MASTER

Distribution and ordering decisions in a retail supply chain

van der Lee, Philip A.M.

Award date:
2023

Master Thesis

Distribution and ordering decisions in a retail supply chain

P.A.M. van der Lee
Student number: 1014034

Supervisors:

dr. ir. H.P.G van Ooijen - Supervisor TU/e

dr. ir. R.A.C.M. Broekmeulen - Second Supervisor TU/e

drs. R.P.J. Dohmen - Supervisor MediaMarkt Saturn

Eindhoven, 19th December 2022

Abstract

The need for efficient supply chain management in the retail industry is high due to the increased competition from online sales and small profit margins. Traditionally, in the retail industry, a central warehouse is used for keeping bulk of a company's stock and physical retail stores that order products from this warehouse. However, the introduction of cross-dock distribution provided supply chain managers with multiple options of distribution. Cross-dock strategies provide significant benefits: considerable savings in handling costs and the elimination of warehouse inventory. Nevertheless, choosing the appropriate distribution strategy for the products remains challenging. This thesis explores the options for cross-dock strategies at MediaMarkt Saturn, Europe's largest consumer electronics retailer. A decision support tool is developed for selecting the right distribution strategy for a product. In addition, inventory control policies are proposed for controlling the strategies such that high operational costs can be avoided. We find that cross-docking is interesting for most products with moderate and high demand.

Executive summary

This thesis is conducted at MediaMarkt NL, one of the major consumer electronic retailers in the Netherlands.

Introduction

MediaMarkt has centralized the storage and distribution through its central warehouse. The transformation of the supply chain structure opened new opportunities and challenges for the supply chain managers. The suppliers deliver the products to the warehouse, from where they are distributed to their stores, or to the customers ordering their products online. There are currently three different distribution strategies to their stores: 1) Traditional Warehouse (TW), 2) Break-Bulk Cross-Dock (BBXD), and 3) Pre-Allocated Cross-Dock (PAXD).

The main challenge for the company is that there is no structured approach for selecting the distribution strategy for a product. As a result, sub-optimal strategies are chosen that cause reduced product availability and high operational costs. This creates opportunities for improvement by developing an approach for selecting the right distribution strategy. The goal for this research is to create a tool that allows a quick distribution strategy selection based on the product and business environment characteristics.

Furthermore, the TW strategy is believed to be underperforming due to the high warehousing costs. This research aims to increase supply chain efficiency by integrating warehousing cost factors into ordering decisions. Hence, the inventory control policy should reduce the combined warehousing and inventory costs.

This results in the following assignments:

1. Design a decision support tool for selecting a distribution strategy to reduce costs and maintain product availability

2. Integrate warehouse cost factors into ordering decisions to reduce inventory and operational costs

Current situation

First, the current situation is analyzed to identify important characteristics to develop the solution design. The following characteristics were identified:

- One-Warehouse-Multiple-Retailer (OWMR) divergent structure
- Centralized inventory control
- (R,S)-policy for inventory control
- Low store order quantities
- Seasonality for multiple product groups
- Stochastic demands
- Considerable demand correlation between retailers
- Stochastic lead times

Solution design

The distribution strategies dictate how inventory is positioned within the system. Therefore, the benefit of storing inventory centrally is analyzed and the factors that determine the magnitude of this benefit. The main advantage of keeping inventory centrally is the risk-pooling effect. By pooling the demand variabilities, the system-wide safety stock can be reduced. The three factors that influence the magnitude of the risk-pooling effect are: 1) demand variability, 2) lead time, and 3) demand correlation. The larger the risk-pooling effect, the greater the potential benefit of inventory centralization.

In addition, other factors are relevant as well. Supplier reliability, product popularity, total cubic movement, and product value can all impact the practical value of the cross-dock strategy. As a result, these factors should also be taken into account when selecting the appropriate distribution strategy.

These factors are integrated into the distribution strategy preference (DSP) framework (Figure 2).

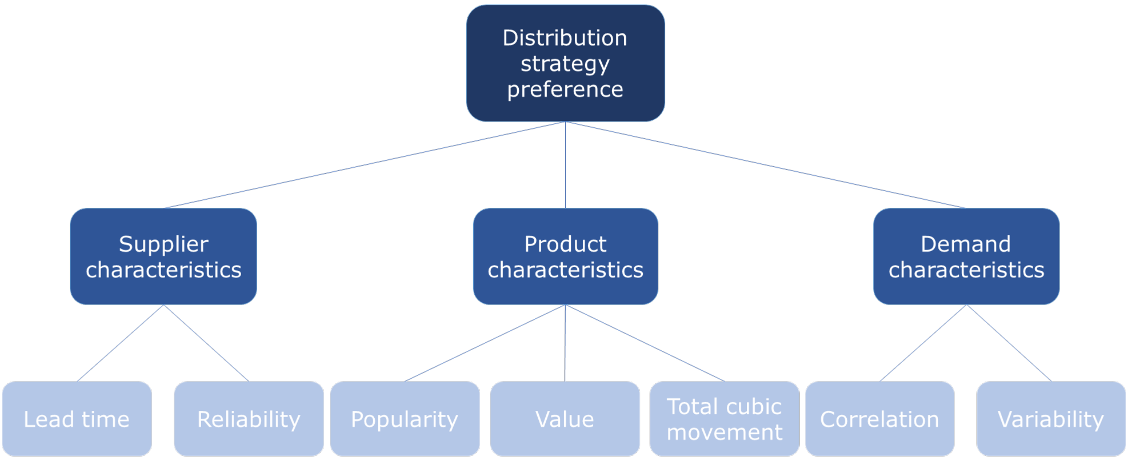


Figure 2: DSP-framework

The distribution strategy selection (DSS) decision tree is proposed (Figure 3) for quick and simple distribution strategy selection. In the decision tree, three distribution strategies are considered that are similar to MediaMarkt's distribution strategies. The Post-distribution cross-dock (Post-C) strategy is similar to the BBXD strategy except for the order allocation that is performed at the warehouse. The Pre-distribution cross-dock (Pre-C) strategy is similar to the PAXD strategy. The decision tree offers a high probability that the right distribution strategy is chosen from an inventory control perspective.

