MASTER

Safety stock positioning in the multi-echelon omnichannel supply chain of MediaMarkt NL

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Safety stock positioning in the multi-echelon omnichannel supply chain of MediaMarkt NL

Master Thesis

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Executive Summary

This research is conducted at MediaMarkt NL, a consumer electronics retailer operating in the Netherlands.

Introduction

MediaMarkt NL is an omni-channel retailer with 48 physical stores and an online webshop. This enables customers to make purchases through both the traditional brick-and-mortar stores and the online channel. Moreover, the company offers delivery options such as in-store pickup for online orders and home delivery for in-store purchases. As a result, the company has integrated its operations to accommodate these various channels.

In the past years, MediaMarkt made a shift from a decentralized towards a centralized supply chain by establishing a central warehouse in Etten-Leur. In this divergent multi-echelon supply chain, all suppliers deliver to the central distribution center, where the products are kept in stock. The distribution center has the dual role of replenishment of the physical stores and meeting customer demand from online sales, making it an integrated warehouse.

Inventory control at MediaMarkt is centralized and the method used by the planning software is based on the (R, S) replenishment system. The system calculates a safety stock value for each product-location, but the exact method to calculate the safety stock was unknown by the company. Additionally, due to the complex structure of omni-channel multi-echelon supply chain, the best safety stock positioning is unknown and MediaMarkt wants this to be researched. The objective is to manage the trade-off between the service levels and inventory holding costs. This results in the following main research question:

How to determine the best safety stock levels and positioning in the omni-channel multi-echelon supply chain of MediaMarkt, to maintain the service levels while minimizing holding costs?

Analysis

The inventory control policy currently uses an installation stock policy, where the replenishment decision at the distribution center is only based on its own inventory position, and the inventory positions at the stores are not taken into account with the ordering decision. The safety stock method used by the planning system is analyzed and the method found is the fill rate in a continuous review system. This method uses the assumption of a Normally distributed demand, but this assumption seems to conflict with the demand observed at MediaMarkt.

Other analytical approaches also assume a Normal distribution and a simulation-based approach can be used to calculate safety stock levels with other demand distributions.

In the integrated warehouse, the inventory is kept at the same physical location in the warehouse and there is physically no separate stock for online customers or stores. Due to risk pooling, the need for safety stock is expected to be lower than with separate warehouses. To manage the allocation of inventory over the two channels, an inventory reservation approach, also called ring-fencing by the company, is used. With this approach, part of the inventory is reserved for online customers. The quantity reserved is the forecasted demand for the period until the next warehouse replenishment arrives. Currently, there is no safety stock in the reservation quantity.

Solution design

A simulation-based approach is used to determine the correct safety stock levels and positioning, to reach the service level targets while minimizing holding costs. A simulation model is established to mimic the multi-echelon omni-channel supply chain where the warehouse is supplied by external suppliers and the warehouse supplies multiple retailers. In this model, the retailers are assumed to be identical. The warehouse acts as an integrated warehouse, which fulfills both online customer orders and store replenishment orders. Inventory reservation can be used for the allocation of inventory in the integrated warehouse. The customer demand observed is stochastic and assumed to follow a Poisson demand distribution. The supplier lead times are assumed to be deterministic.

With the use of the simulation model of the multi-echelon omni-channel supply chain, different safety stock positioning scenarios can be evaluated, to find the scenario which reaches all service level targets while minimizing holding costs. To explore these various scenarios, a greedy heuristic approach is employed which iteratively adjusts the variables in search for a scenario with lower holding costs. The variables to be adjusted are the reorder levels in the warehouse, the reorder levels at the retailers, and the safety stock in the reservation quantity.

Results and recommendations

The greedy heuristic from the solution design is implemented using the demand characteristic computed from the data of MediaMarkt. The assortment is divided into nine categories, and from each category a product is chosen that classifies as the median product. For these nine products, the model is implemented to gain insights into the applicability of inventory reservation. The results show that inventory reservation, and using a safety stock in the inventory reservation quantity, can be profitable for certain products. However, this depends on the demand characteristics of the products. For the tested products with low demand, it is observed that reserving inventory is not justifiable. For the tested products with high demand and a high proportion of online demand, inventory reservation can be useful to reduce holding costs. An analysis of a example product shows that a reduction of 1.52% of the holding costs can be reached with the use of inventory reservation.

The recommendation to the company is to implement the proposed approach to determine the safety stock levels at the distribution center, at the stores, and in the reservation quantity.

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Chapter 1

Introduction

There are different types of distribution network designs that a company can use; single-channel, multi-channel and omni-channel. Single-channel applies to pure brick-and-mortar retailers and e-tailers that only use one channel to sell their products or services. Multi-channel is when a company uses multiple channels to sell its products or services, such as physical stores, online stores, and mobile apps. With omni-channel, the company also uses multiple channels and integrates online and offline channels. This results in a cohesive, interconnected experience for the customer. The customer can trigger full channel interaction and the retailer controls full channel integration (van Woensel, 2021).

In recent years, omni-channel retailing has become increasingly popular as consumers demand a seamless shopping experience across multiple channels. As a result, retailers need to adopt an omni-channel logistics approach to meet the diverse needs of their customers while improving operational efficiency and reducing costs. Building an effective and efficient omni-channel system, however, poses a number of logistical challenges (Hübner et al., 2016).

With the use of multiple sales channels, it is decided to combine these into an integrated warehouse, where the operations for the online and the offline channels are also merged, leading to new challenges with respect to inventory management. To effectively manage inventory in such a complex supply chain, it is important to determine optimal inventory levels and the positioning of inventory for each channel.

Subsequently, in a multi-echelon system, the problem arises of how to allocate safety stock to the various stock locations. In a classic divergent system, it is common that all available stock is pushed to the retailers, close to the customer, because it appears that holding back inventory in a depot yields a lower service level than passing through all inventory (Whybark and Yang, 1996). However, in an integrated warehouse, which has a dual role of meeting both customer demand and replenishing downstream locations, the common approaches such as that from van Donselaar and Wijngaard (1987) and De Kok et al. (1994) cannot be directly applied, as the integrated warehouse is also obliged to serve online customers with a reasonable service level.

To manage the challenge of serving demand from multiple channels, an inventory reservation approach can be applied. With inventory reservation, some portion of the available inventory is exclusively reserved for online customers. This can help with balancing the service levels for both channels, and searching for the best allocation of safety stock over the different locations.

1.1 Company description

This research will be carried out for MediaMarkt NL, hereafter called MediaMarkt. MediaMarkt is a consumer electronic retailer where customers can find an extensive selection of products, including computers, smartphones, televisions, gaming systems, and home appliances. The company was founded in Germany and operates in many different countries in Europe nowadays, including the Netherlands. Every country has its own headquarters and makes decisions for its own country. MediaMarkt NL's headquarter is located in Rotterdam.

Currently, there are 48 MediaMarkt stores in the Netherlands. In these stores part of the assortment is on stock and presented so customers can buy and take the products home immediately from the stores. In addition to its physical stores, MediaMarkt added an online store and app in 2012 that provides customers with a convenient and easy-to-use platform to purchase products. With fast and reliable delivery options, customers can enjoy the benefits of shopping with MediaMarkt from the comfort of their own homes. This changed the company from being a single-channel retailer to a multi-channel retailer. Currently, MediaMarkt is shifting from multi-channel to omni-channel, which expands the multi-channel by a development in the information given online. So whether browsing in-store, online, or in the MediaMarkt app, the operations should be seamless to provide customers with the best possible shopping experience.

This shift to omni-channel is reflected in the different delivery methods MediaMarkt offers at the moment. Currently, the company also offers in-store pickup when ordered online and home delivery when purchased in-store. These operations are added to the traditional brick-and-mortar in-store buying and the standard home delivery from online orders. This leads to the possibility of a customer using multiple channels during its purchasing journey.

1.1.1 Supply chain

The shift from multi-channel to omni-channel resulted in a change in the company's supply chain. Previously, MediaMarkt operated with a decentralized supply chain where products were directly supplied by suppliers to individual stores, and there was a separate warehouse for online sales. In this supply chain there was not one general inventory control model, so inventories were managed locally. However, MediaMarkt made a strategic shift towards centralization by establishing a central warehouse in Etten-Leur. In this divergent supply chain, all suppliers deliver to the central distribution center in Etten-Leur, where the products are kept in stock.

In April 2022, MediaMarkt combined the storage of the online and offline sales within the central warehouse, having an integrated warehouse. In this integrated warehouse, both the stock intended to serve online customers, also called Business to Customer (B2C) by MediaMarkt, and the stock intended for store replenishments, called Business to Store (B2S), are kept at the same physical location. This multi-echelon omni-channel supply chain is visualised in Figure 1.1.1, where the triangles represent inventory points.

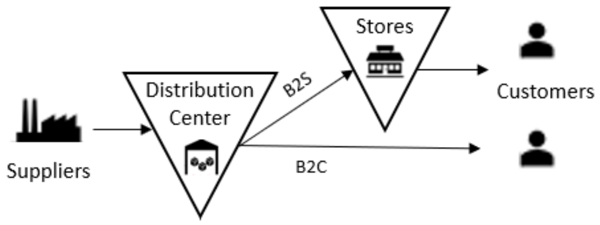


Figure 1.1.1: Multi-echelon omni-channel supply chain

In the distribution center (DC) there is physically no separate stock for online customers or for stores, so the stock for a particular Stock Keeping Unit (SKU) can be ordered by both the stores and customers online. Currently, the allocation of the products between the stores and online customers is executed with the use of inventory reservation, at MediaMarkt called ring-fencing. With this method, part of the available inventory is virtually reserved for online customers. This is done with the planning software of RELEX which creates a sales forecast for the online orders and this quantity will be virtually reserved. The remaining inventory can be distributed over the stores, based on the sales forecast and service levels of the stores.

The transformation to the omni-channel supply chain is still ongoing and opened several new challenges and opportunities for improvement within inventory management. In this Master Thesis, the calculation of the safety stock and the positioning in the omni-channel multi-echelon supply chain will be addressed.

1.2 Report Structure

This study is structured as follows. In chapter 1, the context of the study is outlined, providing an introduction to the research topic. chapter 2 presents the problem statement and outline our research approach. In chapter 3, the relevant literature is presented on the topics of the research. chapter 4 contains the analysis and diagnosis, where the relevant concepts of the current situation of the company are analysed. In chapter 5 contains the solution design, where the model to solve the problem is presented. chapter 6 contains a case study on the data of MediaMarkt, to validate the solution design. Lastly, chapter 7 contains the conclusions from this research and the recommendations given to MediaMarkt.

Chapter 2

Research Design

2.1 Problem statement

As explained in chapter 1, the interest at MediaMarkt in the safety stock calculation and the positioning in the omni-channel multi-echelon supply chain leads to the following problem statement:

Currently MediaMarkt operates in an omni-channel multi-echelon supply chain and keeps safety stock in the omni-channel distribution center and in the stores. The best safety stock positioning in the omni-channel multi-echelon supply chain is unknown and the method to calculate the best safety stock levels per product-location is unidentified. So, MediaMarkt wants the safety stock calculation and positioning in the omni-channel multi-echelon supply chain to be researched.

2.2 Research Objective

The problem definition highlights the lack of adequate knowledge on determining the appropriate safety stock settings, which currently rely heavily on the automatic replenishment system RELEX. The calculation method used is not fully understood, thus indicating a need for guidelines to determine the correct strategy and safety stock settings at the correct location in the supply chain for a certain product. Additionally, there is a need for insights into managing the trade-off between service levels and inventory costs.

Based on the problem statement and the literature review, there is a need for a safety stock setting approach that is applicable to MediaMarkt. The approach should determine the best amount of safety stock and the best positioning in the supply chain. The uncertainties that are relevant for MediaMarkt should be taken into account in this approach. This results in the following research goal:

Design and develop an approach that determines the best safety stock positioning in the multi-echelon omni-channel supply chain and calculates the safety stock levels for each product at every inventory point to maintain the desired service level against minimal holding costs, while taking into account the important uncertainties.

2.3 Research Questions

The problem statement is translated into a research question, for which answering should result in solving the problem. Provided with the business context and the research goal it was possible to aggregate one main research question:

How to determine the best safety stock levels and positioning in the omni-channel multi-echelon supply chain of MediaMarkt, to maintain the service levels while minimizing holding costs?

The following paragraphs outline the approach to answer the main research question including the corresponding research questions. We classify the research into four phases, namely Analysis and Diagnosis, Literature, Modeling, and Evaluation. The process including the relations between these phases is schematically visualized in Figure 2.3.1.

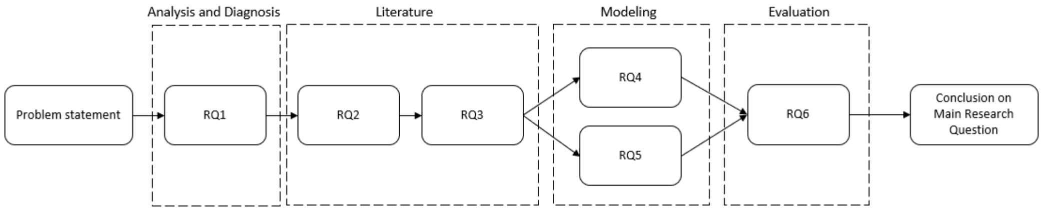


Figure 2.3.1: Visualisation and Approach of RQs

Analysis and Diagnosis

The first phase is the analysis and diagnosis of the current situation at MediaMarkt. The following research question is defined for this phase:

RQ1: How does MediaMarkt currently set its safety stock levels, both in the DC and in the stores? What is the performance of this method?

The analysis and diagnosis will focus on the current situation within MediaMarkt. The multi-echelon omni-channel supply chain will be mapped and the supply chain structure, fulfilment strategy and customer journey will be addressed. Thereafter, the replenishment policy will be researched, with a special focus on the safety stock calculation methods and positioning in the multi-echelon supply chain. This will answer RQ1. Subsequently, the assortment and demand of MediaMarkt are analyzed. Eventually, the performance of the current method will be analyzed, answering the second part of RQ1.

Literature

The second phase is the search for relevant literature on the topic of safety stock in an omni-channel multi-echelon supply chain. The following research questions are defined for this phase:

RQ2: Which methods to determine the safety stock levels in a multi-echelon omni-channel supply chain are available in the literature? Which factors should be considered and what are their impact?

RQ3: Which strategies for positioning safety stock in the omni-channel multi-echelon supply chain are there available in the literature?

The search for relevant literature requires two steps. First, the different safety stock calculation methods that are available in the literature are searched, focusing on their applicability to the demand of MediaMarkt and the multi-echelon omni-channel supply chain. For each method, the relevant factors and assumptions will be explored, which will help answer RQ2. Secondly, the literature is searched for strategies for positioning safety stock in a multi-echelon omni-channel supply chain. This will answer RQ3 and has as its goal to find a suitable approach for this research.

Modeling

Based on the outcome of the analysis and diagnosis of the current situation and the relevant literature, an approach to determine the safety stock levels and positioning in the omni-channel multi-echelon supply chain is designed and developed. Therefore, the corresponding research questions for this phase are:

RQ4: What is the best method to calculate the safety stock level per product-location?

RQ5: What is the best positioning of the safety stock at the various stock points in the multi-echelon omni-channel supply chain?

Based on the analysis & diagnosis and the literature on the different methods, a method is chosen to determine the safety stock levels. Subsequently, a model is established that simulates the multi-echelon omni-channel supply chain. This model takes into account the interdependencies among the multiple stock points within the supply chain. With the help of this model, a heuristic is set up that aims to determine the safety stock levels and positioning within the different stock points, to reach the service level targets while minimizing holding costs. These two research questions are executed interchangeably.

Evaluation

The designed approach will need to be evaluated, to asses its applicability on the situation of MediaMarkt.

RQ6: What is the performance of the designed approach, compared to the current situation?

The designed approach will be evaluated, by a case study on the demand of MediaMarkt. The model is simulated using various demand scenarios derived from the historical demand data of MediaMarkt. This analysis aims to provide valuable insights into the performance of the model when applied within the company's operations. By analyzing the outcomes, conclusions can be drawn regarding the effectiveness and applicability of the model within the context of MediaMarkt.

2.4 Contribution to scientific literature

There has been research on keeping safety stock in divergent multi-echelon supply chain systems. In the literature, a common assumption is having a normally distributed demand, on which the standard safety stock formulas existing in the literature can be applied. This research relaxes the assumption of a normal distribution, and will provide a simulation approach to determine the safety stock values. Additionally, the contribution of this research will be the addition of an integrated warehouse where stock for both online and store replenishment needs to be kept. To the author's knowledge, research has not provided an approach to model this specific type of supply chain. Therefore, this thesis will contribute to the literature by developing an approach to determine the best safety stock values and positioning in an omni-channel multi-echelon supply chain.

2.5 Scope

When classifying the products based on van Donselaar et al. (2005), the products of the assortment that are in the scope of this research are the regular products. This leaves the promotion items, products with a short life cycle, purchasing driven items and capacity driven items out of the scope. Furthermore, only the products in the multi-echelon supply chain are in the scope of the research, meaning that the products only displayed but not sold in the stores, are out of scope. Additionally, solely the products kept on stock in the DC are taken into account and cross-docking is out of the scope of this assignment.

Chapter 3

Literature Review

3.1 Omni-channel

In a single-channel distribution network a company uses only one channel to sell its products or services; through its own physical retail stores or only online. In a multi-channel distribution network a company uses multiple channels to sell its products or services, such as physical stores, online stores, and mobile apps. However, these channels may not be integrated and may not provide a consistent experience for the customer. In a omni-channel distribution network a company integrates all its channels into a cohesive, interconnected experience for the customer. The customer can trigger full channel interaction and the retailer controls full channel integration (Van Der Heijden et al., 1997). Where in multi-channel supply chains direct shipments and store supply operate independently, these channels are merged in omni-channel networks and both store and direct shipments are fulfilled from the same stock and via the same network (Tetteh and Xu, 2014). Therefore, the difference between omni-channel and multi-channel, is in the cooperative management between the channels (Cai and Lo, 2020). In omni-channel retail management, the focus is on optimizing the customer experience at different retailer channels and touch points, leading to an enhanced level of customer service.

