MASTER

A decision rule for a periodic review inventory system with emergency ordering, demand lead times, and high demand variability

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A decision rule for a periodic review inventory system with emergency ordering, demand lead times, and high demand variability

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in partial fulfilment of the requirements for the degree of

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**PREFACE**

I proudly present my master thesis report as the final piece of work for my master studies Operations Management & Logistics at the Eindhoven University of Technology. This master thesis report is the final result of the time I spent researching an interesting and relevant topic at Sligro Food Group N.V. With the completion of this project I am looking back on not only a pleasant time working on the project, but also on my time as a student.

Without the help, support, and unconditional love of some people, I would not have been able to reach this moment. Therefore I want to take this opportunity to thank a few people.

First of all, I would like to thank my first university supervisor Rob Broekmeulen. Our sessions were always inspiring and I always left with more questions than answers. However, your guidance helped me in shaping, understanding, and solving the thesis’ problem. Additionally, I would like to thank my second university supervisor Karel van Donselaar. Your expertise on the topic and the useful feedback that you have provided helped me to further shape the thesis’ problem.

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I want to thank my boyfriend Robbert van Genuchten for his unconditional love and support in the last couple of years, and especially during this project. You were there for all the ups and downs and you were always able to lift my spirit. Without you this project would not have been here.

Also, I want to express my gratitude to my family, in particular my parents. You always wanted the best for me and you always encouraged me to get the best out of myself. You taught me to be critical on every decision that I made and through that I am very proud of everything that I have been able to achieve thus far. I am so grateful for providing me with everything I needed, to become the person I am today.

Finally, I would like to thank all of my friends that made my time as a student unforgettable. Because of you, I can look back at a period which has been filled with so many joyful memories. Special thanks to Hilde Weerts and Karlijn van den Hoogenhof for reviewing the final report.

*Renée Albers, July 2018*
ABSTRACT
This research aimed to find a solution for sudden surges in demand, or high demand variability, in the setting of a retailer that delivers orders from a regional warehouse. In this situation, demand is known for a certain time period, the customer orders with varying quantities, and the retailer aims to satisfy all orders. A model is designed with a decision rule that proactively recognizes a surge in demand that will disturb the regular inventory system and treat those surges in demand as emergency shipments. The intention is to receive the emergency replenishment within the demand lead time. The decision rule makes its decision based on the characteristics of the order; the cutoff order size and the demand lead time. A factorial design was performed to explore the behavior of the model. Results showed that a large reduction in the inventory level and costs can be achieved. An important insight was that the more the variability in the order sizes increased, the more the inventory and the costs could be reduced. Concluding, this research showed that surges in demand can be cost-efficiently managed by introducing an emergency option that is controlled by a decision rule based on the order size and demand lead time.
MANAGEMENT SUMMARY

PROBLEM INTRODUCTION
Sligro, a Dutch food wholesaler, experiences sudden surges in demand for their regional warehouses. This is caused by the customer that does not order with a fixed order pattern, but quantities can vary greatly between mutual orders. Sligro wishes to satisfy the complete demand of the customer delivered by the regional warehouse, as to prevent this high volume purchasing customer to deplete the stock in the regional outlets or the high volume purchasing customer going to a competitor. As a result, Sligro introduced all possible imaginable emergency shipments as last case scenarios in their supply chain to uphold their customer service targets. The emergency shipments are discouraged and unstandardized, but in reality used daily.

This thesis project therefore aims to provide more insight for Sligro in how to deal with the sudden surges in demand and finding a balance between regular and emergency replenishment. More generally, this research is aimed at finding a solution for surges in demand in the setting of a retailer that delivers orders from a regional warehouse. Demand is known for a certain time period, the customer orders with varying quantities, and the retailer aims to satisfy all orders. The main research question defined in this thesis is:

When and how can emergency ordering be beneficial to manage sudden surges in demand?

SOLUTION DESIGN
A model is designed with a decision rule that proactively recognizes a surge in demand that will disturb the regular inventory system and treat those surges in demand as emergency shipments. The intention is to receive the emergency replenishment within the demand lead time. The decision rule makes its decision based on the characteristics of the order; the cutoff order size and the demand lead time.

![Figure 1 Hypothetical erratic order pattern with cutoff order size](image)

The decision rule first classifies the orders as regular and irregular based on the cutoff order size. A visual representation of this distinction is shown in Figure 1, where the cutoff order size (at a potential level of 25) is shown for an order pattern. Figure 2 shows the actual distinction, where the left part represents the customer orders that should be satisfied by regular replenishments to the warehouse and the right part represents the customer orders that should be satisfied by emergency replenishments to the warehouse. After this
classification, the demand lead time decides for the orders classified as irregular whether the demand will be filled with the issue of an emergency replenishment or with either a proactive or reactive enlargement of the regular replenishment.

Figure 2 Representation of the separation of regular and irregular shipments

Figure 3 shows the simplified flow chart of the decision rule. If the order size is smaller than the cutoff order size, the demand is filled from stock when the demand lead time has passed. If there is not sufficient stock-on-hand, orders are (partially) backordered. If the order size is bigger than the cutoff order size, the demand lead time verifies whether an emergency replenishment is issued. When the demand lead time is smaller than the emergency lead time, the order is backordered. To minimize cost, the order is solved via regular replenishment by enlarging the next replenishment. When the demand lead time is larger than the emergency lead time, but also larger than the time to the next review moment plus the regular lead time, no emergency replenishment will be made. In that case, the size of the regular replenishment order closest to the due date is increased with the customer order size to minimize cost. However, when the demand lead time is larger than the emergency lead time and smaller than the time to the arrival of the next regular replenishment, an emergency replenishment is issued.

Figure 3 Simplified flow chart of the decision rule
The model was compared to another scenario: the basic model where all demand must be filed from stock and no emergency options are possible. Two different KPIs were introduced to verify the performance: 1) expected inventory on hand, and 2) expected cost.

RESULTS
A factorial design was performed to explore the behavior of the model. In general for each of the experiments a large reduction in the inventory level (on average 59%) and the expected costs (on average 70%) can be achieved compared to the basic scenario. An important insight was that the more the variability in the order sizes increased, the more the inventory and the costs could be reduced. However, these reductions will be lower in practice as not the full potential of the advance order information is used in the proposed model. Likewise, the proposed model performed better on costs when the average demand interval is high while the inventory level reduction stayed relatively stable under different arrival rates. Next to that, sensitivity analysis on the weight of the two compounding distributions showed that when relatively more sudden surges occur, the dual sourcing model is more of added value. Remarkable was that when only the first compounding distribution was used (which means that no sudden surges occur), the direct mode was not used. Customer satisfaction remained the same or slightly increased. On average, an increase of 1% in the fill rate is achieved. However, the distribution of backorders per order size shifted from dispersed over all order sizes to on or just below the cutoff order size.

Thus, the proposed model greatly reduces the inventory needed at the warehouse under scope. This means that scarce space can be better utilized and that investments on the expansion of the network are needed less quickly. Likewise, a consideration can be made between the customer satisfaction (in fill rates or in order rates) and the cost reduction. With current knowledge on inventory management achieving a higher service level is normally associated with very high costs. Using the proposed model, these associated costs could be controlled. The proposed model also provides more potential to manage the trend of customers increasingly ordering with shorter demand lead times and placing their orders later on the day.

RECOMMENDATIONS
The main recommendation for science is to see the effect on the model of when the demand lead time is used in a greater extent. The information on the customer orders that is present during the demand lead time could be used in the single sourcing model and the regular part of the dual sourcing model to proactively adjust for unforeseen surges in demand. Without using emergency options, already demand uncertainty can be decreased.

Additionally, the model should be compared to other models and scenarios, for instance scenarios that do not assume a FCFS policy or models already described and validated in literature. Further, the model considered in this thesis should be extended such that the customer order information is used to proactively adjust for unforeseen surges in demand for regular orders.

The main recommendation for Sligro and companies in similar situations is to investigate for which products the proposed model outperforms. When the proposed model is implemented, attention must be paid to the reduction of emergency set up cost, the shift of
storage and complexity in inventory management from the regional warehouses to suppliers, and the way changes in demand patterns are handled, e.g. promotions, trends.

**Relevance**

This thesis differs from the reviewed literature in that it does not assume that a possible backorder situation should be solved immediately with expediting, but that a certain demand lead time is given per order in which the system might be able to prevent the backorder situation. Moreover, the decision rule presented in this thesis is based on the characteristics of the order and not on the inventory position or inventory on hand. Additionally, this thesis considers an unexamined situation where the arrival of demand has been modelled by a combination of two compound Poisson processes as the customer varies in ordered quantities. Likewise, the use of a cutoff order size to determine the distinction between regular and emergency replenishments creates a rather simple but elegant method to exactly evaluate the proposed inventory system, while the examined literature has mainly focused on solving their systems with Markov models and dynamic programming. However, to the knowledge of the author, the proposed model has never been researched before. Last, the proposed model is applicable to a variety of sectors apart from the foodservice sector.

Next to the design of a new model with a unique position in literature, this research showed that surges in demand can be cost-efficiently managed by introducing an emergency option that is controlled by a decision rule based on the order size and demand lead time. By revealing this potential, the analysis and its possible impact for science/the industry becomes even more relevant.
LIST OF ABBREVIATIONS

ADI  := Average Demand Interval
B2B  := Business to Business
CDC  := Central Distribution Center
CV²  := Squared Coefficient of Variation
DC   := Distribution Center
DS   := Dual Sourcing model
EBITDA := Earnings Before Interest, Taxes, Depreciation and Amortization
FCFS := First Come, First Serve
FIFO := First In, First Out
IOQ  := Incremental Order Quantity
KPI  := Key Performance Indicator
MOQ  := Minimum Order Quantity
OOS  := Out Of Stock
PLOP := Paper Less Order Picking
PMF  := Probability Mass Function
CDF  := Cumulative Distribution Function
Sligro := Sligro Food Group N.V.
SS   := Single Sourcing Model

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1 Introduction

This chapter functions as the introduction to this master thesis performed for the completion of the master Operations Management & Logistics of the Technical University of Eindhoven. The master thesis is performed in cooperation with Sligro Food Group N.V., a leading wholesaler for professionals in food. This chapter provides the background information on Sligro Food Group N.V. and the problem definition. The problem definition consists of the problem context, the research questions, the scope, and the research design.

1.1 COMPANY DESCRIPTION

In this section an overview of the company at which the project took place is provided. The information is extracted from the 2016 Annual Report and the corporate website.

Sligro Food Group N.V. (called Sligro from here) was founded in 1935 as a wholesaler in margarine, fats, and oils. Through the years it has become one of the major players in the Dutch grocery retail business (B2C, Foodretail, or ‘at home’) and Dutch wholesale business (B2B, Foodservice, or ‘out of home’) serving food and food-related non-food products to both Dutch and Belgian customers. Among the customers are leisure facilities, caterers, company restaurants, gas stations, small and medium-sized enterprises, small-scale retail companies, and the institutional market. The (online) assortment includes dry groceries, vegetables, non-food, and cooled and frozen food items with varying degrees of perishability. The total number of different items that a customer can order is on average 75,000.

In the Dutch food retail market, Sligro is currently still represented with their 133 EMTÉ supermarkets, of which 30 are independently operated by franchisers. The market share in the food retail industry has been around 2.7% the last few years, but has declined to 2.6% in 2016. Recently, Jumbo and Coop have come to an agreement with Sligro to take over the EMTÉ supermarkets. The foodservice market is split into two parts: cash & carry and delivery-service. Sligro has 50 cash & carry outlets and 11 delivery-service outlets spread throughout the Netherlands. Sligro is the market leader in the foodservice industry with an increasing market share of 24.0% in 2016. Alongside these facilities, Sligro owns a few production facilities and has participations in some suppliers responsible for fresh products (the fresh partners). The organization is managed from the head office in Veghel. Recently, Sligro has made a deal with Heineken to take over all logistical activities in the Netherlands. Part of the takeover are 13 delivery service DCs of which 4 mainly function as small depots.

<table>
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<tr>
<td>Net Sales</td>
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<td>Gross margin</td>
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<td>EBITDA</td>
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<td>EBITDA/Net Sales (x € million)</td>
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<td>Net Profit</td>
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In 2016, net sales increased to € 2.8 billion while the net profit decreased with €8 million to € 73 million. A financial overview for the previous two years are stated in Table 1. The division of the net sales between the different parts of the organization can be found in Figure 4.

![Figure 4: Distribution of sales amongst the different facilities](image)

1.2 PROBLEM CONTEXT

On average Sligro offers 75,000 different products to customers. These products are offered in the cash & carry outlets, but for customers with high volume purchasing behavior a delivery service from the delivery-service outlets is offered. These high volume purchasing customers can order their products online and get their ordered products delivered the next day. This is advantageous for both Sligro and the high volume purchasing customer, since the high volume purchasing customer gets their products delivered and the stock in the cash & carry outlets is not completely depleted by high volume purchasing customers.

To facilitate the total assortment to the high volume purchasing customers within a day, regional delivery-service outlets have been introduced. However, due to restrictions in capacity and resources, Sligro is not able to keep all products on stock on the delivery-service outlets and to daily replenish all products within the delivery-service outlets. To still be able to deliver this fast and to provide this wide assortment, Sligro has designed their supply chain in such a way that the non-perishable fastmovers are kept on stock in the delivery service facilities and replenished regularly, perishables are cross docked from the fresh partners, and slowmovers are cross docked from a nearby service facility.

However, the mutual orders of a high volume purchasing customer can vary greatly in ordered products and in ordered product quantity, e.g. a caterer serving an one-off event. Due to this variability, Sligro claims to experience not only stochastic demand, where demand is not stable over time and is subject to fluctuations, but also demand that is subject to sudden peaks or drops. This makes forecasting challenging and in the case of a sudden peak too little is held on stock. This is troublesome considering Sligro wishes to be able to satisfy the complete demand of the high volume purchasing customer as to prevent the high volume purchasing customer to deplete the stock in the cash & carry outlet or the high volume purchasing customer going to a competitor.

As Sligro does not reserve stock, works on a first come-first serve basis, and products are not replenished daily, a surge in demand can cause a stock out and many normal-sized customer orders to be backordered until the next replenishment arrives. As a result, Sligro had to introduce emergency shipments from multiple different locations in their supply chain to uphold their customer service targets. Nowadays, almost all possible emergency options are used daily and interchangeably, resulting in an embroilment of product flows. Likewise,
during the years, the emergency shipment processes have changed under different management and have never been truly standardized. For those reasons, emergency shipments are expensive, error-prone, and discouraged but necessary.

Next to that, the delivery operation of recent years has been associated with returns that are declining in relative terms, and growth in sales has been accompanied by a similar rise in costs. In other words, there seem to be no economies of scale taking place. Moreover, Sligro experiences increased competition from supermarkets, such as Jumbo and Albert Heijn, who started operating a grocery delivery service. For Sligro it is hard to compete with the low-threshold order quantity, the flexible daily delivery and the customer service provided by these supermarkets. Likewise, recently Sligro has taken over all the logistical activities of Heineken, causing the volume of products that flow through their supply chain to increase abruptly.

As a result, Sligro is forced to take a critical look at their supply chain. In particular, Sligro is ambiguous and uncertain how to deal with the sudden surges in demand and how their supply chain should be adapted to it. Similarly, it is interested in finding the balance between emergency product flows and regular product flows and in creating oversight of the product flows within the company.

1.3 RESEARCH QUESTIONS

Based on the problem context, the research questions for this research are formulated. In order to achieve the primary goal of the research, the following main research question needs to be answered:

When and how can emergency ordering be beneficial to manage sudden surges in demand?