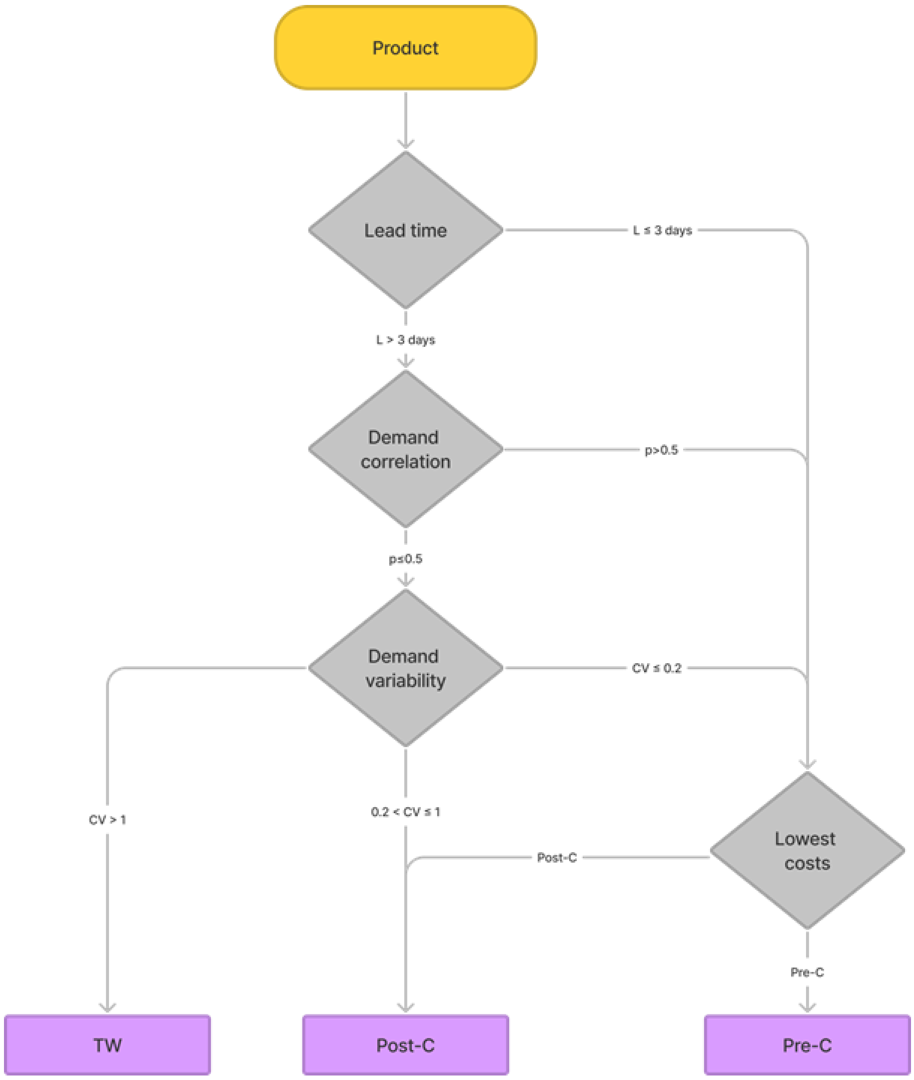


Figure 3: DSS-decision tree

For the TW strategy, an echelon periodic review order-up-to-replenishment (R,s,S)-policy is proposed to integrate warehousing costs into the ordering decisions. The order up to level is based on the economic order quantity (EOQ) that makes the trade-off between order setup costs and inventory holding costs.

Results

A case study is performed to validate the solution design and to test the practical relevance of the solution. The case study showed that cross-docking a significant proportion of the sales volume could be beneficial since handling costs for these strategies are considerably lower. Especially products with moderate and high demand are candidates for cross-dock strategies as they generally observe less demand variability. The TW strategy remains a robust choice for most products, as most products observe high demand variability.

Furthermore, implementing an order-up-to-level based on the economic order quantity is especially interesting for store orders with low product value. For those products, the order-setup costs are relatively high compared to the holding costs. As a result, increasing order quantities for those products reduces the combined inventory and operational costs.

Recommendations

The following recommendations were made to MediaMarkt.

First, under the BBXD strategy, the order-to-store allocation must be postponed to the warehouse. Late allocation allows for risk-pooling over the supplier-to-warehouse lead time and is therefore capable of dealing with higher levels of uncertainty.

Second, supplier lead times should be determined more accurately. Currently, the lead times used in the replenishment policy deviate significantly from the actual lead time. This results in over- and understocking of the system. This can have critical effects on inventory control performance.

Third, the PAXD strategy should only be implemented under strict conditions. The PAXD strategy is sensitive to uncertainties as lead times are long. Additionally, the benefit of handling costs could be small due to extra fees from suppliers. Therefore, the benefits for switching to this strategy should be substantial.

Fourth, order-up-to levels should be implemented for slow-moving products with low value. This order-up-to level could be estimated with the EOQ. Case-pack sizes can be used instead of the EOQ if they are reasonably close to the EOQ.

Last, the safety stock calculation should be revised. Currently, the standard deviation is calculated over the lead time while a periodic review policy is utilized. Also, lead time uncertainty should be included, as we found that lead times are highly uncertain.

In conclusion, there are multiple recommendations that could easily be implemented in practice. The expected benefit from these changes could already be substantial. The DSP framework, combined with the DSS decision tree, can aid managers in selecting the right distribution strategy for the product. Due to implementing an EOQ in the existing replenishment policy, frequent ordering can be avoided. Warehouse operational efficiency is likely to increase significantly as order quantities are currently low in many instances.