The success of omni-channel depends on the performance of its distribution network. In the omni-channel and multi-channel networks design, a distinction can be made between separated and integrated networks. The separated networks can be divided into networks where the online and the offline business are independently organized in parallel or in sequence (Hübner et al., 2015). In the integrated network, there is an integrated warehouse for both channels. According to Prabhuram et al. (2020) a network design with an integrated warehouse and transport—delivery taking place from all nodes performs best. In this situation, the warehouse and logistics activities are integrated and both online and offline demand are fulfilled from the same distribution center. Moreover, the online demands can be fulfilled via a store, or directly from the distribution center to a customer.

In an integrated warehouse, effectively managing the fulfillment of large store replenishments and small online orders is a major challenge challenge (Hübner et al., 2015). To accommodate for this growing complexity in the omni-channel distribution network an integrated information system should be implemented (Oh et al., 2012). An integrated system makes it possible to facilitate the decision-making process of how and where orders should be fulfilled in order to improve service levels while decreasing total costs (Mahar and Wright, 2009).

To manage the challenge of fulfilling store and web orders in an integrated warehouse, it is recommended to define processing priorities, as the different channels share inventories and picking capacities, and orders may arrive at the same time (Wollenburg et al., 2018). Retailers usually prioritize their online over store channel through reservations and earlier processing in the warehouse because products ordered online are already sold to the customer, whereas store orders are only for replenishment. The research of Kembro et al. (2018) is an example, in which the case companies give web orders priority so that products are available for web customers, who directly contribute to cash payment.

3.2 Customer journey

With omni-channel, all channels work together with the customer as the central point. Consumers can switch easily and continuously between the channels and they experience all channels together as one complete channel (van Delft, 2013). Therefore, the customer journey during the omni-channel shopping behaviour should be taken into account.

The customer journey refers to the series of interactions and experiences that a customer has with a company. It is a holistic view of the customer's experience with a brand that takes into account all touch points, including marketing, sales, and customer service. According to van Delft (2013), it is the journey a customer takes to purchase products and services, starting from stimulation and search for information, to purchase, delivery and even after-sales services. This customer journey is visualised in Figure 3.2.1.

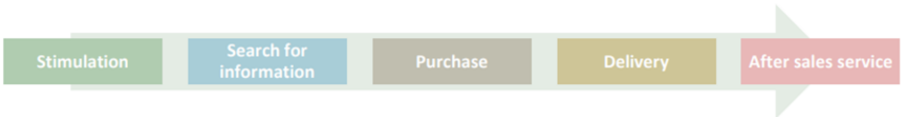


Figure 3.2.1: Customer journey (van Delft, 2013)

The stimulation phase is the initial stage in which the customer becomes aware of a product or brand through various sources such as advertising, word-of-mouth, or social media. This phase aims to create interest and generate a desire for the product. During the search for information, the customer begins to gather information about the product, such as its features, benefits, and price. Depending on the available channels, they may conduct online research or visit a physical store to experience the product. In the purchase phase, the customer makes a purchase decision and buys the product. This can occur through an online store, a physical retail store or a mobile app. In the delivery phase, there are few options depending on the channel where the product is bought; take the product home directly, delivery at home or at work, collect from a pick-up point or pick-up later in the shop. During the after sales service, the company should provide excellent customer service if the customers may require support or have questions.

Every phase in the customer journey requires the right information in order to go to the next phase. As result, the customer journey is not always linear and customers may revisit previous stages or skip stages depending on their needs and experiences. A well-designed customer journey can help to build trust, foster customer loyalty, and drive sales and revenue for the company.

In the context of omni-channel retailing, the question arises if it is possible to influence customers' channel choices during the shopping and fulfilment process, that is, steering customers toward a specific channel (Thomas and Sullivan, 2005). According to Myers et al. (2004) retailers should steer customers to channels to reduce service costs, increase revenue per customer, and penetrate underserved segments. Nevertheless, it is crucial to acknowledge that customers cannot be directly controlled; they can only be encouraged into using a specific channel. Generally, customers tend to gravitate towards his or her most convenient channel in a specific situation. (Wollenburg et al., 2018).

3.3 Multi-echelon

A multi-echelon supply chain refers to a complex network of interconnected suppliers, manufacturers, distributors, and retailers involved in the production and delivery of a product to the final customer. The items will move through more than one location in the multi-echelon supply chain before reaching the final customer (Ganeshan, 1999). The customer demand at the most downstream echelon creates the demand on the echelon upstream. Where single-echelon inventory control problems focus on determining the appropriate inventory level for an individual unit within the supply chain network, multi-echelon inventory optimisation takes a holistic approach by focusing on the correct inventory levels across the entire network. Ekanayake et al. (2016) show that using multi-echelon systems results in lower inventory levels while maintaining higher fill rates for the entire supply chain network, compared to when using single-echelon systems.

Two general policies used in a multi-echelon inventory system are the echelon-stock policy and the installation-stock policy. In an installation-stock policy, the replenishment decision of each installation is exclusively made based on its own inventory position. In the echelon-stock policy, the replenishment decision is based on the echelon stock, which includes the downstream stock of an item. The performance of the echelon and installation stock policies depends on the structure of the system; in serial and assembly multi-echelon systems echelon-stock policies dominate installation-stock policies (Axsäter and Rosling, 1993). In divergent systems, it depends on the structure of the inventory system; echelon stock policies seem to dominate installation stock policies for long warehouse lead times, while the opposite is true for short warehouse lead times (Axsäter and Juntti, 1996).

According to Xu and Evers (2003) the multi-echelon network has two distinct effects: the joint-ordering effect and the depot effect. The joint-ordering effect is the quantity discount offered by suppliers due to ordering in large quantities and the advantage of risk-pooling during the lead times from the supplier to the depot. The depot effect refers to the phenomenon where stock is being held at intermediate echelons such as depots or distribution centers, in order to postpone the allocation to the stores and reduce lead times. In the research of Jackson (1988), the risk-pooling effect is substantial and they indicate that significant amounts of warehouse inventory are justified to reduce back-order costs. However, according to Nozick and Turnquist (2001) there is still an important trade-off between inventory costs, transportation costs and the service level.

3.4 Inventory control model

In this document, the classification and the notation of Silver et al. (1998) us used. The inventory control methods of Silver et al. (1998) differentiate between the type of review period and the order size. The time between two moments when the inventory levels are reviewed is called the review period and is denoted with the R. There are two review types: 1) periodic review and 2) continuous review. Under a periodic review, the inventory level is checked at regular moments, while the inventory is checked continuously under continuous review. In practice, in most situations, a periodic review is applied e.g. if delivery schedules are fixed (van Donselaar and Broekmeulen, 2019).

For the order size, the distinction is made on if the order quantity is replenished in (integer multiples of) a fixed quantity Q or if the replenishment quantity is variable. In the case of a variable ordering quantity, the replenishment quantity depends on the inventory position (IP) at the moment of ordering. The inventory position is the virtual inventory level, and it increases immediately when an order is placed. The inventory position is raised to a specific level, which is the order-up-to level S. The decision to replenish the inventory depends on whether the inventory position has dropped below a critical level called the reorder level, denoted by the small letter s. If the inventory level at a review moment is above the reorder level, no order is placed.

Based on these two classification criteria there are four basic inventory control systems, shown in Table 3.4.1. The (R, s, nQ) checks the stock level at a review moment and if the inventory position is below the reorder level s then n times Q units are ordered which is needed to bring the inventory position after ordering back to or above the reorder level s. The (R, S)-policy orders every review period such that the inventory position is equal to the order-up-to level S. The (R, s, S)-policy only orders to order-up-to-level S if the inventory position falls below reorder level s. The (s, Q) policy reviews the inventory position continuously and if the inventory position drops below reorder level, the fixed order quantity (Q) is ordered. The (s, S)-policy operates similarly except a variable amount can be ordered to bring the inventory position back to the order-up-to-level S.

		Periodic review period	Continuous review period
Order size	Fixed	(R, s, nQ)	(s, Q)
	Variable	$(R, s, S)/(R, S)$	(s, S)

Table 3.4.1: Classification of inventory control systems

Regarding the reorder level s, it would be straightforward that the reorder level should be equal to the demand during the lead time, under the assumption of deterministic supply and demand. However, in practice, the demand faced is often stochastic and to buffer against these uncertainties seen in real-life operations, the reorder point needs to be increased to achieve the target service level. The extra inventory carried to prevent stock out due to demand and supply variability is called the safety stock.

$$s = \text{Lead time demand} + \text{Safety stock}$$

3.5 Safety stock

Safety stock is a critical component of inventory management, serving as a buffer to mitigate the impact of uncertainties and variations in lead time demand. It represents a strategic capital investment aimed at safeguarding the supply chain against potential disruptions and ensuring high service levels to customers. The possible disruptions in the supply chain are mainly due to demand and supply variability. Supply variability refers to the uncertainties in the availability and timing of supply for products. It contains variations in the delivery schedules, lead times, quality, and quantities of goods received from suppliers. Additionally, demand variability refers to the fluctuations or variations in customer demand for a product over a given period. Demand variability can be influenced by various factors such as market trends, seasonal fluctuations, promotional activities, economic conditions, and customer preferences. Forecasting customer demand accurately is challenging, and deviations from the demand forecast can result in inventory imbalances.

Traditionally, safety stocks are determined in advance based on models from inventory theory Silver et al. (1998). Extensive research and practical efforts have been devoted to calculating safety stock levels, with a significant body of literature addressing this topic. The majority of these approaches are based on statistical parameters, such as the demand's standard deviation or mean, and incorporate simplifications regarding the distribution of these statistical parameters (Schmidt et al., 2012). In this section, various methods commonly described and discussed in publications for calculating safety stocks are explored. A split is made between the formulas used to compute the safety stock itself and the methods employed to determine the safety factor, which is a key component in safety stock calculations. By examining these different approaches, insights can be gained into the diverse strategies employed in practice and their underlying assumptions.

Safety stock formulas

One of the methods for calculating safety stock which is frequently referred to as the standard formula, multiplies a safety factor with the standard deviation of the demand during the lead time, as seen in Equation 3.5.1. It should be noted that this formula assumes a normally distributed demand.

$$ss = k * \sigma_D * \sqrt{L} \tag{3.5.1}$$

Here, ss represents the safety stock level, k denotes the safety factor depending on service level, and $\sigma_D * \sqrt{L}$ signifies the standard deviation of the demand during the lead time.

While the method adequately addresses the needs of stationary demand, it can be far from optimal when applied to non-stationary demand scenarios. This is primarily due to the reliance on the mean and standard deviation of demand, which becomes problematic when the mean and variance of per-period demand are not known but rather require forecasting (Prak et al., 2017).

Therefore, establishing the true estimation of the standard deviation on the forecast error can be more accurate than the standard deviation of the demand when demand is non-stationary (Van Donselaar and Broekmeulen, 2014). This results in formula Equation 3.5.2, where $\sigma_F * \sqrt{L}$ signifies the standard deviation of the forecast error for the demand during the lead time. The standard deviation of the forecast error is computed by analyzing historical data and measuring the mean squared deviation between the forecasted demand and the actual demand.

$$ss = k * \sigma_F * \sqrt{L} \tag{3.5.2}$$

In the context of demand and lead time stochasticity, a widely used method for calculating the safety stock is presented by Eppen et al. (1988). The quantity under the square root expressed the variance of the lead time demand, assuming that demand and lead time are normally distributed.

$$ss = k * \sqrt{\sigma_D^2 * L + \sigma_L^2 * \mu_D^2} \tag{3.5.3}$$

The aforementioned formulas incorporate the standard deviation during the lead time as a key parameter. However, it is important to note that these formulas are designed under the assumption of a continuous review policy. In the case of a periodic review policy, a different approach is required. Instead of considering only the lead time (L), the standard deviation during the lead time plus the review period (L+R) should be taken into account. So instead, the standard deviation should be multiplied with $\sqrt{L+R}$, when using periodic review.

To analyse the performance of these approaches, Schmidt et al. (2012) did an extensive simulation study on the performance of the methods. The conducted simulation study illustrates that there is no one superior approach, and each of the presented methods has its respective strength depending on the particular conditions. The method corresponding to Equation 3.5.1 performs well with a low variance of the lead time, however, for the cases of a medium or high variation of the lead time other methods are more suitable. With a medium or high variation of the lead time and a low to medium variation of demand, Equation 3.5.2 seems to fit best. With a high variance in both the lead time and demand, Equation 3.5.3 outperforms the other methods.

Safety factor

The safety stock formulas mentioned above incorporate a safety factor (k) to calculate the appropriate level of safety stock. The determination of this safety factor can be achieved through various methods. In the following section, the most commonly employed methods found in the literature for determining the appropriate safety factor are explored and discussed.

This method is often referred to as the standard method used and the safety factor relies on the service level and results from using the inverse of the standard normal distribution. The service level used in this calculation is the no-stockout probability (P_1).

$$k = \Phi^{-1}(P_1) \tag{3.5.4}$$

If the fill rate (P_2) is considered, then the safety factor is determined by the standard loss function $G(k)$, which expresses the expected amount of shortage per cycle. The calculation of the safety factor (k) is more difficult with the use of this method. There are some numerical calculations, such as the one discussed by Silver et al. (1998), or the safety factor can be determined from a table when the parameters of the right-hand side of the equation are known. An advantage of this method is that it considers the order size Q.

$$G(k) = \frac{Q}{\sigma_D * \sqrt{L}}(1 - P_2) \tag{3.5.5}$$

The methods mentioned above are all analytical approaches to calculate the safety stock. The advantage of the analytic method is its relative simplicity, and this is why the analytic approach is preferred by many companies. However, in practice, the conditions on which the methods are based are often not met, for example the assumption of the normal distribution of demand (Zizka, 2005). In real-world scenarios, demand distributions can often deviate from the normal distribution, leading to infeasible results.

Therefore, simulation-based approaches can be used to calculate safety stock levels. During simulation, experiments are carried out with a model of a real inventory supply system in order to understand its behaviour and assess the various safety stock levels. Simulation-based approaches offer a flexible and dynamic way to evaluate safety stock levels and this can be especially beneficial in cases where demand is not governed by some theoretical model distribution (Zizka, 2005). However, the results from a simulation study are not necessarily optimal, as it searches for an appropriate solution through an iterative solution approach.

3.6 Safety stock positioning

In a multi-echelon distribution system, the supply of products in the most downstream location is dependent on replenishment from the upstream echelon. If the on-hand inventory in the upstream echelon is not sufficient to completely fill the replenishment order, then the whole replenishment order or part of it is back ordered and delivered on a later moment in time. In this case, the replenishment lead time seen by the retailer is a stochastic variable because of the possible delay due to the unavailability of stock in the upstream location (Tempelmeier, 1993).

These shortages at the warehouse can lead to a lower service level at the retailers. Therefore, an inflated service level should be used as target fill rate for the central warehouse. The research of van Donselaar (1990) gives a rough approximation for the inflated service level, given by Equation 3.6.1, and this should yield sufficient results.

$$\text{Inflated}P_2 = \frac{1}{3} + \frac{2}{3} * P_2 \tag{3.6.1}$$

To protect against the stochastic variable lead time between the echelons, and the risks of demand and supply variability, a certain amount of safety stock is required. Safety stock can be located primarily centralised at the warehouse, or completely decentralised at the retailers. When safety stock is primarily located at the retailers, it accounts for demand variability and variability in warehouse replenishment lead time at the depot level. If the safety stock is mainly located centrally at the warehouse, this will have the advantage of a reduced lead time to the downstream locations and if the safety stock in the warehouse is relatively low, the safety stock at the lower level of the inventory system has to be comparatively high because of the long replenishment lead times (Tempelmeier, 1993). Because of this trade-off, the question arises of how to allocate the safety stock to the various stock locations.

In a classic divergent system, it is common that the majority of available inventory is pushed to the retailers, close to the customer, because it appears that holding back inventory in a depot yields a lower service level than passing through all inventory (Whybark and Yang, 1996). In the research of van Donselaar and Wijngaard (1987) a simulation study is performed on a two-echelon system, resulting in the statement that one should be careful in holding much central stock because an increase in the central stock only yields a small reduction of end stock point stocks.

However, in the context of an omni-channel supply chain, the structure is not purely arborescent, because the integrated warehouse has a dual role of meeting both customer demand and replenishing downstream locations. Therefore, the assumptions used in these common approaches do not hold and they cannot be directly applied. However, there is no theory or analytical solution available in the existing literature to address this multi-echelon omni-channel supply chain (Cattani et al., 2011).

3.7 Multi-item system

Classical inventory models typically focus on a single-item system, but in real-world situations, multi-item inventory systems are more appropriate for retailers who sell multiple products and use joint replenishment. In the literature, papers either study one specific inventory control policy for all items or separately compare multiple policies across items. However, in practice, many inventory systems contain thousands of stock-keeping units (SKU's). In general, it is not computationally (or conceptually) feasible to implement SKU-specific inventory control methods (Ernst and Cohen, 1990). Therefore, there is a need to group SKU's into categories when making inventory control policy decisions because it is easier to group items with similar patterns and apply appropriate strategies to each group.

