in the most right part of Table 7.4. These values are even closer to the validation points. However, the correlation values are lower compared to the simulation of the realized fill rate. Also, the WRS *p-values* indicate that the group-level line fill rate differs significantly from the validation values.

Based on above discussion, the conclusion is drawn that the simulation of the realized fill rate is sufficiently validated. The fill rate values match within 2% of their validation values, the correlation coefficients are high and the Wilcoxon test indicates the simulated group-level fill rates are not significantly different from the validation points. For this reason, the simulation of the realized fill rate can be used as base point for further analysis.

Type	**Validation**	**Simulation of realized fill rate**			**Simulation without delays**		
		Simulated	Correlation	WRS	Simulated	Correlation	WRS
Item	66.68%	69.11%	0.88	0.85	67.01%	0.81	0.40
Line	86.84%	88.83%	0.94	0.42	86.37%	0.83	0.03

Table 7.4: Summary of group-level validation of realized fill rate

Validation of model fill rate. Table 7.5 provides a summary of the validation of the model fill rate simulation. The table provides the simulated values, as well as the *run*, *9 month* and *steady state* validation values calculated by the part replenishment model. First of all, the 9 month validation point meets the simulation of the model fill rate within almost 1%. The run and steady state values differ much more. For this reason, the decision is made to proceed with the 9 month validation point as reference in the remainder of this thesis. Moreover, the correlations are also sufficiently high. Finally, the WRS *p-values* indicate a lack of evidence to reject the null hypothesis, i.e., the simulated model fill rates are statistically equal to the validation points. For this reason, it is concluded that the simulation of the model fill rate performs as expected.

Type	**Simulated**	**Run**	**9 months**			**Steady state**
		Validation	Validation	Correlation	WRS	Validation
Item	69.85%	79.70%	70.30%	0.95	0.91	57.90%
Line	92.39%	95.20%	93.50%	0.82	0.78	88.80%

Table 7.5: Summary of group-level validation of model fill rate

Concluding, the simulation model is validated sufficiently on part- and group-level to proceed with the analysis. For the remainder of the thesis, the simulated realized- and model fill rates are considered, instead of the validation points.

7.3 Analysis method

In this section, the procedure used to analyse the fill rate gap at Fokker is explained. First, the way in which the simulation model is used in the case study is discussed. Then, the use of the Monte Carlo simulation aspect of the model is elaborated.

7.3.1 Analysis setup

The aim of the case study is to identify and analyse a fill rate gap in practice using the simulation model. To achieve this in a structured manner, three questions are formulated based on the shortlist causes (Table 4.2). These will guide the case study.

1. What is the impact of human involvement in the inventory control process of Fokker?
2. What is the impact of the lead times in the inventory control process of Fokker?
3. What is the impact of demand forecasting in the inventory control process of Fokker?

In order to answer these questions, the developed simulation model has to be arranged accordingly. To achieve this, the sequential analysis method is used as illustrated in Figure 7.2.

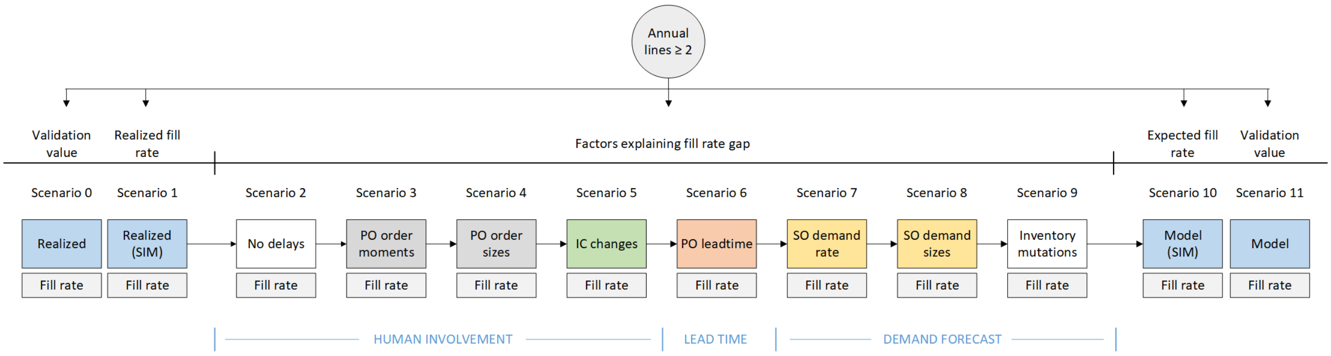


Figure 7.2: Setup of case study

The case study is performed for the sample group and time periods discussed in Section 7.1. Using this information, first, a simulation of the realized fill rate is created for the simulation period. This is indicated by the blue box on the far left of the figure. Next, the model fill rate, as predicted by the part replenishment model, is simulated for the simulation period, indicated by the blue box on the right. The difference between these fill rate values represent the actual size of the fill rate gap. Then, in order to understand how the fill rate gap is composed, intermediate what-if scenarios are created based on the three questions introduced earlier. Therefore, Figure 7.2 shows that the intermediate scenarios can be broken down into three main blocks: human involvement (question one), lead time (question two) and demand forecast (question three). Note that the used colors in the figure correspond with the causes of Table 4.2.

Concluding, we start with a simulation of what really happened in the simulation period. Then a scenario is created in which all human involvement is taken out. This is achieved by taking four steps, namely eliminating delays, use the inventory policy to determine the order moment, use the inventory policy to determine the order size and eliminate the changes made to the optimized inventory policies. For every step the fill rates are calculated, making it possible to state something about all these aspects of the human involvement cause. The resulting scenario fill rate after these four steps provides insights into the impact of human involvement on the fill rate gap. Next, a scenario is created in which the realized lead times are replaced by the model lead times. The fill rates of this scenario provide insight into the impact of lead times on the fill rate gap. Finally, the same method is used to test the impact of demand forecasting by replacing the actual demand with a simulation of the forecasted demand. This is achieved by taking three steps, namely using the Poisson rate to determine the demand moment, use the compounding distribution to determine the demand size and removing all inventory mutations. By taking all these intermediate steps, we move from a simulation of what really happened with the fill rate to a simulation of the part replenishment model, quantifying fill rate gap causes along the way.

Finally, Appendix I provides an overview of the parameter settings used to create every intermediate what-if scenario. Every column represents a block in Figure 7.2. At every step, one, or multiple, parameters are changed, building on the changes made in earlier steps.

7.3.2 Monte Carlo simulation duration

As discussed in Section 6.2.5, and also shown in Appendix I, a Monte Carlo simulation is required when the Poisson rate or compounding demand size distribution are used as parameter values. To determine the number of runs required to reach a desired level of accuracy ε, Equation 6.1 is used in combination with the two steps explained in Subsection 6.2.5.5.

1. Run model for small value of n to estimate σ
Using $n = 30$, the sample σ is calculated to be 0.0171.

2. Compute required number of runs
In order to use Equation 6.1 several parameter values have to be known. First, we aim to achieve a 95% confidence interval. This means that $z_{\alpha/2}$ should be equal to 1.96. Second, the maximum size of the half-width of the fill rate estimate is set to 0.0015, providing the value for ε. Using these values, Equation 6.1 can be filled in.

$$n > \left(\frac{1.96 \cdot 0.0171}{0.0015}\right)^2 \implies n > 498.19 \tag{7.1}$$

From the formula, it is concluded that the minimal number of runs to achieve an accuracy of ε is 499. For the sake of this thesis, the number of runs for the Monte Carlo simulation is set to 500.

Chapter 8

Result overview

This chapter provides an overview of the results gathered by using the analysis method discussed in Chapter 7. Section 8.1 visualizes the results of the sequential output analysis and discusses several observations. In Section 8.2 the impact of the shortlist causes on the fill rate gap are reviewed. Finally, Section 8.3 provides a discussion on the robustness of the found results.

8.1 Output overview

For every scenario (i.e., block) illustrated in Figure 7.2 an item- and line fill rate measurement is made. These results are depicted in Figure 8.1 (line fill rate) and in Figure 8.2 (item fill rate).

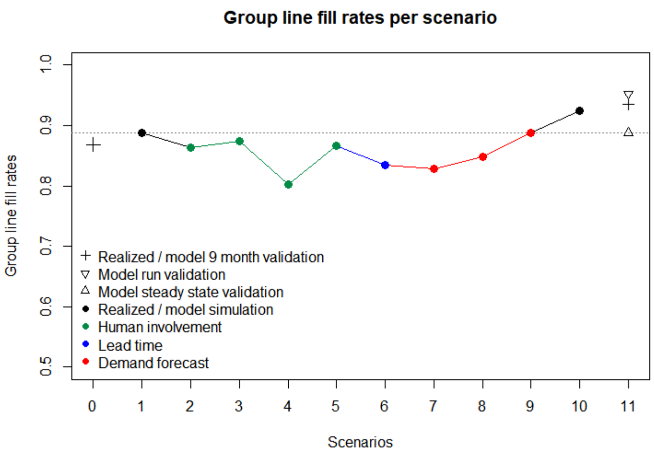


Figure 8.1: Results line fill rate

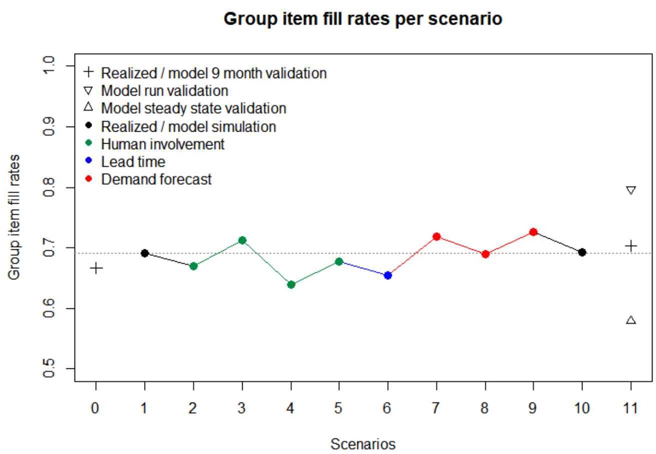


Figure 8.2: Results item fill rate

The left and right plus signs represent the validation values of the realized- and model fill rate, respectively. For the model simulation, the *run* and *steady state* validation values are also added (see Table 7.5). However, as explained in Section 7.2.2, only the *9 month* validation point is used for further analysis. Furthermore, the black dots indicate the fill rates of the simulations of the realized- and model validation values. A horizontal dotted line intersects with the black dot of the realized fill rate to act as base line. Finally, every colored dot represents a fill rate measurement of a specific scenario illustrated in Figure 7.2. The green dots are the four steps of human involvement, the blue dot is the lead time scenario and the three red dots represents the demand forecast block. In addition, Table 8.1 summarizes the changes made in every scenario and the direction of the fill rate change between scenarios.

Legend	Scenario	Scenario	Line	Item
+	0	Realized (validation)	NA	NA
●	1	Realized (simulation)	NA	NA
●	2	No delays	-	-
●	3	PO order moment based on policy	+	+
●	4	PO order size based on policy	-	-
●	5	No IC changes on policies	+	+
●	6	PO lead time based on model	-	-
●	7	SO demand rate based on Poisson	-	+
●	8	SO demand size based on compound distribution	+	-
●	9	No mutations	+	+
●	10	Model (simulation)	+	-
+	11	Model (validation - 9 months)	NA	NA

Table 8.1: Summary of scenarios and direction of cause impact on fill rate

Using the two result figures and the additional table, several aspects stand out. These are discussed in the remainder of this section.

8.1.1 Identification of fill rate gap

From Figure 8.1 and 8.2 it is clear that a fill rate gap exists for both the line- and item fill rate. The black dots, indicating the simulation of the realized- and model fill rate, are not aligned on a perfect horizontal line. For both the line- and item fill rate, the realized fill rate is lower compared to the model fill rate. This gap is larger for the line fill rate, as the distance from the black dot of the model simulation to the horizontal base line is bigger than for the item fill rate. For the latter fill rate type, the gap is very small, but present. Furthermore, note that the line- and item fill rates are placed on the same vertical axis, ranging from a 50% fill rate to 100%. The figures show that, for all scenarios tested, the line fill rate is larger than the item fill rate. In addition, the minimal **line** fill rate of around 80% is achieved for scenario 4, while the maximum **item** fill rate is achieved for scenario 9 having a value of around 73%. Finally, the average line fill rate over all plotted scenarios is 86.19%, while the item fill rate is averaged at 68.79%. This seems to indicate that from the lines that are not delivered fully, a substantial part of the ordered items could not be delivered.