Contents

List of Figures

List of Tables

List of abbreviations

- TW: Traditional Warehouse
- BBXD: Break-Bulk Cross-Dock
- PAXD: Pre-Allocated Cross-Dock
- DSP: Distribution Strategy Preference
- DSS: Distribution Strategy Selection
- OWMR: One-Warehouse-Multiple-Retailer
- EOQ: Economic Order Quantity
- SKU: Stock-Keeping Unit
- CV: Coefficient of Variation
- Pre-C: Pre-distribution Cross-docking
- Post-C: Post-distribution Cross-docking
- KPI: Key Performance Indicator
- MOQ: Minimum Order Quantity
- PE: Portfolio Effect
- DV: Demand Value

Chapter 1

Introduction

Today's retail sector has faced rapidly evolving conditions with the continuous growth in online product sales at the expense of sales in brick-and-mortar stores. The COVID-19 pandemic only accelerated this process with the closure of many stores. The new circumstances force companies to revitalize their business plan and their entire supply chain operations. The retail sector's profit margins are small, and competition is high. As a result, companies are faced with the need to manage their supply chain efficiently.

Supply chain management is the practice of efficiently integrating all actors and processes within the supply chain. This includes suppliers, manufacturers, warehouses and stores. The goal is to produce and distribute the products at the quantity, location and time, such that the overall system costs are minimized while satisfying the service level requirements (Simchi-Levi, Kaminsky & Simchi-Levi, 2008). In this practice, management activities such as production, purchasing, inventory management, distribution, and sales are included (Mangan & Christopher, 2005).

Inventory management is a key element within the supply chain, as it links the different partners, and it is a mechanism of material flow (Power, 2005; Handfield, Handfield & Nichols Jr, 2002). To manage inventory efficiently, managers have to make decisions on three fundamental questions:

1. *How much should be ordered?*
2. *When should be ordered?*
3. *Where should it be stored?*

These interdependent decisions serve as the input for the inventory control system. Traditionally downstream stores order their products from a central warehouse with ample inventory. The central warehouse orders from their external supplier that orders from their suppliers. The warehouse has three roles in this case: 1) a buffer against uncertainty from suppliers and demand, 2) a consolidation point for products from multiple sources, and 3) shortening the lead time to the stores (Tompkins, White & Bozer, 1996). Today, retailers recognize that a central warehouse can be solely used as a consolidation point without keeping stock, a so-called cross-dock station. The principle of cross-docking is defined by Van Belle, Valckenaers and Cattrysse (2012) as: *'the process of consolidating freight with the same destination (but coming from several origins), with minimal handling and with little or no storage between unloading and loading of the goods'*. Cross-docking has the advantage that it eliminates costly warehouse processes such as order picking and the need for warehouse inventory. Many organizations combine the cross-docking distribution strategy with the traditional warehouse strategy to benefit from both approaches (Apte & Viswanathan, 2010).

This thesis aims to integrate inventory and distribution strategy decisions. Our goal is to provide insight into how an appropriate distribution strategy can be chosen and how inventory can be effectively managed under this strategy. This thesis is conducted at MediaMarkt Saturn, the leading European consumer electronics retailer. Currently, the company is re-evaluating the applicability of their distribution strategies and inventory control methods. Therefore, this thesis could provide valuable insight into how this challenge could be approached.

1.1 Company Description

MediaMarkt Saturn is active in 13 countries with over 1000 stores and 50 thousand employees. Their product portfolio consists mainly of electronics and electronic-related products. These products can range from as small as telephone cases to as large as a fridge. This thesis is focused on the division of MediaMarkt Saturn in the Netherlands. Currently, MediaMarkt Saturn, now referred to as MediaMarkt, has 49 stores and approximately 4000 employees.

Competitors of MediaMarkt in the Netherlands are, amongst others, coolblue, BCC, and bol.com. MediaMarkt has brick-and-mortar stores throughout the Netherlands at high-value locations. The stores are part of MediaMarkt's omnichannel strategy.

The main benefit of an omnichannel strategy is that sales channels complement each other to provide a high-quality customer experience that is both seamless and effortless.

MediaMarkt used to have a decentralized supply chain where the stores received the products directly from the suppliers, and inventories were managed locally. This meant that each store had its procurement and inventory replenishment staff. However, in 2020 the construction of the central warehouse in Etten-Leur allowed MediaMarkt to centralize the storage and coordination of all their inventories. In April 2022, MediaMarkt further exploited the new supply chain structure by combining the storage of the online and offline sales within the DC. The transformation of the supply chain structure opened new opportunities and challenges.

1.1.1 Characteristics

- OWMR system:
  The warehouse is supplied by external suppliers, while the warehouse supplies the retailers
- Consumer electronic retail:
  A variety of electronic products are sold to consumers both online and offline
- Centralized inventory control:
  Inventory replenishment is centrally coordinated from the headquarters in the Netherlands
- Multi-item product portfolio:
  The product portfolio consists of approximately 15,000 products, including fast and slow-moving goods

1.2 Problem Description

MediaMarkt has centralized the storage and distribution through their DC. The suppliers deliver the products to the warehouse, from where they are distributed to their stores or to the customers ordering their products online. Currently, the products are distributed through two distribution strategies, and a third is in development. First, under the TW strategy, products are ordered from a supplier and stored in the central warehouse. Upon order arrival, the products are received and put into storage. When a store needs replenishment or a customer orders a product, the product is picked from storage and shipped to the destination. Second, under the BBXD strategy, the ordered products are sorted and consolidated at the warehouse with other orders. The consolidated shipments are sent off as quickly as possible to the respective destination. Third, under the PAXD strategy, the products are already sorted at the supplier and shipped to the warehouse on different pallets. Since the products are already sorted, it does not require any sorting at the central warehouse. The inbound pallets are consolidated with other store orders and shipped to the stores.

MediaMarkt recognizes the incredible opportunity that the BBXD and PAXD strategy offer. Due to immediately shipping the products to the final destination, expensive storage and picking processes in the warehouse can be avoided. Nevertheless, the amount of total purchases distributed by the BBXD strategy has declined from 37% to only 12%. There is currently no structured approach for determining if the product should be distributed by the BBXD strategy.