The ABC-classification of Nahmias and Olsen (2015) categorizes items based on their sales into three groups: A, B, and C. Category A includes the items with the highest sales and are considered the most important but make up a small percentage of the total number of items. Category B contains moderately important items that account for a moderate percentage of the total number of items and sales value. Category C items are considered the least important, making up the largest percentage of the total number of items but accounting for a small percentage of the total sales value. The classification parameters usually used are 0-80% for category A, 80-95% for category B, and 95-100% for category C, based on the accumulated consumption value (Scholz-Reiter et al., 2012).

The XYZ analysis categorizes items according to their fluctuations in consumption. Category X items have constant consumption, category Y items have stronger fluctuations, and category Z items have completely irregular consumption. The coefficient of variation is used, which is the ratio of the standard deviation and the average consumption. In the research of Scholz-Reiter et al. (2012), the critical values of the coefficient of variation (CV) are set as: Category X has a CV < 0.5, Category Y has a CV between 0.5 and 1, and Category Z has a CV > 1.

The ABC analysis is widely used and often supported by the XYZ analysis, resulting in the ABC-XYZ classification. This evolves in a classification matrix with 9 categories (AX, AY, AZ, BX, BY, BZ, CX, CY, CZ). According to Pandya and Thakkar (2016), this combined approach provides better results, compared to ABC or XYZ separately.

	Forecast ability		
	AX	AY	AZ
Sales revenue	BX	BY	BZ
	CX	CY	CZ

Table 3.7.1: ABC-XYZ classification matrix

The method of Syntetos et al. (2005) categorizes consumer demand into four types based on the average demand interval (ADI) and the squared coefficient of variation (CV^2). ADI measures the time between demand occurrences and CV^2 measures the relative variability of demand. The four demand categories are: erratic demand, lumpy demand, intermittent demand, and smooth demand. Erratic demand has low ADI and high CV^2, lumpy demand has high ADI and high CV^2, intermittent demand has high ADI and low CV^2, and smooth demand has low ADI and low CV^2

A method described by van Donselaar et al. (2005) classifies products into five categories: phasing in/out items, promotion, purchasing driven, capacity driven, and regular items. Phasing in/out items are products with a short product life cycle. Promotion items are part of the regular assortment but are temporarily offered at a reduced price or with additional visibility. Purchasing driven items are items purchased due to a special buying or selling opportunity. Capacity driven items are items used to smooth handling and/or transportation capacities. Regular items are products which cannot be assigned to another product category.

Chapter 4

Analysis and diagnosis

4.1 Supply chain structure

The supply chain of the company is visualised in Figure 4.1.1. The two-echelon supply chain can be described as a One-Warehouse-Multiple-Retailer (OWMR) system, in which an integrated warehouse, also called the Distribution Center (DC), is supplied by external suppliers, while the DC supplies the 48 stores and serves online customers. Demand D_i faced at the store i and at the DC D_0. Each SKU has its own lead-time L_0 to the DC and L_i to store i. The triangles represent an inventory point.

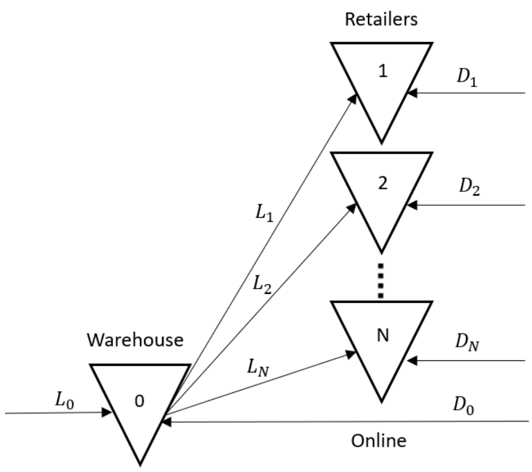


Figure 4.1.1: Distribution structure

The fulfilment strategy explained in section 4.2 determines from which location an order should be fulfilled, depending on the delivery method. This determines the demand faced at the locations. Demand D_i faced at the store i consists of the demand from in-store buying, store shipment and click-and-reserve. Demand D_0 faced at the DC consists of the demand from DC shipments and click-and-collect. Furthermore, the stores rely on the DC for replenishment, creating a demand for the DC.

4.2 Fulfillment strategy

The fulfilment strategy determines from which location a retailer will fulfil its customer orders. The location from which a retailer fulfils its orders also depends on its delivery methods. The company utilizes different delivery methods based on customer preferences and operational efficiency. Each delivery method offers distinct advantages in terms of convenience and speed. The delivery methods MediaMarkt is using in their omni-channel network are depicted in Table 4.2.1.

Delivery method		Fulfillment
Store delivery	In-store buying : traditional brick-and-mortar	Store
Home delivery	DC shipment: home delivery from the DC	DC
	Store shipment: home delivery from a store	Store
Store pick-up	Click-and-reserve: same-day-pickup (SDPU)	Store
	Click-and-collect: next-day-pick-up (NDPU)	DC

Table 4.2.1: Delivery methods used by the company

Store delivery involves in-store buying, where the product is picked from the in-store inventory. For home delivery, DC shipment is the preferred method for the company, because customer orders can be batched at the DC, allowing for efficient cross-customer picking. Because DC shipment is the preferred method, an item is shipped from the DC and only if the DC does not have enough stock, store shipment will be utilised as an alternative. This is because stores are not designed for efficient order picking and transport will be less efficient. In the case of store pick-up using click-and-reserve, the product is reserved from the store stock in the store where the customer can pick up the product on the same day, also known as same-day-pick-up (SDPU). With click-and-collect, the product is delivered from the DC to the store for the customer to pick it up at the store on the next day, also known as next-day-pick-up (NDPU). Due to the shorter lead time for the customer. click-and-reserve is preferred over click-and-collect. This means that if the store has the product in stock, it is fulfilled by the store stock, otherwise it will be fulfilled from the DC stock.

This leads to the utilization of different delivery methods for a specific fulfilment location. Specifically, items obtained through in-store buying, store shipment, and click-and-reserve are fulfilled by the respective stores. In contrast, when employing DC shipments and click-and-collect, the fulfilment of items takes place from the stock available at the DC. In this situation, the warehouse and logistics activities are integrated and both online and traditional demands are fulfilled from the same DC. In addition, the online demand can be transferred via a store, or directly from the DC to a customer. This corresponds to a network design with an integrated warehouse and transport-delivery taking place from all nodes.

4.3 Customer journey

In this section, the customer journey, which refers to the series of interactions and experiences that a customer has with a company, is analysed using the framework of van Delft (2013). Because of its relevance for this research, the focus is on the search for information, purchase and delivery phases. This customer journey is summarised in Figure 4.3.1 and will be explained in the next sections.

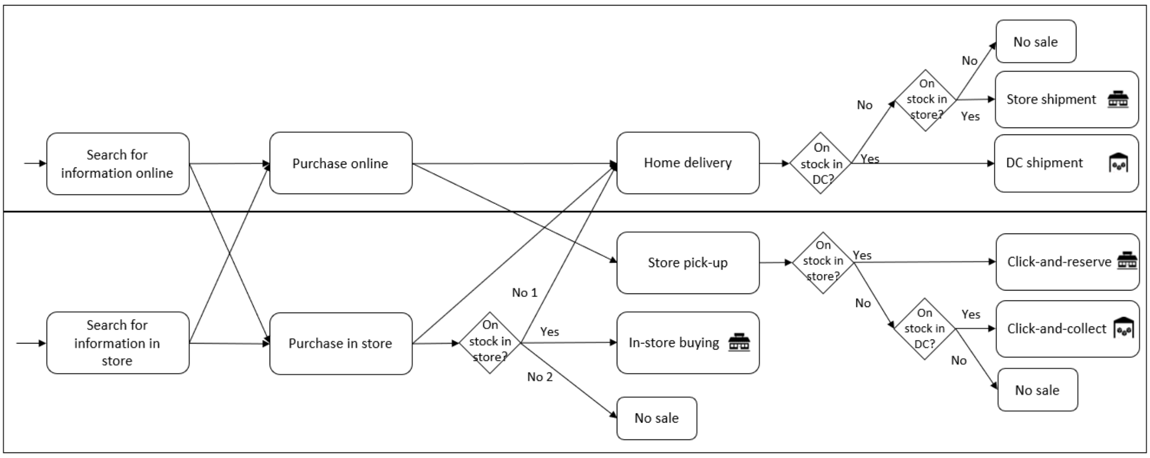


Figure 4.3.1: Customer journey of MediaMarkt

MediaMarkt is an omni-channel retailer that uses two channels to sell products to customers; online, via the web shop or app, and offline, via the brick-and-mortar stores. Customers can continuously switch between both online and offline while receiving a seamless experience through all channels. There are several factors that determine which channel is used at each stage of the customer journey.

The search for information can be done online through the website or the app, and in-store. The online channel offers advantages such as no travel time, access to the full assortment and high availability of information. On the other hand, the offline channel provides the experience of touching and feeling products and receiving personalized recommendations from staff. At the purchasing stage, the online channel provides the convenience of shopping anytime and anywhere without the need to travel to a physical store. Additionally, physical stores have the disadvantage of only carrying a limited selection of products, compared to the entire assortment available online.

At the delivery stage, a trade-off needs to be made between the different delivery options, listed in Table 4.2.1. The delivery options available to customers depend on the channel that the purchase is made. If a product is purchased in a physical store, customers can take it home directly, eliminating delivery time. Alternatively, customers may opt for home delivery for products purchased in-store. This type of home delivery is common for white goods and large televisions due to their size. When making an online purchase, customers are presented with the alternatives of home delivery or in-store pickup. Home delivery offers high convenience for customers who prefer to avoid visiting a physical store. However, for orders below €50, the company charges a shipping fee, making store pickup a potentially more favourable option.

Furthermore, store pickup can be favorable when the customer needs the product urgently.

The journey a customer chooses depends on his or her shopping preferences and customers tend to gravitate towards their most convenient channel in a specific situation. However, retailers sometimes try to steer customers toward a specific channel or delivery option, to reduce service costs or in case of insufficient stock levels at the fulfilment location. So, when a delivery option is unavailable due to insufficient stock levels in the fulfilment location, the customer is steered into using another delivery option. Nevertheless, it is crucial to acknowledge that customers cannot be forced; they can only be encouraged. So, the customer can also choose to not switch to another delivery option and terminate the sale, which results in a lost sale.

If the customer chooses to purchase in-store and the product is out of stock, home delivery will be offered to the customer. If the customer is not willing to switch, there will be no sale, and the customer is likely to turn to a competitor. Regarding home delivery, when utilizing DC shipments, the customer can expect to receive the product on the subsequent day. However, if the desired item is not available at the DC but is present in a store's inventory, the company will offer shipping the product from the store with an estimated delivery time frame of 2-4 working days. In cases where the product is unavailable at both the DC and the store, or if the customer is unwilling to wait for the extended delivery duration, the sale will be lost. Furthermore, with in-store pick-up, if the corresponding store carries the product and it is in stock, the product can be collected on the same day. If it is not in stock in the store but is available at the DC, the DC will fulfil the order, allowing customers to collect the product on the following day. When the product is unavailable at both the DC and store, or if the customer is unwilling to wait until the next day, the sale will be lost.

4.4 Replenishment policy

The replenishment policy ensures that items are reordered in the right quantities and at the right time to meet demand. The planning system RELEX generates an order quantity proposal based on the replenishment policy. The replenishment policy works according to the following logic: If at a review moment, the inventory position minus the demand forecast for the period R (review period) + L (lead time) is below the safety stock, then the number of units are ordered which are needed to bring the inventory position after ordering minus the demand forecast for the period R and L back to or above the safety stock. This makes sure the inventory remains above the safety stock at all times. Due to the periodic review period and the variable order size this is comparable to a (R, S) inventory control system, where the reorder level (S) is the demand forecast during R+L plus the safety stock. The replenishment policy is visualised in Figure 4.4.1.

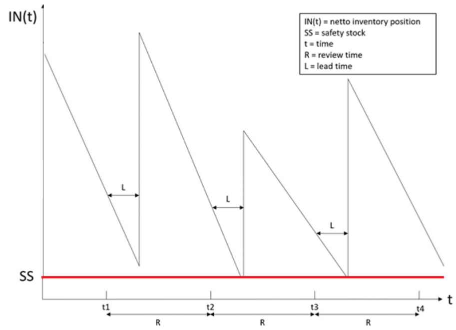


Figure 4.4.1: Replenishment policy

In the calculation of the order quantity, lead time and demand variability need to be accounted for. To account for lead time variability, an additional buffer known as safety lead time is employed. Safety lead time is the extra time added to the estimated lead time to accommodate for uncertainties or unexpected delays in the replenishment process. The safety lead time used by the system is the period till the next possible delivery moment, also called the second delivery date. The second delivery date is used by the system as the lead time for the calculations. Demand variability is accounted for by incorporating a safety stock.

This results in Equation 4.4.1 for the order quantity for a specific product at a store i at time t, in which the commercial shelf value U_i, safety stock $ss_{i,t}$, inventory position $IP_{i,t}$ and the demand forecast of store i for the period R (review period) and L (lead time) $D^{fcst,i}_{t,t+R_i+L_i}$ are taken into account.

The commercial shelf value, also known as the minimum fill or min fill by the company, is the minimum amount of products on the shelves to maintain an attractive shelf for customers. This ensures a commercially appealing appearance of the store, which is crucial for the customer experience and sales. This value is a constant number for each SKU in each store and is set by the store manager in the planning software. In practice, the commercial shelf value works as an alternative for the safety stock if the minimum fill value is higher than the safety stock.

$$Q_{i,t} = \max\left\{ \left\lceil D^{fcst,i}_{t,t+R_i+L_i} + \max\{U_i, ss_{i,t}\} - IP_{i,t}+ \right\rceil, 0\right\} \tag{4.4.1}$$

The $\lceil\rceil$ symbol is used to round the number up to the nearest integer because the order amount should be in integers. The maximum between the calculated value and zero is taken, as it is impossible to order negative units.

The order quantity of a specific product in the DC is calculated similarly. The demand forecast of the DC for the period $R_{DC} + L_{DC}$ is calculated by summing the forecast of all n stores and the demand forecast for the online sales ($D^{fcst,o}_{t,t+R_{DC}+L_{DC}}$). The DC order quantity calculation is given in Equation 4.4.2. In the DC there is no commercial shelf value as there are no customers there physically.

$$Q_{DC} = \max\left\{ \left\lceil \sum_{i=1}^{n} D^{fcst,i}_{t,t+R_{DC}+L_{DC}} + D^{fcst,o}_{t,t+R_{DC}+L_{DC}} + ss_{DC,t} - IP_{DC,t} \right\rceil, 0\right\} \tag{4.4.2}$$

The order quantity resulting from this calculation is set in the order proposal. The demand planners in the headquarter check the order proposal and, if correct, an order is created in SAP, the Enterprise Resource Planning (ERP) system. If perceived as incorrect, the demand planners at the headquarter are able to overrule the order proposal, and manually change the ordering quantity. The DC order is placed at the corresponding supplier and will arrive at the DC after the lead time. The products will be placed in the DC as inventory until ordered. The store orders will be placed at the DC and will arrive at the store after the lead time. The products will be placed in the store inventory until bought by a customer.

4.4.1 Commercial shelf value versus safety stock

As stated in Equation 4.4.1, the maximum value between the commercial shelf value and the safety stock parameter is chosen to calculate the order quantity. To gain insight into the usage of the safety stock, it is interesting to know which of the two parameters is used in practice. In the Thesis of Van Duijse (2021) this is examined on the data of 2021. It was found that 87.8% of these combinations used the commercial shelf value rather than the safety stock. So, in 87,8% of the cases, the min fill was higher than the safety stock and the safety stock value is not used in the calculation of the order quantity.

To study the effects of using the commercial shelf value instead of the safety stock, an analysis is done in the Thesis of (Van Duijse, 2021). The situations when only considering the safety stock versus when both the commercial shelf value and the safety stock are used to calculate the order quantity are compared. This analysis shows that the current performance of the stores is largely influenced by the commercial shelf value and not the target service levels imputed in the system. The effect on the fill rate is analysed for different product categories and visualised in Figure 4.4.2. This results in the fact that the fill rate is at least 1.9 percentage points lower when the system only used the safety stock calculated according to the imputed target performance, compared to when also the commercial shelf value is used. This means that the current fill rates are highly influenced by the commercial shelf value, and when only the safety stock would be used by the system, the current fill rates would be lower.

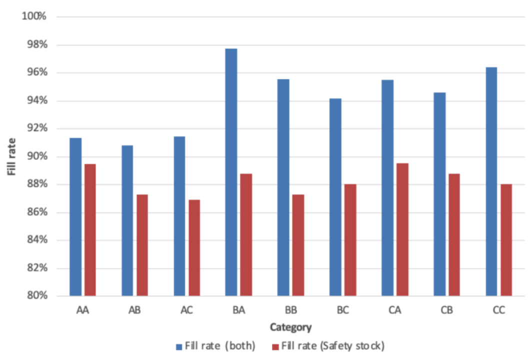


Figure 4.4.2: Difference for the fill rate with and without the commercial shelf value (Van Duijse, 2021)

4.4.2 Safety stock calculation

The planning software RELEX proposes a value for the amount of safety stock per SKU per location. According to the systems manual and interviews with employees of the Forecast & Replenishment team, there are two methods used by the system. In both methods, the safety stock is calculated with the formula given in Equation 4.4.3, where k is the safety factor and $\sigma_D * \sqrt{L}$ is the standard deviation of the demand during the lead time. The safety factor depends on the formula type and the service level. The service level is defined as the fraction of demand directly satisfied from the shelf, also known as the fill rate. Because non-stationary demand is implicitly assumed, this safety stock value is updated weekly by the system, to account for changes in the demand statistics.

$$ss_t = k * \sigma_D * \sqrt{L} \tag{4.4.3}$$

Using the first formula type, k is derived from the standard deviation of the demand assuming that the demand is normally distributed. k will be obtained by taking the inverse of the standard normal distribution Φ^{-1} (mean 0, standard deviation 1) of the service level (P_2) as is shown in Equation 4.4.4. If stock-outs are allowed a maximum 5% of the time, i.e. satisfy 95% of demand, then $k = 1.64$ as $P(X < Z) = 0.95$, if X follows a standard normal distribution. Naturally the greater the service level, the larger the resulting safety factor.

$$k = \Phi^{-1}(P_2) \tag{4.4.4}$$

In the second formula type in Equation 4.4.5, the value for k is calculated with the use of the expected value of the number of units of shortage per replenishment cycle $G(k)$, where Q represents the order batch size, $\sigma_D * \sqrt{L}$ the standard deviation of the demand during the lead time and P_2 the fill rate also known as the service level. The goal is to find what value for k gives the desired number of expected shortages. This will be calculated with the use of approximations.

$$G(k) = \frac{Q}{\sigma_D * \sqrt{L}}(1 - P_2) \tag{4.4.5}$$

The safety stock approach employed by the system was assessed in the thesis of Van Duijse (2021) through a comparison of various methods. In this analysis, the coefficient of variation (CV) of the outcome of the different methods is used to compare the values and the method with the lowest CV is assumed to be used by the replenishment system. This results in the conclusion that the safety stock method used by MediaMarkt correspond to Equation 4.4.5, which uses the fill rate (P_2) in the continuous review system.