8.1.2 Differences between scenarios

The result figures provide a first indication that different fill rates are achieved per scenario. However, to understand the impact of every scenario on the fill rate gap, it is imperative to determine whether every scenario actually impacts the fill rate and whether they all represent an unique cause. A correlation measure is used to establish if a specific cause impacts the fill rate by testing the strength of the linear relationship between the part fill rates of two scenarios. The more the part fill rates differ, the larger the impact on group fill rate, the larger the difference between the correlation coefficient and 1. A Wilcoxon rank-sum test is used to determine the uniqueness of the cause. This method is discussed in Section 5.3.

Correlation. Table 8.2 provides the correlation coefficients of the item- and line fill rates for every combination of scenarios. Based on these values, several conclusions can be drawn. First of all, using the first row of both matrices, it is shown that the correlation coefficients of all scenarios change compared to the simulation of the realized fill rate (scenario 1). This means that every scenario affects the part fill rates and, thus, has an effect on the resulting scenario fill rate.

Moreover, the same first rows show that the correlation coefficients for every scenario decrease sequentially compared to the simulation of the realized fill rate (scenario 1). In other words, with every step taken, the part fill rates diverge more from the fill rates in reality. This patterns corresponds with the expectations based on the case study setup.

Furthermore, the largest change in correlation coefficient between two successive scenarios is achieved when moving from scenario 2 to 3 for both the line- and the item fill rates. Here, the purchase order moments are scheduled based on the policy instead of using the actual historical moments. This decrease is equal to 0.28 for the line- and 0.26 for the item fill rate. So, using the policy to determine the order moment instead of the current method influences the part level fill rate the most. Closely second are the line- and item correlation changes when introducing the Poisson rate to schedule demand moments in scenario 7, with 0.18 and 0.19 respectively.

Finally, the change in correlation for every main fill rate gap cause is determined. From this, it is showed that the decrease in correlation is the largest for the demand forecast. This change is 0.56 for both the line- and item fill rate. The human involvement cause impacts the correlation with 0.28 and 0.26 for the line- and item fill rate respectively. The lead time only causes a change of 0.06 and 0.05. Therefore, it is expected that the demand forecast cause has the largest impact on the fill rate gap.

The above discussion results in the conclusion that every main cause, and its corresponding scenarios, actually impact the fill rate as they result in different part-level fill rates.

CORRELATION MATRIX OF LINE FILL RATE									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1	1.00	0.97	0.68	0.72	0.72	0.71	0.69	0.50	0.47
2	-	1.00	0.69	0.74	0.73	0.74	0.68	0.49	0.45
3	-	-	1.00	0.86	0.92	0.87	0.70	0.47	0.40
4	-	-	-	1.00	0.88	0.94	0.73	0.49	0.41
5	-	-	-	-	1.00	0.94	0.75	0.50	0.43
6	-	-	-	-	-	1.00	0.76	0.52	0.44
7	-	-	-	-	-	-	1.00	0.78	0.69
8	-	-	-	-	-	-	-	1.00	0.90
9	-	-	-	-	-	-	-	-	1.00
CORRELATION MATRIX OF ITEM FILL RATE									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1	1.00	0.97	0.70	0.74	0.74	0.74	0.70	0.51	0.45
2	-	1.00	0.71	0.75	0.75	0.75	0.70	0.51	0.45
3	-	-	1.00	0.88	0.94	0.89	0.71	0.50	0.40
4	-	-	-	1.00	0.90	0.95	0.73	0.52	0.41
5	-	-	-	-	1.00	0.95	0.75	0.53	0.44
6	-	-	-	-	-	1.00	0.76	0.55	0.44
7	-	-	-	-	-	-	1.00	0.81	0.71
8	-	-	-	-	-	-	-	1.00	0.89
9	-	-	-	-	-	-	-	-	1.00

Table 8.2: Correlation matrix of item- and line fill rates per what-if scenario

Wilcoxon rank-sum test. In order to determine whether the scenarios can be separated from each other and represent an unique cause, the Wilcoxon rank-sum test for matched pairs is used. Table 8.3 displays the results for this test for every scenario combination. A *p-value* lower than 0.05 indicates that, for a significance level of 5%, the group fill rates of two scenarios are not equal (see Section 5.3). For the sake of readability, this is indicated as *Diff* in the table, while *No diff* indicates the compared group fill rates are equal. Appendix J displays the actual *p-values*.

An interesting way to look at the table is by following the diagonal indicated in red. These values follow the sequential set-up of the case study and indicate whether two successive scenarios differ significantly from each other based on fill rate. For the line fill rate, every step in the sequential method proves to create a significantly different fill rate. However, for the item fill rate the elimination of delays (scenario 2) does not prove to significantly change the group-level fill rate. The same holds for scenario 7, in which the Poisson rate is used to schedule sales orders. All other scenario combinations of the sequential analysis do indicate a significant difference in item fill rate with every step taken.

From the test results, it is concluded that (almost) all scenarios represent an unique cause and can be separated from the other causes.

WILCOXON RANK-SUM TEST RESULT MATRIX OF LINE FILL RATE									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1	No diff	Diff	No diff	Diff	Diff	Diff	Diff	Diff	Diff
2	-	No diff	Diff	Diff	Diff	Diff	Diff	Diff	Diff
3	-	-	No diff	Diff	Diff	Diff	Diff	Diff	Diff
4	-	-	-	No diff	Diff	Diff	Diff	No diff	No diff
5	-	-	-	-	No diff	Diff	Diff	Diff	Diff
6	-	-	-	-	-	No diff	Diff	Diff	Diff
7	-	-	-	-	-	-	No diff	Diff	Diff
8	-	-	-	-	-	-	-	No diff	Diff
9	-	-	-	-	-	-	-	-	No diff
WILCOXON RANK-SUM TEST RESULT MATRIX OF ITEM FILL RATE									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1	No diff	No diff	Diff	Diff	Diff	No diff	No diff	No diff	Diff
2	-	No diff	Diff	Diff	Diff	No diff	No diff	No diff	Diff
3	-	-	No diff	Diff	Diff	Diff	Diff	Diff	Diff
4	-	-	-	No diff	Diff	Diff	Diff	Diff	Diff
5	-	-	-	-	No diff	Diff	Diff	Diff	Diff
6	-	-	-	-	-	No diff	No diff	No diff	Diff
7	-	-	-	-	-	-	No diff	Diff	Diff
8	-	-	-	-	-	-	-	No diff	Diff
9	-	-	-	-	-	-	-	-	No diff

Table 8.3: Results of Wilcoxon rank-sum test for item- and line fill rates per what-if scenario

Combining the findings based on the correlation coefficients and the Wilcoxon test, it is clear that every scenario actually impacts the fill rate and they also represent unique causes.

Finally, note that in both Table 8.2 and 8.3 scenario 10 is not included. This is because the simulation of the model fill rate has more observations (i.e. parts) than the previous scenarios (see Section 7.1.2). As a result, correlation calculations and the Wilcoxon test are not possible.

8.1.3 Compensation

Both Figure 8.1 and 8.2 show a form of compensation between scenarios. For some scenarios, or causes, the impact on the fill rate is positive, while for others the impact is negative. This collection of fill rate movements together form the total fill rate gap. Therefore, the causes seem to influence each other and result in either a negative or positive impact on the fill rate. To visualize this, Table 8.4 depicts the numerical values of the fill rates illustrated in Figure 8.1 and 8.2.

The table indicates that for every tested cause, the impact on the fill rate is different from zero, indicating that the scenarios indeed test actual causes of the fill rate gap. Otherwise, a fill rate impact of zero would have been observed, accompanied with no change in correlation between scenarios and non-significant *p-values* for the *Wilcoxon test*. This strengthens the argumentation that every scenario impacts the fill rate and represent unique causes.

Scenario	Line	Diff	Item	Diff	Change
1	*88.83%*	-	*69.11%*	-	*Realized (sim)*
2	86.37%	-2.46%	67.01%	-2.10%	No delay
3	87.41%	1.04%	71.19%	4.18%	PO order moment based on policy
4	80.29%	-7.12%	63.92%	-7.27%	PO order size based on policy
5	86.71%	6.42%	67.72%	3.80%	No IC changes on policies
6	83.50%	-3.21%	65.48%	-2.24%	PO lead time based on model
7	82.84%	-0.66%	71.93%	6.45%	SO demand rate based on Poisson
8	84.83%	1.98%	68.90%	-3.04%	SO demand size based on compound
9	88.75%	3.92%	72.83%	3.93%	No mutations
10	*92.39%*	*3.65%*	*69.85%*	*-2.98%*	*Model (sim)*

Table 8.4: Fill rates of result overview

Furthermore, the table shows that the impact of one cause could be larger or smaller compared to another cause. Thus, not every cause is as important in explaining the fill rate gap. The largest negative impact on the realized fill rate is achieved by introducing the policy to determine the purchase order sizes. This could indicate that the inventory controllers have more knowledge to their disposal when making purchasing size decisions, leading to a better fill rate in reality. The biggest positive impact on the line fill rate is achieved by using the optimized inventory policies. This indicates that, theoretically, the changes made to the policies do not result in a better fill rate. The item fill rate has the most benefit of using the Poisson demand rate to schedule demand instead of using the actual demand moments. This could suggest that actual demand arrives more frequently than the Poisson rate would suggest.

Finally, it is concluded that, for almost all scenarios, the line fill rates are lower than the realized fill rate in practice. Only the simulation of the model fill rate (scenario 10) results in a larger fill rate. For the item fill rate, however, there are several scenarios achieving larger fill rates than realized, namely using the policy to determine purchase order moments (scenario 3), using the Poisson rate to schedule demand (scenario 7), eliminating the inventory mutations (scenario 9) and the simulation of the model fill rate (scenario 10).

8.1.4 Opposing cause impact

From Table 8.1 some interesting findings can be deducted as well. The plus- and minus signs indicate the direction in which the line- and item fill rate change per scenario. For example, going from scenario one to two, results in a decrease in both line- and item fill rate, while the step to scenario three increases both measures.

From the table it is concluded that the direction of fill rate changes are equal for scenarios two through six and nine. In all these cases the line- and item fill rate either increase or decrease, but both in the same direction. Scenario seven and eight, however, distort this pattern. When moving to scenario seven, the line fill rate decreases, while the item fill rate increases. For scenario eight, the line fill rate increases, while the item fill rate decreases. The same holds for scenario ten. This will be further discussed in the next chapter.

8.2 Cause impact

Based on the discussions so far, the three questions imposed in Section 7.3.1 can be partly answered. For this purpose, Table 8.5 is created. This table indicates the total size of the fill rate gap for the line- and item fill rate, which is then broken down based on the three questions. With this representation, a part of the compensation effect is not visible anymore, as the scenarios used for a specific question are grouped.

The total fill rate gaps are 3.56% and 0.74% for the line- and time type respectively. This means that the actual achieved fill rates are lower by those percentages as compared to what the

Cause	Line	Item
Total gap	**3.56%**	**0.74%**
No human involvement	*-2.12%*	*-1.39%*
Model lead times	*-3.21%*	*-2.24%*
Demand forecast	*8.89%*	*4.37%*

Table 8.5: Results per fill rate gap cause

model predicted.

Taking all human involvement out of the simulation of the realized fill rate results in a fill rate decrease of 2.12% and 1.39% respectively. So, a negative aspect is added to the simulation: no human involvement. In other words, the fact that humans are interacting with the model has a positive effect on the realized fill rate.

Then, the real purchase order lead times are replaced with model lead times. As a result, the line- and item fill rates decrease with 3.21% and 2.24% respectively. Again, a negative aspect is added: model lead times. In other words, the real lead times have a positive effect on the realized fill rates as compared to the model lead times.

Finally, the real demand is replaced with a simulation of the demand forecast using a compound Poisson process. This results in an increase of the line- and item fill rate of 8.89% and 4.37% respectively. Here, a positive aspect is added: the demand forecast. In other words, the actual demand has a negative effect on the realized fill rates as compared to the demand forecast.

Concluding, human involvement and real lead times have a positive influence on the realized fill rate. This positive effect is compensated by the use of a demand forecast method. These results coincide with the conclusions drawn in the previous sections of this chapter.