Furthermore, the primary focus for inventory management under the TW strategy has been inventory minimization. The current method of order quantity calculation minimizes the inventory levels in the replenishment interval, reducing inventory costs. However, the pure focus on inventory minimization has led to small replenishment quantities and frequent replenishment. These quantities have caused inefficient picking operations in the warehouse, one of the most costly processes. The current inventory order quantity calculation fails to consider these costs, leading to high warehousing costs.

Chapter 2

Research Assignment

2.1 Literature Review

2.1.1 Distribution Strategy

Literature shows that the performance of the distribution strategy is related to the product and business environment characteristics. Therefore, based on these characteristics, an initial choice for the right distribution strategy can be made.

Demand characteristics

The most researched factor in the literature is the impact of the demand characteristics on the distribution strategy performance. The demand rate determines the order quantity and order frequency. The bigger the demand rate is, the more inventory costs are saved with a cross-dock strategy (Li, Low, Lim & Ma, 2008). In addition, higher quantities and more frequent shipments lead to more efficient cross-docking operations as well (Vogt, 2010). Furthermore, demand variability determines the safety stock need. Since the cross-dock strategy has no buffer in the warehouse to deal with these uncertainties, extra safety stock is needed at the stores. Many researchers argue that variability negatively impacts a cross-dock strategy since it does not have the risk-pooling effect of the traditional warehouse strategy (Li et al., 2008; Benrqya, Estampe, Vallespir & Zied Babai, 2014; Benrqya, Babai, Estampe & Vallespir, 2020; Apte & Viswanathan, 2010; Yan & Tang, 2009). On the other hand, demand correlation can eliminate this risk-pooling effect. Since cross-docking requires less handling, the preference for a cross-dock strategy increases (Yan & Tang, 2009).

Lead time characteristics

Another factor that is widely researched is the lead time characteristics. Generally, cross-dock strategies are preferred under short supply lead time (Yan & Tang, 2009; Benrqya et al., 2014, 2020). This is because short lead times allow for quick responses to fluctuations in demand. As a result, the impact of the observed demand variability is small. Also, short lead times reduce the risk-pooling effect as the variability is pooled over a short period (Yan & Tang, 2009). Consequently, the preference for a traditional warehouse strategy decreases. In addition, there is a lot of interdependence during cross-docking. Hence, lead time reliability is crucial (Vogt, 2010). To summarize, short supply lead times can overcome the weakness of cross-docking, which is the long store lead time that can cause high safety stocks.

2.1.2 Inventory management

EOQ

The model that makes a trade-off between inventory holding costs and order setup costs is the EOQ model (Nahmias & Olsen, 2015). The EOQ model considers the following setting:

- Deterministic demand rate λ
- Instantaneous delivery (can be relaxed)
- Continuous review
- No stockouts

Two costs are considered within the model: fixed ordering/setup costs (K) and linear variable holding costs (h). The model under the assumptions of the EOQ policy is depicted in Figure 2.1.

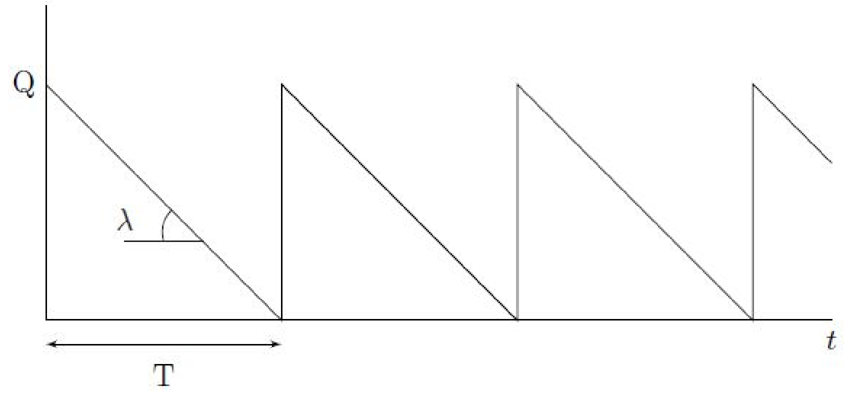


Figure 2.1: Inventory under the EOQ policy assumptions

The trade-off within the model is between the fixed ordering costs and the inventory holding costs. A large order quantity will lead to fewer orders and more inventory storage. Small order quantities will lead to frequent ordering and low inventory storage. The optimal order quantity Q^* can be determined by using the following formula:

$$Q^* = \sqrt{\frac{2K\lambda}{h}} \tag{2.1}$$

Replenishment policies

Inventory is often managed by replenishment policies. These policies can be distinguished by review type and order size. There are two review types: 1) continuous review and 2) periodic review. Under continuous review, the stock level is continuously monitored while under periodic review, the inventory level is checked after a specific period. This is the so-called review period and is often notated as R. In retail practice, replenishment is most often performed based on a periodic basis (van der Vlist, 2007). Furthermore, the order size can be variable or fixed and is often notated by Q and S, respectively. The classification of Silver, Pyke and Thomas (2016) will be used.

Table 2.1: Replenishment policy classification

		Order size	
		Fixed = Q	Variable = S
Review type	Continuous	s,Q	s,S
	Periodic	R,s,nQ	R,S / R,s,S

The first considered considered inventory control policy is the (s,Q)-policy. This policy reviews the inventory position continuously and has a fixed order size. The fixed order quantity Q is ordered if the inventory position drops below reorder level s. Q is often estimated by the EOQ given in section 2.1.2 or is equal to a specific case-pack size. The (s,S)-policy operates similarly except for the order-up-to level S that is variable. The optimal S is often hard to determine, nevertheless, $s + EOQ$ is often a good estimation (Silver et al., 2016).

Under periodic review, the system stock level is reviewed every R periods. The (R,s,nQ)-policy orders n times a fixed order quantity Q when the inventory position is below s after review period R, such that the inventory position exceeds the reorder level s. The (R,S)-policy orders every review period such that the inventory position is equal to 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.