In order to be able to build the supporting knowledge to answer this main research question, the following research questions have been formulated:

1. To what extent are the sudden surges in demand experienced?
2. Based on what variables should the decision be made to use emergency ordering?
3. What are the relevant scenarios to investigate the impact of the decision rule?
4. How will the performance of the selected scenarios be analyzed?
5. How can a generic model be built to analyze the performance of the selected scenarios?
6. How do the scenarios perform on flexibility, responsiveness, uncertainty, costs, and customer service?
7. Which possible strategic implications can be deducted based on the gained insights?

The research questions above are marginally different from the research questions in the research proposal. The proposed topic described in the research proposal has been subject to refinement and has become more profound, resulting in the topic considered in this thesis. In comparison, more emphasis is placed on emergency ordering and a decision-making rule. To create clarity, the research questions have been adjusted accordingly.
1.4 Scope
Due to time limitations, this research focusses specifically on the delivery service DC’s of the foodservice sector of Sligro. This choice was based upon the fact that the delivery service DCs as well as the foodservice sector in general are the largest growing sectors for the Sligro. The 7 regular delivery service DCs will be taken into account, while the 3 open delivery service DCs (a combination of a delivery service DC and a cash & carry outlet), the delivery service DC van Hoeckel, and the delivery service DCs that once belonged to Heineken are not. The open delivery service DCs are not taken into account due to the combined storage of assortment and ordering process. Likewise, the delivery service DC van Hoeckel will not be taken into account as the assortment, clientele, and the logistical processes differ from the other delivery service DCs due to their specialization in healthcare clients. Moreover, this DC will soon be converted to a slowmovers DC. Last, as the logistical activities of Heineken have been recently taken over by Sligro, the delivery service DCs of Heineken have not yet been fully integrated into the supply chain of Sligro. No information is yet available on the demand, performance, or costs of these delivery service DCs. Likewise, the future of each delivery service DC has not yet been determined. For these reasons, the delivery service DCs of Heineken are not part of the scope.

Next to that, the items in scope are all products that are put in inventory at the delivery service DCs, where the demand for those items is subject to sudden surges.

1.5 Research Design
The research will be designed based upon the model of Mitroff et al. (1974), displayed in Figure 5. The model aims to solve the operations management problem in four phases; conceptualization, modeling, model solving, and implementation. As indicated by the arrows, this is often not a clearly defined path that completely follows a direct route. Rework, feedback and validation are an important part of quantitative modelling. The framework helps to make sure all steps in proper research are completed.

![Figure 5 Quantitative research model of Mitroff et al. (1974)](image_url)

The model ideally starts with a certain problem or question. This problem must first be scoped and stakeholders must be defined. Likewise, the goal and the relevance of the problem must be determined. After that, the first phase ‘conceptualization’ can be started. The conceptual model defines the problem in the most basic and broadest terms. The
conceptual model is then transformed in the phase ‘modelling’ into a scientific model such that it adds value to science. The scientific model is then solved, as to which a solution is obtained. The insights gained from the scientific model are then implemented in the real business problem. After modelling and testing through (partial) implementation has been performed, the results will be evaluated. The results are reflected upon academically and recommendations for future research that are detected in the process are acknowledged.

This master thesis will run through these steps, starting with the problem situation described in this chapter and the AS-IS situation described in part I. At that point, research question 1 can be answered. In Part II the conceptual model and subsequently the scientific model will be presented. In Chapter 6, the conceptual model will be created and research questions 2, 3, and 4 are answered. Thereafter, the quantitative model will be presented in Chapter 7, where research question 5 is answered. Model solving and implementation are done in Part III, where respectively the research questions 6 and 7 are answered. Moreover, the main research question will be reflected upon.
Part I – AS-IS Situation

This part describes the AS-IS situation of Sligro. First, it will introduce the food service supply chain of Sligro and the functions of the different facilities. Next, the policies and processes to supply the delivery service customer when all processes go as planned are explained. Subsequently, the policies and processes to supply the delivery service customer when an unforeseen out-of-stock situation occurs at the respective delivery service DCs are described. Last, the demand that occurs at the delivery service DCs is analyzed.

2 Supply Chain

The food service supply chain of Sligro Food Group N.V., as provided in Figure 6, consists of the wholesale outlets, the delivery service DCs, and a central distribution center (CDC). Note that the food service supply chain is only part of the larger supply chain of the entire company, as the supply chain (at this moment) also entails a food retail supply chain.

Percentages shown are estimates of sales during 2017 (in sales units)

![Figure 6 Flows in the foodservice supply chain](image)

Flows not shown are the transshipments between the food retail supply chain and the food service supply chain. Also, the flows concerning the delivery service DCs of Heineken are not included, as no estimates of these flows are available yet. Moreover, transshipments between outlets and/or delivery service DCs (being routed through the CDC) and return flows are not displayed. These flows are not relevant for this thesis, except for transshipments between outlets and delivery service DCs or between delivery service DCs. These transshipments are emergency transshipments and leaving them out makes Figure 6 more readable. The emergency transshipments will be further explained in Chapter 4. Note that Figure 6 considers 11 delivery service DCs while only 7 of them are in scope.

2.1 CDC

The central distribution center (CDC) is a combination of a central expedition platform to receive all products and five different storage locations for bulk, fresh, frozen, food and non-food products. All these facilities are located closely to each other in Veghel and are perceived as one location by Sligro Food Group N.V. In reality, trucks may drive to multiple facilities of the CDC to pick up or deliver products.
The main function of the CDC is to temporarily store large amounts of products to achieve economies of scale. With ordering large quantities, gains can be made in inbound handling costs and discounts from the supplier can be achieved due to more efficient transportation. Moreover, risk over the supplier lead times can be pooled. A drawback is that the total lead time to the customer is longer than direct delivery to the local warehouse.

2.2 Delivery Service DCs

The delivery service distribution centers are local warehouses where orders are prepared for delivery. The orders can be gathered either through picking the articles that are stored locally, through the dedicated pick-to-zero zones, or through cross dock delivery from other (supplier) facilities. An example of a cross dock delivery from a facility is the service stream from a service store, explained more in detail in subsection 3.4.2.

The delivery service DCs decrease the distance towards the customer, thus decreasing last mile transportation costs as well as adding the ability to quickly respond to demand. Moreover, knowledge about local factors and events can be used to better respond to the needs of the customer. Further, due to the dedicated DCs for delivery, the volumes handled can be larger and more scalable compared to when operating from the wholesale outlets.

Sligro Food Group N.V. operates 24 delivery service DCs of which 13 are DCs recently taken over from Heineken and not yet integrated in the supply chain, 3 are open delivery service DCs, 1 is a delivery service DC dedicated to the healthcare industry, and 7 are regular delivery service DCs. Note that only the 7 regular delivery service DCs are part of the scope. Specific descriptions of the delivery service DCs out of scope is given in Appendix A.

2.3 Wholesale Outlets

The wholesale outlets are local cash & carry outlets where customers can visit and buy products. Every outlet offers a national and complete assortment supplemented with regional products. Sligro Food Group N.V. operates 50 wholesale outlets, of which 3 also operate as service stores.

2.3.1 Service Stores

Service stores are wholesale outlets where, after closing time for regular customers, orders are picked within the outlet containing products that are not part of the assortment of a delivery service DC, but are still ordered by the delivery service customer. This construction is designed to offer a wider assortment. Likewise, products are picked that are part of the assortment of a delivery service DC but at the moment are out-of-stock (OOS) at that particular delivery service DC. Items picked are mainly slowmovers. As Figure 6 shows, this flow constitutes about 2% of sales volume that passes through a delivery store DC.

Each delivery service DC is assigned to one of the three service stores. The delivery service DCs are assigned based on the proximity of the service store, to be able to deliver the missing items as fast as possible. The choice to assign service stores permanently to a delivery service DCs has been based upon the benefits of having a fixed daily transportation schedule and easier planning. Because of this construction, delivery service customers are enabled to order the whole assortment until the cut-off time at 23:00. Moreover, out-of-stock probability towards the delivery service customer is reduced and thus higher fill rates can be achieved.
Further, the inventory of slowmovers has been pooled into three locations instead of eleven, lowering the total inventory investment. Also, the wholesale outlet experiences more rotation and volume in their assortment, enabling them to offer more fresh products and a better store presentation. However, it often occurs that store shelves are completely depleted during the picking process, leaving the outlet customer with empty hands the next day.

3 Regular replenishment
This chapter covers the policies and processes to supply the customer from a delivery service DC when all processes go as planned. These policies and processes can be divided into five parts; ordering, inventory control, storing, order picking, and delivery.

3.1 ORDERING
Customers are able to place their orders online, via fax, or via telephone every day until the cut-off time of 23:00. When the threshold quantity of €230 euro for one drop is achieved regularly, customers have the possibility to have it delivered the next day (or later, but not on Sundays). Exceptions exist to this threshold quantity, e.g. when other locations of the client do achieve the threshold quantity but a certain location does not.

3.2 INVENTORY CONTROL
As discussed in section 2.2, orders arriving at the delivery service DC can be gathered either through picking the articles that are stored locally, through the dedicated pick-to-zero zones, or through cross dock delivery from other (supplier) facilities. The inventory of the articles that are stored locally is controlled by a single echelon forecast-driven approach. Even though the current inventory management practices in the fulfilment supply chain were already explained by Van Pelt (2014) and Van Eijden (2015) a quick summary is provided in this section. First, the inventory control policies per type of facility will be explained. Subsequently, the review period, lead times, base replenishment quantities, service level, and assortment of the delivery service DCs will be explained.

Delivery service DC
The inventory control policy at the delivery service DC uses an automated ordering system, also called ABS in short. To control the inventory levels, an in-house built software program is used that assumes non-stationary demand and sets the order-up-to levels according to a demand forecast. Demand forecasts are generated per item and per day based on final customer demand from the previous six weeks, excluding any days during which the item was on a promotion. This is also called a six-week moving average forecast. The inventory positions (on hand inventory minus backorders) of the articles are reviewed periodically. When at a review moment \( R \) the inventory position is below the reorder level \( s \), a replenishment order is made. The size of this replenishment order is equal to the forecasted demand needed until the next review moment. Likewise, the size of the replenishment order is rounded up to the nearest multiple of the base replenishment quantity \( Q \). Minimum reorder levels are manually set according to rules of thumb and are different per item category. The value of the minimum reorder levels are set equal to a certain number of weeks of expected average sales, where in general this number is two weeks. As such, the inventory control policy used by the delivery service DCs can be described as a \( (R,s,nQ) \) policy, although the base replenishment quantities to the CDC are not strict.
CDC
A large part of the articles stocked in the delivery service DC are replenished from the CDC. The CDC also uses an automated ordering system to replenish their inventory. Although the CDC also replenishes their inventories periodically, the CDC uses a different system to control the inventory levels; the software program SLIM4. The forecast of demand is based on the observed demand over the previous 24 months and allows for trends and seasonality patterns. Exponential smoothing ($\alpha=0.2$) is used to create the monthly sales forecast for the upcoming year. The inventory positions of the articles are also reviewed periodically. Whenever an inventory position is below the reorder level, an order is created. The size of the order is then based on the forecasted demand needed until the next review moment, the minimum order quantities and incremental order quantities and an order-up-to level ($S$). The desired order-up-to-level is determined by combining the reorder level with possible additional buffers to protect against supplier reliability and demand variability. While the inventory control policy can be described as a ($R, s, S$) policy with $MOQ = S - s + 1$, the inventory control policy can be better classified as a ($R, s, nQ$) policy due to the many restrictions regarding the final base replenishment quantities. Note that the forecasted demand of the CDC does not base its decisions on the customer demand arriving at the delivery service DCs. In other words, there is no integrated inventory management approach in the supply chain of Sligro. Van Pelt (2014) showed that enabling this integrated inventory management approach would potentially greatly reduce the inventory levels at the CDC while maintaining the same fill rates at the delivery service DCs. Up until now, Sligro has not been able to implement this.

Service store
A small part of the articles routed through the delivery service DC originates from the service store. The inventory control system of the service stores is the same as for a delivery service DC.

3.2.1 REVIEW PERIOD
The review periods for the different articles stocked in the delivery service DCs are not the same for all articles. The review periods for the articles replenished from the CDC are set per product category. The main objective of this is to achieve a stable workload for the order picking process at the CDC. This means that certain delivery service DCs are not allowed to order a certain product category on Mondays while other delivery service DCs can. To achieve this rotation schedule, periodically a negotiation round is held between the CDC and the delivery service DCs during which the settings of the review periods are evaluated and adjusted. The review period for any item delivered from the CDC is minimally once per week and maximally five times a week. Note that no orders can be placed on Saturdays and Sundays as the CDC does not operate on these days. The review periods for placing orders at outside suppliers are mostly set on daily as the direct suppliers mainly supply products with a critical shelf life. The review periods for the other outside suppliers are rather set on gut feeling.

3.2.2 LEAD TIME
The lead time of replenishment orders from the CDC to the delivery service DC is in general two operating days after an order is placed. However, as the CDC does not operate in the weekends, the lead time can increase. Replenishment orders ordered on Monday to
Wednesday are supplied two operating days later. For orders placed on Thursday or Friday, replenishment will arrive after the weekend, respectively on Monday and Tuesday the next week. In conclusion, lead times from the CDC are either 2 or 3 days, depending on the day of placing the replenishment order.

The lead time of replenishment orders from outside suppliers is dependent on the supplier. The lead time per supplier is agreed upon in cooperation between Sligro and the outside supplier.

3.2.3 Base Replenishment Quantities
The base replenishment quantities for the products sourced from the CDC are set manually. The decision as to what value the base replenishment quantity should be, is based on gut feeling where at the same time cost minimization is taken into account. For instance, too high base replenishment quantities can lead to unnecessary high inventory levels, capacity issues and possibly more inventory shrinkage and outdating.

Van Eijden (2015) analyzed the values of the base replenishment quantities of 476 different items. It was found that around 50% of all items had a base replenishment quantity set identical to either one case pack, a pallet layer or a full mono pallet. 39% of the items were set equal to a multiple of a case pack, pallet layer, or full mono pallet. Another 4% of items were set equal to one sales unit and 3% of the items did not have a value, but are automatically processed as equal to one sales unit as well. However, the last 4% of items are set to a value larger than one but not related to a case pack, pallet layer or a full mono pallet. The settings of these items seem rather illogical and cause very inefficient picking as the order picker will have to either break open a case pack and/or put another pallet on top of the pallet layer to continue picking. This is very time consuming and increases the risk of damage. Van Eijden (2015) recommended creating decision-support for setting the optimal base replenishment quantities. Unfortunately, up to now, this has not been created yet.

3.2.4 Service Level
The delivery service DC aims to deliver all customer orders on time and complete, however due to various reasons this is not always possible. When an out-of-stock situation occurs, procedures described in Chapter 4 are executed. Sligro defines the service level as the fraction of demand delivered directly from stock or from a cross-dock flow, which is commonly known as the (P2) fill rate measure. This also includes the substitute articles that have been accepted because of an out-of-stock situation. The target service level is currently set on 98% in total for all items, although the goal for 2020 is to have a target service level of 98% for each item.

3.2.5 Assortment
The assortments kept by each of the seven delivery service DC’s on stock are not identical. The difference in the assortment of the delivery service DCs is caused by the following factors:

- demand patterns observed in the region
- so-called national accounts, or client-only inventory
- direct deliveries from suppliers
- available space in the delivery service DC
Demand patterns
The rule of thumb for including a certain item in the assortment of a delivery service DC is when the demand for an item exceeds two sales units per week on average. Due to regional differences, the demand pattern of certain items may exceed this cutoff in a certain region and cause these items to be included in the assortment where in other regions the cutoff might not be achieved and thus sourced from the service store. However, there are some exceptions to this rule of thumb, as the inventory turnover ratio for a specific item may drop significantly at the service store due to the inclusion in the delivery service DC and thus the freshness to the customers of the service store cannot be guaranteed. Apart from this rule of thumb, some items might only be demanded in specific regions and therefore only locally supplied by regional suppliers. Due to the reasons described above, the assortment is not fixed and subject to continuous changes.