The calculations used by the system utilize the standard deviation of the demand during the lead time, which conflicts with research indicating that determining the accurate estimation of the standard deviation on the forecast error is more precise than relying on the standard deviation of the demand when non-stationary demand is present Van Donselaar and Broekmeulen (2014). Subsequently, a continuous review policy is used with the standard deviation during the lead time, despite that a periodic review inventory policy is employed in practice. In a periodic review policy, the standard deviation should be computed for the review interval and the lead time. Lastly, in these calculations, a normally distributed demand is assumed. In subsection 4.6.4, the demand distribution is analysed to investigate if this assumption is reasonable.

4.4.3 Demand forecast methods

The planning software RELEX generates a demand forecast for each day, on a product-location level. This means that a demand forecast is generated for each SKU at each store on each day. The system uses 16 different forecast methods to calculate the demand forecast. The historical sales data is used to select the best forecast method and every week, the best-performing forecast method is chosen for each SKU in each store. The forecasts methods used by the planning software are given in Appendix A.

In the Thesis of Van Duijse (2021), the forecast methods used in the DC of MediaMarkt at the beginning of 2021 are analysed. This concluded that out of the sixteen different forecast methods, only four different forecast methods are chosen by the system to be used as the forecast method. Of all the products, 91.2% use constant time series forecasting methods consisting of 77.9% moving average and 13.3% exponential smoothing. 8.1% Of products uses the aggregated seasonal model and finally, 0.7% of the prediction methods use Croston's method.

At the moment of performing this research, there is insufficient data to accurately determine the performance of the forecast, making it difficult to estimate the forecast bias with any degree of confidence.

4.5 Integrated warehouse

In the past, the company used separate warehouses for online sales and store replenishment and they would hold separate stock for both the online and store channels. Additionally, to account for the demand and supply variability, safety stock would need to be kept at both locations.

Currently, the company uses an integrated warehouse with shared stock, meaning that the inventory in the DC is intended for both online sales and store replenishment. The inventory is kept at the same physical location in the warehouse and there is physically no separate stock for online customers or stores. This means that stock for a particular SKU can be ordered by both stores and online customers. By using an integrated warehouse, the company can benefit from inventory pooling and flexibly allocate inventory based on the demand from both physical stores and online orders. Due to this risk pooling, it is expected to lead to a lower total reorder level and therefore safety stock, compared to using separate warehouses.

$$s_{shared} \leq s_{split}$$

4.5.1 Inventory reservation

To manage the challenge of handling the fulfilment of store and online customers in the integrated warehouse, inventory reservation, called ring-fencing by the company, is used. With inventory reservation, some portion of the available inventory is exclusively reserved for specific customer classes. In this specific case of inventory reservation, there are two customer classes demanding inventory from the DC, the online customers and the stores. The online customers are a combination of home delivery by DC shipment and click-and-collect. In the company's strategy, it is decided that online customers receive priority over store replenishment, so the online customers are perceived as the higher priority class and the stores as the lower priority class. Therefore, part of the inventory is reserved for online customers. The steps outlined below are used by the software to determine the reserved quantity.

Let IOH_t denote the inventory on hand in the DC at time t. For each SKU, the planning system creates a demand forecast for the total online orders, for the period until the next delivery arrives. This corresponds to the demand forecast for online for 1 period multiplied with the amount of periods it takes until the next delivery arrives. This quantity, denoted by a_t, is the inventory reserved for the high-priority online customers at time t ($0 \leq a_t \leq IOH_t$). This results in Equation 4.5.1.

$$a_t = D_t^{fcst,o} * t_d \tag{4.5.1}$$

The reserved quantity is frozen for a period of a day. During this frozen time period, store orders arrive depending on the review moment, because of its periodic review policy, and online orders arrive continuously over the day. The store orders arrive according to the store replenishment policy, explained in section 4.4. Orders from stores can only utilize the remaining, unreserved portion of the available inventory ($IOH_t - a_t$). If the unreserved portion is not enough to serve all store orders, the available inventory is distributed over the store orders proportionally based on respective demand ratios. The remaining unfulfilled store demand is backordered and will be delivered in the next shipment when enough inventory is available.

Afterwards, the inventory reservations are unfrozen, inventory on hand is updated based on orders committed and any new information about arrivals of inventory receipts is incorporated into the subsequent calculation of available inventory. Also, the demand forecast may be updated to accommodate any new demand information received. This procedure of calculating the reserved quantity is repeated daily by the planning software.

In the calculation of the reserved inventory quantity, the demand forecast for the periods until the next delivery arrives is used. The time until the next delivery arrives is based on the review period (R) and lead time (L). For the lead time, MediaMarkt uses a safety lead time, by applying the second possible delivery date as the lead time by the system, to account for lead time variability. To account for demand variability, safety stock is regularly used. However, it should be noted that the reservation quantity does not take into account any safety stock for online customers. This means that a possible variability in demand is not taken into account in the reservation, which might have an influence on the product availability for online customers.

Because of the lack of safety stock, the allocation of stock is not determined by any service level for either online customers or physical stores. Despite the perception that online customers are perceived as high-priority customers in the Dc and stores as low-priority, this priority is not quantified in any service level. Subsequently, there is no minimum service level for the replenishment of stores, so in the case of scarcity, it can occur that all stock will be reserved for online sales and the fill rate from the DC to the store will be influenced, also negatively influencing the service experienced in stores.

4.6 Demand analysis

By utilizing the daily sales data from 01-01-2022 to 31-12-2022, this analysis aims to enhance our comprehension of the various products in the assortment and their distinctive characteristics. The insights gained from this analysis will assist in selecting the appropriate safety stock calculation method for each product.

4.6.1 Data cleaning

The sales data is cleaned and any negative sales are set to zero. Negative sales correspond to products that are returned by the customer. Although these products are no longer sold, they were physically stocked in either the store or distribution center, and a transaction occurred when they were bought by the customer. Therefore, returned products are not deducted from the sales data and are instead recorded as zero. Consequently, the sales data encompasses both actual sales orders and orders that were eventually returned by customers.

Because the sales forecast for promotions and other events is done through manual input rather than the replenishment model, sales data are adjusted by removing promotions and events that are assumed to have been corrected through manual input. This is done by using the 3-sigma rule, where the values of 3 standard deviations (σ) above or below the mean are deleted. This will remove the events that are replenished through human intervention, specifically Black Friday, the Christmas period, and VAT-days.

To assure the data only contains mature and regular products, the data set is filtered. Only the products that were in the active assortment on 02-12-2022 are used in this research. The products with a release date after 01-09-2022 are also deleted, as they correspond to new product introductions, which are out of the scope of this research. Additionally, the product groups that do not refer to a physical product are left out, e.g. 'PC software'.

4.6.2 Assortment analysis

MediaMarkt offers a wide assortment of customer electronic products. By examining the performance of each individual product, valuable insights can be gained into which items are contributing the most to the overall sales and profitability. One way to visually represent this data is through the use of a Pareto Curve, which shows the distribution of the sales across all products. The Pareto Curve demonstrates the principle that a small percentage of products contribute to the majority of the sales, while a large percentage of products contribute to a smaller portion of the sales. Sometimes simplified to the 80-20 rule, Pareto suggests that 80% of the sales comes from only 20% of products (Harvey and Sotardi, 2018).

Figure 4.6.1 displays the Pareto curve using the total sales value of both the stores and online sales combined. This curve plots the cumulative percentage of sales value against the items sold. The curve shows a steep slope that plateaus into a gradual slope, demonstrating that indeed, a small percentage of products contribute to the majority of sales, while a larger percentage of the products contribute to a smaller portion of the sales. According to the figure, 80% of the sales comes from 14.98% of the products which is a slightly more concentrated distribution than the typical 80/20 rule of Pareto. This suggests that the sales value of the company is reliant on a small number of products.

Because the interest of this research is in the number of products to keep as safety stock, insights need to be gained into the quantity of the products sold. In Figure 4.6.2, a Pareto curve using the total sales quantity of both the stores and the online sales is visualised. The image presents a comparable pattern, characterized by a incline that transitions into a more gradual slope. However, the line in this image is slightly less steep. Similar to the previous figure, the current figure shows that a concentrated distribution of sales exists, where 80% of the total sales quantity comes from 26,44% of the products. This distribution compares to the typical 80/20 rule of the Pareto principle. This shows that there are many slow-movers within the assortment and the fast-movers are responsible for a large part of the sales.

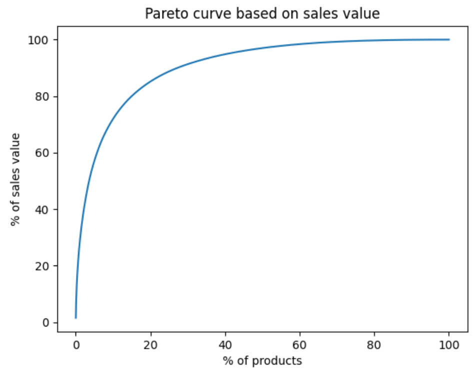


Figure 4.6.1: Pareto curve Sales value

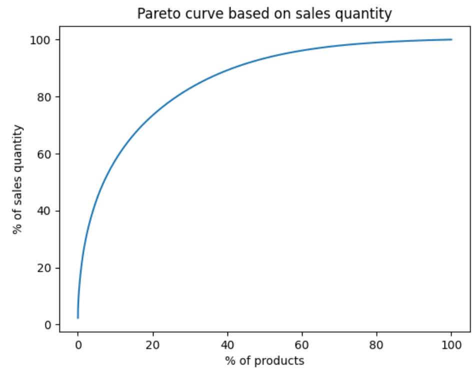


Figure 4.6.2: Pareto curve Sales quantity

In response to this concentrated sales distribution, the company has implemented strategic product assortments that receive priority attention, called the TOP, VP and T50. The TOP category includes the 280 best-selling products, based on both volume and turnover. The C60 subcategory within the TOP consists of the best-selling products. Similarly, the VP category contains the 240 products with the highest profit margin, and the V60 subcategory within the VP consists of the products with the highest sales volume. Lastly, the T50 category comprises 100 best-selling accessories. By categorizing products in this way, the company can focus its efforts on the most profitable and high-performing items in its inventory. This is realised by setting a higher service level for the strategic assortments in comparison to the remaining products in the assortment. More information on the corresponding service levels is in subsection 4.6.7.

All the products within the active assortment are accessible online, but physical stores only carry a selected part of the total assortment. This complies with the research of Praneet Singh et al. (2006), which states that it is cost-efficient for a wholesaler in the online channel to offer a larger assortment to her customers than the retailer in the traditional channel. In that case, the preferred products should be stocked at the retail locations and the online channel should be used for the less popular products.

MediaMarkt strategically determines the optimal product mix for each store by utilizing assortment formulas that range from XS, S, M, L, and 00, with increasing size and where the larger assortments are an extension of the prior assortment formula. For each formula, the depth of products offered, the number of variations of a particular product available in-store, the width of the product variety, and the range of different types of products carried are carefully determined. Each store is assigned an appropriate formula, based on store size and sales performance.

The assortment of MediaMarkt is changing at a relatively quick pace because of the developments in the consumer electronic market. Therefore, there is a lot of phasing in and out of products.

4.6.3 Online and store demand

As MediaMarkt sells its products via two channels, online and via stores, the demand for these channels can be analyzed separately. This can give an insight on the importance of the online channel. By distinguishing between online and store sales within the total demand, it becomes possible to determine the proportion of sales occurring online compared to the total sales quantity. This proportion of demand, also called the channel ratio, will be stated as the percentage of online sales quantity compared to the total sales quantity. It seems that the online sales quantity comprises of 3,09% of the total sales quantity. Comparing the online sales to that of a single store, the findings indicate that, on average, the online sales quantity is 1.5 times greater than the sales quantity of an average store. The sales value of online sales is 6.27% of the total sales value, indicating the significance and impact of the online sales channel.

It is expected that the channel ratio will vary across different products, as product characteristics may influence customer to make the purchases either online or in the store. To assess the channel ratio per product, the percentage of online sales is calculated and visualized in Figure 4.6.3. The y-axis represents the percentage of online sales out of the total sales, while the x-axis ranks the products based on their respective percentages. This visual representation provides insight into the distribution of the percentages across different products.

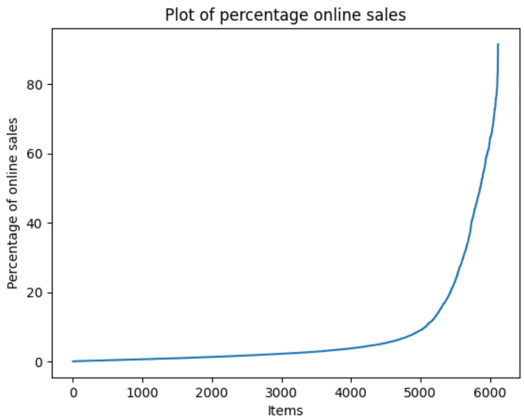


Figure 4.6.3: Percentage of online sales

Analysing this figure reveals that the majority of the products have a low percentage of online sales. Subsequently, there are a few products that have a significantly large percentage of online sales.

4.6.4 Demand distribution

In the context of inventory management at MediaMarkt, the demand distribution that is, implicitly or explicitly, used, is the Normal distribution. The Normal distribution has both advantages and disadvantages. On the positive side, the Normal distribution is characterized by its simplicity and it is easily implementable and comprehensible. Consequently, many safety stock calculation formulas found in the literature are designed under the assumption of Normally distributed demand.

Nevertheless, it is essential to recognize that demand patterns may not always conform to this assumption. Especially for low-demand scenarios, this assumption seems to be inadequate. The normal distribution assumes continuous and unbounded values. However, in practice demand quantities are discrete and non-negative integers, so the normal distribution may not be an appropriate choice for accurately modelling the demand distribution of MediaMarkt. As seen in the previous section, a large part of the demand of MediaMarkt comprises slow-moving products with low demand. Consequently, there is a to move beyond the Normal distribution and explore alternative distributions that offer a better fit for the observed demand patterns.

4.6.5 Stationarity

Stationarity means that the statistical properties of a process generating a time series do not change over time. In other words, stationary demand implies that the average, variance, and covariance of the demand observations do not change systematically with time.

To assess the stationarity of the data, the Augmented Dickey-Fuller (ADF) test was conducted, which is a commonly used statistical test in time series analysis. Applying the Augmented Dickey-Fuller test to the cleaned dataset of 2022, excluding the promotions, revealed that 96.39% of products exhibited stationarity in their demand patterns. The calculated p-values for these products exceeded the threshold, indicating that their time series data was stationary. This finding suggests that the statistical properties of these products' demands remained constant over time, with consistent mean and variance.

Only a small part of the assortment seems to be non-stationary. Further analysis revealed that products of the product group 'SDA luchtbehandeling', containing household air conditioners, serve as an example of a product with non-stationary demand. This product group seems to have a strong seasonal influence in the summer.

In the current inventory model of MediaMarkt, non-stationary demand is implicitly assumed, where the demand forecast, and therefore the reorder level and safety stock, per time period varies. This is because the demand forecast also takes into account promotions and the phasing-in and out of products. However, in this research only mature products are in the scope, leaving out the promotions, end of life, and new product introductions. Therefore, the results of our analysis shows primarily stationary demand.

4.6.6 Correlation

The correlation of the demand patterns between stores is analyzed. The analysis includes an examination of the correlation between stores to assess the relationship between demand patterns. The degree of demand correlation determines the extent to which changes in demand for one store are associated with changes in demand for other stores within the network. Understanding the correlation is crucial as it can impact the determination of safety stock levels within the system (Zinn et al., 1989).

With positive correlation, the joint impact of correlated demand fluctuations can lead to increased demand variability and higher safety stock requirements. Conversely, negative correlation offers a certain degree of risk reduction as the demand for one product tends to offset or counterbalance the demand for others. In these instances, the need for safety stock may be relatively lower compared to positively correlated demand scenarios.

The demand correlation between the MediaMarkt stores is analysed by Van Der Lee (2023), using the Pearson correlation coefficient. The study also calculates the average Pearson correlation of store demands. The findings reveal that approximately 71% of the products exhibit low correlation ($-0.3 < \rho < 0.3$), 23% exhibit moderate correlation ($0.3 < \rho < 0.5$), and 6% exhibit strong correlation ($\rho > 0.5$). These results indicate that while there are some products with correlation, the level of correlation observed is generally low.