Echelon stock

Inventory can be controlled via numerous methods. When a decentralized approach is taken, the inventory decision is based on the information of a specific installation. When only the installation stock is considered, the belonging policy is named an installation stock policy. This policy has the advantage that it does not require information about inventory at other installations and is relatively straightforward to use. However, the cost-effectiveness of an installation stock policy is limited by the lack of information about the rest of the system (Axsäter & Rosling, 1993). A method to incorporate more stock information is to use echelon stock. The echelon inventory position of a stock point is defined as the stock in transit to this stock point plus its physical stock plus that in transit to or on hand at its downstream stock points minus back orders at its end-stock points. Axsäter and Rosling (1993) show that the echelon stock policy requires less stock to be held at more upwards stock points in the system. Hence, inventory holding costs can be reduced by using this policy. Nevertheless, the use of echelon stock makes the analysis of the systems usually more complicated and has to deal with the problem of imbalance.

Balance assumption

The balance assumption allowed for the decomposition of divergent systems such that optimal base-stock policies for all stock points could be found (Dogru, 2006).

The balance assumption states that the allocation result into only nonnegative allocation quantities.nThis allows the system to remain balanced without retaining inventory at the central warehouse. In other words, the system performs well without keeping a central inventory. However, research shows that systems optimized based on the balance assumption can be significantly sub-optimal. Dogru (2006) shows that the balance assumption performs well as long as:

- the coefficient of variation of the downstream points is low or moderate ($0 \leq CV \leq 1$)
- the added value at the warehouse is negligible relative to the retailer
- the warehouse lead time is short, and the retailer lead times are long

2.2 Assignment

The main challenge for the company is that there is no structured approach for selecting the distribution strategy for a product. As a result, sub-optimal strategies are chosen that cause reduced product availability and high supply chain costs. This creates opportunities for improvement by developing an approach for selecting the right distribution strategy. The goal is to create a tool that allows quick distribution strategy selection based on the product and business environment characteristics. Furthermore, the traditional warehouse strategy is believed to be underperforming due to the high warehousing costs. The goal is to increase supply chain efficiency by integrating warehouse cost factors into ordering decisions. Hence, the inventory control policy should reduce the combination of operational and inventory costs.

This results in the following assignments:

1. *Design a decision support tool for selecting a distribution strategy to reduce costs and maintain product availability*
2. *Integrate warehouse cost factors into ordering decisions to reduce inventory and operational costs*

The current distribution strategies dictate how the warehouse is used. For example, the traditional warehouse strategy uses the warehouse as an intermediary stock point, while the central warehouse is used as a stockless consolidation point under the cross-dock strategies. Therefore, the advantages of inventory centralization and the factors that determine inventory positioning should be investigated. Consequently, the following research question is stated.

1a. Which factors drive the advantage of inventory centralization?

The next step is combining these factors with possible other factors that determine the performance of the distribution strategy.

1b. Which factors drive distribution strategy performance?

Based on the previous two questions, we should have identified the factors that influence the performance of a distribution strategy. Then, these factors should be integrated into a decision support tool to select the right distribution strategy.

1c. How can the factors be integrated into a structured approach for selecting a distribution strategy?

To reduce warehouse operational costs, we have to investigate which processes cause these costs. Also, by looking at these processes, it can be verified whether changing the ordering decisions reduces costs.

2a. Which processes are the main driver of warehouse operational costs?

Then, it is analyzed how changing the ordering decisions would influence the process efficiency.

2b. What is the influence of ordering decisions on these processes' efficiency?

Last, we investigate how the improved ordering decisions could be implemented into the current inventory control policy.

2c. How can the newly developed ordering decisions be integrated into the existing replenishment policy?

Answering the research questions will provide the necessary insights to complete the assignment.

2.2.1 Contribution to scientific literature

Although inventory management has been studied extensively during the past decade, researchers have not developed a singular distribution strategy optimal for a specific situation. Instead, research has provided many factors that influence distribution strategy performance. However, to the author's knowledge, research has not provided exact decision criteria for making a correct choice. Moreover, an approach for choosing a suitable distribution is missing. Therefore, this thesis will contribute to the literature by developing a decision-support tool from which the appropriate distribution strategy can be selected. The tool should generally apply to retailers that sell consumer electronics.

2.2.2 Scope

For this thesis, only the distribution strategies employed by MediaMarkt are considered. This is the TW strategy, the PAXD strategy and the BBXD strategy. Furthermore, promotional influences or product scarcity are also considered out of scope since replenishment decisions can be different in such circumstances. Also, transportation costs are not considered in the decision for the distribution strategy. Although a cross-dock strategy can influence whether economic loads can be achieved, the supplier-to-warehouse transportation costs are paid by the supplier. In addition, it is relatively easy for the company to attain economic loads for warehouse-to-store transportation as shipments from different strategies are combined. Therefore, these transportation costs are relatively stable.

Chapter 3

Detailed Analysis

This Chapter contains the analyses to describe the current situation of the system. Describing the system's current state helps identify the appropriate solution to the problem. In addition, it can identify the root cause of issues within the system and find possible opportunities for improvement.

First, section 3.1 analyzes the system structure. Second, section 3.2 analyzes the currently employed distribution strategies. Third, section 3.3 analyzes the current replenishment policy. Fourth, the demand forecast methods are reviewed in section 3.4. Fifth, the demand characteristics are analyzed in section 3.5. Last, the supplier characteristics are investigated in section 3.6.

3.1 System Structure

The supply chain of MediaMarkt can be described as a two-echelon supply chain where one central warehouse supplies 49 stores and serves online customers. In this system, the SKUs are supplied by outside sources. Demand D_i is faced at the store i from regular customers and at the warehouse D_0 from online customers. This system is a OWMR system. This distribution system is visualised in Figure 3.1. Each SKU has its own lead-time L_0' to the warehouse and L_i' to store i. Further analysis of the demand and lead time is given in section 3.5 and section 3.6, respectively.