So far, the impact of different causes on the fill rate gap is quantified. However, in order to really explain why some impacts are positive, while others are negative, and why some impacts are larger than others, a deeper understanding is required. This is provided by the next chapter.

8.3 Robustness of result

The results presented in this chapter are gathered based on a particular history- and simulation period and for a specific group of parts. As the selected group contains a large variety of parts having different characteristics, the found results are quite general. However, performing the analysis again for a group of parts only having expensive parts, for example, could provide different results. The same holds for the chosen time periods. When performing the same analysis a half year later, the results could be different.

However, this is exactly the purpose of the simulation model. By performing the same analysis for a different group of parts, a better understanding of the part characteristics having a large impact on the fill rate gap can be gained. Also, by using different analysis setups, different interactions effects can be investigated and a better understanding of the inventory process is the result. Finally, using the model for different time periods, helps in gaining knowledge on the impact of specific decisions made during this new period of time.

The model is versatile, flexible and can be used in any way the user sees fit. By performing multiple analysis, for different groups and different times, and learning from the results, the fill rate gap should become smaller over a period of time.

Chapter 9

Breakdown of fill rate gap causes

So far, the causes of the identified fill rate gap are quantified. Using the output of the simulation model, this chapter focuses on explaining how the causes affect the fill rate in more detail. The three main causes explained in previous chapter are discussed in Section 9.1, 9.2 and 9.3. Then, several other interesting findings are elaborated in Section 9.4, 9.5 and 9.6.

9.1 Human involvement

To support a deeper understanding of the impact of human involvement on the realized fill rate, Table 9.1 is created. Every column represents the summarized results of a specific scenario. Scenario one is the simulation of the realized fill rate, while in scenario five all human involvement in taken out. In the intermediate scenario, changes are made to the delays, order moment, order size and finally the IC changes made to the optimized inventory policies. For every scenario the item- and line fill rate are given, as well as the percentage of time the inventory position is below the reorder points of the parts. The number of placed purchase orders per scenario are provided as well, together with the average size of the orders. Finally, a scenario score is provided. This score is the summation of the average inventory, backorders and orders placed per part per day. With this information, the impact of the scenario on the most prominent cost components can be investigated.

Based on the table, the results of every scenarios will be shortly discussed and conclusions are drawn by mutually comparing the scenarios. In the first scenario, a summary of the results of the simulation of the realized fill rate is provided. Delays are allowed, the order moments and order sizes are determined by the inventory controllers and the optimized inventory policies are adjusted before entered into the *ERP* system. The item- and line fill rate coincide with the findings of Chapter 8.

In the second scenario, the delays are taken out of the simulation, resulting in a lower item- and line fill rate. Non-surprisingly, the percentage of time the inventory position of all parts is below the reorder levels increases from 21% to 23%. The number of orders placed, and their average size, remain equal. The average score of the scenario is lower compared to scenario one. This has to do with the decrease of the average inventory per part per day from 552 to 532. On the other hand, the average size of backorders per part per day increases. So, the decrease in average inventory results in the increase in backorders with the same demand and purchasing decisions, explaining the decrease in fill rate. Concluding, the delays seem to be strategically chosen by the inventory controllers in order to maintain a higher fill rate. Possibly, using business insights on arriving purchase orders or incoming demand, the controllers make decisions to delay placing new purchase orders or wait to fulfill specific backorders. This is the first indication that human involvement may have a positive impact on the realized fill rate.

In scenario three, the order moments are scheduled based on the inventory policies. Whenever the inventory position is smaller than, or equal to, the parts reorder level a purchase order

Scenario	1	2	3	4	5
			Description		
Delays	Yes	No	No	No	No
Order moment	IC	IC	Policy	Policy	Policy
Order size	IC	IC	IC	Policy	Policy
IC changes (inventory policies)	ERP	ERP	ERP	ERP	Model
			Fill rates		
Item fill rate	69.11%	67.01%	71.19%	63.92%	67.72%
Line fill rate	88.83%	86.37%	87.41%	80.29%	86.71%
% time under reorder	21%	23%	13%	31%	10%
			Orders placed		
Orders placed	3540	3540	2347	5323	2560
Average size	408	408	541	139	482
			Score		
Total	558	540	604	478	591
Avg INV per part per day	552	532	593	459	580
Avg BO per part per day	5	8	11	20	11
Avg ORDER per part per day	0.0033	0.0033	0.0022	0.0050	0.0024

Table 9.1: Summary of human involvement

is placed with the same size as in scenario two. This has a significant positive impact on the item- and line fill rate of 4.18% and 1.04% respectively. Moreover, the number of orders placed decrease significantly with 33% from 3540 in nine months to 2347. However, the average size of the orders increases. With this, the average held inventory per part per day increases, while the average backorder sizes also increases. This seems contradictory. However, this scenario provides biased results, as the order size is not adjusted based on the new order moments. Something the inventory controllers have done in the previous scenario.

In order to fairly state the impact of using the inventory policies to schedule purchase orders, the PO size should be taken into account as well. This has been done in scenario four. By comparing scenario one and four, conclusions can be drawn on the impact following the adjusted ERP inventory policies precisely as compared to the inventory controllers having full decision freedom.

First of all, the item- and line fill rate are drastically lower as compared to reality. The item fill rate decreases with an absolute value of 5.19% to 63.92% while the line fill rate decreases to 80.29% resulting in an absolute decrease of 8.54%. This is the result of the inventory position being under the reorder level in 31% of the time with the same demand process as in scenario one.

Secondly, the inventory controllers buy less frequently than the adjusted policy suggests. In the nine month period, the adjusted policy theoretically suggests to place a total of 5323 purchase orders, while the inventory controllers only place 3540. However, the inventory controllers place, on average, larger orders at the time. The average size of the purchase orders placed by the inventory controllers is 408 items, while the adjusted policy suggests an average size of 139 items. This, of course, has an impact on the average inventory kept and order costs. The score illustrates that in reality the average level of kept inventory is larger with a value of 552, compared to 459 when the adjusted ERP policy would be followed precisely. This increase results in a lower number of backorders in reality, as well as lower ordering costs. This, explains the increase in fill rate achieved in reality as compared to scenario four.

Thirdly, additional research has been performed on the reasons why inventory controllers decide to purchase less frequently, but more items at the time, as compared to the adjusted policy suggestions. Using a data set of *minimal order quantities* (MOQ) and supplier discount information per part, a rough idea of their impact on the purchasing decisions can be provided. For 27% of the investigated parts, the minimal order quantity resulted in purchasing more items than the policy suggested. Such a *MOQ* is the minimal amount of items Fokker has to purchase from a specific supplier per order. Discounts resulted in larger order sizes for 9% of the parts, while for 7% of the parts a minimal order quantity and the discounts seem to influence the decision to purchase more. Moreover, using interviews with purchasers a more extensive list of reasons to purchase more items is gained. They also mention MOQ and discounts, but experience, capacity shortages due to vacations, supplier lead times and price increases are mentioned as well. Appendix K provides the full list. Placing purchase orders of larger sizes results in a smaller number of total orders placed, as the inventory levels reach the reorder level at a later time. This, however, results in larger average on-hand inventory level, which was also discussed.

Finally, in scenario five, the adjustments made to the optimized inventory policies are taken out. This scenario represents the situation in which the inventory controllers would perfectly follow the optimized inventory policies as suggested by the part replenishment model. Comparing this scenario with scenario four, conclusions can be drawn on the impact of adjusting the optimized inventory policies.

First of all, adjusting the policy parameters forces the purchasers to buy more frequently (5323 versus 2560), but less items at the time (139 versus 482), compared to the optimized model policies. With adjusting the parameters like this, theoretically, a decrease of average kept inventory is achieved. However, the number of backorders increases, as well as the ordering costs. This results in a lower item- and line fill rate as when the optimized inventory policies would be followed precisely.

Secondly, taking the actual inventory controllers behavior into account using scenario one, it is concluded that the controllers do not follow the adjusted policy precisely. Instead, they buy less frequently and more items at a time. Their behavior lies between the adjusted and non-adjusted policy of scenario four and five respectively, while achieving a larger item- and line fill rate. The strategically chosen delays seem to explain this result.

Concluding, the experience and knowledge of the inventory controllers have a positive impact on the realized fill rate. The adjustments made to the optimized policies should theoretically result in much lower fill rates, but the inventory controllers deal with the adjustments in such a way the fill rates are even larger than following the model policies exactly.

9.2 Lead time

After the human involvement cause, the lead times are investigated. Starting from scenario five, in which no human involvement is present anymore, the actual lead times are replaced by the model lead times used in the part replenishment model. The absolute impact of this change on the line- and item fill rate is −3.21% and −2.24% respectively (see Table 8.5). Thus, the real lead times result in a larger fill rate compared to the model lead times. To understand this better, the average realized- and model lead times are calculated and depicted in Table 9.2. The lead time values are categorized based on the parts having a larger or slower lead time in reality compared to their model counterpart.

First of all, the table shows that for 1527 parts (39% of total parts) an order is placed in the simulation period, while the remaining 2363 parts have not been ordered. Only 20 of the ordered parts have a realized lead time that is equal to their model lead time. For the bulk of the ordered parts (1117 of the 1527 parts), the average realized lead time is 74.46 days shorter than the model lead time. The realized lead time is 23.71 days on average for these parts, while the model assumes an average lead time of 98.17 days. For a considerable smaller number of ordered parts (390 of the 1527 parts), the average realized lead time is larger than the model assumes. For these parts,

Category	Count of parts	Avg LT difference	Average LT realized	Average LT model
Faster in reality	-	-	-	-
Order	1117	-74.46	23.71	98.17
Slower in reality	-	-	-	-
Order	390	17.53	50.57	33.04
Tie	-	-	-	-
No order	2363	0.00	85.66	85.66
Order	20	0.00	21.30	21.30
Grand Total	**3890**	**-19.62**	**64.02**	**83.64**

Table 9.2: Summary of lead time

the model uses an average value of 33.04 days, while in reality the lead times is 17.53 days longer on average.

Taking all 3890 parts into account, the average realized lead time is 19.62 days shorter than the lead time used when optimizing the inventory policies. So, the part replenishment model uses a lead that is 19.62 days larger than in reality. This affects the demand during lead time distribution, resulting in larger policy parameters. When these policies are used in practice, the actual supplier lead time is around 20 days shorter, resulting in larger fill rates and costs as the reorder- and order up to levels are higher than required. This explains the impact on the line- and item fill rate of -3.21% and -2.24% when the model lead times are used in scenario six.

9.3 Demand forecast

Demand forecasting is the third main cause of a fill rate gap and will be explained in this section. As illustrated in Table 8.5, demand forecasting is the only cause negatively impacting the realized fill rate and also has the largest impact. The total absolute impact on the line- and item fill rates are 8.89% and 4.37%, respectively, and consist of introducing the Poisson rate to schedule sales orders, determine SO sizes using the compound distribution and eliminating any inventory mutations. These three steps are divided over scenarios seven, eight and nine. The final step, from scenario nine to ten, is discussed separately in Section 9.5.

In scenario seven, the sales orders are scheduled based on the Poisson rate calculated using the data from the history period. This change decreases the line fill rate with an absolute value of 0.66%, while the item fill rate increases with 6.45%. To explain this difference in effect on the item- and line fill rates, Table 9.3 is created. The table illustrates the average demand rate in the simulation period and based on the forecast of demand. These rates are divided over parts having a cost larger than the average value of €142.44, and the parts with a lower cost. This categorization can prove to be useful as the item fill rate is calculated using the (expected) revenue as weights.

The resulting demand rates indicate that the overall annual demand rate decreases from 5.37 to 5.05 when moving from the actual rate to the model rate. This means that, on average, the demand forecasting method predicts smaller rates than actually occurred. Moreover, the average demand rate of the 490 expensive parts decrease much more compared to the 3400 cheaper parts. As the item fill rate highly depends on the fulfillment of expensive parts (see Section 9.4), the large decrease in demand rate may explain the increase of the item fill rate, while the line fill rate changes only very little.