National accounts
Some items are exclusively admitted to the assortment to supply to a certain customer. Likewise, in some cases, customers outsource the distribution operation and put away their entire inventory in the delivery service DCs of Sligro. Depending on the regions where these clients operate, the assortment of these delivery service DCs needs to be adjusted to be able to supply these exclusive items. This inventory is called client-only, sometimes referred to as national account.

Direct deliveries
Some (regional) suppliers deliver directly to the delivery service DC, instead of via the CDC, as for certain products such a high volume is obtained that it makes more sense to skip the CDC echelon. However, these suppliers might as well deliver products with low sales volume along with the high volume products to reduce the number of deliveries needed in total to Sligro. For example, it is possible that a delivery to the CDC is avoided because of this construction. Therefore, these low sales value products are admitted to the assortment as well.

Available space
The amount of space that is available to store the assortment is different for each delivery service DC. Depending on the customer base and the size of the warehouse, each delivery service DC has different strategies to fill their warehouse with stock. In general, the assortment of a delivery service DC can be larger as there is more space available. When there is lack of space, the items will be sourced from the service store even though including these items in their assortment is preferred.

3.3 Storing
Once the replenishment is delivered to the delivery service DCs, the process of storing will start. This process has been described in detail by Van Eijden (2015) and a small summary will be given here.

Before the replenishment can be stored, the freight should be ordered and organized. The replenishment normally consist of three different categories: mixed pallets, pallets with different pallet layers, and full pallets. Mixed pallets are heterogeneous pallets with multiple
products stacked in an arbitrary way without any extra pallets in between to sort the different products. These pallets are mostly created when orders for products were placed in an amount unequal to the quantity that fits on pallet layers or on a full mono pallet. For both mixed pallets and pallets with different pallet layers, the step of ordering and organizing is of importance. The pallet layers or different order lines on the mixed pallet need to be stacked separately on their own pallets. For pallet layers this process is rather efficient, but for a mixed pallet each handling unit needs to be moved by hand in a FIFO manner. Because of this, a mixed pallet is seen as a labor intensive activity.

Subsequently, the pallet with a single product is brought to the pick location of that specific product. When this pick location is (almost) depleted and no other stock with a shorter remaining shelf life is present in the delivery service DC, the pallet is placed in the pick location. If not, the pallet is put into a bulk location. When the pick location becomes depleted an arbitrary moment later, a notification is sent to inbound to replenish the pick location on short notice with a pallet from a bulk location. Inbound will search for a pallet in the bulk location with the shortest remaining shelf life and replenish the pick location of this products.

3.4 ORDER PICKING

During the day, orders are picked that should be delivered at the customer the next day. When customers place their order for a date later than the next day, this order will be put on hold until it should be delivered the next day. Only then the order will be gathered. Hence, no stock reservations are made.

The picking process can only start after a planner first takes the replenishment orders placed by the customer and combines them to create picking orders per picking area. The picking orders can be combined on several different ways, e.g. per customer or per article. The combination of picking orders is dependent on the situation and the time left to pick.

Once the picking orders are created, they can be picked by order pickers who travel by electric pick carts through the different picking areas. The electric pick cart can carry three containers, hence it is possible to create batches of three container in total to minimize the total navigation time per picking order. The picking process is largely automated by a PLOP system (Paperless Order Picking system). The PLOP system uses the Pick-to-light system to navigate the order pickers. The system directs the picker to the pick location of a product that needs to be picked. The cart contains lights above the containers and will illuminate the specific containers that require this product. The quantity to pick will be indicated per container as well. To confirm a pick, the order picker needs to press the indicator of the specific container after retrieving the required units from the pick location and putting them in the container. The route of the order picker through the picking area (and the pick locations in the delivery service DC) is organized in such a way that heavy items are picked first, but also that navigation time is minimized.

There are some exceptions to this picking process. A small part of the order picking process is not done via the Pick-to-light system, but via paper. This is mainly done for rapidly changing assortment where creating a pick location via the system needs more time and money than picking the products via paper. Likewise, a part of the order picking process is
done via a Pick-to-zero methodology and outside of the PLOP system. Pick-to-zero is used for items with a critical shelf life that are delivered daily fresh to the delivery service DC. The pick-to-zero methodology means that the supplier exactly supplies the amounts that were ordered in total for the next day and that because of this at the end of the day no inventory remains at the delivery service DC. While this methodology is technically possible with the aid of the PLOP system, this process is done by hand by Sligro.

As the delivery service DC is supplied by outside suppliers, the CDC, and the service store, picking processes take place there as well. For the last two, the picking process will be explained shortly.

3.4.1 CDC
Delivery service DCs are able to place their replenishment orders from Monday to Friday until 22:00h. The next day, the CDC will pick the replenishment orders, such that the day after the replenishment order can be delivered at the delivery service DC in the early morning. The order picking process of the CDC is described in detail in Van Eijden (2015) and will be explained shortly in this subsection.

The picking process of the CDC is similar to the picking process of the delivery service DC. The PLOP system in combination with the Pick-to-light system is used for the large part of all replenishment orders as well. However, the order pick cart can only contain two pallets. The picking orders are based on the different areas in the CDC and the combination of ordered products that create a full pallet. Next to the Pick-to-light system, the Pick-to-zero methodology is used as well for items with a critical shelf life. Last, a put-to-light methodology is used for items that will be on promotion. This methodology is performed by designating an area with locations that represent the delivery service DCs and the cash & carry outlets and distributing pallets of the promotion items accordingly to those locations based on the illuminating lights and displays belonging to those locations.

3.4.2 Service Store
The service store picks the needed products in the cash & carry outlet per zone. These zones are mainly based on the different areas in the store, such as dry, cooled, and frozen food products as well as non-food products. For all food products, the products are picked by the PLOP system and Pick-to-light system as well. However, now the pick cart contains 20 different crates for which each crate represent a customer order. The crates are later divided per delivery service DC. For non-food products, the products are picked by paper and by hand. All needed products are taken together and gathered in the specific area and subsequently all gathered products are divided into crates specific for that customer.

As the locations of the products change regularly in the store, picking in the cash & carry outlet is time-consuming, a large part of the order picking is done by hand and therefore very error prone, and order pickers have to take into account that the store representation is maintained, this process is a very expensive and inefficient flow.
3.5 Delivery

When all orders have been picked and have been brought to the loading dock, delivery to the customer can start. As soon as a truck is allocated to a route and to a driver, the truck is put on the dock and the driver loads the truck with the freight allocated to that route. As there is a limited capacity of docks and not all freight fits on the loading docks, a number of waves have been set up to specify when trucks leave. Due to this construction, efficient use of docks is achieved and the operation is able to efficiently collect and prioritize the freight needed per wave. These waves are between 02:00h and 06:45h in the morning. Most cross-dock flows arrive before and around 03:00h in the morning, so a few trucks already have departed at the time a cross-dock flow arrives. Some trucks also leave in the afternoon; a driver then has two (smaller) routes a day and has already returned from the first route.

When the driver arrives at the customer, the driver transfers the freight of the customer in the truck to the facility of the customer. After that, the driver loads the empty crates, containers, and other packaging used in previous deliveries in the truck. Last, the driver notes the arrival and departure time at the customer, the mileage, the times of loading and unloading of the truck, the temperature of the cooling and freezer section of the truck, and the amount of empty packaging loaded in the truck in a portable computer.

4 Irregular replenishment

This chapter covers the policies and processes to supply the customer from a delivery service DC when an unforeseen out-of-stock situation occurs or will occur at the respective delivery service DCs.

Due to the choice to extend the review period of the different product categories to minimize the handling time at the CDC as well as a limited capacity in storage space, the delivery service DC is less flexible in solving variability in demand. Therefore, an unforeseen out-of-stock situation can occur because of multiple reasons:

- Seasonal influences that spike the demand for a certain product
- Temporarily not-deliverable products due to problems with the product or supplier
- Customers that organize a large event and did not notify Sligro beforehand
- Customers that change their normal order pattern and did not notify Sligro beforehand (especially for products that are included especially for them in the assortment)
- Surge in demand, not particularly related to a certain customer
- Articles that are being phased out, but the replacement article is not yet available
- Bad practices of the stock manager; e.g. not paying attention, or being influenced by operational requests (e.g. few personnel present to process the incoming goods) that causes them to order less, but eventually causes an out-of-stock situation

When the inventory of a product at the delivery service DC has been depleted and an order for this product arrives, then automatically the order will be redirected to the assigned service store. However, when the inventory of this item at the assigned service store has been depleted as well, or when the needed quantity of that item is more than 75% of the total inventory of that item in the assigned service store, the order will be taken out of the system and put in a problem basket (in dutch: de KB bak). This problem basket is continuously
reviewed by the customer service departments. The customer service department will call
the customer to discuss the out-of-stock situation and to inform whether the customer might
be interested in a substitute article or a different delivery date. If the customer is not
interested in an alternative article, a consideration is made to use an emergency procedure.
Depending on the delivery date and the associated cost, a specific emergency procedure is
used. The inventory management and customer service department collaborate with each
other to make the emergency procedure happen. On average, when customers are not
interested in substitute articles and the products are not needed right away, a new delivery
date can be agreed upon. The new delivery date can either be achieved by regular
replenishment or by the use of emergency procedures. Thus, for these cases backorders are
observed. However, in some cases a lost sales situation is observed.

The use of emergency procedures is discouraged, as the emergency shipments are not
standardized, more costly, and more prone to errors. Due to this, the customer service
department is also not able to ensure the customer that the emergency shipment will arrive
as planned and thus that the customer will receive his products on time. Likewise, using
many emergency shipments is seen as a signal that the inventory management department
of that specific delivery service DC does not control the situation. Because of this, the
inventory management is fixed on making sure that almost all orders are solved from stock,
resulting in high stock levels. However, in the end the customer is king for Sligro and almost
all shortages are solved with emergency procedures. Especially customers that have been
disappointed in the past, new customers, customers with tight customer service agreements,
and important customers for Sligro are being favored. On the other hand, it is a strong
believe by many employees that the customers should be educated to order on time.

The different emergency procedures possible are:
- Emergency shipment from the assigned service store
- Emergency shipment from the central distribution center (CDC)
- Emergency shipment from surrounding cash & carry outlets
- Emergency shipment from various Sligro facilities using a courier
- Emergency shipment from an outside supplier

The different emergency procedures are ordered in the number of times used (and quantity
needed), where an emergency shipment from the assigned service store is most used (and
with largest volume) and an emergency shipment from a supplier is least used. The number
of times that a specific emergency procedure is used depends on the specific customer base
that a delivery service DC has. In the rest of this chapter, these emergency procedures are
explained in more detail.

4.1 EMERGENCY SHIPMENT FROM THE ASSIGNED SERVICE STORE

As explained above, automatically shortages of stock in the delivery service DC are sent to
the assigned service store. These missing products are gathered together with the regular
orders from the delivery service DC meant for the service store (as assortment expansion).
The missing products are then cross-docked daily to the delivery service DC and
immediately available for delivery. It is advantageous that this emergency option makes use
of an already built-in flow. However, the orders gathered in the service store are already
relatively expensive.
Around 25% of the complete flow between the service store and the delivery service DC shown in Figure 6 is due to out-of-stock situations. To minimize the automatic flow to the service store for out-of-stock situations, the delivery service DCs evaluate weekly which products most frequently use this emergency procedure and adapt their inventory control settings to it.

4.2 EMERGENCY SHIPMENT FROM THE CDC

An emergency shipment from the CDC is a widely used emergency option. On average between 2 and 12 pallets each day per delivery service DC are needed to fulfill the needed products. This emergency shipment is only suitable when the product is not needed urgently, as the products are only available for picking at the delivery service DC the next day. Likewise, this emergency shipment is also suitable for all volume sizes. The daily emergency order from a specific delivery service DC contains multiple articles. The need for this articles may be based on shortages in stock, expected shortages in stock, backorders of previous days, or shortages of products in orders that have arrived before the deadline. The order size of the emergency articles is based on an efficient quantity to transfer (e.g. a full pallet layer).

Each day the delivery service DCs have the possibility to place an emergency shipment for multiple products at the CDC. This is only for the product groups that are not open for ordering regular replenishment that day for the specific delivery service DC. This emergency shipment has to be placed before the deadline specified for the delivery service DC (between 10:00h and 12:00h). After this, the emergency orders are evaluated and entered manually. In general all requested products are approved if sufficient stock is available. Next, the emergency orders are picked and put next to the freight meant for regular replenishment to the delivery service DCs. An indication on the pallet may or may not be given that this pallet represents an emergency order. When the truck for regular replenishment is being loaded, priority is given to the pallets containing emergency orders. However, there might be multiple trucks heading towards the same delivery service DC for replenishment on different times and it is unknown for the delivery service DC which truck will contain the pallets with emergency orders. It is also possible that the orders are all gathered too late and all trucks may already have left. In that case, the pallets containing emergency orders are delivered the next day. Last, when arriving at the delivery service DC, the pallets containing emergency orders are put in stock the same way as the regular replenishment.

While this emergency option only adds a few extra costs, this process has a lot of downsides. The whole process is outside of the normal system and thus almost no information exchange takes place. It often happens that pallets containing emergency orders are forgotten, are lost, are not recognized as emergency shipment, or are ready for transport after the last truck has left. This leaves the inventory management departments of the delivery service DCs in doubt whether the products will come and when they will come. It is difficult to communicate this doubt to the customer and a too late delivery might mean that the customer doesn’t need the product anymore. Likewise, when the emergency order contains products that are normally not stocked in the delivery service DC, the inbound of the delivery service DC needs to turn especially to the inventory management department to inform about those products. Likewise, as large volumes are allowed, it is possible that the complete stock
available at the CDC is used for an emergency order and the central inventory management department is confronted with an unforeseen stock-out for regular replenishments after that. Aside from that, the inventory managers often have the tendency to overreact and order more than needed. On top of that, each emergency order is a violation on the forecast and inventory administration of the CDC as well as of the delivery service DC. Last, the procedure leaves room for misuse, e.g. not ordering regular replenishment of a product until a more favorable best before date is available and then quickly replenishing the product with an emergency order.

4.3 **EMERGENCY SHIPMENT FROM SURROUNDING CASH & CARRY OUTLETS**

An emergency shipment from surrounding cash & carry outlets can be done in two different ways; using the return flow of a regular replenishment or via a service sprinter. Note that the assigned service store is also a surrounding cash & carry outlet.

4.3.1 **RETURN FLOW OF A REGULAR REPLENISHMENT**

Milk, fries, and tobacco are products that need to be daily replenished to all regional facilities. The supply chain has been designed that these products are daily delivered fresh from outside suppliers to the delivery service DCs. To have these products in the surrounding cash & carry outlets, the products are sourced from the delivery service DCs to the outlets once a day. As these deliveries are made daily and the truck is empty on the way back to the delivery service DC, this return flow can be used to transfer the necessary products. However, this emergency option can only be used when the delivery of the fresh products has not been made yet, the missing products are on stock, and an employee is able to prepare the items for transmission. This is a relatively cheap emergency option that is used daily by delivery service DCs.

4.3.2 **SERVICE SPRINTER**

The service sprinter is a small van owned by a cash & carry outlet. The service sprinter can deliver missing products from the stock of the cash & carry outlet to the delivery service DC or directly to the client. This emergency option is less expensive than the courier, however is less used. This is because not all cash & carry outlets own a service sprinter, the specific cash & carry outlet should have the missing products on stock, and personnel of the cash & carry outlet is ripped from their daily operations to deliver the products. The service sprinter is fast and makes delivery for the same day possible and is most suited for relatively small sizes of volume. This option is used on average once a day, but differs greatly between delivery service DCs (depending on how many service sprinters are in the neighborhood).