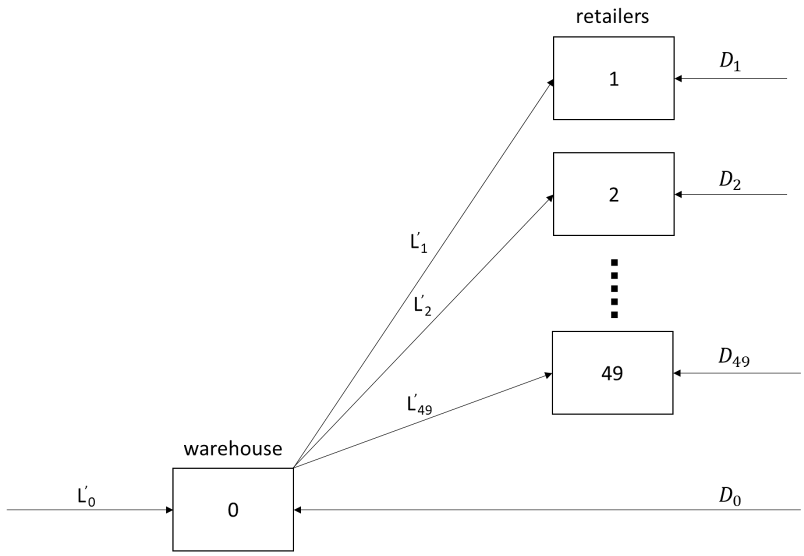


Figure 3.1: Distribution System MediaMarkt

The inventory replenishment planners centrally coordinate inventory replenishment to the warehouse and stores. They can access the stock level information at both the warehouse and the stores. The stock levels are updated daily based on the sales during that day.

3.2 Distribution Strategy

The warehouse processes under different distribution strategies are analyzed to determine where the warehousing costs arise. This provides insight into which distribution strategy causes the high warehousing costs. Currently, MediaMarkt distributes its products through two distribution strategies to the stores, and a third one is in development.

First, under the TW strategy, the orders are shipped from the supplier to the warehouse. The products are unloaded, sorted and received before they are stored in either the racking or the mezzanine, depending on the product type. Larger order quantities are generally held in the racking, while products with low volume or low amounts are stored in the mezzanine. This inbound process is visualized in Figure 3.2.

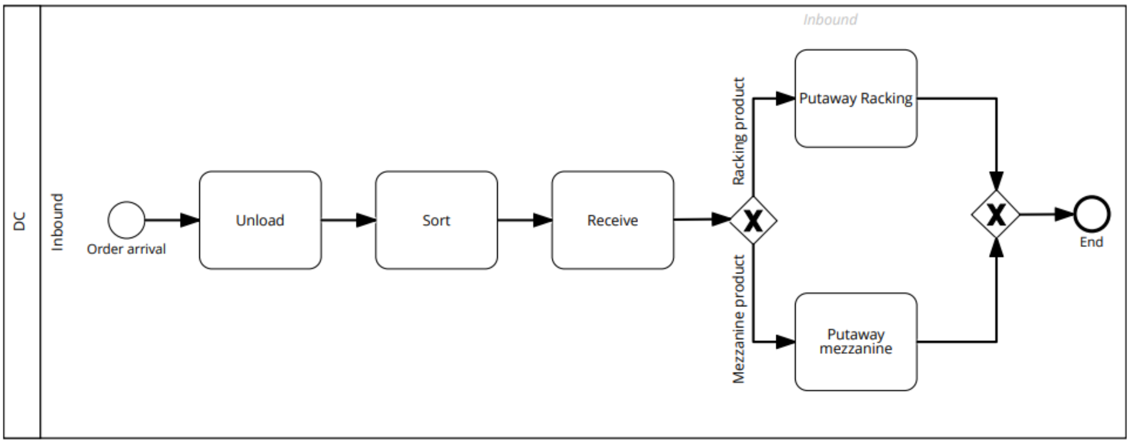


Figure 3.2: Inbound process flow warehouse strategy

Upon an order from the store, the warehouse transforms the order into a pick order. The items are picked in the mezzanine or racking, depending on the product. A product picked from the racking is placed directly on a pallet with other products of the pick order. When the picker finds an empty storage location, replenishment from a high storage location is performed with a reach truck by another employee while the picker continues to collect the rest of its pick order. Pick orders less than a full pallet are consolidated with other pick orders.

Pick orders in the mezzanine are collected into boxes and sent to the consolidation area. In the consolidation area, products with the same destination are consolidated on a pallet. Furthermore, products retrieved from the high-value site in the mezzanine are always checked on proper packaging and correct quantity. The pallets are wrapped in foil, staged, and brought to the dock before they are shipped to their destinations. Full pallet pick orders, which are pick orders of full homogeneous pallets, are already wrapped and, therefore, can skip the wrapping task. The outbound process is visualized in Figure 3.3.