To further strengthen this argumentation, Table 9.4 is created. In this table, the number of sales orders arriving when either positive- or no inventory is present in the simulation period is compared between scenario six and seven. Again, the distinction is made between parts having a cost higher or lower than average. The values presented in the table indicate that the number of sales orders arriving when no on-hand inventory is present decreased from 1888 to 1618 when the

	# parts	Average rate simulation period	Average rate forecasted
Cost higher than average	490	4.74	3.38
Cost lower than average	3400	5.46	5.29
Grand Total	**3890**	**5.37**	**5.05**

Table 9.3: Average demand rates per cost category

model demand rates are used (scenario seven). Of these sales orders, the share of expensive parts decreases from 28% to 16%. This, again, shows why the item fill rate increases so much when the model demand rates are used instead of the actual rates.

Category	Scenario 6				Scenario 7			
	Positive inventory		No inventory		Positive inventory		No inventory	
	# SO	%	# SO	%	# SO	%	# SO	%
Cost higher than average	1214	9%	528	28%	991	8%	254	16%
Cost lower than average	12584	91%	1360	72%	12136	92%	1364	84%
Grand Total	**13798**	**100%**	**1888**	**100%**	**13127**	**100%**	**1618**	**100%**

Table 9.4: Sales order arrival with negative and positive inventory per cost category

Next, in scenario eight, the demand sizes are determined based on the compound distribution instead of using realized sizes. This adjustment increases the line fill rate with an absolute value of 1.98%, compared to scenario seven. The item fill rate decreases with 3.04%. To understand this behavior better, Table 9.5 is created. In this table, the average demand sizes are depicted for the simulation period and the forecast. These are again divided into expensive and cheap parts.

On average, the demand sizes decrease from 57.97 to 41.85 items when comparing the realized values to the model values. However, for the 490 parts having a cost larger than average, the size increases with 17%, while for the 3400 cheaper parts the average size decreases with 28%. Based on the sensitivity of the item fill rate for expensive parts (see Section 9.4), it makes sense that the item fill rate decreases with 3.04%, while the line fill rate increases with 1.98%.

	# parts	Average size simulation period	Average size forecasted
Cost higher than average	490	2.22	2.59
Cost lower than average	3400	66.01	47.51
Grand Total	**3890**	**57.97**	**41.85**

Table 9.5: Average demand sizes per cost category

Finally, remember that the inventory mutations were still included in the previous scenarios. In scenario nine, all inventory mutations are removed. Without these mutations, the line- and item fill rate increase with 3.92% and 3.93% respectively. In other words, the mutations reduce the achieved fill rate in practice. This result is not entirely surprising, as the current forecast method is not able to take these mutations into account when predicting future demand. Table 9.6 provides an overview of the impact on the fill rate per mutation type. The sales orders placed in the history period, but that arrive in the simulation period, appear to have the largest impact on the realized fill rate.

To summarize, based on the discussions in this section, it is concluded that the demand forecasting method predicts smaller rates and sizes than actually occurred. So, the part replenishment model optimizes the inventory policies with a particular Poisson rate and compounding distribution. When these policies are then used in practice, the actual demand rate and sizes appear to

Type	Line fill rate	Item fill rate
No PO history	-0.68%	-1.17%
No SO history	3.73%	5.47%
No mutations	0.87%	-0.37%
Total	**3.92%**	**3.93%**

Table 9.6: Fill rate impact per mutation type

be higher on average. The reorder and order up to levels are not sufficiently calibrated for this demand, resulting in realized item- and line fill rates that are lower than predicted by the model. Moreover, the inventory mutations increase this effect and the impact is less predictable for the item fill rate due to its sensitivity for expensive parts. These relationships explain the impact on the line- and item fill rate of 8.89% and 4.37% when the forecasted demand is used instead of the actual demand.

9.4 Item fill rate sensitivity

This section aims to illustrate the sensitivity of the item fill rate more structurally, as it was often mentioned in the previous discussions.

To do so, three separate scenarios are created as displayed in Table 9.7. Of the total 3890 parts, the 30 most expensive are taken. Their initial inventory is adjusted to zero, one and their order up to level in turn. The latter value is often 0, 1 or 2 due to the low demand rate and size of expensive parts. For each of these scenarios, the line- and item fill rate are simulated. As can be seen in the table, the line fill rate stays very stable, while the item fill rate increases significantly per scenario. As the expensive parts have low demand rates and small order sizes (see also Table H.1), the total number of order lines is often small and, therefore, has a minor impact on the total line fill rate. However, being able to fill expensive parts does have a large impact on the item fill rate, as it is weight based on annual revenue.

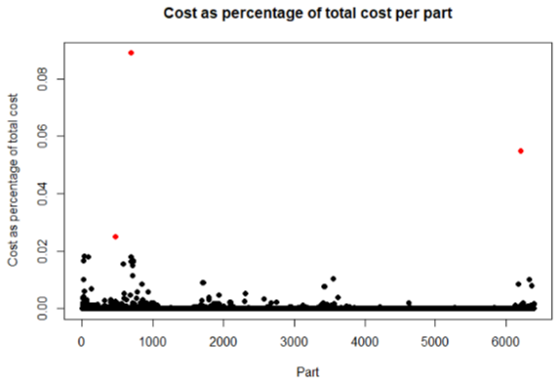
Initial inventory	Line fill rate	Item fill rate
0	91%	55%
1	91%	61%
order up to level	91%	68%

Table 9.7: Impact of changing initial inventory of 30 most expensive parts

A similar analysis is performed with a sample of 6400 parts, only now the three most expensive parts are investigated. Figure 9.1 shows a visualization and table representation of these parts. The graph shows all parts on the horizontal axis, while the vertical axis provides the cost of the part as percentage of the total costs of the group of parts. The three most expensive parts are colored red and their details are provided in the table. Together, these three parts account for almost 17% of the total costs.

To test their impact on the fill rate, their current fill rates are adjusted from their actual values to a value of 100%. As a consequence of this change, the item fill rate increases with an absolute value of 5.49%, while the line fill rate only increases with 0.02%. Again, the sensitivity of the item fill rate measure is showed.

Concluding, the sensitivity of the item fill rate does not provide a solid base for performance measurements.



ID	Cost	Cost % total
468	€26477	2.50%
689	€94266	8.90%
6212	€58172	5.49%

Figure 9.1: Cost as percentage of total cost per part

9.5 Theoretical model

Scenario ten represents the simulation of the model fill rate. Compared to scenario nine, the line fill rate increases with 3.65%, while the item fill rate decreases with 2.98%. The only change made between these two scenarios is the number of parts used in the simulation.

As discussed using Table 7.2, the sample group of parts exists of 5983 parts based on the history period. Moreover, due to interchangeability, this number increases to 6395 demand generating parts. When these parts are translated to the simulation period, only 3890 demand generating parts remain, as for 2505 parts no demand occurred. However, the part replenishment model optimizes its inventory policies with data on all 6395 parts from the history period. Therefore, in order to simulate the model fill rate, these parts have to be used as well.

To explain the resulting changes in fill rate, Table 9.8 is created. In this table, the average demand rate, demand size and part cost are displayed, divided over the 3890 parts in the simulation period and the 2505 parts that are only present in the history period.

	# parts	Average rate	Average size	Average cost
IN HIST AND SIM	3890	3.79	41.85	142.44
ONLY IN FULL MODEL	2505	1.83	26.99	201.45
Grand Total	**6395**	**3.02**	**36.03**	**165.56**

Table 9.8: Summary of step to theoretical model

The average demand rate and size of the 2505 parts added to the simulation of the model fill rate are significantly lower compared to the 3890 parts in the simulation period. Due to the low rate and size, the newly added parts are easily filled, explaining the increase in line fill rate of 3.65%. However, the average cost per part is higher for the added parts. This, in combination with the sensitivity of the item fill rate for expensive parts, explains the decrease in item fill rate of 2.98%.

9.6 Lost sales

An additional finding using the simulation model is the identification of lost sales. In theory, the compound Poisson process should result in a percentage of time with positive inventory that is comparable to the percentage of sales orders arriving when inventory is positive. If this is not the case, lost sales could be present. Table 9.9 provides a summary of the percentage of time with positive inventory, as well as the percentage of sales orders arriving when there is on-hand inventory available. The values are provided for scenario six and seven. The only difference between these scenarios is the fact that in scenario seven the sales orders are scheduled using a

Poisson rate, while in scenario six the actual realized demand is used. The percentages are also divided over fast-, medium- and slow movers, where slow movers have an annual demand of two or less lines, fast movers experience eight or more lines annually and medium movers are in between.

	Slow movers		**Medium movers**		**Fast movers**		**Total**	
	6	**7**	**6**	**7**	**6**	**7**	**6**	**7**
% time inventory > 0	83%	81%	89%	90%	89%	91%	88%	90%
% demand when inventory > 0	91%	81%	88%	89%	87%	91%	88%	89%
Ratio demand to time	**1.09**	**1.00**	**0.99**	**0.98**	**0.98**	**1.00**	**1.00**	**0.99**

Table 9.9: Summary of lost sales

For all types of parts, scenario seven shows a demand to time ratio of around one. This is in line with the theoretical expectations of the compound Poisson process. The same holds for the medium- and fast moving parts of scenario six. However, for the slow movers in scenario six, the ratio is 1.09. The percentage of demand arriving when the on-hand inventory is positive is 91%, while the percentage of time with positive inventory is 83%. In other words, customers seem to arrive more often when inventory is positive. In theory this does not happen as customers also place orders when there is no inventory. In practice, however, it seems that customers look for alternative suppliers for slow movers instead of placing an order when inventory is zero.

To verify whether this observation holds statistically, several calculations are made. First, note that the results of scenario seven are based on 500 Monte Carlo simulation runs. The standard deviation of the number of sales orders that arrive when demand is positive can therefore be calculated. This value is 29.93 sales orders. Next note that the discrepancy experienced in scenario six is $91\% - 83\% = 8\%$, over a total of 1094 slow moving sales orders. This translates to a difference of $8\% * 1094 = 87$ sales orders. This value is almost three times as large as the expected standard deviation of 29.93, indicating the found difference is not a coincidence.

Consequently, it is concluded that lost sales exist for slow moving parts at Fokker. From a practical perspective, this result holds as well as Fokker uses an online platform for potential customers on which inventory can be checked. When the inventory is zero, customers look for alternatives. Especially as slow movers are less of a priority, providing sufficient time to do so. Increasing availability of these parts could, therefore, result in more sales.

Chapter 10

Conclusion

10.1 Literature gap

In this thesis, insights were created into the difference between realized- and model fill rates (*fill rate gap*) for groups of spare parts. From theory, it is known that optimized model output is bound to deviate from achieved results in practice, as models are simplifications and abstractions of reality. However, recognizing model limitations and understanding what drives the fill rate gap is essential in managing its consequences and proposing solutions to bring theory closer to practice. Nonetheless, very little research has been performed on actually understanding this relationship and its impact in more detail. To address this literature gap, this thesis went beyond the theoretical insights by translating them to a practical environment. A shortlist of potential causes of a fill rate gap were identified, forming the requirements of a discrete-event simulation model. This model was then used to investigate the fill rate gap causes in more detail.

The developed model provides a first step into placing inventory control systems in a more holistic perspective, covering its internal relationships. With this knowledge, mitigation strategies can be developed to narrow the fill rate gap, consequently gaining a better control of the process and potentially resulting in more effective inventory management. With this, the circle is closed.

10.2 Implications of main findings for practice

This section discusses the implications of the main findings from the case study performed at Fokker. The focus is placed on the key ideas that can be used in practice. The results of the case study suggest that human involvement, lead time inaccuracies and demand forecasting are the main causes of the discrepancy between realized- and model fill rates.

Human interaction. The inventory control system is subject to human interactions, which are shown to positively influence the realized fill rate. This result corresponds with the findings of Syntetos et al. (2009b) and Dietvorst et al. (2018), who show that allowing users to modify model outputs does not necessarily lead to worse forecasts. In fact, managerial judgemental adjustments can be effective for demand experiencing intermittent patterns.

This thesis distinguished between two types of human interaction, namely adaptations to the optimized inventory policies and adjustments made during the purchasing process. First, it is shown that adjusting optimized inventory inventory policies decreases the achieved item- and line fill rate with 3.8% and 6.43% respectively, compared to exactly following the optimized policies. Moreover, these changes result in more frequent order placements, while each order has a smaller size on average. This decreases the average holding costs, but increases the ordering costs. This relationships should be taken into consideration when altering the optimized policies. Second, allowing users to apply their knowledge and experience in making purchasing decisions based on the adjusted policies is shown to increases the realized item fill rate with 5.19%, while the line fill rate is positively effected with 8.54%. Consequently, it is strongly recommended to use the knowledge and experience of the inventory controllers and try to understand the reasons why certain decisions are made in practice when procuring items.