4.6.7 Service level

The system's objective is to determine the safety stock levels while maintaining a target service level, minimizing holding costs. The service level target is closely linked to the amount of safety stock needed for each product. A higher service level requires a greater amount of safety stock to be maintained.

In order to prioritize certain products, the company has implemented a service level differentiation approach. Each product is assigned a service level target, depending on the assortment formula it is part of and its importance. The various assortment formulas including their corresponding service level targets are depicted in Table 4.6.1. This service level is defined as the fill rate: the specified fraction (P_2) of demand to be satisfied directly from available inventory.

Assortment	**Service level target**
T50, V60, C60	97%
TOP, CA, VP	96%
XS, S	95%
M	93%
L, OO	90%
Remaining products	90%

Table 4.6.1: Service level per assortment group

The service level differentiation approach is implemented on a product level. This results in the fact that a specific SKU has the same service level, regardless of the channel or location where the product is bought. There is no distinction made based on if a product is ordered online or bought in the store. Additionally, there is no service level differentiation used in the DC with the allocation of inventory to online customers and the replenishment of stores, by using inventory reservation. So, both customer classes are given the same service level target and no differentiation is made.

Chapter 5

Solution Design

This research aims to provide a framework that guides the company to determine the correct safety stock levels, and positioning in a multi-echelon omni-channel supply chain. Based on the analysis & diagnosis, a model is proposed that aligns with the characteristics of the company's distribution system, depicted in Figure 5.0.1.

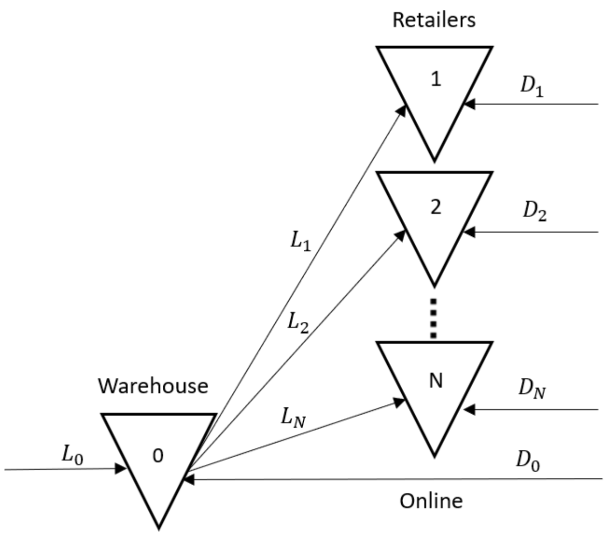


Figure 5.0.1: Model of the distribution system

First, section 5.1 describes the assumptions used in the model for which the solution design is applicable. Second, section 5.2 describes the simulation model used to analyse the inventory control policy in the system. The simulation model is split between the single-echelon situations from both the retailer and the warehouse. Thereafter, the multi-echelon system is simulated, where the influence of the reservation quantity is being analysed. These findings will eventually be used for the determination of reorder levels, safety stocks and the positioning in the supply chain.

5.1 Model Assumptions

The model can be described as a One-Warehouse-Multiple-Retailer (OWMR) system with a divergent structure, where the warehouse is supplied by external suppliers and the warehouse supplies multiple retailers. Transshipments between retailers are not allowed. The retailers are assumed to have identical demand and the external supplier is assumed to have unlimited capacity. The warehouse acts as an integrated warehouse, which fulfils both online customer orders and store replenishment orders. Stochastic demand is observed at the retailers and at the warehouse, stochastic demand of online customers is observed, in addition to the store replenishment orders. The demand for the products is assumed to arrive following a Poisson distribution for both the online and offline demand. The Poisson distribution is a widely-used discrete probability distribution, having one parameter: lambda (λ), and is particularly useful for modelling low-demand scenarios. As such, the assumption of a Poisson distribution appears to be a reasonable choice. No demand correlation between stores is assumed, because the level of correlation observed at the company is generally low. However, it might be interesting to relax this assumption in future research to asses the effect of correlation on the safety stock levels. The supplier lead times are assumed to be deterministic in this model. However, this assumption may not accurately represent the variability associated with the lead time of the company. Assuming a deterministic lead time allows for a simplification of the analysis, but it might be useful in the future to relax this assumption using a stochastic lead time.

Inventory replenishment of the warehouse and retailers is executed with the use of an R,S replenishment policy. Retailers can order according to a fixed review period, and there is no minumum order quantity. Given the substantial proportion of the overall assortment exhibiting stationarity, it is reasonable to make the assumption that the demand is stationary. With stationary demand, a fixed reorder level, and therefore safety stock, can be applied. However, when promotions are taken into account the assumption of stationarity might not hold, and variable reorder levels, and thus safety stock, should be applied. An echelon stock policy is used, where the inventory levels are controlled centrally based on information on all stock levels throughout the system. Customer demand, both online and offline, that cannot be met with inventory on hand is lost, referring to a lost sales policy. Store replenishment orders arriving at the warehouse follow a backorder policy.

In the case of stockouts, penalty costs are incurred to compensate for factors that negatively affect the organization. The penalty costs are assumed to be equal across all sales channels. Subsequently, holding costs are assumed to be equal at all stock points and are not dependent on where the stock is stored. The target service level is assumed to be equal across different sales channels, as there is no service level differentiation between channels. This service level is defined as the fill rate (P_2): the specified fraction of demand to be satisfied directly from available stock. The system's objective is to achieve the target service level at a minimum cost.

As there are no analytical approaches to calculate the safety stock under the assumption of Poisson demand, a simulation-based approach is used to analyse the system and determine the safety stock levels and the positioning.

5.2 Simulation model

In this section the inventory management process, which is responsible for managing the inventory levels for each product at each retailer and the warehouse, is simulated. The model operates at the product-location level, and adjusting the input parameters allows for its application to each individual product-location.

First, the two echelons will be examined as separate single-echelon systems, corresponding to the installation stock policy, where each stock point determines its order quantity based on its own inventory position, operating autonomously from one another. Once all the locations have determined their policies, their combined operation creates a demand process for orders placed in the upstream stock point. After examining the single-echelon scenario, the multi-echelon situation will be explored, wherein the decisions made at one echelon can have an impact on the other echelon. By considering the interdependence between echelons, insights can be gained into the broader dynamics of inventory management in a multi-echelon setting. These insights will be used in the determination of the safety stock values and positioning in the multi-echelon supply chain.

5.2.1 Single-echelon retailer

Stochastic demand arrives at the retailer, following a Poisson distribution with a given constant arrival rate (λ). Because of the properties of the Poisson distribution, the demand has a mean of λ and a variance of λ, leading to Equation 5.2.1 for the demand forecast. At each time period, the demand at each retailer is generated independently.

$$D_t^{fcst} = \lambda \qquad\qquad D_{t,t+R+L}^{fcst} = \lambda * (R + L) \tag{5.2.1}$$

Subsequently, at each time period, the inventory position (IP) is calculated, referring to the inventory on hand at a specific point in time, also taking into account any outstanding orders and backorders. For each time period, the demand, inventory on hand, inventory position, inventory on order and order quantity are reported, leading into Equation 5.2.2 for the calculation of the inventory position.

$$IP_t = IOH_t + IO_t - BO_t \tag{5.2.2}$$

At a review period (R) an order is placed to bring the inventory position back up to the reorder level (s). The reorder level is determined by the demand forecast for the period L+R, plus the safety stock. As a Poisson distributed demand is assumed, with a constant mean, this leads to Equation 5.2.3, for the reorder level s.

$$s = D_{t,t+R+L}^{fcst} + ss \qquad\qquad s = \lambda * (R + L) + ss \tag{5.2.3}$$

The order quantity is based on the formula for the order quantity of the stores of the company, in Equation 4.4.1. However, in this model, the commercial shelf value used by the company is not taken into account, as the interest of this research is in the performance of the model using the safety stock. Additionally, as stationarity is assumed, the safety stock is constant over time. This leads to Equation 5.2.4, for the calculation of the order quantity (Q) at time t.

$$\begin{aligned} Q_t &= \max\left\{s - IP_t, 0\right\} \\ Q_t &= \max\left\{D_{t,t+R+L}^{fcst} + ss - IP_t, 0\right\} \end{aligned} \tag{5.2.4}$$

If there is not enough inventory on hand to meet the demand, a stock-out occurs and the sale is lost, because of the assumption of a lost sales policy at the retailer. To evaluate the performance of the system, the fill rate (P_2) is used as a performance measure, the fraction of demand delivered from stock immediately.

$$P_2 = 1 - \frac{EIOH(L) - EIOH(R+L)}{\mu_R} \tag{5.2.5}$$

The R,S replenishment process at the retailer is simulated, using the above formulas. To validate the simulation of the inventory control model, the DoBr tool developed by Broekmeulen and van Donselaar (2015) was utilized. The DoBr tool is an Excel file with functions coded in VBA to calculate several Key Performance Indicators (KPIs) for multiple inventory policies. By comparing the results of the simulation model with those of the DoBr tool, using the same input parameters, identical results were obtained. This process was repeated multiple times with varying input parameters, consistently resulting in similar results. Thus, it can be concluded that our simulation model is valid for the single-echelon system.

Our research aims to determine the appropriate safety stock level for the retailers. The safety stock is a key factor in determining the reorder level, which in turn impacts the fill rate. The reorder level must be set to achieve a specific target service level. To find the correct reorder level and therefore safety stock, the reorder levels are adjusted and by observing the resulting fill rate, the correct reorder level can be determined to achieve the target service level. The results of this simulation is visualised in Figure 5.2.1, where the fill rates are plotted against different reorder level values and the reorder level value first reaching a target fill rate of 0.95, is the correct reorder level, depicted with the dotted red line. With this reorder level, the corresponding safety stock can be derived by using formula Equation 5.2.3. It is important to notice that it is also possible to obtain a negative or non-integer safety stock value. This can result from the fact that the mean demand is not necessarily integer, but the reorder level has to be integer due to the discrete demand. A negative safety stock value can stem from a reorder level smaller than the demand forecast.

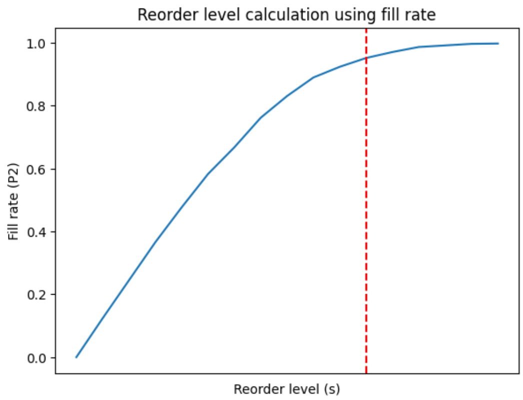


Figure 5.2.1: Reorder level calculation using the target fill rate

5.2.2 Single-echelon warehouse

The demand arriving at the warehouse comprises two parts: demand from online customers and demand from store replenishment orders. The demand from online customers follows a Poisson process with a constant arrival rate (λ). The demands for online arrive continuously, based on this rate. The store replenishment orders arrive periodically, based on the replenishment policy of the retailer. Because the retailers have a periodic review policy, the store replenishment orders only come in on the review days of the corresponding retailers. The total demand from store replenishment is calculated by adding up the orders from all retailers.

Even though the demand at the store is Poisson, the suspicion arises that the store replenishment orders do not follow a Poisson distribution. The reason for that, is that the stores do not have a service level of 100% and due to the lost sales policy, the mean demand of store replenishment orders will be lower. Subsequently, the store replenishment orders are generated by the replenishment system, at periodic intervals. This violates the memorylessness property of the Poisson distribution, stating that the time until the next arrival is independent of any past events. Therefore, our hypothesis is that the store replenishment orders do not follow a Poisson distribution. To test this hypothesis, the fitting procedure of Adan et al. (1995) is applied, resulting in a $a \neq 0$, confirming the hypothesis of not having a Poisson distribution. Consequently, it is decided to use the simulated store replenishment orders as demand input, for the simulation of the warehouse.

This system cannot be validated with the BoBr tool of Broekmeulen and van Donselaar (2015), because the assumptions do no hold. The aggregate mean and standard deviation do not accurately represent the demand distribution, because of the combination of Poisson and non-Poisson demand. Additionally, there is a combination of lost sales and backordering in the warehouse, which is not incorporated in the DoBr tool. However, with a high service level for online, there is only a minor deviation visible.

The inventory management of the warehouse is executed similarly to the retailer replenishment described above, using a R,S replenishment policy. At each time period, the inventory position (IP_t) at the warehouse is calculated using Equation 5.2.2. At a review period (R) an order is placed to bring the inventory position back up to the reorder level (s). The order is assumed to arrive after a fixed lead time (L). The reorder level is determined by the demand forecast for the period R+L, plus the safety stock, as stated in Equation 5.2.6.

$$
\begin{aligned}
s_{DC} &= D^{fcst,DC}_{L_{DC}+R_{DC}} + ss_{DC} \\
s_{DC} &= \sum_{i=1}^{N} D^{fcst,i}_{L_{DC}+R_{DC}} + D^{fcst,o}_{L_{DC}+R_{DC}} + ss_{DC}
\end{aligned} \tag{5.2.6}
$$

The demand forecast is the forecast for both online sales and store replenishment orders combined. As online demand follows a Poisson process, the expected demand for a period is equal to λ. However, the store replenishment orders do not follow a specific demand distribution and the historical mean of the store replenishment orders should be applied as the demand forecast, as demand is stationary. The sum of the mean demands from the retailers and the mean for online comprise the mean of the total demand experienced by the warehouse. The order quantity of the warehouse can be calculated, using Equation 5.2.4.

If there is not enough inventory on hand to meet the demand, a stock-out occurs. When demand comes from online customers, the sale is lost, because of the assumption of a lost sales policy from online. However, the store replenishment orders follow a backorder policy and backorders will be delivered to the store on the next delivery moment after the warehouse has received a replenishment. Subsequently, the fill rate (P_2) is used as a performance measure, which is the fraction of demand delivered from stock immediately.

To determine the correct reorder level and safety stock for the warehouse, the same method as mentioned before can be applied, where the safety stock levels are adjusted and the resulting fill rates are observed. For the demand, the sum of the simulated store replenishment orders and the online demand can be utilised. Based on a target service level set for the product in the warehouse, the reorder level and safety stock can be obtained. It is important to notice that a negative safety stock value is also feasible, as this corresponds to a reorder level smaller than the demand forecast.

5.2.3 Inventory allocation in warehouse

As the warehouse is used as an integrated warehouse, the inventory on hand is intended for both store replenishment and online orders. Therefore, an allocation policy should be established that determines the distribution of inventory between the online orders and store replenishment orders. The company uses an inventory reservation policy to allocate the products between the two streams. This policy will be investigated, with different values for the reservation quantity. The situation of not utilizing any reservations is also investigated, as this corresponds to a reservation quantity of zero. If the reserved quantity is zero, this implies that the online demand stream is treated equivalently to the demand from store orders, without any preferential treatment.

The moment of arrival of the store and online orders at the warehouse is expected to have a large effect on the need for reservation. Orders from the retailers that are able to order on a specific day arrive periodically, at the same moment, and online orders are received continuously throughout the day. However, the picking of these orders does not occur continuously, so for the purpose of this analysis, it is assumed that there exists a distinct moment when both the online orders and store replenishment orders are present simultaneously. It is at this precise moment that the allocation is executed. If the moment of arrival of both order streams were not assumed to be equal, the need for reservation quantity is expected to be different.

The algorithm used for the allocation policy is described below. Let IOH_t denote the inventory on hand in the warehouse at the beginning of a planning period. The company wishes to reserve an amount of inventory (a_t), intended solely for meeting the demand from online orders. The actual reserved quantity at time t (a_t) is calculated by taking the maximum value of the reserved quantity (a) and the inventory on hand, ensuring that the reserved quantity does not exceed the actual stock level. The remaining inventory for retailers ($IOH_{rem,t}$) will be calculated by subtracting the reserved quantity from the inventory on hand. This remaining inventory can be used to fulfill the orders from the retailers. If there is enough inventory on hand to serve the total demand from stores and online combined, and the remaining inventory for stores is enough to serve the total demand from stores, all orders can be fulfilled with the inventory on hand and the allocated stock is equal to the demand for each store and online.

If the total demand exceeds the total inventory on hand or the demand from the retailers surpasses the remaining inventory, there will not be enough inventory to fulfill all orders and the inventory should be allocated over the outstanding orders. The allocation process begins by fulfilling online orders using the reserved inventory. If the reserved quantity proves sufficient to fulfill all online orders, any remaining inventory will remain in stock. Thereafter, the unmet demand will be calculated, for both the stores and online, because if the reserved quantity was not sufficient there will still be outstanding online orders. In this allocation policy standard nesting is used, where the online demand first consumes the reserved quantity a; once and if a is entirely consumed, online demand competes equally with demand from retailer orders for any remaining unreserved inventory.

The allocation of inventory is based on the proportion of each order's demand relative to the total demand. For online orders, the outstanding orders after the allocation of reserved inventory are taken into account. To prevent excessive allocation, the calculated initial allocation quantity is rounded down to the nearest integer value. Any remaining unallocated inventory is randomly assigned to a location with outstanding orders, ensuring a balanced distribution across different retailers. This random allocation process continues iteratively until all available inventory is allocated.

Thereafter, the unmet demands are recalculated by subtracting the allocated products from the initial demand. At the retailer level, the outstanding orders are back ordered, while any unmet demand from online orders is considered as lost sales. With the use of the unmet demand, the service levels per store can be calculated. It becomes apparent that, over the long term, these service levels are equal. This outcome aligns with expectations since there is no service differentiation between the retailers, resulting in a uniform level of service across all locations. This is a result of the assumption of identical retailers and the random allocation of the remaining unallocated inventory. It is worth noting that if non-identical stores are assumed and the retailers were to have distinct demand characteristics or if the allocation of the remaining unallocated inventory was based on another policy non-random, variations in service levels are expected between the retailers.