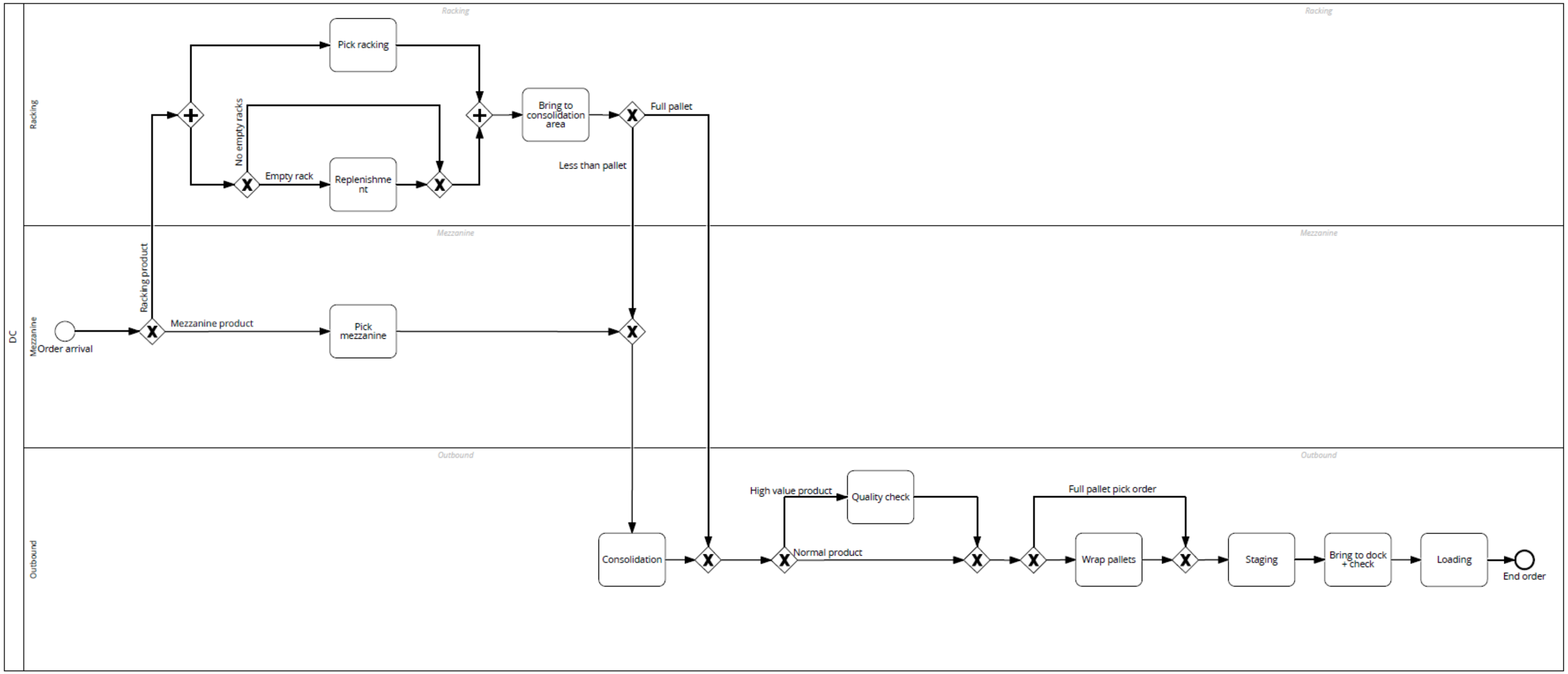


Figure 3.3: Outbound process flow warehouse strategy

We observe that larger order quantities would affect the TW strategy efficiency in the following manner. Larger order quantities would lead to fewer put-away and pick tasks. The pick and put-away tasks are more efficient since the worker can collect multiple products before moving to the next storage location. This means that manhours spent on picking and put-away tasks are expected to decrease if order quantities become larger. Other processes, such as sorting and consolidation, would likely become more efficient as well.

Second, products are ordered based on aggregate demands under the BBXD strategy. Upon an order from the external supplier, the products are immediately allocated to their final destination and shipped to the warehouse. Upon arrival, the goods are sorted and received similarly to the regular warehouse inbound. However, instead of storing the order, the goods are sorted on different pallets based on their final destination. The pallets are wrapped, staged and loaded with other orders from the warehouse outbound process. Stock meant for online sales is directly put into storage in the warehouse through the cross-dock strategy. The cross-dock process is visualized in Figure 3.4.

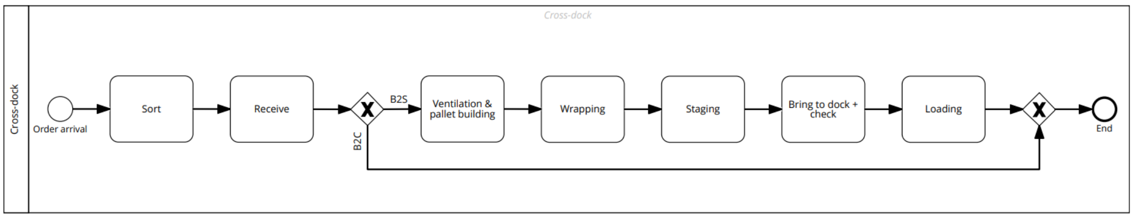


Figure 3.4: Cross-dock process flow

We observe that combining the cross-dock order with the warehouse orders makes it relatively easy to reach economic loads. Therefore, the ordering policy does not have to focus on reducing transportation costs. The efficiency of the cross-dock process can be improved slightly if the company orders higher quantities, as sorting and receiving would require less time. However, this effect is expected to be minimal.

Furthermore, the percentage distributed via cross-dock is noticeably low and has declined over the past year. Figure 3.5 shows that currently, only 12% of the total sales volume is being cross-docked. Employees explain that the products of one of the largest suppliers used to be cross-docked. These products were delivered from a distribution center in Europe that was relatively close to the central warehouse. Nowadays, these products are shipped directly from the factory in Asia. Hence, lead times are considerably larger. These long lead times made it difficult to cross-dock the products since the order-to-store allocation already happens at the supplier.

As a result, it was chosen to use a TW strategy resulting in a major decrease in percentage of the sales volume being cross-docked.