Based on the found results with regards to both types of human adaptations, it is recommended to include inventory controllers in decision making when changing model outputs and dealing with these outputs in practice. The policy changes are shown to result in the best fill rate when inventory controllers are allowed to use their knowledge and experience when making purchasing decision.

Lead time. The actual achieved lead times are shown to be 20 days shorter on average compared to the model lead times, resulting in a larger realized fill rate. This finding on lead time uncertainty influencing the fill rate gap corresponds with the theoretical understanding of inventory control systems. However, this thesis has also shown its actual influence on the gap by quantifying its effect. The observed lead time discrepancy increases the realized item fill rate with 3.21%, while the line fill rate increases with 2.24%. Thus, aligning the model lead times with the actual lead times will result more accurate fill rate predictions, consequently decreasing the fill rate gap. To achieve this, multiple options are available. The standard lead times provided by the suppliers can be discussed to better match actual expectations, the model lead times can be adjusted based on past lead time results or the framework suggested by Axsäter (2006) can be used to introduce stochastic lead times.

Demand forecasting. Forecasting demand is shown to negatively influence the fill rate gap. Its impact is larger than the summation of the positive influence of human interaction and lead time discrepancies together. The difficulties involved in forecasting lumpy demand patterns, as is the case at Fokker, has been stated frequently in the literature before (e.g., Hu et al. (2018), Kranenburg and van Houtum (2015), Mobarakeh et al. (2017), Teunter and Sani (2009)). Croston (1972), Watson (1987), Eppen and Martin (1988) and Downing et al. (2011) also show that forecasting errors actively disfigure predictions of customer service levels. The large negative effect of forecasting demand on the realized fill rate found in this thesis, thus, corresponds with these results.

Moreover, this thesis reviewed the forecast of demand sizes and moments, but also investigated the impact of inventory mutations and the sensitivity of the forecast method for the non-occurrence of demand in practice that has been forecasted (Section 9.5). First of all, it is shown that using a Poisson process to forecast demand in a spare part context does not represent the realized demand sufficiently. Predicted demand rates and sizes tend to be lower as compared to reality. This results in the actual achieved fill rate to be 3.41% and 1.33% lower for item- and line fill rate measures respectively. Secondly, is is shown that, from all inventory mutations, sales orders that are placed before a new policy update, but that arrive after the implementation of this update, contribute to the fill rate gap to the largest extent. The realized line fill rate is 3.75% lower and the item fill rate 5.47%. The current forecasting method does not take these sales orders into account when making a demand forecast. However, the effects of other mutations, such as stock updates and stolen parts, is shown to to be rather small (item: 0.37%, line: 0.87%), while DeHoratius and Raman (2008), Shteren and Avrahami (2017) and Avrahami et al. (2013) show that these inventory inaccuracies have a large effect in a retail context. Finally, the forecasting method is very sensitive for demand that is forecasted, but does not occur in reality. The realized item fill rate increases with 2.98%, while the achieved line fill rate decreases by 3.65%.

Concluding, it is shown the current demand forecasting method results in a total negative impact on the realized fill rate of 4.37% and 8.89% for item- and line fill rate measurements respectively. This method could be improved in several ways. A method should be devised that provides a better prediction of the real demand sizes- and moments, includes SO inventory mutations and can better deal with the non-occurrence of particular forecasted demand. If the forecast method is better able to predict demand, the resulting optimized decision variables are more likely to result in similar objective values in practice.

Lost sales and item fill rate sensitivity. Lost sales were identified for slow moving parts. It is recommended to focus on creating availability for these parts, as this will increase sales. Note, however, that a trade-off has to be made between sales revenue and additional costs of stocking these items. To support this trade-off, actual holding-, ordering and backorder costs could be determined and added to the simulation model. Scenarios could then be ran to assess the impact of additional inventory of slow moving parts as a function of costs. This also aids in developing scenarios that improve the fill rate at minimum additional cost.

Finally, the item fill rate is extremely sensitive for expensive parts and does not provide a solid base for performance measurement. This finding, in combination with the identification of lost sales, make it interesting to investigate the possibility of a profit optimization model that uses the line fill rate measure to make a trade-off between holding- and ordering costs and potential sales revenue. This could especially help in dealing with the identified lost sales.

10.3 Limitations of research

The thesis also contains a number of limitations. Several of these limitations suggest possible directions for further research that Fokker can perform.

Model generalization. The developed simulation model only deals with (s, S) inventory policies. However, by making small adjustments to the model rules, other types of inventory control systems could be simulated and tested as well. Moreover, the realized- and model fill rates are determined on group level. These measurements represent a weighted average of the fill rates of all parts contained in the group, weighted based on a annual (expected) revenue or annual (expected) demand rate. It would be interesting to generalize the model to allow for different types of fill rate calculation methods to be used. With this adaptation, the model could be employed for different inventory management systems as well. Furthermore, by using more data sources, additional fill rate gap causes could be added to the model to get an even more detailed overview of the fill rate gap causes.

Automation of model output. The simulation model is able to create over $16,000$ different chains of scenarios with the current parameter set. The case study only considers a specific chain of sequential what-if scenarios from this large set of possibilities. It would be interesting to develop a method that analyses all different kind of chains automatically. As the run time for an individual scenario is small (ranging between 2 to 30 seconds), simulation runs could be automatized to create a large set of output. Using machine learning, or other data analysis methods, patterns could be identified and high impact fill rate gap causes could be found more easily.

10.4 Implications of main findings for inventory research

Based on above discussions, several implications of the main findings are found with respect to the field of inventory research. Together they form directions for future research in this field.

Periodic process. Part replenishment models often calculate steady state fill rates, while, in practice, the inventory policies are updated regularly. These updates introduce periodic moments of transient system behavior that stabilize over time to reach (near) steady state. However, demand rates are low for spare parts and inventory policies are not precisely followed by purchasers, as was shown in this thesis. Consequently, the situation of (near) steady state is often not achieved. As transient fill rate calculations are difficult to make, the resulting model fill rate is bound to differ from reality. On top of this, the sales order inventory mutations (placed in the history period, but handled in the simulation period) are a result of the periodic policy updates, which negatively impact the achieved fill rate as well.

Therefore, the question arises whether models that assume steady-state behavior are the best suited solution to inventory management. Practical environments often do not meet the assumption of steady-state and assuming it does results in the discussed consequences. Research can be conducted to investigate whether models that allow for continuous, or at least more gradual, adjustments of optimized inventory policies perform better from a fill rate perspective.

Holistic perspective. Current literature on inventory control often focuses on optimizing a specific aspect of the inventory control system, assuming input parameters are given. However, this does not allow for the inclusion of the complexity and uncertainty that arises in the system as a whole. This thesis has shown that large deviations occur due to the different parts of the inventory control system and their mutual interplay. Taking a holistic perspective allows for the identification and quantification of these relationships. Consequently, actions can be taken to close the fill rate gap. Therefore, performing research on the inventory system as a whole is strongly recommended instead of only optimizing its separate aspects.

Feedback loop. In current literature, the need to reflect on optimized model values that are used in practice is very limited. However, this thesis has shown that performing such a reflection helps to narrow a fill rate gap. Whenever optimized model values are used in practice, it is highly recommended to create a form of feedback loop to monitor whether the achieved values in practice correspond with model predictions and take action if this is not the case. The simulation model developed in this thesis is an example of such a monitoring system, but more research can be performed on standardizing such a feedback loop. A possibility would be the use of daily sales- and purchasing order information to detect deviations between realized- and model values in an early stage.

Moreover, the next step would be to investigate the use of more assertive models. Creating simulations based on human knowledge or known future circumstances could help to anticipate on upcoming changes. It would be interesting to investigate possibilities to use the passive simulation model as building block for a more assertive monitoring- and purchasing strategy system.

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Appendix A

Inventory relationships

Formulas for the inventory position at time t ($IP(t)$) and the inventory level at time t ($IL(t)$).

$$\begin{aligned} IP(t) &= \textit{stock on hand at time } t + \textit{outstanding orders at time } t - \textit{backorders at time } t \\ &= I(t) + IO(t) - B(t) \end{aligned} \tag{A.1}$$

$$\begin{aligned} IL(t) &= \textit{stock on hand at time } t - \textit{backorders at time } t \\ &= I(t) - B(t) \end{aligned} \tag{A.2}$$

Stochastic demand in the interval between t and $t + \tau$.

$$D(t, t+\tau) = D(\tau) = \textit{stochastic demand in the interval } (t, t+\tau] \tag{A.3}$$

Key inventory relation, stating the expected value of the inventory level at time $t + L$.

$$IL(t+L) = IL(t) + IO(t) - D(t, t+L) = IP(t) - D(t, t+L) \tag{A.4}$$

Appendix B

Part replenishment model evaluation and optimization

B.1 Replenishment model evaluation

In order to evaluate the replenishment model mathematically, some notation has to be introduced. The following notation is used throughout the thesis.

- $\mathcal{J}$: set of all spare parts
- $\mathcal{G}$: set of spare part groups (every group consists of a combination of spare parts)
- $\mathcal{C}$: set of all inventory policies
- $j \in \mathcal{J}$: part j
- $g \in \mathcal{G}$: group g
- $c \in \mathcal{C}$: inventory policy c
- $\mathcal{J}_g \subseteq \mathcal{J}$: subset of parts contained in group g
- $\mathcal{C}_j \subseteq \mathcal{C}$: subset of inventory policies possible for part j
- h_j : annual inventory holding costs per item of j
- o_j : annual fixed ordering cost for part j
- L_j : deterministic lead time of part j
- $H_j(c)$: holding costs for part j when inventory policy c is used
- $O_j(c)$: ordering costs for part j when inventory policy c is used
- a^g : fill rate objective for group g
- D : random variable denoting total demand process

Using the notation, expressions are derived for spare part demand in Section B.1.1. Based on these relationships, part- and group level performance (fill rate) expressions are derived for a given inventory policy in Section B.1.2.

B.1.1 Demand

The part replenishment model assumes the demand for every part follows a compound Poisson process (item 3). Therefore, customers arrive according to an annual demand rate λ_j for every part j. λ_j is estimated based on historical data. Calculating the compounding distribution for the size of the demand is done using the same historical data. Bootstrapping is applied to find the probability mass function of the demand size distribution for every part j. This method is described in Algorithm 2. Let $f_{j,q}$ be the probability of demand size q for item j, with $f_{j,0} = 0\ \forall j \in \mathcal{J}$ (no demands of size zero).

Using the probability mass functions for part demand ($f_{j,q}$), Equation B.1 is used to find the

Algorithm 2 Construction of part demand probability mass function

for all j in $\mathcal{J}$ **do**
  get demand size q in historical period for part j
  $count_j + 1$
  if q is new **then**
    make new counter $count_{j,q}$ for part j and demand size q
  end if
  $count_{j,q} + 1$
end for
for all $count_{j,q}$ **do**
  $f_{j,q} = \frac{count_{j,q}}{count_j}$
end for

probability that n customers give a total demand q for part j. This probability is denoted as $f^n_{j,q}$.

$$f^n_{j,q} = \sum_{i=n-1}^{q-1} f^{n-1}_{j,i} f_{j,(q-i)}, \; n = 2, 3, 4, ... \tag{B.1}$$

Combining Equation B.1 with the Poisson arrivals of customers, provides an expression for demand during lead time. This is depicted in Equation B.2, with L_j being the supplier lead time for part j. This lead time is determined based on standards provided to Fokker by the suppliers.

$$P(D_{j,L} = q) = \sum_{n=0}^{\infty} \frac{(\lambda_j L_j)^n}{n!} e^{-\lambda_j L_j} f^n_{j,q} \tag{B.2}$$

B.1.2 Performance expressions

Using the distribution of part demand during lead time, performance expressions are determined in the form of part- and group level fill rates.