4.4 **EMERGENCY SHIPMENT USING A COURIER**

A courier can be used to collect the missing products from other facilities and deliver these to the delivery service DC or even directly to the client. The courier can go to any of the facilities of Sligro where stock of this product is available; all delivery service DCs, all cash & carry outlets, all service stores, and the CDC. This emergency option is used on average 2-3 times a day per delivery service DC. Like the service sprinter, a courier is fast and is most suited for relatively small sizes of volume, as a courier often only has the size of a van. Moreover, as long as the facility, where the stock is held, is open, this emergency option can be used (so also during the night). However, using a courier is expensive.
4.5 Emergency Shipment From an Outside Supplier

Shipments from an outside supplier is an emergency procedure that is hardly ever used; about once a month. In general, only suppliers that already deliver directly to the delivery service DC are willing to make an extra shipment. Through this, the usage of this emergency procedure is dependent on the number of direct suppliers a specific delivery service DC has.

Outside suppliers are commonly only willing to make an extra delivery when a high volume of products is asked. Next to that, outside suppliers often charge high costs to deliver an extra supply and this only makes it profitable when high volumes are necessary. Additionally, the outside supplier should be willing to deviate from their normal production schedule. In most cases, relatively small suppliers are more flexible as more revenue is welcomed. Apart from this, a willing outside supplier generally delivers the emergency shipment within a day.

5 Demand

This chapter analyzes the demand that arrives at the delivery service DCs. In the first section, the accumulation of demand is examined. A comparison is made with the accumulation of demand in 2014. In the second section, it is verified to what extent Sligro experiences sudden surges in demand. This chapter will answer the first research question: ‘To what extent is dynamic and stochastic demand experienced?’.

5.1 Demand Accumulation

The customers can place orders online every day, and have the option to have it delivered already the next day (or later, but not on Sundays). Data analysis over January 2018 showed that about 62% of all orders needed to be delivered the next day, 13% of all orders needed to be delivered in two days, and the remaining 25% had longer customer lead times. Compared to January 2014, where the ratio was respectively 50%, 15%, and 35% (Van Eijden, 2015), more customers prefer shorter customer lead times.

Since the cut-off time is at 23:00, some orders need to be ready within hours because the first trucks commence their routes already between 02:00 and 06:00 six days a week. The majority of orders however, 72%, are received before 16:00. Also in terms of sales, 79% of sales units is roughly ordered before 16:00 each day. Compared to January 2014, the majority of orders that are received before 16:00 has declined from 80% to 72%, while the percentage of sales units ordered before 16:00 each day has remained roughly the same (Van Eijden, 2015).

Appendix A shows an overview of how different orders accumulated over the month January in 2018. A distinction is made between the accumulation of orders with all customer lead times, one day customer lead time, two days customer lead time, and longer customer lead times. What one can deduct from the graphs is that customers that order with one day customer lead time on average order later in the day, that on average the largest orders have a customer lead time longer than two days, as well as that large orders for all customer lead times are mainly made early in the day.
5.2 DEMAND CLASSIFICATION

To be able to classify the demand patterns of the different products of Sligro, the framework of Syntetos (2001) is used. The framework of Syntetos (2001) categorizes demand patterns by determining the characteristics of a demand history with two coefficients:

- **Average demand interval (ADI)**, which measures the regularity of a demand in time by computing the average interval between two demands.
- **Square of the Coefficient of Variation (CV²)**, which measures the variation in the demand quantities.

Based on these two dimensions, Syntetos (2001) classifies the demand profiles in four different categories:

- **Smooth demand** (ADI<1.32 and CV²<0.49): The demand is very regular in time and in quantity
- **Intermittent demand** (ADI>=1.32 and CV²<0.49): The demand shows very little variation in demand quantity but a high variation in the interval between two demands
- **Erratic demand** (ADI<1.32 and CV²>=0.49): The demand has regular occurrences in time with high quantity variations
- **Lumpy demand** (ADI>=1.32 and CV²>=0.49): The demand is characterized by a large variation in the quantity of demand and in the interval between two demands

The categorization rules are based on algebraic comparisons of mean square error expressions, and later rigorously checked via simulation on theoretically generated demand data and via a large sample of empirical data. Figure 7 shows a representation of the four different categories with possible demand histories.

*Figure 7 Framework of demand patterns by Syntetos (2001) Source: (FREPPLE, 2017)*
To examine the extent in which Sligro experiences sudden peaks and drops in demand, this thesis is mainly interested in the number of products in the categories ‘lumpy’ and ‘erratic’ as the variability in demand quantity in these categories is high. Figure 8 shows the categorization of the demand patterns of all products from Sligro. From Figure 8 can be derived that 39% (14% erratic and 25% lumpy) of the products experience a high variability in demand quantity. The classification of the demand histories of all products of Sligro has been based on the weekly demand (excluding promotions) of all delivery DCs of the years 2015, 2016, and 2017. Note that the variability in demand timing and demand quantity might be higher when using daily demand. Unfortunately, this information was not available.

To further visualize the erratic and lumpy demand of Sligro, Figure 9 shows the demand history of a product in March 2018 with an erratic demand pattern ($CV^2 = 0.63, ADI = 1.19$). This product is a package of four yoghurts (90 grams) with a banana and strawberry flavor. Moreover, Figure 10 shows the demand history of a product in March 2018 with a lumpy demand pattern ($CV^2 = 0.99, ADI = 1.85$). This product is mushroom soup (1L).

In conclusion, this section shows that Sligro experiences sudden surges and drops in demand. In particular, a large share of the products (39%) that Sligro offers, experience a high variability in demand quantity. This answers the first research question: ‘To what extent is dynamic and stochastic demand experienced?’.
Figure 10 Visualization of a lumpy demand pattern at Sligro
Part II – Solution design

This part describes the solution design of this thesis. The problem context is transformed into a conceptual model in Chapter 6. Scenarios for comparison and KPIs are introduced. Likewise, the position in and addition to literature is determined. An answer for the second, third, and fourth research question is provided. Further, in Chapter 7 the expressions will be given to solve the chosen scenarios and the fifth research question is answered.

6 Conceptual model

In this thesis, the generalized version of the problem context is considered. Thus, the conceptual model considers a retailer that delivers orders from a regional warehouse. Due to the online nature of the business, demand is known for a certain time period before it has to leave the warehouse. The customer does not order with a fixed order pattern as quantities can vary greatly between mutual orders. As a consequence, the warehouse experiences sudden surges in demand. However, the retailer aims to satisfy all orders, also the extremely large orders.

The aim is to find a solution of how to best cope with the sudden surges in demand. The sudden surges in demand can also be described as that the demand pattern has a high variability in demand quantity. A high variability in demand quantity makes forecasting very challenging and maintaining low cost as well as a high service level difficult. In Chapter 5, the framework of Syntetos (2001) is introduced to categorize the demand patterns. This categorization is based on the characteristics of the demand history with two coefficients: Average demand interval (ADI), which measures the regularity of a demand in time, and Square of the Coefficient of Variation (CV$^2$), which measures the variation in demand quantities. Figure 7 shows a representation of the framework of Syntetos (2001).

As the retailer experiences high variability in demand quantity, or a high CV$^2$, the demand history of his products will either be classified as lumpy or as erratic. Ideally, the solution presented in this thesis should decrease the variability in demand quantity by such extent that the products of the retailer can be classified as smooth or intermittent. Namely, these two categories are a lot easier to forecast for.

As a consequence, the idea arose to remove the demand quantities that cause the high variability from the regular system and deliver these demand quantities to the customer in a different way. Thus, the extremely large demand quantities, also called the surges in demand, should be treated separately. This is most likely advantageous for the normal-sized customer orders following after an extremely-sized customer order as the stock is not depleted completely. Likewise, due to the reduced variability, the inventory level can be reduced. However, costs may rise due to the use of two order fulfillment processes.

This idea can be implemented by regularly replenishing the warehouse for normal-sized customer orders and supplying these orders from stock, and by emergency replenishing the warehouse for extremely-sized customer orders. Moreover, before the customer order has to be delivered, the retailer has a buffer period to gather the order; the demand lead time. Because demand is known for a certain time period, the retailer is able to proactively order and receive an emergency replenishment if necessary (if the demand lead time is reasonable).
To find this distinction between normal-sized customer orders and extremely-sized customer orders, a cutoff order size should be introduced. Thus, for order sizes at or below the cutoff order size, customers are supplied from stock, which is the regular mode. For order sizes larger than the cutoff order size, emergency replenishment is used, which is from now on called the direct mode. A visual representation of this distinction is shown in Figure 11, where the cutoff order size (at a potential level of 25) is shown for an erratic demand pattern, and Figure 12, where the left part represents the customer orders that should be satisfied by the regular mode and the right part represents the customer orders that should be satisfied by the direct mode. Note that complete orders are either classified as regular or direct and thus no orders are being split.

As such, in the proposed model, the problem is to handle situations when an extremely-sized customer order has arrived. The aim of the model is to proactively recognize a surge in demand that will disturb the regular inventory system and treat those surges in demand as emergency shipments. The intention is to be able to receive the emergency replenishment within the demand lead time. This could mean that even though there is sufficient on stock, certain customer orders are still treated as emergency shipments as not to disappoint probable future customers with regular order sizes in the same potential delivery cycle. Note that in the proposed model an underlying assumption is that customers are not interested in substitution articles. Although this is not compliant with reality, the assumption has its added value since offering substitution articles disrupts the forecasting. Also, no orders are withdrawn after they have entered the system, also called perfect advance demand information, to enhance the tractability of the model.
The warehouse is regularly replenished from a supplier according to a periodic review reorder point policy with deterministic lead time and a fixed order quantity. No stock reservations are made and customers are served via a FCFS principle. This means that orders that have entered the system are served on a first come first serve basis after their demand lead time has passed. Additionally, unmet customer demand is backordered. The previous assumptions are made to stay as close as possible to the situation of Sligro. Likewise, the warehouse can issue emergency replenishments from the same or an outside supplier. These emergency replenishments incur additional costs. Furthermore, the direct mode is reviewed continuously and the emergency order has variable size and deterministic lead time. Note that the emergency lead time does not have to be smaller than the regular lead time. The possibility for an emergency replenishment is reviewed continuously as to optimally use the given demand lead time. Further, the direct mode is not dependent on a fixed order quantity as the emergency order is specifically issued to satisfy one large customer order and thus at arrival of the emergency order the complete order can immediately be prepared for delivery to the customer. Likewise, a deterministic emergency lead time is assumed to stay as close as possible to the situation of Sligro. Last, it is assumed that the outside supplier(s) has ample inventory. The underlying assumption here is that all the quantities of the customer orders are within reason. A representation of the inventory system is given in Figure 13, where the notation of the representation can be found in Table 2 in Chapter 7.

To distinguish the customer orders between regular replenishments and emergency replenishments, a decision rule is introduced that makes its decision based on the cutoff order size and subsequently the given demand lead time. Thus, the decision rule is based on the characteristics of the order. This rule is then used repeatedly as a heuristic. An emergency replenishment is only issued when an order arrives with an order size larger than the cutoff order size and has a certain demand lead time. When the demand lead time runs out before a potential emergency replenishment can arrive, no emergency replenishment will be used. The order will be satisfied by enlarging the next regular replenishment with the order quantity and awaiting the arrival of the regular replenishment. In the meantime, the order will be completely backordered as irregularly classified orders (order size larger than the cutoff order size) are not filled from the stock held in the regional warehouse. It makes sense to not make use of the expensive emergency shipment if the complete order will be backordered anyway. Additionally, when the demand lead time is longer than the time to the next regular replenishment being issued and the time to deliver that regular replenishment, the irregular customer order quantity will be included in the next regular replenishment as also here it makes no sense to issue an expensive emergency order. As a consequence, no additional set up costs for these two scenarios are incurred. Additionally, it is assumed that the time between the delivery of the closest replenishment moment and the demand lead time in this case is negligible and thus no extra inventory costs need to be incurred. However, if the demand lead time is between the emergency lead time and the time to the arrival of the next replenishment and the order is classified as irregular, the emergency option will be used and associated costs will be incurred. The decision rule will be explained in more detail in section 6.1.
The proposed model minimizes the total costs to find the optimal cutoff order size. While minimizing the total costs, the optimal reorder level can be determined. This optimal reorder level is used as a basis for the calculations of the model and gives the ability to evaluate the performance of the model compared to other scenarios. Furthermore, the costs considered in this model are the standard holding costs and fixed ordering costs for both regular and direct replenishments. Variable ordering costs for both regular as direct replenishments are left out of scope as in practice they differ minimally, however can be easily added. Moreover, standard backordering costs for every regular customer order that has not been delivered before the due date are considered. Last, the model is subject to a base replenishment quantity, however finding the optimal base replenishment quantity is not considered in this thesis.

In the remaining part of this chapter, the decision rule is explained in detail, the scenarios considered in this thesis are presented, the KPIs to analyze the performance of the scenarios are introduced, and the position in literature is determined.

6.1 DECISION RULE
To be able to recognize the surge in demand, a decision rule is presented. This decision rule is visualized in Figure 14. When demand arrives, the decision rule first inspects if the customer order size \( (d) \) is bigger than the cutoff order size. The idea behind this step of the decision rule is to verify whether the customer order is a surge in demand and to proactively classify the customer order as regular (NO) or direct (YES). The cutoff order size detects extremely large orders that normally complicate and blur the forecasting of the single sourcing model. The model determines the cutoff order size by minimizing the costs. The expressions of how the cutoff order size is determined, is covered in Chapter 7. After the classification of the order, the demand lead time, or in other words the remaining time until the order should be delivered, is determined. The effect on the demand lead time on the regular and direct mode is covered in section 7.1. The decision rule in this section provides an answer to the second research question: ‘Based on what variables should the decision be made to use emergency ordering?’

If the order is classified as regular, the complete order waits until the demand lead time \( (T) \) has passed. When the delivery moment arrives, it is checked whether there is sufficient stock-on-hand. If so, the demand is filled from stock and the system is updated. If not, the possible remaining stock-on-hand is used to fill part of the demand \( (q) \) and the rest of the demand \( (d - q) \) is backordered until regular replenishment arrives. Subsequently, the system is updated with the new information.
If the order size is bigger than the cutoff order size and the direct mode should be used, the next step of the decision rule is to investigate whether the remaining demand lead time is smaller than the emergency replenishment lead time. In that case, an emergency order will not prevent the order from being backordered. To minimize cost, the order should be solved via the regular replenishment. First, the replenishment order size of the next replenishment will be enlarged with the ordered quantity. Secondly, after the demand lead time has passed, the total order will be backordered. Even though there might be sufficient stock available, large customer order sizes are not allowed to be filled from stock. Last, when the enlarged replenishment arrives, the backorder is immediately filled.

However, if the remaining demand lead time is larger than the emergency replenishment lead time, the next step of the decision rule is to verify whether the remaining demand lead time of the customer order is larger than the time that it takes to order and to receive a regular replenishment. This time is equal to the time until the next review moment plus the lead time of a regular replenishment. If the demand lead time is larger than the time to the next replenishment then the inventory system has enough time to adapt to the surge in demand. Therefore, it does not make sense to use the more expensive emergency option. In that case, the size of the regular replenishment order closest to the due date is increased with the customer order size. Hereafter, the order is filled after $T$ time units. It is assumed that the replenished quantity to satisfy the order is reserved even though it might be put on stock until the demand lead time runs out. In other words, no backlogging will occur.