Algorithm 1 Allocation policy

Determine the reservation quantity $a_t = max(a, IOH_t)$
Determine the remaining inventory $IOH_{rem,t} = IOH_t - a_t$
if $IOH_t \geq D_{tot}$ and $IOH_{rem,t} \geq D_{stores}$ **then**
    Allocate stock equal to the demand for each store and online
else
    Serve the demand from online with the reserved quantity
    Calculate the unmet demand from this period, for both online and all stores
    Allocate the remaining inventory proportionally, based on the percentage of the total demand $Alloc_i = \lfloor \frac{D_i}{\sum_{i=0}^{N} D_i} * IOH_{rem,t} \rfloor$
    Calculate the total allocated stock
    while Total allocated stock < stock available to allocate **do**
        Calculate the unmet demand, for both online and all stores
        Randomly allocate a product to an a location with unmet demand
        Add 1 to the total allocated stock
    end while
    Calculate the unmet demand, for both online and all stores
end if

Reservation quantity

The amount of inventory reserved for online, should be determined by the company. In the current policy of the company, the reserved inventory quantity at time t (a_t) is based on the demand forecast for online sales ($D_t^{fcst,o}$) for the period until the next delivery (t_d) is expected. In other words, the system reserves the inventory expected to be sold to online customers until the next delivery arrives. The demand forecast of a period is stationary in our model, but the time until delivery (t_d) depends on the review period (R) and lead time (L) of the warehouse.

This calculation did not incorporate any safety stock in the reservation quantity. In this research, it will be analysed if it is desirable to keep an extra amount of safety stock in addition to the already existing reservation amount. The safety stock in the reservation quantity will be denoted with ss_{res}, resulting in Equation 5.2.7 for the reservation quantity in period t. In the existing policy implemented by the company, the reservation quantity does not incorporate any safety stock, corresponding to a value of $ss_{res} = 0$. To determine the optimal value for parameter ss_{res}, simulations are conducted with varying values of ss_{res} to observe the system's response to different reservation quantities. This analysis will provide valuable insights into the requirement for a safety stock within the reservation quantity, in addition to the demand forecast for the time until delivery.

$$a_t = D_t^{fcst,o} * t_d + ss_{res} \tag{5.2.7}$$

For this analysis it should be determined which values for the reserved quantity (a_t), and consequently ss_{res}, should be investigated. For this, the scenario is considered in which separate warehouses are used for online and store replenishment and safety stock would also be kept for both online and retailers independently. The amount of safety stock that should be kept for the online demand in case of separate stocks (ss_{sep}), can be determined by using the single-echelon simulation. It is reasonable to allocate the same quantity of safety stock for reservation as when inventories are maintained separately. Allocating a higher amount of safety stock in the reservation cannot be justified. Therefore, the reserved quantity (a_t), should satisfy the condition $0 \leq a_t \leq D_t^{fcst,o} * t_d + ss_{sep}$. Rewriting this condition leads to $-D_t^{fcst,o} * t_d \leq ss_{res} \leq ss_{sep}$, where the value of ss_{res} should be between minus the demand forecast for the time until delivery, and the safety stock when kept separate. This is visualised in Figure 5.2.2. It is important to notice that there is a possibility of a negative value for ss_{res}, corresponding to a reservation quantity less than the demand forecast for the time until delivery.

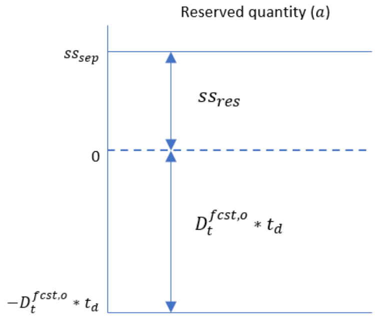


Figure 5.2.2: Visualisation of the reservation quantity

The calculation of the reservation quantity takes into account the number of periods it takes until the next delivery comes in. Therefore, the reservation quantity differs depending on the period. However, reservation is only used in periods of insufficient demand in the warehouse. The period where the inventory is the lowest is right before a potential delivery moment. This depends on the service level in the warehouse, as when the service level is high, the stockouts are likely to occur only in the last period before a delivery arrives when the time until delivery corresponds to one period. In this case, this corresponds to a formula of the reservation quantity of $a_t = D_t^{fcst,o} + ss_{res}$, and the condition of the safety stock in the reservation becomes $-D_t^{fcst,o} \leq ss_{res} \leq ss_{sep}$.

A simulation study is conducted to examine the impact of the allocation policy under various values of ss_{res}. This analysis aims to provide insights into the effect of reservation on the system. In the simulation, the safety stock levels at both the retailers and the warehouse are kept constant, while only the values of ss_{res} are altered. The outcomes are depicted in Figure 5.2.3, which presents the fill rate from the warehouse to the retailer and online customers across each iteration of the simulation.

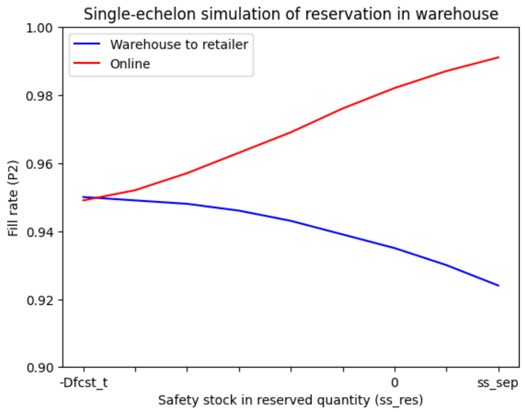


Figure 5.2.3: Single-echelon results of the reserved quantity and the fill rate

The figure demonstrates that when no reservation is used, the fill rate of online is similar to the fill rate of the warehouse to the retailers. This is expected because online is treated equivalently to the demand from store orders, without any preferential treatment. Subsequently, it can be seen that increasing the value of ss_{res} results in an increase in the fill rate for online, but a decrease in the fill rate for the retailers. The reasoning behind this is straightforward - with a higher value of ss_{res} more inventory is reserved for online orders, thereby improving their service level. However, this also implies less inventory being available for store replenishment, thereby negatively impacting their service level.

The findings obtained from this analysis provide valuable insights for determining the appropriate safety stock levels and optimizing the positioning of inventory within the supply chain. The utilization of reservations can prove to be a valuable strategy for enhancing the service level specifically for online customers, while simultaneously maintaining or even reducing the overall inventory levels within the warehouse.

5.2.4 Multi-echelon simulation

In the single-echelon retailer simulation, it was assumed that there is an infinite supply available to meet the demand at the retailers. Due to the multi-echelon system, the warehouse supplies the retailers, so it is implicitly assumed that the store orders can always be met in full, without any backorders or stockouts at the warehouse. However, in the single-echelon warehouse simulation, it is visible that the retailers do not receive a service level of 100% from the warehouse. In case of stockouts at the warehouse, the unmet demand will be backordered and the backorders at the retailers will be redeemed in the next possible delivery moment with enough stock. Therefore, the assumption of infinite supply is incorrect and the lead time at the retailers will be experienced as a variable lead time.

The presence of a multi-echelon system introduces an interdependent relationship between the service level provided by the warehouse and the resulting service level experienced by the individual retailers. The service level offered by the warehouse towards the retailer plays a crucial role in determining the overall service level at the retailer level. A lower service level from the warehouse to the retailer has a direct impact on the occurrence of backorders at the retailer. As the service level diminishes, the likelihood of encountering stockouts or insufficient inventory to fulfil store orders increases. Consequently, the retailers face challenges in meeting customer demand, leading to an elevated number of lost sales, resulting in a lower service level at the retailer level.

In order to establish a multi-echelon simulation model, the connection should be made between the warehouse and the individual retailers. At each time period, the retailers experience a Poisson distributed customer demand, and subsequently, they place replenishment orders at the warehouse on predetermined review moments. The warehouse, in turn, receives orders from both the retailers and online. The inventory on hand at the warehouse is utilized to fulfil these incoming orders. In the event of a stockout at the warehouse, where the inventory on hand is insufficient to meet the total demand, the inventory on hand is allocated, based on the policy explained in subsection 5.2.3. The unmet store orders will be backordered and scheduled for delivery in the subsequent delivery cycle, contingent upon the availability of adequate stock. At the retailer stores, the orders are expected to arrive after the lead time. However, when a stockout occurs at the warehouse, the subsequent delivery to the retailer is incomplete, resulting in a lower quantity of inventory on hand. This increases the probability of stockouts at the retailer, leading to lost sales.

To evaluate the impact of the allocation policy on the service levels in the multi-echelon supply chain, a simulation study is conducted under various values of a. This analysis aims to provide insights into the effect of reservation on the retailers. In the simulation, the safety stock level at both the retailers and the warehouse are kept constant, while only the values of a are altered. The outcomes are depicted in Figure 5.2.4, which illustrates the effect on the service level encountered by the retailers, represented by the green line.

Under the assumption of infinite supply, an expected service level was anticipated by the retailer. However, due to the impact of declining fill rates from the warehouse to the retailer, a lower service level is experienced at the retailers. As the fill rate from the warehouse to the retailers gradually decreases, a corresponding decline is observed in the fill rate experienced at the retailers. However, when investigating the blue and green lines, it becomes apparent that the decline in service level at the retailers is not with the same rate as the decline in the service from the warehouse to the retailer. This is as expected, as it corresponds to the inflated fill rate from van Donselaar (1990), which has both a constant and a proportional part.

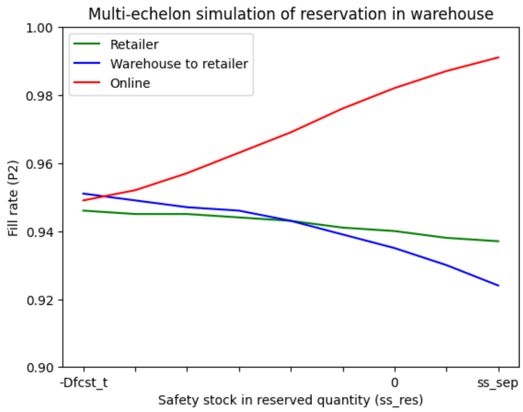


Figure 5.2.4: Multi-echelon results of the reservation quantity and the fill rate

This analysis has given insight in the effect of reservation in the multi-echelon system. With an increase in the reservation quantity, there is an improvement in the service provided to online customers. However, this improvement comes at the expense of a decrease in service from the warehouse to retailers, which influences the service experienced at the retailer gradually. These insights are valuable for determining the appropriate safety stock levels and optimizing the positioning of inventory within the supply chain. The utilization of reservation can prove to be a valuable strategy for enhancing the service level specifically for online customers, while simultaneously maintaining or even reducing the overall inventory levels within the warehouse. However, this comes at a cost of reduced service levels at the retailer.

5.2.5 Safety stock positioning in multi-echelon simulation

This research aims to determine the best safety stock values and positioning in the multi-echelon supply chain. Using the multi-echelon simulation of the previous section, different scenario's can be analysed. The variables to be set are the safety stock level in the stores, the safety stock level in the warehouse, and the reserved quantity. The aim is to find the values for these variables for which the target service levels are reached, while minimizing holding costs.

The holding costs are determined by the average of the expected inventory on hand after a potential delivery and before a potential delivery, as seen in Equation 5.2.8. The holding costs are directly influenced by the safety stock level employed at each specific location. A higher safety stock leads to a larger expected inventory on hand, resulting in higher holding costs. In the model holding costs are assumed to be equal at all stock points and are not dependent on where the stock is stored. Hence, this factor can be left out of the equation.

$$h = \frac{E[I^{OH}(\tau + L)] + E[I^{OH}(\tau + R + L)]}{2} \tag{5.2.8}$$

The service level is defined as the fill rate: the specified fraction (P_2) of demand to be satisfied directly from available inventory. The target service levels consist of the service level set for the individual SKU. This service level can differ per SKU, as the company has implemented a service level differentiation approach where each product is assigned a service level target, depending on its importance. A specific SKU has the same service level, regardless of the channel or location. There is no distinction made based on if a product is ordered online or at a retailer.

Additionally, it is decided to add a target service level for the warehouse to the retailers. When there is a low service from the warehouse to the retailers, the lead time experienced by the retailer will be highly variable. This can create an environment of uncertainty and unpredictability for store managers. In an attempt to mitigate the risk of stockouts and meet customer demand, store managers may resort to ordering larger quantities than necessary. This behavior is known as the bullwhip effect, and can lead to higher order variability and increased inventory levels at the warehouse and upstream suppliers. To mitigate this bullwhip effect, it is decided that a target fill rate from the warehouse to the retailers ($P2_{wr,target}$) of 0.8 should be implemented in the model.

To summarize, this can be written as the optimisation problem in Equation 5.2.9.

$$
\begin{aligned}
&\min\{\sum_{r\in R} h_r + h_w\} \\
&s.t. P2_r \geq P2_{target} \\
&\quad P2_o \geq P2_{target} \\
&\quad P2_{wr} \geq P2_{wr,target}
\end{aligned}
\tag{5.2.9}
$$

In the multi-echelon supply chain, it is a challenge to balance the customer service levels for the online channel and at the retailers. There exists a trade-off between the holding inventory at the stores, at the warehouse, and the reservation of inventory in the warehouse. The lower the safety stock level at the warehouse, the lower the service level is to the retailers. When the service level to the retailer becomes too low, the target service level at the retailer is not reached. The retailer can decide to increase its safety stock level, to account for the lower-than-expected service level. However: this might not always be cost-effective for the whole system. Additionally, the lower the safety stock level at the warehouse, the lower the service level for online customers. When the target service level for online is not reached, increasing the inventory reservation quantity can help to reach the target. However, the service level from the warehouse to the retailers will be negatively influenced by this action, leading to a decrease in the service level at the retailers as well. This shows that there is a trade-off between the three variables.

Greedy heuristic

To explore various scenarios, a greedy heuristic approach is employed. This heuristic systematically explores different combinations of variables to find the configuration that yields the lowest holding costs. By iteratively adjusting and evaluating the variables, the algorithm navigates through the solution space in search of a scenario that balances the service levels at both the retailers and online, and the holding costs effectively. This greedy heuristic is simplified and presented in algorithm 2, and will be explained below. The exact Python code of the heuristic is presented in Appendix C.

The starting point in the heuristic uses the scenario of adopting an installation stock policy, in which the locations determine its safety stock value exclusively based on its own inventory position. This approach involves employing the single-echelon simulation, allowing the retailer

Algorithm 2 Greedy heuristic

Set the safety stock levels at the retailers (s_r), for the target service level ($P2_{target}$)
Set the safety stock levels at the warehouse (s_w), for a target service level of 0.99
Set the safety stock in reservation quantity at $ss_{res} = -D_t^{fcst,o}$
Determine the safety stock for online when kept separate ss_{sep}, for the target service level ($P2_{target}$)
while $P2_r \geq P2_{target}$ and $P2_o \geq P2_{target}$ and $P2_{wr} \geq 0.8$ **do**
    Lower safety stock levels warehouse with 1: $ss_w = ss_w - 1$
    while $P2_r \leq P2_{target}$ **do**
        Raise safety stock levels each retailer with 1: $ss_r = ss_r + 1$
    end while
    while $P2_o \leq P2_{target}$ and $ss_{res} \leq ss_{sep}$ **do**
        Increase safety stock in reservation quantity with 1: $ss_{res} = ss_{res} + 1$
    end while
    while $P2_{wr} \leq P2_{target,wr}$ **do**
        Raise safety stock levels warehouse with 1: $ss_w = ss_w + 1$
    end while
end while

to establish its reorder level and corresponding safety stock level in order to achieve the target service level, based on the demand forecast and the assumption of infinite supply. Thereafter, the safety stock level at the warehouse is determined with the installation stock policy, based on the forecasted store replenishment orders and online demand. To mimic the scenario of infinite supply at the retailer, the service level target for the warehouse is set at 0.99, ensuring reliable delivery to the retailers. This initial safety stock level serves as an upper bound value for the heuristic. Furthermore, the heuristic begins by considering a scenario in which no inventory reservation is used. In this context, the safety stock associated with the reservation quantity should fall within the range of negative of the demand forecast and the safety stock when inventory is managed separately, as stated in the condition $-D_t^{fcst,o} \leq ss_{res} \leq ss_{sep}$. To establish this upper bound, the safety stock when inventory is managed separately is computed using the installation stock policy, with the demand forecast for online.

With these initial values in place, the multi-echelon scenario is simulated. The results of the simulation will present, per scenario, the total holding costs from all locations combined, and the service level at the retailers, at the warehouse, and from the warehouse to the retailer. Starting from this scenario, the heuristic embarks on a search for a scenario with lower holding costs while still meeting the service level targets.

The key part of the heuristic is to gradually reduce the reorder level at the warehouse, using discrete steps of one due to the discrete nature of demand. With the decrease in the safety stock level, a scenario is searched with lower total holding costs, as a decreasing safety stock level leads to a corresponding decrease in holding costs. However, this also results in a lower service level to online, from the warehouse to the retailer, and ultimately at the retailer. The safety stock level at the warehouse is lowered until one of the service levels falls below its target service level.

When the service level at the retailer drops below the target service level, it becomes necessary to restore the service level above the target. The retailer can do this, by increasing its safety stock levels at the store in discrete steps of 1. Because of the assumption of identical stores in this model, each retailer will raise its safety stock level. This increase in the safety stock level at the stores leads to an increase in the holding costs at the retailer, and therefore an increase in the total holding costs.