Let $F^g_j(c)$ be the fill rate of part j in group g when policy c is used. Then, the fill rate of every part j, subject to policy c, can be expressed in terms of the fill rates for base-stock $(S-1, S)$ policies (van Jaarsveld et al., 2015). This is expressed in Equation B.3 with $k \in \{0, ..., S-s-1\}$.

$$F^g_j(c) = F^g_j(s, S) = \sum_{k=0}^{S-s-1} P(IP_j = S-k) F^g_j(S-k-1, S-k) \tag{B.3}$$

Equation B.3 demands the probability of visiting a specific inventory position between $s+1$ and S to be known. Since the part demand is assumed to follow a compound Poisson process, these probabilities are not uniformly distributed as would be the case with a pure Poisson process (Axsäter, 2006). Therefore, let $m_{j,k}$ denote the probability of visiting inventory position $S-k$ during an arbitrary order cycle. As we order up to level S, every cycle is started in $IP = S-0$. This implies that $m_{j,0} = 1$, meaning $m_{j,k}$ can be evaluated recursively using the compounding distribution of demand for part j (Axsäter, 2006). Equation B.4 displays this relationship.

$$m_{j,k} = \sum_{a=(S-k)+1}^{S} m_{j,(S-a)} f_{j,a-(S-k)} \tag{B.4}$$

Now, let the expected lengths of an order cycle for part j be equal to $\frac{M_{j,S-s}}{\lambda_j}$, with $M_{j,S-s} = \sum_{k=0}^{S-s-1} m_{j,k}$. Then, the probability of the inventory position of part j being equal to $S-k$, is derived using Equation B.5.

$$P(IP_j = S-k) = \frac{m_{j,k}}{M_{j,S-s}} \tag{B.5}$$

With these newly derived expression, Equation B.3 can be rewritten by filling in Equation B.5. Equation B.6 shows the reformulation of the fill rate of part j in group g when policy c is used in terms of base-stock fill rates (van Jaarsveld et al., 2015).

$$F_j^g(s,S) = \frac{1}{M_{j,S-s}} \sum_{k=0}^{S-s-1} m_{j,k} F_j^g(S-k-1, S-k) \tag{B.6}$$

Finally, Equation B.6 requires the fill rate of part j in group g for different base-stock policies. In order to derive these expressions, the type of fill rate restriction used is relevant. Either an item or line fill rate can be used in the part replenishment model. The expressions for both types are provided next.

Item fill rate for base-stock policies
For a pure Poisson demand process, the item fill rate of part j is equal to $P(IL_j > 0)$ (Axsäter, 2006). For a compound Poisson process, however, the demand size can vary per customer arrival. First, note that at the time of a customer order arrival, there will be a net inventory of S–n with probability $P(D_L = n)$, i.e, $P(IL = S-n) = P(D_L = n)$. Then, Equation B.7 expresses the expected amount that can be delivered immediately from stock of that order for part j.

$$\sum_{a=1}^{S-n} a f_{j,a} + (S-n)(1 - \sum_{b=0}^{S-n} f_{j,b}) \qquad = \sum_{a=1}^{S-n} (a - S + n) f_{j,a} + S - n \tag{B.7}$$

Focusing on the left equation, two factors are added together. First, the expected part of this order size which can be delivered immediately from stock is calculated. This is done by multiplying all order sizes a that are smaller than the inventory level $S-n$ by their probability of occurring ($f_{j,a}$), and adding them together. The second part multiplies the probability that the order size is larger than the current inventory level and multiplies this with the maximum amount that can be the delivered to the customer immediately, namely the current inventory level $S-n$. Adding these two parts together gives the expected order amount that can be delivered from stock.

The item fill rate for a given base-stock policy is then the ratio between the expected part of the order delivered from stock and the expected total demand size. This is shown in Equation B.8.

$$F_j^g(S-k-1, S-k) = \frac{\sum_{n=0}^{(S-k)-1} P(D_{j,L} = n) \left[\sum_{a=1}^{(S-k)-n} (a - (S-k) + n) f_{j,a} + (S-k) - n \right]}{\sum_{a=0}^{\infty} a f_{j,a}} \tag{B.8}$$

Line fill rate for base-stock policies
As opposed to the item fill rate, the line fill rate considers total order lines delivered from stock instead of the amount of items. Following the same reasoning as before, at the time of a customer order arrival, there will be a net inventory of S–n with probability $P(D_L = n)$, i.e, $P(IL = S-n) = P(D_L = n)$. The probability that this order for part j can be delivered to the customer in total is equal to the probability that the order is smaller than or equal to the current inventory level $S-n$. This can be expressed as $\sum_{a=0}^{S-n} f_{j,a}$. The line fill rate for policy $(S-k-1, S-k)$ (base stock policy S) is then equal to Equation B.10.

$$F_j^g(S-k-1, S-k) = \sum_{n=0}^{(S-k)-1} P(D_{j,L} = n) \sum_{a=0}^{(S-k)-n} f_{j,a} \tag{B.9}$$

$$= \sum_{n=1}^{S-k} P(D_{j,L} \leq (S-k) - n) f_{j,n} \tag{B.10}$$

B.2 Replenishment model optimization

In this subsection, the optimization problem is formulated.

B.2.1 Optimization problem

The derived performance expressions form the basis for evaluating the performance of a group of spare parts. In order to optimize the inventory policy c for every part j in group g, restricted to achieving a particular group fill rate, an optimization problem can be formulated. This problem can be described in the form of a Mixed Integer Linear Program (MILP), illustrated below.

$$\text{Minimize} \quad \sum_{j \in J} \sum_{c \in C_j} x_{jc}(H_j(c) + O_j(c)) \tag{B.11}$$

$$\text{Subject to} \quad \sum_{j \in J_g} \sum_{c \in C_j} x_{jc} \frac{w_j^g F_j^g(c)}{\sum_{j \in J_g} w_j^g} \geq a^g \qquad \forall g \in G \tag{B.12}$$

$$\sum_{c \in C_j} x_{jc} = 1 \qquad \forall j \in J \tag{B.13}$$

$$x_{jc} \in \{0, 1\} \qquad \forall j \in J, c \in C_j \tag{B.14}$$

The objective of the *MILP* is to minimize the total holding- and ordering costs over all parts. For the purpose of linearization, the variable $x_{j,c}$ is introduced. $x_{j,c} = 1$ indicates that policy $c = (s, S)$ is used for part j. The main goal is to find a policy (s, S) for every part $j \in \mathcal{J}$ for which the overall costs are minimized.

Minimizing the total costs has to be done while still meeting the fill rate restrictions presented in constraint B.12. It is clearly seen a weighted average is used based on part fill rates $F_j^g(c)$, as was explained in Section 3.1.1 and item 5. Depending on the type of fill rate used for group g, different weights w_j^g are used (item 6). For the item-based variant the weight for part j in group g is equal to the annual revenue per part ($cost\ price * amount\ ordered$), while the line-based weight uses the annual demand rate for that part calculated using demand history. Constraint B.12 then states that the weighted average should be larger than or equal to the fill rate target associated with its group. Furthermore, constraint B.13 makes sure that one, and only one, policy can be chosen for every part $j \in \mathcal{J}$, while restriction B.14 indicates that the decision variable $x_{j,c}$ can only take the values zero or one.

Finally, to solve this optimization problem, column generation is used. However, this subject goes beyond the scope of this research. Therefore, the reader is directed to van Jaarsveld et al. (2015), which provides an example of this method applied in a repair shop at GKN Fokker Services. Note that the procedure is similar, but not exactly equal. However, it does give a good indication of the steps that have to be taken to solve the optimization problem.

Appendix C

Cause identification from longlist

	Theoretical causes on longlist	**Observed**	**From discussion**	**Color**
Included	**Before model causes**			
	Spare part characteristics			
X	Demand pattern	X		
	Maintenance dependency			
X	Large variety		X	
	Obsolescence risk			
X	*Model is an abstraction of reality*		X	
	Input causes			
X	*Stochastics introduce uncertainty*	**X**		
X	Demand	X		
X	Lead time	X		
X	*Model parameters (incorrect / impact on output)*		X	
	Model causes			
X	*Continuous review (s,S) inventory policy*	**X**		
X	*Compound Poisson demand process*	**X**		
X	Distribution of demand during leadtime	X		
X	Distribution of the inventory position	X		
	Output causes			
X	*Difference in framework or calculation method*	**X**		
X	*Service level is a random variable in itself*		X	
	After model causes			
X	*Human interaction*	**X**		
X	*Inventory inaccuracies*		X	
X	*Poor supplier quality*	**X**		

Table C.1: Overview of cause identification from interplay (process model) and further discussion

Appendix D

Part-level Excel output

Inventory trajectory

- Part level inventory position at every simulated day.
- Part level backorder level at every simulated day.
- Part level on-hand inventory at every simulated day.
- Part level available inventory at every simulated day.

Inventory snapshots

- Part level simulated and snapshot inventories for every snapshot day.
- Part level simulated and snapshot inventories differences for every snapshot day.
- Part level overall percentage difference between simulated and snapshot inventories.
- Group level overall percentage difference between simulated and snapshot inventories.
- Group level count of parts experiencing a overall percentage difference between simulated and snapshot inventories larger than zero.

Scenario overall performance

- Category count.
- Part level sales order sizes delivered and not delivered.
- Part level time between placement of sales order and customer receiving its items in total.
- Part level delay between placement of sales order and acting on it.
- Part level purchase order sizes placed.
- Part level supplier lead time.
- Part level delay between undershoot moment and the placement of a purchase order.
- Part level total time backorder is in the system.

Scenario result summary

- Part level demand rate, average demand size, weights (line and item) and fill rates (line and item).
- Group level scenario score (summation of total backorders, purchase orders placed and on-hand inventory over all simulated days)
- Part level scenario score, divided into total backorders, purchase orders placed and on-hand inventory over all simulated days.

Fill rate

- Group level item fill rate.
- Group level line fill rate.
- Part level weights and item fill rates.
- Part level weights and line fill rates.
- Part level line fill rate including weight.
- Part level item fill rate including weight.

Appendix E

Discrete-event simulation model

E.1 Detailed model entities and attributes

Part

double	ID	*ID of part*
double	reorder	*Reorder level of part*
double	orderUpTo	*Order up to level of part*
double	modelCost	*Cost used in optimization model*
double	multiplier	*Forecast multiplier used*
InvTracker	invTracker	*Inventory tracker*
SizeSelector	sizeSelector	*Size selector*

SO

Part	part	*Part for which SO is placed*
double	size	*Size of SO placed*
double	orderTime	*Time at which SO is ordered*
double	finalDeliverTime	*Time at which full SO is delivered*
double	sizeFilled	*Size instantly filled from stock*
double	sizeUnfilled	*Size not instantly filled from stock*
double	sizeFilledBO	*Size of outstanding BO filled*
String	status	*Status (filled, fullBO, partlyBO)*
BO	backorder	*Backorder caused by SO*
boolean	BODelivered	*Is BO fully delivered?*
boolean	isFulfilled	*Is total SO delivered?*

Inv_I

Part	part	*Part for which mutation applies*
double	size	*Size of mutation*
double	occurrenceTime	*Time at which mutation occurs*

PO

Part	part	*Part for which PO is placed*
double	size	*Size of PO placed*
double	placementTime	*Time of PO placement*
double	receivingTime	*Time at which PO is received*
double	orderDelay	*Ordering delay*
boolean	isReceived	*Is part received at Fokker?*

Inv_D

Part	part	*Part for which mutation applies*
double	size	*Size of mutation*
double	occurrenceTime	*Time at which mutation occurs*

BO

Part	part	*Part for which the backorder applies*
double	size	*Size of the backorder*
double	occuranceTime	*Time at which the backorder occurred*
double	resolvedTime	*Time at which the backorder was fully resolved*
double	sizeResolved	*Current size of the backorder that is resolved*
ArrayList<Double>	receiverPO	*Receiver of the corresponding purchase order resolving the backorder*
SO	salesorder	*Sales order responsible for creating the backorder*
boolean	isResolved	*Is backorder fully resolved?*

Figure E.1: Model entities and attributes (one of two)

InvTracker		
Int	partID	*ID of part accompanied with the tracker*
double	startInventory	*Inventory of the part at the start of the simulation*
double	currentInventory	*Current on-hand inventory level of the part*
double	availableInventory	*Current level of available inventory (current inventory minus any reservations)*
double	onOrder	*Current amount of parts on order for the part*
double	sizeBackorders	*Size of the current amount of backorders for the part*
double	IP	*Current inventory position of the part*
ArrayList<Double>	IPunderReorder	*Times at which the inventory position drops below the parts reorder point*
HashMap<Double,Double>	invMap	*Tracker of parts current inventory per simulation time instance*
HashMap<Double,Double>	availableInvMap	*Tracker of parts available inventory per simulation time instance*
HashMap<Double,Double>	backorderMap	*Tracker of parts current backorders per simulation time instance*
HashMap<Double,Double>	ipMap	*Tracker of parts inventory position per simulation time instance*
boolean	IPandBOinitialized	*Are the inventory position and amount of backorders initializes in the simulation?*
boolean	inventoryUnderReorder	*Is the current inventory under the parts reorder point?*