In the case that a new regular replenishment would arrive after the due date of the customer order, an emergency replenishment will be used. If the remaining demand lead time is larger than the emergency replenishment lead time, then the total customer order can be filled on time and customer disappointment can be prevented. After $T - L_E$ time units (demand lead time minus the emergency lead time) an emergency replenishment of $d$ units is ordered. The emergency replenishment will arrive just in time to satisfy the demand. For all scenarios described above, the decision rule is concluded after the system information is updated.
6.2 **SCENARIOS**

To verify the performance of the proposed model, a comparison should be made to other scenarios. This section answers the third research question: ‘What are the relevant scenarios to investigate the impact of the decision rule?’ While all scenarios described here could provide interesting insights, the proposed model will only be compared with the traditional backorder model in this thesis. This decision is made as the traditional backorder model and proposed model both are executed with the FCFS principle and through this an exact evaluation can be made, using the DoBr tool based on the expressions of Van Donselaar & Broekmeulen (2014). The two other scenarios described in this section at this moment cannot be evaluated exactly and because of this are not considered in this thesis. However, these scenarios are interesting for future research.

The traditional backorder model is the model that represents the current scenario of Sligro the best. Considering that Sligro discourages the use of emergency shipments and aims to satisfy all orders from stock, it is the most obvious model to verify the proposed model with. The traditional backorder model is a model where emergency ordering is not an option and all shortages are backordered. Moreover, this scenario assumes a \((R,s,nQ)\) inventory policy and satisfies orders via a FCFS policy. The flowchart of the traditional backorder model is shown in Figure 15.

![Flow chart of the decision rule for the traditional backorder model](image)

Another scenario that could also solve the problem at hand is when stock reservation is an option. Orders that go above the cutoff order size are immediately prepared and reserved, even though the demand lead time is not close to running out. Orders below the cutoff order size are only prepared when the demand lead time is close to running out. This means that orders are not solved through the FCFS principle, but priority is given to large order sizes.
A variant on this scenario is that the inventory position is modified when a large customer order arrives. Instead of reserving the stock for this order, the inventory position is lowered with the large customer order. The adapted inventory position causes the inventory system to replenish faster and/or with a larger amount. When the demand lead time is close to running out for this large customer order, the order is taken out of the inventory and replenishment that has taken this large order into account might already have arrived or is arriving soon. Although orders are solved through the FCFS principle, the inventory position does not process them in this order. Again here, priority is given to large order sizes.

To prevent further confusion, the proposed model in this thesis with emergency shipments is from now on called the dual sourcing model (or DS) as two different flow types (regular and emergency replenishments) serve the inventory system. The second scenario is called the single sourcing model (or SS). The name is derived from that only one source, the regular replenishments, is available. The single sourcing model faces demand with a certain demand lead time as well. In Chapter 7, the dual sourcing model as well as the single sourcing model will be extended with the corresponding expressions.

6.3 KPIs
To be able to analyze the performance of the two selected scenario’s, key performance indicators (KPIs) should be introduced. This section answers the fourth research question: ‘How will the performance of the selected scenarios be analyzed?’ The performance is measured by the following two KPIs:

- Expected inventory on hand
- Average expected cost

Expected inventory on hand
The expected inventory on hand measures the amount of products kept on stock during a certain time period. It indicates the average height of the inventory level.

Average expected cost
The average expected cost measures the total average costs made during a certain time period. The costs consist of the setup costs for both emergency and regular replenishments, the holding cost, and the backorder cost.

6.4 Position in Literature
This thesis is related to the literature that focuses on multiple supply modes and emergency replenishments. Moinzadeh & Nahmias (1988) review the literature on multi-supplier inventory models with fixed ordering costs and Minner (2003) reviews these models in general. The first reference, Moinzadeh & Nahmias (1988), considers a standard single-item continuous review inventory control system in which there exist two options for resupply, with one having a shorter lead time. The paper considers reorder point policies both for normal and emergency orders. Reorder decisions are based on the on-hand inventory only and orders are subject to a fixed order quantity. The model is validated by simulation. Johansen & Thorstenson (1998) present Markov models for determining optimal values for the reorder point policies both for normal and emergency orders. They assume that demand is pure Poisson and normal orders may only be issued when no other orders are outstanding.
Likewise, emergency orders are only allowed when one normal order is already outstanding and the lead time of emergency orders should be quite short. Their Markov decision model is designed to minimize the inventory cost rate with state dependent emergency orders and depends on both the inventory on hand and the remaining delivery time for a possible outstanding normal order. Their simple model depends on the stock on hand only.

Axsäter (2007) presents a heuristic decision rule in a continuous review setting that determines the timing and size of the emergency orders based on the reorder point and lot size for normal orders and the real-time information of the remaining delivery time of a normal order. The decision rule can be used more in a general setting compared to the article of Johansen & Thorstenson (1998). This is because the decision rule of Axsäter (2007) allows for several outstanding normal orders and the lead time for emergency orders does not have to be very small. In Axsäter (2014) this decision rule is improved. They modify the system such that emergency replenishments are evaluated in a periodic review system, as well as add an improvement step that gives the option to postpone deciding whether or not to issue an emergency order by letting emergency orders be evaluated and initiated in a periodic review system. Although the work of Axsäter (2014) is related to the proposed model because of the emergency orders to be based on the real-time information, this thesis differs from Axsäter (2014) in that the due date of the order is in the nearby future but does not have to be immediately expedited. Likewise, the models of Axsäter (2007, 2014) are based on the inventory position, while in this thesis the model is based on the characteristics of the customer order. Like this thesis, Axsäter (2014) and more recently Zhou & Yang (2016) allow for compound Poisson process. Zhou & Yang (2016) study a class of single-index (s,nQ) policies based on the inventory position to compute the expected long-run average cost. Mohebbi & Posner (1999) also develop an inventory system with emergency orders under compound Poisson demand but they assume that all shortages are lost sales. While the above literature has focused on applying continuous review (except for Axsäter (2014)), this thesis applies periodic review for issuing normal replenishment orders. Tagaras & Vlachos (2001) suggest a policy where control is created by properly designing the review period. An approximate cost model is developed which is later on used as the basis for a heuristic algorithm. Chiang & Gutierrez (1998) suggest to control emergency orders on a continuous basis. Thus, the policy of Chiang & Gutierrez (1998) is essentially a mixture of periodic review (for normal orders) and continuous review (for emergency orders), which is the same as in this thesis. The problem is analyzed within a dynamic programming model and an optimal control policy is derived, which is complex, especially if the two lead times differ by more than one time unit. Both Chiang & Gutierrez (1998) and Tagaras & Vlachos (2001) allow for the possibility that the emergency lead time may be shorter than the review period of the normal replenishment. Chand, Li, & Xu (2016) consider an inventory model with age-and-period-dependent backlogging cost, the emergency delivery lead time is negligible, and the normal delivery lead time is less than the length of the review period. They prove that the optimal policy for both order types is specified by base stocks. A different stream of literature focuses on order splitting between multiple suppliers. The interested reader can be referred to the overview of Minner (2003).

Moreover, this thesis is also related to the stream of literature that considers advance demand information (ADI). In this thesis a system is considered where customer-order demand information is present a certain time before the actual due date of a customer order.
and that this knowledge can be used to optimize the dual supplier model. Hariharan & Zipkin (1995) define the time from a customer’s order until the due date of that order as the demand lead time. They conclude that advance-ordering information improves the system performance in precisely the same way as a reduction in supply lead times. Gallego & Özer (2002) review the literature on ADI as well as on demand lead times. Likewise, Van Donselaar, Kopczak & Wouters (2001) consider a situation where a manufacturer is confronted with two types of demand: regular demand from many small orders and very irregular, lumpy demand from infrequent, large orders. On top of that, they consider imperfect ADI: demand is known for a certain time beforehand, but there is a probability that orders will be withdrawn. They show that advance demand information is particularly valuable when potential demand for large projects is irregular and the probability that orders will be withdrawn is small. While the irregularity of the demand is similar to the situation considered in this thesis, this thesis considers perfect ADI (no orders will be withdrawn) and tries to solve the irregularity of the demand by introducing a different mode. While considerate literature has focused on this topic, none of them has combined demand lead times with multi-supplier inventory models and only one article uses ADI in combination with a multi-supplier inventory model. This article from Huang et al. (2011) studies the inventory system of an online retailer with compound Poisson demand according to a continuous review (R, nQ) policy with a constant lead time. They assume a committed service time; the time a customer is willing to wait after the order has been placed. They provide a decision rule that analyzes whether in a stock-out situation after the committed service time the customer order needs to be satisfied by the emergency supplier or be backordered with a time-dependent backorder cost. This decision rule minimizes the expected costs under the assumption that no further emergency orders will occur.

6.4.1 ADDITION TO LITERATURE

This thesis differs from the reviewed literature in that it does not assume that a possible backorder situation should be solved immediately with expediting, but that a certain demand lead time is given per order in which the system might be able to prevent the backorder situation. Moreover, the decision rule presented in this thesis is based on the characteristics of the order and not on the inventory position or inventory on hand.

Additionally, this thesis considers an unexamined situation where the arrival of demand has been modelled by a combination of two compound Poisson processes as the customer varies in ordered quantities. In literature, it is often assumed that customers either order large quantities or small quantities. Because no distinction can be made between the customers, the service to the customer when both large or small quantities are ordered can give interesting insights.

Likewise, the use of a cutoff order size to determine the distinction between regular and emergency replenishments creates a rather simple but elegant method to exactly evaluate the proposed inventory system, while the earlier mentioned literature has mainly focused on solving their systems with Markov models and dynamic programming. However, to the authors knowledge, the proposed model has never been researched before.
7 Scientific Model

This chapter discloses the expressions used to generate and solve the single and dual sourcing model. In this chapter, expressions for the generation of demand, single sourcing model, dual sourcing model, and KPIs are given. Likewise, the effect of the demand lead time on the demand and the two scenarios is disclosed. This chapter answers the fifth research question: ‘How can a generic model be built to analyze the performance of the selected scenarios?’. Before proceeding, the following notation is introduced which is used throughout this thesis:

*Table 2 List of variables and parameters*

<table>
<thead>
<tr>
<th>Variable/Parameter</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>( b )</td>
<td>Backordering cost per unit backordered</td>
</tr>
<tr>
<td>( BO )</td>
<td>Number of backorders</td>
</tr>
<tr>
<td>( h )</td>
<td>Inventory holding cost per unit of inventory on hand</td>
</tr>
<tr>
<td>( IP )</td>
<td>Inventory position of the regular mode</td>
</tr>
<tr>
<td>( i_{OH} )</td>
<td>Inventory on hand</td>
</tr>
<tr>
<td>( K_R )</td>
<td>Fixed ordering cost for using the regular mode</td>
</tr>
<tr>
<td>( K_D )</td>
<td>Fixed ordering cost for using the direct mode</td>
</tr>
<tr>
<td>( L_R )</td>
<td>Lead time of the regular mode</td>
</tr>
<tr>
<td>( L_D )</td>
<td>Lead time of the direct mode</td>
</tr>
<tr>
<td>( \lambda )</td>
<td>Customer arrival rate</td>
</tr>
<tr>
<td>( M )</td>
<td>Cutoff order size</td>
</tr>
<tr>
<td>( \mu )</td>
<td>Mean</td>
</tr>
<tr>
<td>( OL )</td>
<td>Order line</td>
</tr>
<tr>
<td>( p )</td>
<td>Weight of the compounding distributions</td>
</tr>
<tr>
<td>( P )</td>
<td>Fill rate</td>
</tr>
<tr>
<td>( P^o )</td>
<td>Order fill rate</td>
</tr>
<tr>
<td>( \Pi )</td>
<td>Expected average cost</td>
</tr>
<tr>
<td>( Q )</td>
<td>Incremental order quantity</td>
</tr>
<tr>
<td>( Q^k_t/Q^r_t )</td>
<td>Ordered quantity at time ( t ) (for the regular/irregular replenishment)</td>
</tr>
<tr>
<td>( R )</td>
<td>Review period for the regular mode</td>
</tr>
<tr>
<td>( r(\tau) )</td>
<td>Time until the next review moment</td>
</tr>
<tr>
<td>( s )</td>
<td>Reorder point for the regular mode</td>
</tr>
<tr>
<td>( \sigma )</td>
<td>Standard deviation</td>
</tr>
<tr>
<td>( T )</td>
<td>Demand lead time</td>
</tr>
<tr>
<td>( \tau )</td>
<td>Moment of customer order arrival</td>
</tr>
</tbody>
</table>

Throughout this paper, the notation \( x^+ = \max(x, 0) \) and \( x^- = \max(-x, 0) \) is assumed.

The two models are developed in an Excel based spread sheet with underlying VBA code to approach a \((R, s, nQ)\) inventory control policy. This VBA code is also known as the DoBr tool, developed by Van Donselaar & Broekmeulen (2014). The functions in the DoBr tool are able to exactly evaluate the dual sourcing and single sourcing model, and through this most of the results can be acquired. However, with the use of the DoBr tool an assumption must be made that the models are subject to stationary demand. This means that the demand is constant over time and does not vary due to seasonality, trend, or other factors.
7.1 DEMAND LEAD TIME
The demand lead time is the buffer period the inventory system has to gather the customer order. It is the time until the customer order has to be delivered. The demand lead time of an order is denoted as $T$. With $T = 0$, there is still an agreed time to deliver the order to the customer. The demand lead time follows a distribution in the number of time units after which a customer wants their orders to be delivered.

Adapting the demand distribution with arrival of demand at time $t$ with the distribution for the demand lead time, results in a demand distribution with arrival of the demand at time $t + T$. However, as arrivals occur according to a Poisson distribution and demand is satisfied via a FCFS principle, the demand distribution for time $t + T$ is not different from the demand distribution at time $t$. Namely, the Poisson distribution has the property to be memoryless and thus the arrivals of the orders are not influenced by the delay for the demand lead time. On top of that, as the orders are satisfied in the order that they have arrived when the demand lead time has passed, it does not matter when an order is announced. However, it is assumed that this advance demand information has no (positive) effect on the variance, i.e. it is too small to reduce the demand uncertainty for the replenishment decisions.

Nevertheless, the demand lead time given still specifies whether the direct mode should be used. With a deterministic demand lead time for all customer orders, the following situations for order sizes greater than the cutoff order size can be distinguished:

1. The demand lead-time is greater or equal than the lead time of the direct mode ($T \geq L_D$), such that the large order is always satisfied (no backorders).
2. The demand lead-time is less than the lead-time of the direct mode ($T < L_D$), resulting in a backorder situation. In those situations, the order is added to the regular order and the direct mode is not used.

Note that if the customer order arrives at moment $\tau$ and and $r(\tau) < R$ is the remaining time until the next review moment, the direct mode should not be used if $T \geq L_R + r(\tau)$. In that situation, a regular replenishment order at the supplier can be placed (or the regular order can be increased with the large order size). In that way, the retailer benefits from the advance demand information through the demand lead-time.

Concluding, the direct mode is only interesting if $L_D \leq T < L_R + r(\rho)$. To improve the tractability of our model, this is further limited to $L_D \leq T < L_R$.

7.2 DEMAND GENERATION
This section covers the generation of the different demand distributions. First, it will be explained how to generate a demand distribution that represents the customer of the retailer. Subsequently, it will be described how to find the different demand distributions of the regular and irregular orders.
7.2.1 **Mixed Compound Poisson Distribution**

To generate the erratic and lumpy demand as assumed in the conceptual model, a mixed compound Poisson distribution is assumed. In literature, the demand is often assumed to be a compound Poisson process (Axsäter, 2006; Axsaeter, 2014; Mohebbi & Posner, 1999; Zhou & Yang, 2016). When demand is a compound Poisson process, customers arrive via a Poisson process with an arrival rate of $\lambda$. The size of the customer demand is stochastic and is determined via a compounding distribution.