Moreover, if the service level to online falls below the target service level, it also becomes necessary to search for a scenario to restore the service level above the target. This can be done by raising the safety stock in the reservation quantity by one unit. This will ensure that with the same safety stock level at the warehouse, the service level of online is elevated. This also leads to the desired decrease in the holding costs. When the reservation quantity is raised, the safety stock at the retailers is restored to its initial value, to search for a feasible scenario with lower holding costs.

This process, of iteratively reducing the safety stock level at the warehouse, raising the safety stock levels at the retailers and modifying safety stock in the reservation quantity, continues until all reservation quantities within the predefined bounds are explored. For each reservation quantity considered, the minimum costs are reported. Based on the obtained results, conclusions can be drawn on the scenario with the lowest total holding costs. Furthermore, valuable insights can be obtained regarding the effectiveness of inventory reservation.

One of the key characteristics of a greedy heuristic is that it does not revisit or reconsider choices made in previous steps. This shows the fact that, with the greedy heuristic, not all scenarios are visited. Therefore, it does not guarantee to find the globally optimal solution, only a locally optimal solution and this may not be the overall optimal solution. However, the greedy heuristic is computationally efficient and provides a reasonable solution.

Chapter 6

Case study

In chapter 5, a method is developed that should be applicable to a divergent multi-echelon omni-channel supply chain system with an integrated warehouse. This Chapter aims to validate the solution design and is designed to test the practical relevance of the solution. To achieve this, a case study is conducted at Media Markt NL to validate the solution design and determine the optimal safety stock values for each product-location in MediaMarkt's multi-echelon omni-channel supply chain. The results of this process provide insights into the effectiveness of the solution design.

First, section 6.1 describes the company data used to validate the design, and a demand classification is executed to assist with the selection of products. Thereafter, the other input parameters used in the system are explained. Secondly, the results of the solution design will be presented. These results will be analysed and specifically, the effectiveness of inventory reservation in the integrated warehouse will be discussed.

6.1 Company data

The solution design is implemented using the demand characteristic computed from the data of MediaMarkt NL. The daily sales data from 01-01-2022 to 31-12-2022 is utilised, which has already undergone cleaning in section 4.6. However, given the extensive assortment, it is impractical to apply the solution design to every individual product. Therefore, a more manageable approach is adopted, focusing on a few selected products for testing the solution design. The aim is to ensure that the chosen products provide a representative sample of the important aspects of the assortment. To achieve this, the assortment is classified in a manner that allows for meaningful testing and evaluation of the solution design.

6.1.1 Demand classification

The sales quantity is a relevant aspect in our research, because the interest of this research is the quantity of products to keep as safety stock. In the literature, the ABC-classification is a widely employed method to categorize items based on the sales. However, instead of using the sales value the total assortment is divided into three groups: A, B and C, based on their total sales quantity. The classification parameters used are 0-80% of the total sales quantity in category A, 80-90% in category B, and 90-100% in category C.

The ABC analysis is widely used and often supported by the XYZ-analysis, which categorizes items according to their fluctuations in demand. However, this classification method does not seem to be useful, as a Poisson demand is assumed in the solution design. In the Poisson distribution there is only uses one parameter for the mean demand value and the variation in demand. Therefore, this classification method will not give the right insights, and it is decided not to use this classification method.

Another important aspect in the determination of the safety stock positioning in the omnichannel system is the spread of the demand between the two channels, online and stores. The proportion of the demand is that is sold online and in the stores is expected to be relevant for the reservation in the integrated warehouse. Therefore, the proportion of the online demand is used as a factor to classify the assortment. The channel ratio is stated as the percentage of online sales quantity compared to the total sales quantity. A higher percentage states a high online sales, compared to the store sales. The products will then be classified, in three categories: K,L and M, ranging from a low to a high proportion of the store sales quantity compared to the store sales quantity. The classification parameters used are determined based on the spread of the demand, as stated in subsection 4.6.3. All the products in the assortment are ranked on the percentage with lowest to highest percentage, and the items in 0-80% are categorized as K, in 80-90% as category L and 90-100% as category M.

Combining the ABC and KLM classification methods evolves in a classification matrix with 9 categories, stated in Table 6.1.1. The products in the demand are all classified according to the parameters. In Figure 6.1.1, a scatter plot is given where the percentage of online sales is plotted against the items, ranging from highest to lowest sales quantities. In this figure the nine categories are visualised with the dotted red lines.

	Sales quantity		
Channel ratio	AM	BM	CM
	AL	BL	CL
	AK	BK	CK

Table 6.1.1: ABC-KLM classification matrix

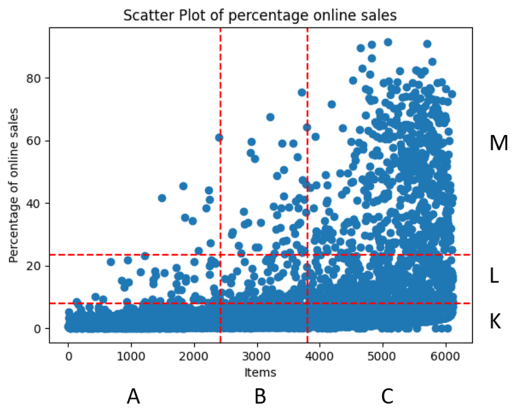


Figure 6.1.1: Scatter plot of ABC-KLM classification

As a result, Table 6.1.2 provides a breakdown of the items into the nine categories. The table presents the number of SKU's and the corresponding percentage of demand within each category.

	Sales quantity		
Channel ratio	AM 4 sku's - 0,06%	BM 18 sku's - 0,29%	CM 589 sku's - 9,62%
	AL 41 sku' s - 0,66%	BL 49 sku's - 0,80%	CL 523 sku's - 8,54%
	AK 1981 sku's- 32,37%	BK 953 sku's - 15,57%	CK 1962 sku's - 32,05%

Table 6.1.2: ABC-KLM classification matrix with quantities

With the use of this classification method, a specific SKU is chosen from each of the nine categories. To give a good representation of the category, and to avoid picking the outliers, the median product from each category is chosen, based on the total sales quantity and channel ratio. For each of these nine SKU's, the mean sales quantity can be calculated based on the total sales quantity. To be able to apply the heuristic from the solution design, the mean of the sales for the online channel, as well as the mean of the sales in the stores is needed. The mean demand for online can be calculated with the total online sales divided by the 365, the total amount of days in a year. The mean demand per store will be calculate with the total store sales divided by 365 and 48, the number of stores. It is divided by 48 because of the assumption of identical stores in our model. The resulting demands for the chosen items from the nine categories are shown in Table 6.1.3.

Category	**Total quantity**	**Online quantity**	**Store quantity**	**Mean online**	**Mean per store**
AM	1107	462	645	1,27	0,04
AL	6718	563	6155	1,54	0,35
AK	6717	138	9735	0,38	0,56
BM	507	168	339	0,46	0,04
BL	588	65	523	0,18	0,03
BK	579	8	571	0,02	0,03
CM	59	29	30	0,079	0,002
CL	88	10	78	0,027	0,004
CK	212	5	207	0,014	0,012

Table 6.1.3: Table of the mean sales per category

Within MediaMarkt a service level differentiation approach is used, where the slow-moving products get a lower service level target assigned than the fast-moving products. Therefore, a service level target is assigned to each category, based on the ABC-classification, as this divides the fast and slow moving products. Category A items (AK, AL, & AM) get a target fill rate of 95% assigned, category B items (BK, BL & BM) get 93% and category C items (CK, CL & CM) get 90%. This is based on the service levels from Table 4.6.1.

6.1.2 Input parameters

In the system the review period and lead time need to be initialised, both for the warehouse to store and from the supplier to warehouse. In this case, the supplier lead time and warehouse review period are both set to 14 days. This lead time is based on the average actual supplier lead time at MediaMarkt, analysed by Van Der Lee (2023), and the review period is also set to 14 days, as the review period should be greater or equal than the lead time. The lead time from the distribution center to the store is set to 2 days, while a review period of 3 days is chosen to allow stores to place orders twice a week at the distribution center. This is based on interviews with employees. With the use of the store review period, a replenishment schedule is established, ensuring an even distribution of stores over the replenishment days. The number of stores in the system is set to 48. Additionally, the target fill rate from the warehouse to the retailers is set on 0.8, as a measure to reduce extreme lead time variability's at the retailer.

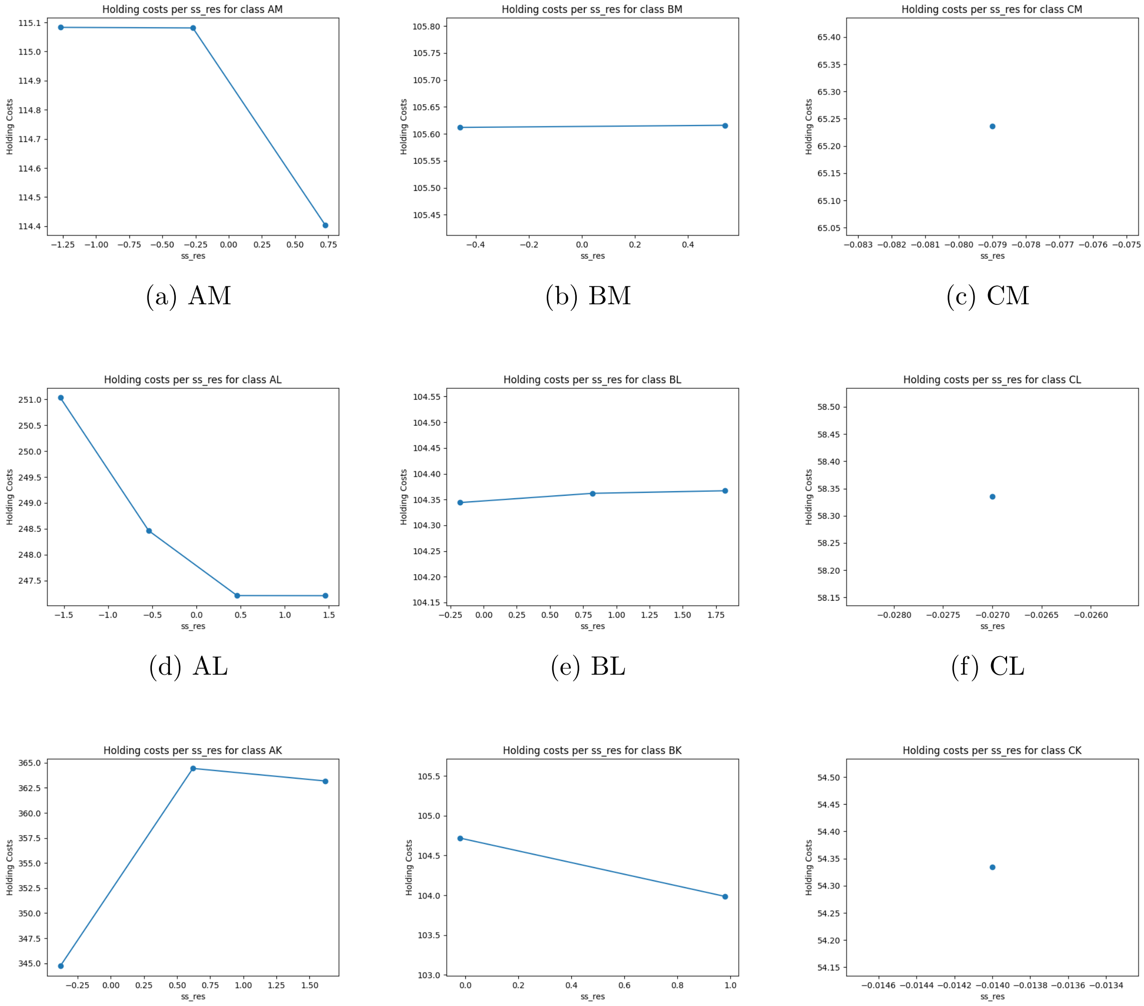
These input parameters remain constant throughout each iteration and for each category. By using the mean demands for each category, the system generates Poisson distributed demand and enables the implementation of the solution design. The simulation length is set to 100,000 days, allowing the system to reach a steady state and ensuring the validity of the results. The results are computed with the use of Python 3.11.1.

6.2 Results

The heuristic presented in the solution design is implemented for each of the nine SKU's from the different categories. This heuristic aims to find the best values for the reorder level in the warehouse, reorder level in the stores, and safety stock for the reservation quantity, with the objective of reaching the service level targets while minimizing holding costs. With the heuristic, the scenario is searched where the parameters are set in a way that all service level targets are met. For each of the values for the safety stock in the reservation quantity, the scenario with the lowest holding costs is presented.

To evaluate the positioning and the impact of the safety stock value in the reservation quantity, the results are presented in a way that the x-axis represents the safety stock in the reservation quantity (ss_{res}), while the y-axis represents the corresponding holding costs. Each point in the figure presents a scenario where the parameters for the safety stock in the warehouse and at the retailer are set in a way that minimises the holding costs, for that specific value for the safety stock in the reservation quantity. This visualization allows us to gain insights into the effectiveness of inventory reservation for these specific products. The results for the nine categories are presented in Figure 6.2.1.

The figures show that category C results stand out immediately, as options for inventory reservation are not being searched. This can be explained by the fact that the items from category C are slow movers, characterized by a significantly low mean demand rate. Consequently, holding back stock for these specific items does not appear to be justifiable. In the items with category B, the options for reservation are searched but the results show that the inventory reservation does not have a significant impact. The demand rates for these items are still fairly low, and reserving inventory for these products does not seem to lead to a reduction in holding costs.



(a) AM (b) BM (c) CM

(d) AL (e) BL (f) CL

(g) AK (h) BK (i) CK

Figure 6.2.1: Results of the solution design for each category

The products in category A show that inventory reservation can have a significant impact on the holding costs. However, if it positively or negatively influences the holding costs seem to differ per sub-category. The product from category AK shows that reserving inventory leads to an increase in holding costs. This can be explained by the fact that category K items have relatively low online sales. So, for the product in this category reserving inventory is not recommended. Category AM shows, that reserving inventory has a positive impact on the holding cost and this can be explained by the fact that the online sales are relatively high. For category AL a decreasing slope is visible, where reserving inventory has a positive impact on the holding costs. In this category, both online and store sales have a fairly high demand.

To conclude, inventory reservation does not seem to be applicable to the slow-moving products from category B and C. For the products with a high demand stream in category A, inventory reservation can be a useful tool. However, this depends on the proportion of online sales compared to store sales.

6.2.1 Inventory positioning

To provide a more comprehensive understanding of the results, the findings for the product in AL category will be examined in greater detail. This example will illustrate the positioning strategy when using reservations. The result from the solution design is highlighted in Figure 6.2.2.

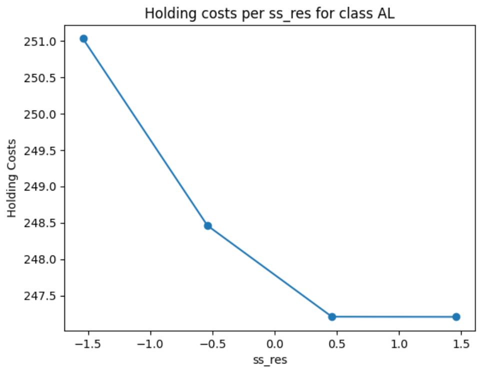


Figure 6.2.2: Result of the solution design for category AL

Each point depicted in the figure represents a specific scenario in which the three variables of the safety stock are assigned specific values. These scenarios are derived using the greedy heuristic. The safety stock values for the warehouse, for the retailer, and in the reservation quantity, corresponding to points in the figure, are depicted in Table 6.2.1. The customer service level target in this specific example was 0.95.

Holding costs	**Safety stock warehouse**	**Safety stock retailer**	**Safety stock reservation**	$P2_o$	$P2_r$	$P2_{wr}$
251,04	-18.7	1.3	-1.54	0,951	0,956	0,933
248,46	-22.7	1.3	-0.54	0,951	0,954	0,921
247,83	-23.7	1.3	0.46	0,952	0,954	0,917
247,21	-24.7	1.3	1.46	0,952	0,953	0,914
-3.83	6	0	3	0,001	-0,003	-0,019

Table 6.2.1: Detailed results for product in category AL

In this example, the heuristic algorithm identified four scenarios with varying safety stock values in the reservation quantity. The results demonstrate that implementing inventory reservation allowed for a reduction in the safety stock at the warehouse while keeping constant safety stock at the retailers. The service level between the warehouse and the retailers sees a slight decrease of 0.019, while the customer service level at the retailers only experiences a decrease of 0.003. This reduction in warehouse safety stock resulted in a decrease of 3.83 units in inventory holding costs, equivalent to a 1.52% decrease compared to not implementing inventory reservation.

The calculations in this example shows that reservation allows for a decrease in inventory holding costs while service level targets are all met.

Chapter 7

Conclusions & Recommendations

In this chapter the conclusions and recommendations for this research are presented. First, section 7.1 provides the main conclusions of this research. The sub research questions will be answered, ultimately answering the main research question. Secondly, section 7.2 presents the recommendations for MediaMarkt based on the research outcomes. Lastly, section 7.3 includes the limitations within this research and provides directions for future research.

7.1 Conclusions

The aim of this research was to develop an approach to find the best safety stock values and determine to best positioning in the multi-echelon omni-channel supply chain. Currently, knowledge about how to determine the safety stock values and where to position it, is missing at MediaMarkt. Consequently, they rely on the values set by the automated replenishment system, of which the specific method is unrevealed. Therefore, the suspicion arises that the current safety stock values and the positioning are not optimal, and a better balance between the service levels and holding costs can be found. This resulted in the following main research question.

How to determine the best safety stock levels and positioning in the omni-channel multi-echelon supply chain of MediaMarkt, to maintain the service levels while minimizing holding costs?