SizeSelector		
double	averageSizePO	*Average size of the purchase orders placed in simulation period (historical data)*
double	minSizePO	*Minimum size of the purchase orders placed in simulation period (historical data)*
double	maxSizePO	*Maximum size of the purchase orders placed in simulation period (historical data)*
ArrayList<Double>	sequenceSizePO	*Sequence of all purchase order sizes placed in simulation period (historical data)*
double	modelSizePO	*Size of purchase order based on inventory policy*
double	averageLeadtimePO	*Average size of lead times of PO placed in simulation period (historical data)*
double	minLeadtimePO	*Minimum size of lead times of PO placed in simulation period (historical data)*
double	maxLeadtimePO	*Maximum size of lead times of PO placed in simulation period (historical data)*
ArrayList<Double>	sequenceLeadtimePO	*Sequence of all lead times of PO placed in simulation period (historical data)*
double	modelLeadtimePO	*Size of lead time based on lead time values used in the part replenishment model*
double	demandRateSO	*Daily demand rate of the sales orders placed in simulation period (historical data)*
double	averageSizeSO	*Average size of the sales orders placed in simulation period (historical data)*
double	minSizeSO	*Minimum size of the sales orders placed in simulation period (historical data)*
double	maxSizeSO	*Maximum size of the sales orders placed in simulation period (historical data)*
ArrayList<Double>	sequenceSizeSO	*Sequence of all sales orders placed in simulation period (historical data)*
ArrayList<double[]>	sizeDistributionSO	*PDF of the size of all sales orders placed in simulation period (historical data)*
Double	leadtimeFactor	*Factor (fraction) used to adjust the lead time size used in the simulation*
Double	purchaseorderSizeFactor	*Factor (fraction) used to adjust the purchase order size used in the simulation*
Double	salesorderSizeFactor	*Factor (fraction) used to adjust the sales order size used in the simulation*
Double	salesorderRateFactor	*Factor (fraction) used to adjust the sales order rate used in the simulation*

Figure E.2: Model entities and attributes (two of two)

E.2 Model events

Event	Type	Category	Definition
INV_I	1	WT	Incoming warehouse transfers
INV_D	2	WT	Sent out warehouse transfers
INV_I	1	WO-P1	Incoming workorder lines (P1 = overhaul)
INV_D	2	WO-P1	Sent out workorder lines (P1 = overhaul)
INV_I	1	WO-P2	Incoming workorder lines (P2 = repair)
INV_D	2	WO-P2	Sent out workorder lines (P2 = repair)
INV_I	1	WO-P3	Incoming workorder lines (P3 = kitting)
INV_D	2	WO-P3	Sent out workorder lines (P3 = kitting)
INV_I	1	WO-P4	Incoming workorder lines (P4 = manufacturing)
INV_D	2	WO-P4	Sent out workorder lines (P4 = manufacturing)
INV_I	1	WO-P6	Incoming workorder lines (P6 = tear down)
INV_D	2	WO-P6	Sent out workorder lines (P6 = tear down)
INV_I	1	WO-P7	Incoming workorder lines (P7 = squawk)
INV_D	2	WO-P7	Sent out workorder lines (P7 = squawk)
INV_I	1	SU	Increasing stock updates
INV_D	2	SU	Decreasing stock updates
INV_I	1	SR	Sales Receivers - incoming unserviceable parts for repair
INV_I	1	RM	Return Material Autorisation - unserviceable Core for Repair
INV_D	2	PS	Purchase Shipper - unserviceable parts sent to 3P repair station
INV_D	2	CL	Claim - return material to supplier due to discrepancies
PO_PLACED_SIMULATION	3	RC	Purchase Receivers - directly related to a purchase order
SO_PLACED_SIMULATION	4	TK	PickTickets - directly related to a sales order
PO_PLACED_HISTORY	5	-	Purchase order placed in history period
PO_RECEIVED	6	-	Purchase order is received at inbound logistics
SO_DELIVERED	7	-	Sales order is delivered to customer
BO_DELIVERED	8	-	Backorder is delivered to customer
SO_PLACED_HISTORY	9	-	Sales order placed in history period

Table E.1: Type and category of events

E.3 Main body of simulation model

Algorithm 3 Main body of simulation

```
Call initializeSimulation
Set time = 0
Set finalTiming to last day of simulation period
Initialize inventory position of all parts
Check, for all parts, if initial IP is below reorder level and order according to policy

while eventQueue is not empty and time ≤ finalTiming do
  Set event equal to first event in 𝓕
  Set part = event.getPart
  Set time = event.getOccurrenceTime

  switch (event.getType)

  case Event type = INV INCREASE:
    Call handleInvIncrease(part)

  case Event type = INV DECREASE:
    Call handleInvDecrease(part)

  case Event type = PO PLACED HISTORY:
    Call handlePOPlacedHistory(part)

  case Event type = PO PLACED SIMULATION:
    Call handlePOPlacedSimulation(part)

  case Event type = PO RECEIVED:
    Call handlePOReceived(part)

  case Event type = SO PLACED HISTORY:
    Call handleSOPlacedHistory(part)

  case Event type = SO PLACED SIMULATION:
    Call handleSOPlacedSimulation(part)

  case Event type = SO DELIVERED:
    Call handleSODelivered(part)

  case Event type = BO DELIVERED:
    Call handleBODelivered(part)

  default: Print to console: "No event was handled":

  end switch

end while

Call performAfterSimulationCalculations
Call askForRepeat
```

E.4 Scenario parameters in code

Parameter	Variable	Type
PO ordering delay	useOrderingDelay	Boolean
PO lead time	typeLeadtimePO	1, 2, 3, 4, or 5
PO moments	importPO ‖ usePolicy	Boolean
PO sizes	typeSizePO	1, 2, 3, 4, or 5
(s,S) policy parameters	useICChanges	Boolean
SO moments	importSO ‖ usePoisson	Boolean
SO sizes	typeSizeSO	1, 2, 3, 4, or 5
Import inventory mutations	importMutations	Boolean
Import PO history	importHistPO	Boolean
Import SO history	importHistSO	Boolean
Reorder level factor	reorderFactor	Double
Order up to level factor	orderUpToFactor	Double
PO leadtime factor	leadtimeFactor	Double
Start inventory factor	startInventoryFactor	Double
PO size factor	POsizeFactor	Double
SO size factor	SOsizeFactor	Double
Demand rate factor	demandRateFactor	Double

Table E.2: Scenario parameters in code

E.5 Event handling

Algorithm 4 handleInvIncrease

Call $addINVIobject$ to create INVI object
Call $increaseInventory$
Call $increaseAvailableInventory$
$backorderList = checkForBackorders$
for each $backorder$ in $backorderList$ **do**
    Set $sizeToBeFilled = backorder.getSize - backorder.getSizeResolved$
    if $availableInventory \geq sizeToBeFilled$ **then**
        Set $resolvedTimeBO$
        if $resolvedTimeBO \leq finalTiming$ **then**
            Create event $BO\ DELIVERED$
        end if
    end if
end for
Call $updateIP$
Call $addToMap$ to register to inventory tracker

Algorithm 5 handleInvDecrease

Call $addINVDobject$ to create INVD object
Call $decreaseInventory$
Call $decreaseAvailableInventory$
Call $updateIP$
Call $addToMap$ to register to inventory tracker
if $usePolicy = true$ **then**
  if $IP \leq reorder$ **then**
    Set $sizePO$ based on $typeSizePO$
    Call $addPOobject$ to create PO object
    Set $occurenceTimePO = event.occurenceTime$
    Set $orderingDelay$
    if $occurenceTimePO + orderingDelay \leq finalTiming$ **then**
      Create event *PO PLACED SIMULATION*
    end if
  end if
  Call $updateIP$
  Call $addToMap$ to register to inventory tracker
end if

Algorithm 6 handlePOPlacedHistory

Call $addPOobject$ to create PO object
Set $placementTime = event.occurrentTime$
Set $receivingTime = event.mutationTime$
if $event.mutationTime \leq finalTiming$ **then**
  Create event *PO RECEIVED*
end if
Call $increaseOnOrder$
Call $updateIP$

Algorithm 7 handlePOPlacedSimulation

Set $supplierLeadtime$ based on $typeLeadtimePO$
Set $receivingTimePO = event.occurenceTime + supplierLeadtime$
if $usePolicy = true$ **then**
  if $receivingTimePO \leq finalTiming$ **then**
    Create event *PO RECEIVED*
  end if
else if $importPO = true$ **then**
  Call $addPOobject$ to create PO object
  if $receivingTimePO \leq finalTiming$ **then**
    Create event *PO RECEIVED*
  end if
end if
Call $increaseOnOrder$
Call $updateIP$
Call $addToMap$ to register to inventory tracker

Algorithm 8 handlePOReceived

```
Call decreaseOnOrder
Call increaseInventory
Call increaseAvailableInventory
backorderList = checkForBackorders
for each backorder in backorderList do
    Set sizeToBeFilled = backorder.getSize − backorder.getSizeResolved
    if availableInventory ≥ sizeToBeFilled then
        Set resolvedTimeBO
        if resolvedTimeBO ≤ finalTiming then
            Create event BO DELIVERED
        end if
    end if
end for
Call updateIP
Call addToMap to register to inventory tracker
```

Algorithm 9 handleSOPlacedHistory

```
Call addSOobject to create SO object
if event.mutationTime ≤ finalTiming then
    Create event SO PLACED
end if
```

Algorithm 10 handleSOPlacedSimulation

```
Call addSOobject to create SO object
sizes = checkFillrate to determine SO size that can be filled
Set sizeFilled = sizes[0] and sizeUnfilled = sizes[1]
if sizeFilled > 0 AND event.occurenceTime ≤ finalTiming then
    Create event SO DELIVERED
end if
if sizeUnfilled ¿ 0 then
    Call addBOobject to create BO object
end if
Call increaseSizeBackorders
Call decreaseAvailableInventory
Call updateIP
Call addToMap to register to inventory tracker

if usePoisson = true then
    Set sizeSO based on compound or actual value
    Create event SO PLACED SIMULATION after exponential time
end if
```

Algorithm 11 handleSODelivered

```
Set SO = event.getSalesorder
if eventSize = remainingSizePO then
    Set SOisFulfilled = true
end if
Call decreaseInventory
Call decreaseAvailableInventory
Call updateIP
Call addToMap to register to inventory tracker
if usePolicy = true then
    if IP ≤ reorder then
        Set sizePO based on typeSizePO
        Call addPOobject to create PO object
        Set occurenceTimePO = event.occurenceTime
        Set orderingDelay
        if occurenceTimePO + orderingDelay ≤ finalTiming then
            Create event PO PLACED SIMULATION
        end if
    end if
    Call updateIP
    Call addToMap to register to inventory tracker
end if
```

Algorithm 12 handleBODelivered

```
Set BO = event.getBackorder
Call decreaseInventory
Set sizeDelivered = eventSize
Set sizeResolvedBO+ = sizeDelivered
if sizeResolvedBO = sizeBO AND BOresolved = false then
    Set BOresolved = true
end if
Call decreaseSizeBackorders
Call updateIP
Call addToMap to register to inventory tracker
```

Appendix F

Monte Carlo simulation

A Monte Carlo simulation is based on the *law of large numbers*, stating that if $F_1, F_2, ...F_n$ are i.i.d. random variables with mean $f := E[F]$ and finite variance, the probability of the sample mean being close to F is large (Boon et al., 2017). In fact, for every $\varepsilon > 0$,

$$\lim_{n\to\infty} P\left(\left|\frac{F_1 + F_2 + ... + F_n}{n} - f\right| < \varepsilon\right) = 1 \tag{F.1}$$

Every time a specific scenario is ran, the resulting group-level fill rate can be seen as one replication of the random variable F, resulting in n i.i.d. outcomes. Here, n is the number of independent runs performed by the model. We are interested in determining the value of the unknown parameter f. Based on Equation F.1, the sample mean depicted in Equation F.2 can be used as estimator for the value of f. This method is known as Monte Carlo simulation.

$$\bar{F} := \frac{F_1 + F_2 + ... + F_n}{n} \tag{F.2}$$

Then, the *Central Limit Theorem* states that the sample mean of a sufficiently large number of random variables converges to the normal distribution. Using the sample variance displayed in Equation F.3, a $100(1-2\alpha)\%$ confidence interval for f can be determined using Equation F.4. Here, z_α is the $1-\alpha$ quantile of the standard normal distribution ($\Phi(z_\alpha) = 1-\alpha$). Finally, the value of $z_\alpha\sqrt{S^2/n}$ is called the *half-width* of the confidence interval. The results of the scenarios subject to stochastics will be presented in the form of such a confidence intervals.

$$S^2 := \frac{1}{n-1}\sum_{i=1}^{n}(F_i - \bar{F})^2 \tag{F.3}$$

$$\left(\bar{F} - z_\alpha\sqrt{\frac{S^2}{n}}, \bar{F} - z_{1-\alpha}\sqrt{\frac{S^2}{n}}\right) \tag{F.4}$$

Appendix G

Data collection tool

G.1 Interface

The user interface of the Access tool for data collection is illustrated in Figure G.1.