A mixed compound Poisson distribution is used to create the sudden surges in demand as described in the problem context. Every customer can order regularly and irregularly sized orders, thus only one arrival rate is needed. However, the arriving customer demand sizes have a high variability and thus the compounding distribution used is a mixture of two different compounding distributions. The first compounding distribution is used to simulate the orders from clients that are regularly sized, while the second compounding distribution represents the irregular orders placed by customers; the sudden surges in demand. The two compounding distributions are mixed using a Bernoulli distribution; When a customer arrives, the size of the demand is either taken from the first compound Poisson process with a probability $p$ or from the second compound Poisson process with a probability $(1 - p)$. Note that part of the demand from the first compounding distribution can be classified as irregular demand as well as part of the demand from the second compounding distribution can be classified as regular demand, because a cutoff order size in the decision rule is used.

The compounding distributions are determined via the fitting procedure of Adan, Van Eenige, & Resing (1996). This method is explained in Appendix C. The compounding distributions are assumed to be delayed compounding distributions, which means that the probability that the size of the customer demand is equal to zero is omitted. Given the mixed compounding distributions and the arrival rate $\lambda$, the distribution of the compound Poisson process can be determined, as explained in Appendix D.

For a certain probability ($p = 0.6$), arrival rate ($\lambda = 0.8$), and two compounding distributions processes ($\mu_1 = 2, \sigma_1 = 2, \mu_2 = 5, \sigma_2 = 5$) the demand history could look like Figure 16. The demand history would be classified as lumpy, as the average demand interval is equal to 1.77 and the squared coefficient of variation is equal to 0.98.

![Generated demand history](image-url)
7.2.2 REGULAR AND IRREGULAR CLASSIFIED DEMAND

When the cutoff order size is determined, the generated demand can either go via the regular or direct mode. Given the probability mass function (PMF) of the mixed compound Poisson distribution derived from the previous subsection, a probability mass function for both the regular and direct mode can be determined. As the decision rule completely splits the system between regular and irregular sized orders and no interdependencies exist, the two PMFs can be derived.

Due to the cutoff order size $M$, the regular and direct mode both have a truncated compounding distribution. For the regular mode, this is equal to:

$$f(x|0 < X \leq M) = \frac{g(x)}{G(M)}$$  \hfill (1)

For the direct mode, the truncated compounding distribution is equal to:

$$f(x|X > M) = \frac{g(x)}{1 - G(M)}$$  \hfill (2)

where $g(x)$ is the PMF of the original shifted compounding distribution and $G(\cdot)$ is the CDF of the original shifted compounding distribution. The arrival rate for the stock point at the regular mode is reduced to $\lambda' = \lambda \cdot G(M)$, and the arrival rate the direct mode is reduced to $\lambda' = \lambda \cdot (1 - G(M))$.

The PMF of the resulting discrete compound Poisson distribution can be calculated using the recursive formulas from Panjer (1981):

$$d(x) = \frac{\lambda'}{x} \sum_{y=1}^{x} y \cdot f(y) \cdot d(x - y)$$  \hfill (3)

$$d(0) = e^{-\lambda'}$$  \hfill (4)

7.3 SINGLE SOURCING MODEL

The single sourcing model considers an inventory system where only one source of replenishments is obtainable; the regular replenishments. In other words, emergency replenishments are not an option and all shortages of stock are backlogged. The single sourcing model assumes a $(R, s, nQ)$ policy and satisfies orders via a FCFS policy. The following expressions are based on the lecture notes of Van Donselaar & Broekmeulen (2014).

The single sourcing model minimizes the average expected costs. As only the regular mode can be used, the following cost factors are included in the cost function:

- Inventory holding cost $h$ during a potential delivery cycle,
- Backorder cost $b$ for having backorders during a potential delivery cycle, and
- Ordering costs $K_R$ for replenishments.
In this scenario, the cost function is as follows:

\[ \Pi_{SS}(M) = h \cdot E[I_{M}^{OH}] + b \cdot E[BO_M] + K_R \cdot E[OL_M] \]  

(5)

where

- \( E[I_{M}^{OH}] \) := expected inventory on hand during a potential delivery cycle
- \( E[BO_M] \) := expected backorders during a potential delivery cycle
- \( E[OL_M] \) := expected number of order lines in a potential delivery cycle

These expressions can be determined as follows:

\[ E[BO_M] = E[BO_M(\tau + R + L)] - E[BO_M(\tau + L)], \]  

where \( E[BO_M(\tau + t)] = E[(D_M(\tau, \tau + t) - IP(\tau))^+] \),

(6)

\[ E[I_{M}^{OH}] = 0.5 \cdot \{ E[I_{M}^{OH}(\tau + L)] + E[I_{M}^{OH}(\tau + L + R)] \}, \]  

where \( E[I_{M}^{OH}(\tau + t)] = E[(IP(\tau) - D_M(\tau, \tau + t))^+] \), and

(8)

\[ E[OL_M] = P(IP(\tau) - D_M(\tau, \tau + R) < s) \]

(10)

where

- \( IP(\tau) \) := the inventory position at time \( \tau \)
- \( D_M(\tau, \tau + t) \) := the demand of size at or below \( M \) during \( t \) time units
- \( s \) := the reorder level

\( D(\tau, \tau + t) \) can be derived by finding the \( t \)-fold convolution of the single period probability distribution.

As there is no direct mode, the optimal cutoff order size \( M^* \) is set to infinity \( (M^* = \infty) \). The optimal \( \Pi_{SS}(M^* = \infty) \) is found by searching for the optimal reorder level \( s^* \) that minimizes the cost function \( \Pi_{SS}(M^* = \infty) \). Note that in regular mode, the demand lead time given by the customers is ignored and orders are delivered from stock just in time, i.e. at the end of the demand lead time.

### 7.4 DUAL SOURCING MODEL

The dual sourcing model considers an inventory system where two sources of replenishments are available; the regular and direct mode. The dual sourcing model is an extension of the single sourcing model and the expressions for the dual sourcing model are an extension from the expressions of the single sourcing model. Again, the following expressions shown are based on the lecture notes of Van Donselaar & Broekmeulen (2014).

Similar to the single sourcing model, the dual sourcing model minimizes the average expected costs. Introducing a direct mode with a cutoff order size \( M \) at a fixed order line cost of \( K_D \) is only interesting if this would be cheaper than having only the regular mode. Before moving further, it is assumed that the demand lead time of all orders is sufficient to use the direct mode.
In that case, a ‘direct only’ scenario can be introduced where all orders are satisfied using the direct mode (based on continuous review of the order sizes). In this ‘direct only’ scenario, $M$ is set to zero. When $M = 0$, the cost of the dual sourcing model are as follows:

$$\Pi_{DS}(M = 0) = K_D \cdot \lambda$$  \hspace{1cm} (11)

For values of $M$ between zero and infinity, the compounding distribution of the regular mode is truncated. Likewise, the costs for the direct mode are as follows:

$$K_D \cdot \lambda \cdot P[X > M]$$  \hspace{1cm} (12)

The average expected cost function for the dual sourcing model becomes:

$$\Pi_{DS}(M) = h \cdot E[I_{R}^{OH}] + b \cdot E[BO_M] + K_R \cdot E[OL_M] + K_D \cdot \lambda \cdot P[X > M]$$  \hspace{1cm} (13)

The optimal $\Pi_{DS}(M^*)$ is found by searching for the optimal reorder level $s^*$ for each cutoff order size $M$ and subsequently finding the optimal cutoff order size $M$ that minimizes the cost function $\Pi_{DS}(M)$. 


Part III – Results & Evaluation

8 Results
In this chapter the scientific model is solved and the results are reflected upon. An answer is given to the sixth research question: ‘How do the scenarios perform on flexibility, responsiveness, uncertainty, costs, and customer service?’

8.1 EXPERIMENTAL SETUP
In order to compare the performance of the two models, the KPIs expected inventory on hand and the expected total relevant costs are measured. In this section a factorial experiment is proposed in which several levels of the input parameters will be tested. The experimental setup is given in Table 3. The 864 different experiments are exactly evaluated in the VBA-based DoBr tool developed by Van Donselaar & Broekmeulen (2014).

<table>
<thead>
<tr>
<th>Input parameter</th>
<th>Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R$</td>
<td>[1]</td>
</tr>
<tr>
<td>$L_R$</td>
<td>[1,2,3]</td>
</tr>
<tr>
<td>$Q$</td>
<td>[5,10]</td>
</tr>
<tr>
<td>$K_R$</td>
<td>[0]</td>
</tr>
<tr>
<td>$K_D$</td>
<td>[35,70]</td>
</tr>
<tr>
<td>$h$</td>
<td>[1]</td>
</tr>
<tr>
<td>$b$</td>
<td>[19,49]</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>[1.1,1.4,2]</td>
</tr>
<tr>
<td>$\mu_1$</td>
<td>[5]</td>
</tr>
<tr>
<td>$\sigma_1$</td>
<td>[2.42]</td>
</tr>
<tr>
<td>$\mu_2$</td>
<td>[5,10,20]</td>
</tr>
<tr>
<td>$\sigma_2$</td>
<td>[4.5,4.8,5.2,6]</td>
</tr>
<tr>
<td>$p$</td>
<td>[0.8]</td>
</tr>
</tbody>
</table>

The different values for the parameters are chosen to analyze the performance of the proposed model and to test the sensitivity of the proposed model. Without loss of generality, the review period of the regular mode ($R$) is set to 1, and the lead time of the regular mode $L_R$ is a multiple of the review period. The lead time of the direct mode is negligible, as the demand lead time is assumed to be sufficient to use the direct mode. The setup costs for the regular mode ($K_R$) are set equal to zero as they are assumed to be sunk cost. Thus, the setup costs for the direct mode ($K_D$) represent the added cost of using an emergency replenishment instead of regular replenishment. The setup costs for the direct mode are based on data of Sligro. The backorder cost $b$ is determined according to the newsvendor model to achieve a certain fill rate ($P_2$). The newsvendor model balances the holding cost and the backorder costs such that by definition it is not more favorable to either backorder more orders nor hold more inventory. To achieve rather standard fill rates of 0.95 or 0.98, $b$ should be respectively 19 or 49. The parameter $b$ is determined via the following formula:

$$b = h \frac{P_2}{1 - P_2} \quad (14)$$
The parameter $\lambda$ determines the ADI of the demand distribution and with the values [1.1, 1.4, 2], the ADI of the demand distribution is respectively a certain amount below 1.32, the value 1.32, or the same amount above 1.32. The input parameters $\mu_1$ and $\sigma_1$ of the first compounding distribution are kept at the same level, while the input parameters of the second compound distribution are varied. While the value for $\mu_1$ is randomly chosen, the value for $\sigma_1$ is based on an estimation of an expression for the standard deviation of food items (Broekmeulen & van Donselaar, 2017). The resulting expression is $\sigma = 0.7 \cdot \mu^{0.77}$. The three different values of the input parameter $\mu_2$ are chosen such that the first value represents a simple compound Poisson process, the second value represents a skewed distribution, and the third value represents a bimodal distribution. Likewise, the four different values of the input parameter $\sigma_2$ are chosen such that for $\mu_2 = 5$, the squared coefficient of variation is a certain amount below 0.49 with $\sigma_2 = 4.5$, the value 0.49 with $\sigma_2 = 4.8$, or the same amount above 0.49 with $\sigma_2 = 5.2$. Similarly, for $\mu_2 = 10$, the squared coefficient of variation is a certain amount below 0.49 with $\sigma_2 = 4.8$, the value 0.49 with $\sigma_2 = 5.2$, or the same amount above 0.49 with $\sigma_2 = 6$. For $\mu_2 = 20$ the squared coefficient of variation given any $\sigma_2$ is above 0.49. Note that the values 1.32 and 0.49 are the cutoff values of respectively the average demand interval and the squared coefficient of variation used in the classification of the framework of Syntetos (2001).

8.2 RESULTS

The performance on the KPIs for the single sourcing (SS) and dual sourcing (DS) model is measured in the difference in percentage. For the two KPIs, the expected inventory on hand and the expected average cost, the reduction in percentage is measured. The differences in percentages are measured as follows:

$$\Delta E[I^{OH}] = 100 \frac{E[I^{OH}](SS) - E[I^{OH}](DS)}{E[I^{OH}](SS)} \quad (15)$$
$$\Delta II = 100 \frac{II(SS) - II(DS)}{II(SS)} \quad (16)$$

In Table 4, the performance is reported for each KPI. It gives the average reduction of the given KPI for the dual sourcing model compared to the single sourcing model for the 864 different experiments, in which one input parameter was kept constant at a certain level.

Performance on the inventory level

The dual sourcing model reduces on average the expected inventory level during a potential delivery cycle with 59%. The dual sourcing model works particularly good for long lead times. This is caused by the introduction of the direct mode; the optimal reorder level for the dual sourcing model relative to the single sourcing model goes farther down as the lead time of the regular mode increases. With longer lead times, the inventory system is less flexible to manage uncertainties in demand and the direct mode therefore becomes more attractive. When increasing the backorder cost $b$ to aim for a higher service level, it becomes more attractive to hold more inventory in comparison to having backorders. Introducing a direct mode in the dual sourcing model is only alluring when the costs of the direct mode ($K_D$) are lower than the increase in inventory. This can be seen for the parameter $b$ that for a higher $b$ more inventory is held and thus in theory the inventory level can be farther reduced. Likewise, it can be seen that for a higher level of the set up costs of the direct mode ($K_D$), reducing the stock level becomes less alluring.
Next to that, for all levels of $\lambda$ a reduction in the inventory level can be found. This means that for either lumpy or erratic classified demand the dual sourcing model outperforms the single sourcing model in reducing inventory. Interesting is that for $\lambda = 1.4$ in comparison to the other levels a larger reduction can be achieved. This is caused by that for an increasing level of $\lambda$ the cutoff order size does not increase linearly but slightly convex and through this effect, the inventory level can be reduced somewhat more for $\lambda = 1.4$. Last, the inventory level is increasingly reduced when the variability in order sizes goes up ($\mu_2$ and $\sigma_2$). The levels of the parameter $\mu_2$ were chosen such that they represent a simple compound Poisson distribution, a skewed distribution, and a bimodal distribution. Logically, the bigger the potential order sizes, the more the inventory can be reduced. Additionally, the levels of the parameter $\sigma_2$ were chosen such that the variability of the demand sizes were just below, on top of, and above the cutoff value of the framework of Syntetos (2001). Table 5 shows the results separated for each level of the parameter $\sigma_2$ and $\mu_2$. The table shows that a reduction of the inventory level can be achieved for any variability of the demand size. However, with a higher variability, the inventory level can be reduced to a greater extent.