A set of six research questions has been formulated, strategically guiding the research process towards the answer on the main research question.

RQ1: How does MediaMarkt currently set its safety stock levels, both in the DC and in the stores? What is the performance of this method?

Currently, the safety stock levels for each specific product-location are calculated by the planning software RELEX, which uses a safety factor and the standard deviation of the demand during the lead time. The safety factor is found by using the fill rate in a continuous review system. However, in practice a periodic review policy is used, so instead of using the standard deviation during the lead time, the lead time plus review period should be employed. Subsequently, the method employed assumes a normally distributed demand.

The safety stock is used in the replenishment policy, in combination with the commercial shelf value, also known as the minimum fill by the company. The maximum value of these two is employed with the determination of the ordering quantity in the stores. However, the commercial shelf value seems to be larger than the safety stock in the majority of the cases. This lead to the conclusion that most of the time, the safety stock is not used in the determination of the order quantity. The usage of the commercial shelf value leads to a higher fill rate than anticipated, resulting in higher holding costs. The performance of solely the safety stock method cannot be quantified because of the interference of the commercial shelf value.

RQ2: Which methods to determine the safety stock levels in a multi-echelon omni-channel supply chain are available in the literature? Which factors should be considered and what are their impact?

With the analytical approach, the safety stock can be calculated with the use of formulas. The standard formula, uses a safety factor and the standard deviation of the demand during the lead time. However, when having non-stationary demand the standard deviation on the forecast error can be more accurate. To account for the lead time variability, a formula can be used where the variance of the lead time demand is taken into account. The safety factor considered in these formula can be determined with the use of the stock-out probability or the fill rate. All these analytical methods assume a normally distributed demand. A simulation-based approach can be used to calculate safety stock levels, when the conditions on which the methods are based are not met. With a simulation-based approach, the demand and lead time variability can be simulated and experiments can be carried out with a model of a real inventory supply system in order to understand its behaviour and assess the various safety stock levels.

Because the safety stock is to buffer against the impact of demand and lead time variability, these uncertainties are the most important factors to consider. The demand variability is reflected in the analytical formulas by the standard deviations of the demand and the forecast error, and there is an analytical formula that takes into account the lead time variability. A higher demand or lead time variability leads to a high safety stock level. Additionally, the service level plays an important role in the determination of the safety factor. An increase in the service level corresponds to a higher safety stock requirement.

RQ3: Which strategies for positioning safety stock in the omni-channel multi-echelon supply chain are there available in the literature?

In the literature on classical multi-echelon divergent systems, it is common that the majority of available inventory is pushed to the retailers, close to the customer. However, in these common approaches, an arborescent structure is assumed. However, when the structure is not purely arborescent, because the integrated warehouse has a dual role of meeting both customer demand and replenishing downstream locations, these methods cannot be directly applied. To the author's knowledge, there is no theory or analytical solution available in the existing literature to address the multi-echelon with the use of an integrated warehouse.

Literature on integrated warehouses points to inventory rationing approaches, to manage the challenge of handling the fulfillment of store and web orders. One specific approach is inventory reservation, where some portion of the available inventory is exclusively reserved for specific customer classes. Retailers often prioritise their online channel over their store channel.

RQ4: What is the best method to calculate the safety stock level per product-location?

To calculate the safety stock level, it is best to use a simulation-based approach, because the conditions on which the analytical methods are based are not all met in the system of MediaMarkt. The assumption of a normally distributed demand does not seem to be reasonable and there are no analytical approaches available in the theory that assume another demand distribution. With the use of a simulation, the multi-echelon omni-channel system should be reproduced, where the distribution center is responsible for the supply of the stores, and because of stockouts at the DC the stores can experience a lead time variability. Subsequently, the integrated warehouse should be simulated, with the inventory reservation policy, with which the stock is allocated between the store replenishment and online customers.

RQ5: What is the best positioning of the safety stock at the various stock points in the multi-echelon omni-channel supply chain?

To determine the best positioning of the inventory over the different stock points, the greedy heuristic from the solution design can be used. This heuristic determines the safety stock levels in the warehouse, at the retailers, and in the reservation quantity. The heuristic returns the scenario that reaches all service level targets and has the lowest holding costs from all scenario's that are searched. From the results, it can be concluded that inventory reservation can be useful, however, this depends on the sales volume and the proportions of online and store demand. Therefore, there is no one best positioning strategy, as it depends on the specific demand characteristic.

RQ6: What is the performance of the designed approach, compared to the current situation?

The designed approach is based on the echelon stock policy, where the order quantity decision at the distribution center is based on its own inventory position, as well as the inventory position at the stores. This is an improvement compared to the current installation stock policy, in which only its own inventory position is used. Additionally, the designed method uses the assumption of a Poisson distributed demand instead of a Normally distributed demand. This distribution fits better to the demand of MediaMarkt.

The answers to these six research questions provide valuable guidance in answering the main research question:

How to determine the best safety stock levels and positioning in the omni-channel multi-echelon supply chain of MediaMarkt, to maintain the service levels while minimizing holding costs?

To determine the safety stock levels, a simulation model of the multi-echelon omni-channel supply chain can be utilized. In this model, the inventory control model is based on an echelon-stock policy, taking into account the dependencies in the multi-echelon supply chain. The omni-channel warehouse will be modeled, and with the use of inventory reservation priorities can be shifted within the warehouse. The best positioning of the inventory can eventually be determined with the use of the greedy heuristic from the solution design, in which the safety stock in the distribution center, at the stores and in the reservation quantity are set in a manner that reaches customer service levels while minimizing holding costs.

7.2 Recommendations MediaMarkt

Based on the findings of this research, the following key recommendations are proposed for MediaMarkt:

Firstly, MediaMarkt should reassess its current method of setting safety stock levels. Instead of relying on the values set by the automated replenishment system, which are based on an installation stock policy and using analytical formulas based on a continuous review policy, they should adopt an approach that considers the echelon stock and does not assume a normally distributed demand. It is recommended to use a simulation-based approach, that considers the demand variability in the omni-channel multi-echelon supply chain. This will provide a better representation of the scenario of MediaMarkt and is expected to lead to more accurate safety stock calculations.

Secondly, it is recommended that MediaMarkt will do more research on the applicability of inventory reservation for different products in the assortment. The effectiveness of inventory reservation seems to depend on the demand characteristics. The current model has been tested on a limited set of nine products, and it is advisable to expand this research to a broader part of the assortment. This expansion will contribute to the generalizability of the findings.

Thirdly, it is recommended that MediaMarkt sets a minimum service level from the distribution center to the stores. When there is a low service from the warehouse to the retailers, the lead time experienced by the retailer will be highly variable. This can create an environment of uncertainty and unpredictability for store managers. In an attempt to mitigate the risk of stockouts and meet customer demand, store managers may resort to changing the commercial shelf value to order larger quantities than necessary. This behavior is known as the bullwhip effect and can lead to higher order variability and increased inventory levels at the warehouse and upstream suppliers. To mitigate this bullwhip effect, it is advised to set a minimum service level target from the distribution center to the stores.

Lastly, it is recommended that MediaMarkt revises its inventory allocation policy in case of stockouts in the warehouse. The current allocation method is based on the relative proportion of demand from a specific store compared to the total demand. However, this method tends to favor large stores with a higher allocation of inventory. Over time, this leads to a higher service level for stores with a high demand rate and this service level differentiation between stores might not be desirable. Alternative allocation policies can be explored to better fit the service level differentiation strategy of the company.

7.3 Limitations & directions for future research

The research has a number of limitations, which are briefly discussed in this section.

Firstly, a limitation of this research is the assumption of a deterministic lead time. The supplier lead time analysis reveals that the lead times are highly variable. The current model focuses solely on determining safety stock levels based on demand variability, overlooking the impact of lead time variability. When lead time variability is experienced, the need for safety stock becomes even more crucial to maintain the service levels. Neglecting to account for lead time variability could potentially have a negative effect on the service levels experienced by the customer. In further research, this model can be extended with the addition of a stochastic lead time, to account for lead time variability in the determination of the safety stock levels.

Secondly, a limitation of the model is its assumption of identical stores. In reality, there are substantial variations among MediaMarkt's physical stores in terms of size and product assortment. Not all stores carry the same products in their assortment, and the demand rates can vary across different stores. Consequently, the safety stock levels required for each store may differ. In future research, it would be beneficial to modify the model to accommodate the non-identical stores.

Thirdly, a limitation of the research is that a Poisson demand is assumed for all products in the assortment. While the Poisson distribution is commonly employed in the literature for slow-moving products, it may not accurately capture the demand patterns of fast-moving products. In further research, the model can be adjusted to account for different demand distributions.

Fourthly, a limitation of the research is the assumption of stationary demand for all products. The research does not consider promotions and the seasonal effects experienced by a part of the assortment are not taken into account. In practice, MediaMarkt runs multiple large promotions throughout the year, future research could investigate the effect of promotions and seasonal effects on the safety stock values and positioning.

Lastly, a limitation is that in the model demand correlation is not taken into account. It would be valuable to explore the effect of demand correlation on safety stock levels in further research. Especially, the demand correlation between the online and store demand might be useful, as this can have an influence on the risk-pooling effect and, therefore, the impact of centralizing stock.

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Appendix A

Forecasting methods

Method
Moving average
Simple exponential smoothing
Exponential smoothing with trend
Exponential smoothing with seasonal indices
Naive season
Additive trend, additive season
Additive trend, multiplicative season (Holt-Winters)
Multiplicative trend, additive season
Multiplicative trend, multiplicative season
Additive damped trend, additive season
Additive damped trend, multiplicative season
Exponential smoothing with trend and seasonal indices
Croston's method
Regression forecasting
Aggregate-level forecasting
Aggregate season model

Table A.0.1: Demand forecasting methods

Appendix B

Inventory allocation

```python
#Determine reservation quantity
if res == True:
    reservation = max(min(math.ceil(lamda_online * until_delivery) + res_ss_dc, max(inventory_oh_L,0)) ,0)
else:
    reservation = 0

inventory_left_L = max(inventory_oh_L - reservation,0)

#If enough inventory, allocate all demand
if inventory_oh_L >= demand and demand_store <= inventory_left_L:
        inventory_oh_LR = inventory_oh_L - demand
        allocated_stock = dem_list
        back_store = [0] * len(dem_list)
        backorder_LR = 0
else:
    allocated_stock = [0] * len(dem_list)

    #Allocate reservation quantity to online
    if res == True and reservation > 0:
        allocated_stock[-1] = min(reservation, demand_online2)
    back_store = [dem_list[p] - allocated_stock[p] for p in range(len(dem_list))]

    #Allocate based on the proportion of outstanding orders
    if inventory_oh_L > 0:
        allocated_stock = [x + math.floor(s/sum(back_store) * min(inventory_left_L, demand_store)) for x, s in zip(allocated_stock, back_store)]
        back_store = [dem_list[p] - allocated_stock[p] for p in range(len(dem_list))]
        allocated_total = sum(allocated_stock)
        while allocated_total < min(inventory_left_L+reservation,demand_store):
            back_store = [dem_list[p] - allocated_stock[p] for p in range(len(dem_list))]
            allocated_stock[random.choice([i for i, value in enumerate(back_store) if value == max(back_store)])] += 1
            allocated_total += 1

    back_store = [dem_list[p] - allocated_stock[p] for p in range(len(dem_list))]
    backorder_LR = backorder_L + sum(back_store[:-1])
```

Figure B.0.1: Python code for inventory allocation

Appendix C

Greedy heuristic code

```python
simulation_length = 100000
nr_stores = 48
service_target = 0.95
service_target_wr = 0.8
lamda_store = 0.04
lamda_online = 1.27

demand_lists = []

for i in range(nr_stores):
    demand = np.random.poisson(lam =lamda_store, size =simulation_length)
    demand_lists.append(demand)


def optimisation_heuristic(lamda_store, lamda_online, service_target, service_target_wr):

    #Initialise the results list
    results_list = []

    #Set the safety stock levels in at the retailers for a target service level. At all stores the same
    # global safety_stock_list
    safety_stock_list = [optimal_sim_st(lamda_store, service_target)[0]]*nr_stores

    #Generate the demand for online and store orders
    demand_online = np.random.poisson(lam =lamda_online, size =simulation_length)
    demand_store = single_echelon_store(safety_stock_list)
    global added_stores_online
    added_stores_online = [demand_store[p] + demand_online[p] for p in range(len(demand_store))]

    #Set the safety stock in the warehouse for a target service level of 0.99, as the upperbound
    ss_dc_upperbound = optimal_sim_dc_alg(added_stores_online, 0.99)[0]
    ss_dc = ss_dc_upperbound

    #Set ss in res quantity on -demand forecast and calculate the upperbound for the reservation quantity
    ss_res= -lamda_online
    upperbound = optimal_sim_dc_alg(demand_online,service_target)[0]

    #Calculate initial values, and print if it reaches all target service levels
    P2_stores, service_online, service_stores, total_costs = multi_echelon(safety_stock_list, ss_dc, ss_res, True)
    if service_stores >= service_target and service_online >= service_target and P2_stores >= service_target_wr:
        results_list.append([ss_dc, total_costs, service_stores,service_online,ss_res, safety_stock_list[0], P2_stores])

    #While loop of the heuristic. While targets are met, lower ss in DC
    while service_stores >= service_target and service_online >= service_target:
        ss_dc -= 1
        #The function multi_echelon contains simulation, with all safety stock levels as input and outcomes are the service levels and costs
        P2_stores, service_online, service_stores, total_costs = multi_echelon(safety_stock_list, ss_dc, ss_res, True)
        if service_stores >= service_target and service_online >= service_target and P2_stores >= service_target_wr:
            results_list.append([ss_dc, total_costs, service_stores,service_online,ss_res, safety_stock_list[0], P2_stores])
        else:
            ss_dc +=1

        #While target to stores not met, look back try to reserve inventory with lower ss in stores
        while P2_stores < service_target_wr and ss_res < upperbound:
            ss_res += 1
            safety_stock_list = [value - 1 for value in safety_stock_list]
            demand_store = single_echelon_store(safety_stock_list)
            added_stores_online = [demand_store[p] + demand_online[p] for p in range(len(demand_store))]
            ss_dc += 1
            P2_stores, service_online, service_stores, total_costs = multi_echelon(safety_stock_list, ss_dc, ss_res, True)
            if service_stores >= service_target and service_online >= service_target and P2_stores >= service_target_wr:
                results_list.append([ss_dc, total_costs, service_stores,service_online,ss_res, safety_stock_list[0], P2_stores])
```

Figure C.0.1: Python code for Greedy heuristic - part 1

```
        #While online target not met, look back try to reserve inventory
        while service_online < service_target  and ss_res < upperbound:
            ss_res += 1
            ss_dc += 2
            safety_stock_list = [value - 1 for value in safety_stock_list]
            demand_store = single_echelon_store(safety_stock_list)
            added_stores_online = [demand_store[p] + demand_online[p] for p in range(len(demand_store))]
            P2_stores, service_online, service_stores, total_costs = multi_echelon(safety_stock_list, ss_dc, ss_res, True)

            if service_stores >= service_target and service_online >= service_target and P2_stores >= service_target_wr:
                    results_list.append([ss_dc, total_costs, service_stores,service_online,ss_res, safety_stock_list[0], P2_stores])

        #If target stores not met, increase ss in stores with 1
        if service_stores < service_target and ss_res >= -lamda_online and ss_res <= upperbound:
            for w in range(len(safety_stock_list)):
                    safety_stock_list[w] += 1

            demand_store = single_echelon_store(safety_stock_list)
            added_stores_online = [demand_store[p] + demand_online[p] for p in range(len(demand_store))]

            P2_stores, service_online, service_stores, total_costs = multi_echelon(safety_stock_list, ss_dc, ss_res, True)
            if service_stores >= service_target and service_online >= service_target and P2_stores >= service_target_wr:

                    results_list.append([ss_dc, total_costs, service_stores,service_online,ss_res, safety_stock_list[0], P2_stores])

            #While online target not met, reserve more inventory
            while service_online < service_target  and ss_res < upperbound:
                ss_res += 1
                ss_dc += 2
                safety_stock_list = [value - 1 for value in safety_stock_list]
                demand_store = single_echelon_store(safety_stock_list)
                added_stores_online = [demand_store[p] + demand_online[p] for p in range(len(demand_store))]
                P2_stores, service_online, service_stores, total_costs = multi_echelon(safety_stock_list, ss_dc, ss_res, True)

                if service_stores >= service_target and service_online >= service_target and P2_stores >= service_target_wr:
                    results_list.append([ss_dc, total_costs, service_stores,service_online,ss_res, safety_stock_list[0], P2_stores])

        #If store target not met, raise ss in stores
        if service_online > service_target and service_stores < service_target and ss_res <= upperbound:
            ss_res += 1
            ss_dc += 1
            safety_stock_list = [value - 1 for value in safety_stock_list]
            demand_store = single_echelon_store(safety_stock_list)
            added_stores_online = [demand_store[p] + demand_online[p] for p in range(len(demand_store))]
            P2_stores, service_online, service_stores, total_costs = multi_echelon(safety_stock_list, ss_dc, ss_res, True)
            if service_stores >= service_target and service_online >= service_target and P2_stores >= service_target_wr:
                results_list.append([ss_dc, total_costs, service_stores,service_online,ss_res, safety_stock_list[0], P2_stores])

        #If target to stores not met but reservation on upperbound, stop heuristic
        if P2_stores < service_target_wr and ss_res >= upperbound:
            break

    #Return the minumum holding costs, if there are equal, return both
    minimum_cost = min(results_list, key=lambda x: x[1])
    minimum_cost_list = [x for x in results_list if x[1] == minimum_cost[1]]

    return minimum_cost, minimum_cost_list, results_list
```

Figure C.0.2: Python code for Greedy heuristic - part 2