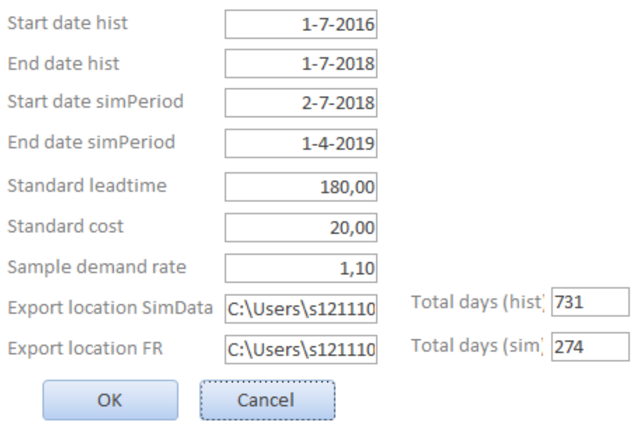

Figure G.1: User interface of Access Tool for data collection

The user should provide information on the start- and end dates of the history- and simulation period. With this information, the different data tables can be scoped accordingly before any linking and calculations are made. Based on these dates, the total days in both periods are automatically calculated in order to facilitate different calculations made by the model. Next, a value for the standard leadtime and costs have to be entered. These values correspond with the values used in the part replenishment optimization model. Whenever no value is found for the lead time or costs, these standard values are used. Then, a group of parts can be selected by entering a required annual demand rate. This rate will be used to identify all parts in the history period having the same, or a higher, rate and adds them to the group. The resulting group of parts is then used for analyzing the fill rate gap. For now, only the demand rate can be used to automatically select the sample group. Manually, all values of Table 3.1 can be used. Finally, the locations on the PC to store the *SimulationData* and *FillrateCompare* Excel files have to be entered. This is the same location the simulation model uses to load its input data.

G.2 Data sources

The main data sources used in the Access tool are summarized in Table G.1.

Table	**Source**	**Content**
Category coding	Manual	Category strings to numbers
Multipliers	Manual	Forecast multipliers used in the optimization model
PartCharacterstics	Standard	Category (price, platform, etc) values of all parts
PartsInfo	Standard	Standard lead time, price and inventory policy values per part
Interchangeability	Standard	Parts and their preferred alternatives
Usage	Standard	Stylized demand table used by optimization model
UM_CONV	Standard	Conversion table for different measures of usage (meter, pieces, etc.)
OverallRecommendations	Standard	Optimized output of part replenishment model
StockWH	Standard	Main warehouse per part
ITR_COMP1	Standard	Recorded inventory levels per part once a month
Deliveries	Standard	Sales orders with indication of stock- or non-stock delivery
Receivers_incl_TimeStamps	Created	Purchase orders placed with time stamps until receive
WHS_TRANS	Created	PO, SO and inventory mutation information for all parts

Table G.1: Data sources used by Access tool

Manual sources are created manually to support different queries. They should be updated when a new simulation run is performed after six month. The *standard sources* are tables that are already available in Fokkers databases. A link is created to them in order to maintain the most recent data. Finally, *created sources* are data tables that did not exist yet, but are created based on input of the researchers.

G.3 Simulation data output

Table G.2 presents the sheets of the *SimulationData* Excel sheet used as simulation input data. The table explains the content of every sheet and the columns used to store information.

CONTENT	
Sheet	**Content**
Parts_sim_sample	Part information for sample group in simulation period
Parts_hist_sample	Part information for sample group in history period
Parts_sim_sample_IC_change	Part information for sample group in simulation period with policy changes
Parts_scenario	Part information that can be manually entered by the user
Events_sim	All inventory mutations that occurred in the simulation period
Monthly_snaps_sim	Monthly inventory snapshot data
Interchangeability_sim	Interchangeability data
SO_dist_sim_sample	Poisson rate and compounding distribution for sample group in simulation period
SO_dist_hist_sample	Poisson rate and compounding distribution for sample group in history period
SO_dist_scenario	Poisson rate and compounding distribution that can be manually entered by the user
InfoPO	Information on PO and lead times for sample group in simulation period
InfoSO	Information on SO for sample group in simulation period
COLUMNS	
Sheet	**Columns**
Parts_sim_sample	Part ID, reorder level, order up to level, cost, multiplier, start inventory
Parts_hist_sample	Part ID, reorder level, order up to level, cost, multiplier, start inventory
Parts_sim_sample_IC_change	Part ID, reorder level, order up to level, cost, multiplier, start inventory
Parts_scenario	Part ID, reorder level, order up to level, cost, multiplier, start inventory
Events_sim	Part ID, type, category, size, occurrence time, mutation time, receiver
Monthly_snaps_sim	Part ID, day, inventory level
Interchangeability_sim	Part ID, Preferred part ID
SO_dist_sim_sample	Part ID, rate, size, probability
SO_dist_hist_sample	Part ID, rate, size, probability
SO_dist_scenario	Part ID, rate, size, probability
InfoPO	Part ID, PO size, lead time size
InfoSO	Part ID, SO size

Table G.2: Simulation data output of the Access tool

Appendix H

Sample group characteristics

Price	Population			Sample		
	Division	Rate	Size	Division	Rate	Size
Cheap	89%	1.67	77.82	95%	3.80	190.20
Expensive	11%	0.83	1.96	5%	2.65	6.78
Total	**100%**	**1.58**	**69.85**	**100%**	**3.74**	**181.28**

Table H.1: Population and sample group compared on price

NHI-part	Population			Sample		
	Division	Rate	Size	Division	Rate	Size
No	87%	1.37	32.39	78%	3.37	78.45
Yes	13%	3.03	324	22%	5.07	552.97
Total	**100%**	**1.58**	**69.85**	**100%**	**3.74**	**181.28**

Table H.2: Population and sample group compared on NHI-part

Platform	Population			Sample		
	Division	Rate	Size	Division	Rate	Size
Airbus only	1%	1.22	15.94	1%	2.39	41.14
ATR	1%	0.59	6.238	0%	2.62	7.61
Boeing only	0%	0.88	1.7	0%	2.43	3.56
Bombardier	2%	0.78	10.74	0%	3.19	44.88
Fokker only	31%	1.14	6.835	25%	3.05	18.51
Fokker plus others	2%	2.09	36.36	2%	4.60	74.73
Lockheed Martin	1%	0.9	20.6	0%	3.13	55.52
NH90	13%	3.02	322.5	22%	5.06	551.30
Non Fokker	9%	0.69	17.11	2%	2.83	54.94
Standard parts any ACT type	37%	1.74	57.71	44%	3.59	115.53
Standard parts NH90	3%	1.38	50.49	3%	2.88	73.54
Total	**100%**	**1.58**	**69.85**	**100%**	**3.74**	**181.28**

Table H.3: Population and sample group compared on platform

Product group	**Population**			**Sample**		
	Division	Rate	Size	Division	Rate	Size
NHI	13%	3.03	324	22%	5.07	552.97
Proprietary part	20%	1.05	4.266	14%	2.96	14.92
Standard part	41%	1.71	57.13	47%	3.54	112.47
Vendor part	27%	1.08	15.71	17%	3.25	36.44
Total	**100%**	**1.58**	**69.85**	**100%**	**3.74**	**181.28**

Table H.4: Population and sample group compared on product group

RNLAF	**Population**			**Sample**		
	Division	Rate	Size	Division	Rate	Size
No	76%	1.44	77.81	65%	3.81	234.43
Yes	24%	2.05	44.14	35%	3.60	81.65
Total	**100%**	**1.58**	**69.85**	**100%**	**3.74**	**181.28**

Table H.5: Population and sample group compared on RNLAF-part

Appendix I

Parameter settings case study scenarios

Variables	Realized	No delays	PO moment	PO size	IC changes	PO leadtime	SO rate	SO sizes	Mutations	Model
BO logic	Actual	FCFS	FCFS	FCFS	FCFS	FCFS	FCFS	FCFS	FCFS	FCFS
SO delay	Actual	No	No	No	No	No	No	No	No	No
BO delay	Actual	No	No	No	No	No	No	No	No	No
PO delay	Actual	No	No	No	No	No	No	No	No	No
PO moments	Actual	Actual	Policy	Policy	Policy	Policy	Policy	Policy	Policy	Policy
PO sizes	Actual	Actual	Actual	Policy	Policy	Policy	Policy	Policy	Policy	Policy
(s,S) policy	ERP	ERP	ERP	ERP	Model	Model	Model	Model	Model	Model
PO leadtime	Actual	Actual	Actual	Actual	Actual	Model	Model	Model	Model	Model
SO moments	Actual	Actual	Actual	Actual	Actual	Actual	Rate	Rate	Rate	Rate
SO sizes	Actual	Actual	Actual	Actual	Actual	Actual	Actual	Compound	Compound	Compound
Mutations	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
PO history	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
SO history	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Parts	Sim	Sim	Sim	Sim	Sim	Sim	Sim	Sim	Sim	Hist
Monte Carlo	No	No	No	No	No	No	Yes	Yes	Yes	Yes

Table I.1: Parameter settings of all case study scenarios

Appendix J

P-values for Wilcoxon rank-sum test

P-VALUES WILCOXON RANK-SUM OF LINE FILL RATE									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1	1.00	0.00	0.26	0.00	0.00	0.00	0.00	0.00	0.00
2	-	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	-	-	1.00	0.00	0.00	0.00	0.00	0.00	0.00
4	-	-	-	1.00	0.00	0.00	0.00	0.56	0.70
5	-	-	-	-	1.00	0.00	0.00	0.00	0.00
6	-	-	-	-	-	1.00	0.00	0.00	0.00
7	-	-	-	-	-	-	1.00	0.00	0.00
8	-	-	-	-	-	-	-	1.00	0.00
9	-	-	-	-	-	-	-	-	1.00
P-VALUES WILCOXON RANK-SUM OF ITEM FILL RATE									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1	1.00	0.65	0.00	0.00	0.00	0.25	0.79	0.27	0.00
2	-	1.00	0.00	0.00	0.00	0.18	0.81	0.29	0.00
3	-	-	1.00	0.00	0.00	0.00	0.00	0.03	0.00
4	-	-	-	1.00	0.00	0.00	0.00	0.00	0.00
5	-	-	-	-	1.00	0.00	0.00	0.04	0.00
6	-	-	-	-	-	1.00	0.71	0.48	0.00
7	-	-	-	-	-	-	1.00	0.04	0.00
8	-	-	-	-	-	-	-	1.00	0.00
9	-	-	-	-	-	-	-	-	1.00

Table J.1: P-values for Wilcon rank-sum test for item- and line fill rate per scenario

Appendix K

Inventory controller interview results on order sizes

The objective of interviewing inventory controllers is to determine reasons as to why more items are procured compared to the model suggestions. The presented table has grouped their answers based on commonality. The groups are then divided into smaller sub-groups presenting more specific reasons.

Main reason	**Subgroups**
Contractual obligations	Negotiation
Human resources	Non-continuous review | Vacations
Supplier insights	Faster lead times | MOQ | Discounts
Business environment	Increasing part prices | Change of supplier
Business strategy	Decrease in sales | Terminating sales of part
External	Recommendations management | Customer demands
Experience	Inventory behavior | Demand pattern | Demand origin | Policy interpretation | Market knowledge

Table K.1: Reasons to buy more items than policy suggests