### Table 4 Results of the factorial design for the KPIs

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Level</th>
<th>$\Delta E[I^{OH}]$</th>
<th>$\Delta \Pi$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$L$</td>
<td>1</td>
<td>27%</td>
<td>28%</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>63%</td>
<td>67%</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>87%</td>
<td>115%</td>
</tr>
<tr>
<td>$Q$</td>
<td>5</td>
<td>64%</td>
<td>77%</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>54%</td>
<td>63%</td>
</tr>
<tr>
<td>$b$</td>
<td>19</td>
<td>56%</td>
<td>62%</td>
</tr>
<tr>
<td></td>
<td>49</td>
<td>62%</td>
<td>78%</td>
</tr>
<tr>
<td>$K_D$</td>
<td>35</td>
<td>84%</td>
<td>99%</td>
</tr>
<tr>
<td></td>
<td>70</td>
<td>33%</td>
<td>41%</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>1,1</td>
<td>56%</td>
<td>56%</td>
</tr>
<tr>
<td></td>
<td>1,4</td>
<td>67%</td>
<td>69%</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>53%</td>
<td>85%</td>
</tr>
<tr>
<td>$\mu_2$</td>
<td>5</td>
<td>21%</td>
<td>23%</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>37%</td>
<td>39%</td>
</tr>
<tr>
<td></td>
<td>20</td>
<td>118%</td>
<td>148%</td>
</tr>
<tr>
<td>$\sigma_2$</td>
<td>4,5</td>
<td>56%</td>
<td>67%</td>
</tr>
<tr>
<td></td>
<td>4,8</td>
<td>57%</td>
<td>68%</td>
</tr>
<tr>
<td></td>
<td>5,2</td>
<td>59%</td>
<td>71%</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>63%</td>
<td>74%</td>
</tr>
</tbody>
</table>

### Table 5 Decrease in inventory level based on $\sigma_2$ and $\mu_2$

<table>
<thead>
<tr>
<th>$\Delta E[I^{OH}]$</th>
<th>$\mu_2$ 5</th>
<th>$\mu_2$ 10</th>
<th>$\mu_2$ 20</th>
<th>Grand Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma_2$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4,5</td>
<td>17%</td>
<td>33%</td>
<td>117%</td>
<td>56%</td>
</tr>
<tr>
<td>4,8</td>
<td>19%</td>
<td>35%</td>
<td>118%</td>
<td>57%</td>
</tr>
<tr>
<td>5,2</td>
<td>22%</td>
<td>37%</td>
<td>119%</td>
<td>59%</td>
</tr>
<tr>
<td>6</td>
<td>27%</td>
<td>42%</td>
<td>119%</td>
<td>63%</td>
</tr>
<tr>
<td>Grand Total</td>
<td>21%</td>
<td>37%</td>
<td>118%</td>
<td></td>
</tr>
</tbody>
</table>

39
Performance on the expected cost

The dual sourcing model reduces on average the expected cost during a potential delivery cycle with 70%. While this is a very high percentage, the actual reduction in cost will be less as not the full potential of the advance order information is used in the dual sourcing model. Similar to the expected inventory on hand, the costs are greatly reduced for long lead times. With longer lead times, the inventory system is less flexible to manage uncertainties in demand and the direct mode therefore becomes more attractive. Further, as the backorder cost increase, a larger cost reduction can be made. A higher backorder cost means that it is more attractive to hold inventory compared to having backorders. This also means that a higher service level will be achieved. The direct mode can offer a more attractive option than holding inventory for all possible demand sizes if the set up costs for this direct mode are not too high. Looking at the levels of the set up costs of the direct mode ($K_D$), both levels are attractive and thus a reduction in costs can be made. However, the difference in cost reduction given the levels of ($K_D$) shows that the set up costs of the direct mode have a large influence on the performance of the dual sourcing model.

It is interesting that for all levels of $\lambda$ a rather similar reduction in the inventory level is found, but that for an increasing value of $\lambda$ a larger reduction in costs is found. This means that a larger cost reduction can be achieved for erratic demand patterns than for lumpy demand patterns. Nevertheless, for both demand patterns a significant reduction in costs can be made. Last, the costs can be increasingly reduced when the variability in order sizes goes up ($\mu_2$ and $\sigma_2$). Again, the levels of the parameter $\mu_2$ were chosen such that they represent a simple compound Poisson distribution, a skewed distribution, and a bimodal distribution. For a simple compound Poisson distribution still a significant cost reduction can be made, however this percentage will be much lower in practice as not the full potential of the advance order information is used in the models. Different studies have tried to solve a problem comparable to the one presented in this work using a simple compound Poisson distribution. In future work, it can be interesting to compare the dual sourcing model to the models described in literature. Nevertheless, the largest potential in cost reduction lies in demand that follows a bimodal distribution. Additionally, the levels of the parameter $\sigma_2$ were chosen such that the variability of the demand sizes were just below, on top of, and above the cutoff value of the framework of Syntetos (2001). Table 6 shows the results in cost reduction separated for each level of the parameter $\sigma_2$ and $\mu_2$. The table shows that a reduction of the inventory level can be achieved for any variability of the demand size. However, the higher the variability in demand sizes, the more the blurring of the forecast can be reduced, and the more the costs can be reduced.

Table 6 Decrease in costs based on $\sigma_2$ and $\mu_2$

<table>
<thead>
<tr>
<th>$\Delta \Pi$</th>
<th>$\mu_2$</th>
<th>5</th>
<th>10</th>
<th>20</th>
<th>Grand Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma_2$</td>
<td>4,5</td>
<td>19%</td>
<td>36%</td>
<td>146%</td>
<td>67%</td>
</tr>
<tr>
<td></td>
<td>4,8</td>
<td>21%</td>
<td>37%</td>
<td>147%</td>
<td>68%</td>
</tr>
<tr>
<td></td>
<td>5,2</td>
<td>24%</td>
<td>40%</td>
<td>150%</td>
<td>71%</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>29%</td>
<td>44%</td>
<td>150%</td>
<td>74%</td>
</tr>
<tr>
<td>Grand Total</td>
<td></td>
<td>23%</td>
<td>39%</td>
<td>148%</td>
<td></td>
</tr>
</tbody>
</table>
Performance on flexibility, responsiveness, and uncertainty

Earlier research on the needs of a present-day foodservice wholesaler concludes that the supply chain of a foodservice wholesaler with a delivery service should be flexible (the ability to easily modify the volume, product mix, and innovations in products within the supply chain), efficient (minimizing total costs), as well as responsive (time between the moment of ordering and the moment a product is delivered at the customer) (Albers, 2018). Namely, the needs of the customers create implied demand uncertainty: the uncertainty that a supply chain faces due to the uncertainty in meeting the portion of customer demand that the supply chain has targeted to satisfy (Chopra & Meindl, 2016).

Because of the introduction of a second delivery mode in the dual sourcing model, the inventory system is more flexible. This is shown in that a larger cost reduction and inventory level reduction can be made by increasing the lead time of the regular mode $L_R$. Note that already some flexibility is assumed that the lead time of the direct mode is at a level that it is able to deliver the customers within the given demand lead times. Likewise, the dual sourcing model only works when the overall inventory system is very responsive; either both the parameters $L$ and $R$ are equal to 1 or the emergency lead time $L_E$ is equal to one.

Last, the demand uncertainty for regular-sized orders has been reduced, as the order sizes that complicate accurately forecasting have been removed from the regular part of the system. However, this demand uncertainty has been removed to the second delivery mode. As the inventory system of the outside supplier is out of scope, it is unknown to what extent the inventory system is affected by this.

8.2.1 Sensitivity analysis

In this subsection a sensitivity analysis is performed on the weight of the compounding distributions ($p$) and the customer satisfaction. The customer satisfaction is measured in the fill rate (the long term fraction of demand that have been delivered on time and complete) and in the order fill rate (the long term fraction of orders that have been delivered on time and complete).

Weight of the compounding distributions

The weight of the compounding distributions ($p$) specifies in which ratio the two different compounding distributions are mixed. As explained in section 7.2, the first compounding distribution is used to simulate the orders from clients that are regularly sized, while the second compounding distribution represents the irregular orders placed by customers; the sudden surges in demand. The weight $p$ represents the probability that a size of the demand of the first compounding distribution is taken.

Figure 17 shows the sensitivity of this weight for two examples with randomly chosen input parameters. The first example has the input parameters $L = 2, Q = 5, K_D = 35, b = 19, \lambda = 1.4, \mu_2 = 10, \text{ and } \sigma_2 = 5.2$. The second example has the input parameters $L = 1, Q = 10, K_D = 70, b = 49, \lambda = 2, \mu_2 = 5, \text{ and } \sigma_2 = 6$. For both examples it can be seen that the costs and the inventory level can be further reduced when probability $p$ is low. Remarkable is that when $p = 1$ and the demand distribution is reduced to the standard distribution with $\mu_1 = 5, \text{ and } \sigma_1 = 2.4$, the introduction of a direct mode is not alluring. This means that for standard distributions in the food retail, the dual sourcing model is not of added value.
Customer satisfaction

The idea behind the proposed model to remove the demand quantities that cause the high variability for the stock point and delivering these via the direct mode was hypothesized to be advantageous for the normal-sized customer orders. Namely, an extremely-sized customer order could deplete the stock completely, leaving the following customers with normal-sized orders empty handed. To verify this, the fill rate for the stock point in the regular mode has been exactly evaluated. Note that the assumptions regarding the direct mode are made such that always a 100% fill rate is achieved.

The fill rate considered in this thesis is the long term fraction of demand delivered on time. It is closely related to the standard fill rate, or $P_2$, which represents the long term fraction of demand delivered immediately from stock. The fill rate is calculated as follows:

$$ P = 1 - \frac{E[BO]}{E[D(\tau + L, \tau + R + L)]} $$

(17)

where

$E[BO]$ := expected backorders during a potential delivery cycle

$E[D(\tau + L, \tau + L + R)]$ := the expected demand during a potential delivery cycle

The performance on the fill rate for the single sourcing (SS) and dual sourcing (DS) model is similar to the other two KPIs measured in the difference in percentage. However, for the fill rate, the increase in percentage is measured. The difference in percentages is measured as follows:

$$ \Delta P = 100 \frac{P(DS) - P(SS)}{P(SS)} $$

(18)
Table 7 shows the performance on the fill rate for the regular mode of the 864 different experiments, in which one input parameter was kept constant at a certain level. The results show that the fill rate for the regular mode given the dual sourcing model remains the same or slightly improves compared to the single sourcing model. Note that the actual fill rate of the dual sourcing model will be equal to or even higher as the results shown in Table 7. This is due to the fill rate of the direct mode, which is always at a 100%. Note that the average fill rate achieved for the single sourcing model is 98.6% and for the dual sourcing model 99.2% for the regular mode.

Table 7 Results of the factorial design for the fill rate of the regular mode

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Level</th>
<th>( \Delta P )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( L )</td>
<td>1</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>2%</td>
</tr>
<tr>
<td>( Q )</td>
<td>5</td>
<td>1%</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>1%</td>
</tr>
<tr>
<td>( b )</td>
<td>19</td>
<td>1%</td>
</tr>
<tr>
<td></td>
<td>49</td>
<td>1%</td>
</tr>
<tr>
<td>( K_D )</td>
<td>35</td>
<td>1%</td>
</tr>
<tr>
<td></td>
<td>70</td>
<td>1%</td>
</tr>
<tr>
<td>( \lambda )</td>
<td>1,1</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td>1,4</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>2%</td>
</tr>
<tr>
<td>( \mu_2 )</td>
<td>5</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td>20</td>
<td>2%</td>
</tr>
<tr>
<td>( \sigma_2 )</td>
<td>4,5</td>
<td>1%</td>
</tr>
<tr>
<td></td>
<td>4,8</td>
<td>1%</td>
</tr>
<tr>
<td></td>
<td>5,2</td>
<td>1%</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>1%</td>
</tr>
</tbody>
</table>

To further investigate if the customer satisfaction has improved for the normal-sized customer orders, the order fill rate is introduced. This order fill rate measures the ratio of all orders that have been delivered on time and complete. In other words, it measures how many customers have been satisfied. The expression for the time fill rate is as follows:

\[
p^o = 1 - \frac{\# \text{ of orders backordered in } [R, L + R]}{\# \text{ of orders in } [R, L + R]}
\]  

(19)

Likewise, as the order sizes incoming for the stock point of the regular mode are truncated due to the cutoff order size and the same or a slightly higher fill rate is achieved, the question is how the customer satisfaction is per order size and how the cutoff order size has affected this. Unfortunately, this rate cannot be exactly evaluated. Therefore, the order fill rate has been simulated in MATLAB.
Figure 18 shows an example of this shift in distribution for the randomly chosen input parameters \( \{L = 3, R = 1, Q = 5, \lambda = 1.1, \mu_2 = 20, \sigma_2 = 4.5, p = 0.8, b = 19, K_D = 35, M = 8\} \). For the single sourcing model an order fill rate of 0.999 was achieved and for the dual sourcing model an order fill rate of 0.998 while iterating for 1.000.000 periods with a warm up period of 1.000 periods. The bar chart shows the frequency of when an order becomes backordered given a certain order size for both the single sourcing as the dual sourcing model. The line chart shows the average order fill rate per order size for both the single sourcing as the dual sourcing model.

\[ \text{Shift in P}^0 \text{ distribution} \]
\[ \{L=3, R=1, Q=5, \lambda=1.1, \mu_2=20, \sigma_2=4.5, p=0.8, b=19, K_D=35, M=8\} \]

It can be seen that for the single sourcing model the backorders are dispersed over the different order sizes, while for the dual sourcing model all backorders are below or equal to the cutoff order size (Note that order sizes above the cutoff order size are classified as irregular). Although the system fill rate increases and the average customer satisfaction rate remains virtually the same, the dual sourcing model dissatisfies more customers with a small order size. In particular, customers on or just below the cutoff order size are more dissatisfied. Appendix E shows two more examples with different input parameters of which the same conclusions can be drawn.

8.2.2 CONCLUSION

In this chapter a factorial design has been performed on 864 different experiments. In general for each of the experiments a large reduction in the inventory level and the expected costs can be achieved. An important insight was that the more the variability in the order sizes increased, the more the inventory and the costs could be reduced. It was found that for a simple compound Poisson distribution still a significant cost reduction can be made, however this percentage will be much lower in practice as not the full potential of the advance order information is used in the proposed model. Different studies have tried to solve a problem comparable to the one presented in this work using a simple compound Poisson distribution. In future work, it can be interesting to compare the dual sourcing model to the models described in literature. Likewise, the dual sourcing model performed better on costs when the average demand interval is high while the inventory level reduction
stayed relatively stable under different arrival rates. Next to that, sensitivity analysis on the weight of the two compounding distributions used to generate the demand showed that the costs and the inventory level can be further reduced when this weight is low. This means that more often sudden surges occur. Remarkable was that when only the first compounding distribution was used (which means that no sudden surges occur), the direct mode was not appealing and thus the dual sourcing model was not of added value.

Furthermore, the demand uncertainty for regular-sized orders has been reduced, as the order sizes that complicate accurately forecasting have been removed from the regular part of the system. However, this demand uncertainty has been removed to the second delivery mode. As the inventory system of the outside supplier is out of scope, it is unknown whether to what extent the inventory system is affected by this. However, the introduction of a second delivery mode in the dual sourcing model makes the inventory system in scope more flexible.

Next to that, the customer satisfaction remained the same or slightly increased due to the dual sourcing model. In general the fill rate remained the same or slightly increased. Further analysis discovered that the distribution of backorders per order size shifted between the two different scenarios. For the single sourcing model the backorders are dispersed over the different order sizes, while for the dual sourcing model all backorders are below or equal to the cutoff order size. Since the same amount of demand can be backordered, relatively more orders are backordered by the dual sourcing model. In particular, customers on or just below the cutoff order size are more affected by this.

In this chapter the research question ‘How do the scenarios perform on flexibility, responsiveness, uncertainty, costs, and customer service?’ is answered.
9 Managerial insights

Based on the results discussed in Chapter 8, some implications for Sligro and other companies can be deducted. In this chapter the seventh research question ‘Which possible strategic implications can be deducted based on the gained insights?’ is answered.

The dual sourcing model greatly reduces the inventory reduction at the warehouse under scope. This means that scarce space can be better utilized and that investments on the expansion of the network are needed less quickly. Likewise, a consideration can be made between the customer satisfaction (in fill rates or in order rates) and the cost reduction. With current knowledge on inventory management achieving a higher service level is normally associated with very high costs. Using the dual sourcing model, these associated costs could be controlled. Further, the dual sourcing model shows the importance of a flexible supply chain. Having at least one mode that is flexible can reduce costs greatly.

From Chapter 5 it became clear that the customers of Sligro increasingly order with shorter demand lead times and increasingly order later on the day. Thus, a flexible and responsive supply chain becomes more and more important. Likewise, results in Chapter 8 showed that the dual sourcing model can reduce costs greatly only if a responsive option exists for the irregular sized orders. However, if the trend continues of increasingly ordering later on the day and with shorter demand lead times, it is beneficial to have the separation of the regular and direct mode in the dual sourcing model to control this trend. For instance, a policy can be introduced that irregular-sized orders should be ordered with a minimum demand lead time. It is more likely that customers accept that large orders must be made more timely. In addition, a bonus structure could be implemented to stimulate customers to order earlier.

Specifically for Sligro, implementing the dual sourcing model can create clarity when to use emergency procedures and more importantly creates peace within the network. Having one flexible emergency option already enables the delivery service DCs to satisfy their customers with less cost. This also means that the emergency option should be structured and optimized in the operation. As shown in the results, the height of the emergency set up costs has a rather large influence on the costs made. Furthermore, on a strategic level, the complete network should be revised. Since the network is already being overhauled by the integration of the logistical activities of Heineken, taking into account that smaller regional warehouses but larger central warehouses are necessary is highly recommended.

Nonetheless, the implementation of the dual sourcing model should not be taken lightly. As stationary demand is assumed in the model, this will most likely not be the case in practice. For instance, changing demand patterns should be taken into account timely. Next to that, in the food sector promotions are omnipresent. Demand for an item in promotion increases greatly and through this more orders are extremely-sized. The question is how best to deal with this in practice; leaving the system in place or excluding the promotion for the item from daily practice? Last, the dual sourcing removes the variability from the regional warehouse to the outside suppliers. This means that inventory management is made easier regional but more complex at the suppliers. In general, complex demand is better manageable centrally than regionally (van Donselaar, 1990), but this shift in uncertainty should be handled with caution.
10 Conclusions

This research aimed at finding a solution for surges in demand, or high demand variability, in the setting of an retailer that delivers orders from a regional warehouse, where demand is known for a certain time period, the customer orders with varying quantities, and the retailer aims to satisfy all orders. The main research question defined was:

*When and how can emergency ordering be beneficial to manage sudden surges in demand?*

A model was designed with a decision rule that proactively recognizes a surge in demand that will disturb the regular inventory system and treat those surges in demand as emergency shipments. The intention is to receive the emergency replenishment within the demand lead time. The decision rule makes its decision based on the characteristics of the order; the cutoff order size and the demand lead time.

The model was compared to another scenario: the basic model where all demand must be filled from stock and no emergency options are possible. Two different KPIs were introduced to verify the performance: 1) expected inventory on hand, and 2) expected cost.

A factorial design was performed to explore the behavior of the model. In general for each of the experiments a large reduction in the inventory level (on average 59%) and the expected costs (on average 70%) can be achieved. An important insight was that the more the variability in the order sizes increased, the more the inventory and the costs could be reduced. However these reductions will be lower in practice as not the full potential of the advance order information is used in the proposed model. Likewise, the dual sourcing model performed better on costs when the average demand interval is high while the inventory level reduction stayed relatively stable under different arrival rates. Next to that, sensitivity analysis on the weight of the two compounding distributions showed that when relatively more sudden surges occur, the dual sourcing model is more of added value. Remarkable was that when only the first compounding distribution was used (which means that no sudden surges occur), the direct mode was not used. Customer satisfaction remained the same or slightly increased. However, the distribution of backorders per order size shifted from dispersed over all order sizes to on or just below the cutoff order size.

Concluding, this research showed that surges in demand can be cost-efficiently managed by introducing an emergency option that is controlled by a decision rule based on the order size and demand lead time.
11 Reflection

11.1 Scientific Contribution
This thesis differs from the reviewed literature in the following way that it does not assume that a possible backorder situation should be solved immediately with expediting, but that a certain demand lead time is given per order in which the system might be able to prevent the backorder situation. Moreover, the decision rule presented in this thesis is based on the characteristics of the order and not on the inventory position or inventory on hand.

Additionally, this thesis considers an unexamined situation where the arrival of demand has been modelled by a combination of two compound Poisson processes as the customer varies in ordered quantities. In literature it is often assumed that customers either order large quantities or small quantities.

Likewise, the use of a cutoff order size to determine the distinction between regular and emergency replenishments creates a rather simple but elegant method to exactly evaluate the proposed inventory system, while the examined literature has mainly focused on solving their systems with Markov models and dynamic programming. However, to our knowledge, the proposed model has never been researched before.

Last, the proposed model is applicable to a variety of sectors apart from the foodservice sector. Similar situations can be found for B2B companies with a limited number of customers, such as a construction wholesaler.

11.2 Limitations
This thesis is characterized by a few limitations.

The first one is the choice to use the DoBr tool. First of all an assumption was needed that demand is stationary, which might not necessarily be true. Because of this, the current actual dynamics of demand patterns are perhaps not fully captured by the DoBr tool. Secondly, the DoBr tool is not (yet) ready to incorporate other policies than the FCFS policy. Through this, other described scenarios could not be exactly evaluated.

Another limitation is the assumption to not include the information on customer orders in the optimization of the reorder level. When demand is known beforehand, adjustments can be made to prevent backorders. The demand uncertainty would decrease for both the single sourcing as the dual sourcing model, but will most likely have the biggest effect on the single sourcing model.

Third, the model assumes that the customer is not interested in substitute articles and that all unmet demand is backordered. In reality, some backorders can be prevented by proactively offering substitute articles. However, this results in that the forecasts of the substitution articles is not reliable anymore. Likewise, in reality, not all unmet demand will be backordered, but some demand will be considered as lost sales.
A fourth limitation is the assumption that the inventory of the outside suppliers is abundant. In reality the inventory of the suppliers is limited and not all ordered replenishments will be delivered in full, especially in the case of emergency orders. However, in general the supplier will have a high fill rate as well.

Last, for the sake of the tractability of the model, the demand lead time given by the customer with an extremely-sized order was assumed to be sufficient to deliver within the lead time of the emergency replenishments. In reality, this means that when the demand lead time is too short to deliver within the lead time of the emergency replenishment, the order will be backordered or will become lost sales. Next to that, the assumption was made that irregular sized orders with long demand lead times can always be filled by enlarging the regular replenishment. Through this, no extra set up costs are added. However, in reality not every review moment a regular replenishment will be issued, especially for small arrival rates and high base replenishment quantities. Likewise, it was assumed that no inventory costs needed to be added as the time between the delivery of the closest replenishment moment and the due date will be very small. Through this, in reality the inventory reduction and cost reduction reported in this thesis will be lower.

11.3 Future Research
Since this thesis considers an in literature unexamined situation and designs a possible solution for this situation, multiple research directions can be determined.

First of all, the most interesting research direction is to see what the effect is when the demand lead time is used in a greater extent. The information on the customer orders that is present during the demand lead time could be used at the stock point for both models to proactively adjust for unforeseen surges in demand. Without using emergency options, already demand uncertainty can be decreased. Next to that, instead of a deterministic emergency lead time, a stochastic emergency lead time can be assumed.

Furthermore, other interesting research directions are to extend the proposed model. For example, this model could be further extended with multiple emergency replenishment options (with different associated costs, lead times, etc.). As there is a separation between the regular and irregular part of the inventory system, extra options can be added quite easily. Through nested procedure the optimal cutoff order size could be found. Likewise, the model could be extended for perishable items. Perishable products cannot be kept in stock for long and thus as little stock as possible is kept. Due to this, managing high demand variability is very difficult to manage and on average more customer orders are backordered. Because of the added flexibility of the model considered in this thesis, there is a great potential to reduce cost and improve the customer satisfaction rate. Furthermore, lost sales can be considered instead of backorders and capacitated inventory at the suppliers can be considered instead of ample inventory. Last, instead of perfect advance demand information, imperfect advance demand information could be assumed.

Last, the model considered in this thesis can be compared with the scenarios that do not assume a FCFS policy, but rather give priority to large orders. On top of that, it would be interesting to examine how the proposed model in this research performs in comparison to the models described in literature.
REFERENCES


Van Donselaar, K., & Broekmeulen, R. (2014). *Stochastic inventory models for a single item at a single location.* [Beta working paper 447].


APPENDICES

APPENDIX A: EXCEPTION DELIVERY SERVICE DCs
The delivery service distribution centers are local warehouses where orders are prepared for delivery. The orders can be gathered either through picking the articles that are stored locally, through the dedicated pick-to-zero zones, or through cross dock delivery from other (supplier) facilities.

The delivery service DCs decrease the distance towards the customer, thus decreasing last mile transportation costs as well as adding the ability to quickly respond to demand. Moreover, knowledge about local factors and events can be used to better respond to the needs of the customer. Further, due to the dedicated DCs for delivery, the volumes handled can be larger and more scalable compared to when operating from the wholesale outlets.

Sligro Food Group N.V. operates 24 delivery service DCs of which 13 are DCs recently taken over from Heineken and not yet integrated in the supply chain, 3 are open delivery service DCs, 1 is a delivery service DC dedicated to the healthcare industry, and 7 are regular delivery service DCs. Note that only the 7 regular delivery service DCs are part of the scope.

Open delivery service DCs
Open delivery service DCs are a combination of a delivery service DC and a wholesale outlet. The region covered by the open delivery service DC does not generate enough revenue to split the delivery service and the outlet service into two locations. Therefore, the whole assortment is located in the wholesale outlet and orders for delivery are gathered by picking in the outlet. Often some small warehousing space is available for fastmovers and articles that are specific for the delivery service. Replenishment of articles are ordered in combination. Depending on the proportion of sales as a wholesale outlet or delivery service DC, the facility is more equipped as respectively a wholesale outlet or delivery service DC.

Van Hoeckel
Van Hoeckel is a delivery service DC that mainly targets the healthcare industry. The needs of the healthcare clientele differ from the regular food service clientele in that they are not particularly looking for diversity in assortment, but a complete package of articles as having something to eat is their main priority. Moreover, the delivery times are less flexible, and the volumes per article and per order are lower. Because of these differences, the operations within this delivery service DC are differently organized. For instance, pick- and bulk location are combined into one location and roll containers need to be organized by specific instructions from their clientele.

Heineken delivery service DCs
Recently, Sligro Food Group N.V. has made an agreement with Heineken to take over all logistical activities in the Netherlands. Part of the takeover are 13 delivery service DCs of which 4 mainly function as small depots. At the moment of writing, a lot of effort is put into integrating these facilities in the supply chain of Sligro Food Group N.V. After the integration, the future and function of these facilities will be determined to create an efficient total supply chain.
APPENDIX B: ORDER ACCUMULATION

Figure 19 Order accumulation of orders at a delivery service DC for all demand lead times

Figure 20 Order accumulation of orders at a delivery service DC for T=1
Figure 21 Order accumulation of orders at a delivery service DC for $T=2$

Figure 22 Order accumulation of orders at a delivery service DC for $T>2$
APPENDIX C: FITTING DISCRETE DISTRIBUTIONS ON THE FIRST TWO MOMENTS

In this Appendix a procedure for fitting discrete distributions on the first two moments of a discrete random variable that is due to Adan, Van Eenige, & Resing (1996) is described.

Let $X$ be a random variable on $\mathbb{N} \cup \{0\}$ with mean $\mu$ and squared coefficient of variation $c_v^2$ and define $a = c_v^2 - 1/\mu$. The squared coefficient of variation $c_v^2$ can be determined by squaring the ratio of the standard deviation to the mean: $(\frac{\sigma}{\mu})^2$. Then the discrete random variable $Y$ matches the first two moments of $X$ if it is chosen as follows:

1. If $-\frac{1}{k} \leq a \leq -\frac{1}{k+1}$ for some $k \in \mathbb{N}$, then $Y$ is a mixture of two binomial random variables such that:

   $$Y = \{ \begin{array}{ll} \text{BIN}(k, p), & \text{with probability } q \\ \text{BIN}(k + 1, p), & \text{with probability } 1 - q \end{array}$$

   where

   $$q = \frac{1 + a(1 + k) + \sqrt{-ak(1 + k) - k}}{1 + a}, \quad p = \frac{\mu}{k + 1 - q}$$

2. If $a = 0$, then $Y$ is a Poisson random variable with mean $\mu$, $Y = \text{Pois}(\mu)$.

3. If $\frac{1}{k+1} \leq a \leq \frac{1}{k}$ for some $k \in \mathbb{N}$, then $Y$ is a mixture of two negative binomial random variables such that:

   $$Y = \{ \begin{array}{ll} \text{NegBIN}(k, p), & \text{with probability } q \\ \text{NegBIN}(k + 1, p), & \text{with probability } 1 - q \end{array}$$

   where

   $$q = \frac{a(1 + k) - \sqrt{(1 + k)(1 - ak)}}{1 + a}, \quad p = \frac{\mu}{k + 1 - q + \mu}$$

4. If $a \geq 1$, then $Y$ is a mixture of two geometric random variables such that:

   $$Y = \{ \begin{array}{ll} \text{Geo}(p_1), & \text{with probability } q \\ \text{Geo}(p_2), & \text{with probability } 1 - q \end{array}$$

   where

   $$p_1 = \frac{\mu(1 + a + \sqrt{a^2 - 1})}{2 + \mu(1 + a + \sqrt{a^2 - 1})}, \quad p_2 = \frac{\mu(1 + a - \sqrt{a^2 - 1})}{2 + \mu(1 + a - \sqrt{a^2 - 1})}$$

   $$q = \frac{1}{1 + a + \sqrt{a^2 - 1}}$$
APPENDIX D: COMPOUND POISSON PROCESS

When demand is a compound Poisson process, customers arrive via a Poisson process with an arrival rate of $\lambda$. The size of the customer demand is stochastic and is determined via a compounding distribution. The information on the compound Poisson process is extracted from Axsäter (2006).

The distribution of the compound Poisson process can be determined via the following expression:

$$P(D(t) = j) = \sum_{k=0}^{\infty} \frac{(\lambda t)^k}{k!} * e^{-\lambda t} * f_j^k$$

where

$D(t)$ is the stochastic demand in the interval $t$

$f_j^k$ is the probability that $k$ customers give the total demand $j$

The first part of the equation expresses the probability for $k$ customers in a time interval of length $t$. The number of customers arriving in a time interval follows a Poisson distribution.

$$P(k) = \frac{(\lambda t)^k}{k!} * e^{-\lambda t}, \quad k = 0, 1, 2, ...$$

The second part of the equation expresses the distribution of the demand size, also called the compounding distribution. The size of the customer demand is a stochastic variable that is independent of other customer demands and of the distribution of the customer arrivals. To determine the probability that $k$ customers give the total demand $j$, let:

$f_j$ is the probability of demand size $j$ ($j = 1, 2, ...$)

where it is assumed that each customer demands an integral number of units, and that

$f_j^k$ is the $k$-fold convolution of $f_j$

Note that $f_j^0 = 1$ and $f_j^1 = f_j$. Given $f_j^1, f_j^k$ can be found by recursively solving

$$f_j^k = \sum_{i=k-1}^{j-1} f_i^{k-1} * f_{j-i}, \quad k = 2, 3, 4, ...$$
APPENDIX E: SHIFT IN CUSTOMER SATISFACTION RATE PER ORDER SIZE

Figures 23 and 24 show an example of the shift in distribution for the randomly chosen input parameters \( \{L = 1, R = 1, Q = 10, \lambda = 1.4, \mu_2 = 10, \sigma_2 = 5.2, p = 0.8, b = 49, K_D = 35, M = 14\} \) and \( \{L = 2, R = 1, Q = 5, \lambda = 2, \mu_2 = 5, \sigma_2 = 5.2, p = 0.8, b = 19, K_D = 35, M = 14\} \). For the first example, the single sourcing model achieved an order fill rate of 0.995 and the dual sourcing model an order fill rate of 0.999. For the second example, the single sourcing model achieved an order fill rate of 0.999 and the dual sourcing model an order fill rate of 0.995. An iteration of 1,000,000 periods was used with a warm up period of 1,000 periods. The bar charts show the frequency of when an order becomes backordered given a certain order size for both the single sourcing as the dual sourcing model. The line charts shows the average order fill rate per order size for both the single sourcing as the dual sourcing model.

![Figure 23](image1)

*Figure 23 The order fill rate and frequency of backorders per order size (example 2)*

![Figure 24](image2)

*Figure 24 The order fill rate and frequency of backorders per order size (example 3)*