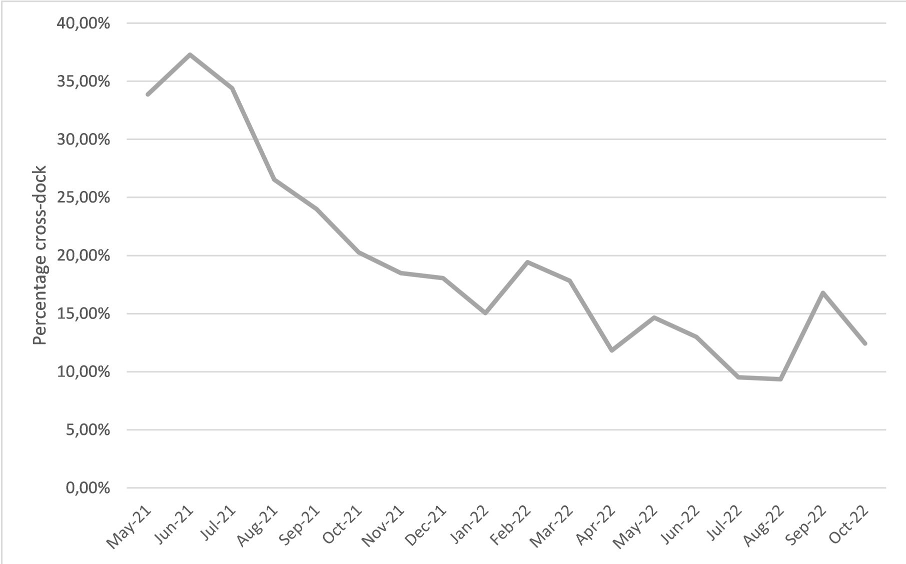


Figure 3.5: Percentage cross-docking of total purchases

Last, the PAXD strategy is still in development. The PAXD strategy prescribes that the orders are sorted and labelled at the supplier level. This means that the allocation to the final destination is also done at the supplier level. The goods are shipped to the warehouse on sorted pallets. In the warehouse, these pallets are combined with shipments from the other strategies to the stores. Outsourcing the processes to the warehouse immediately benefits the company since it does not have to perform the processes. However, it is expected that the supplier will charge MediaMarkt extra for completing this work. Also, order quantity can be a driver of transportation costs under this strategy. If order quantities are low, it is hard to reach economic loads since pallets are partially filled. However, currently, the transportation costs for the shipments to the warehouse are paid by the supplier. Therefore, these costs will not affect MediaMarkt directly. Nevertheless, the supplier would likely provide incentives for more significant quantities or set a minimum order quantity (MOQ) to avoid these extra costs.

Furthermore, we have analyzed the warehouse data to identify the most costly processes in the warehouse. The data consisted of manhours spent on each task and the number of products that went through the process. Analyzing Figure 3.6, it can be seen that the inbound processes, unload, sort, and receive, have the highest contribution to the total costs. This shows opportunities for improvement; however, further investigation revealed that there are administrative problems that cause difficulties in receiving the products in the warehouse. As a result, this cost fraction does not represent the costs spent on these tasks under 'normal' circumstances. It is expected that costs per piece are relatively small compared to processes such as order picking.

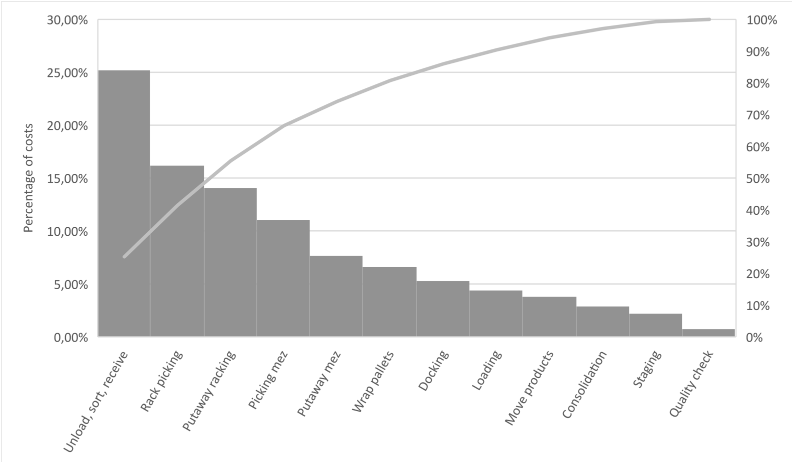


Figure 3.6: Pareto diagram total percentage costs

Also, it can be seen that the pick and put-away tasks combined are responsible for approximately 50% of the warehousing costs. Moreover, these tasks are relatively expensive, as seen from Figure 3.7. Especially rack picking seems to be costly. This is logical since the distances between storage places in the racking are more significant than in the mezzanine. Consequently, it takes longer to retrieve a product and more manhours are needed. Therefore, improving efficiency in the pick and put-away tasks can likely generate considerable savings.

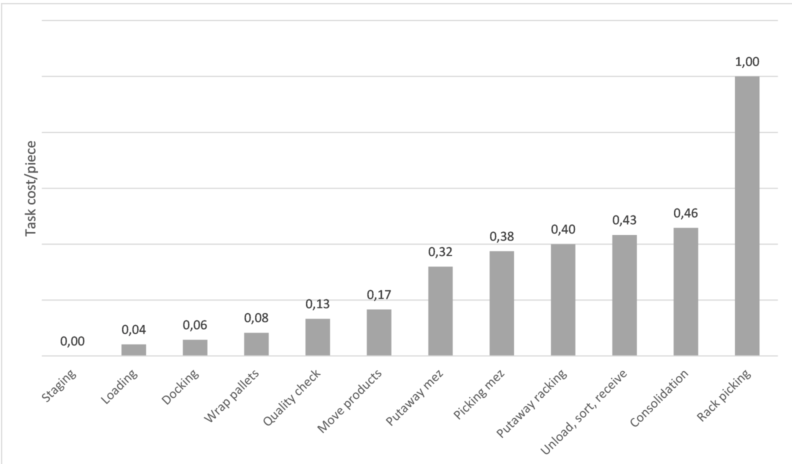


Figure 3.7: Normalized task cost per piece

This is confirmed by looking into the order profile of 27000 store orders over the last period. We observe that approximately 43% of the store orders have an order quantity smaller than 3 units. Moreover, 20% of the orders have an order quantity of 1 unit.

3.3 Replenishment Policy

A replenishment policy controls the replenishment. This policy orders according to the following logic: for every R time units, the system forecasts the necessary inventory over the interval $R + L$, where L is the product lead time. This amount is subtracted from the current inventory position and leads to the required order quantity. Then, additional safety stock is ordered to deal with uncertainties such that a set service level is achieved. The replenishment policy is visualized in Figure 3.8. The replenishment system can be compared to a periodic review order-up-to (R,S)-policy, where S is the forecasted demand during $R + L$ plus the needed safety stock over that interval.

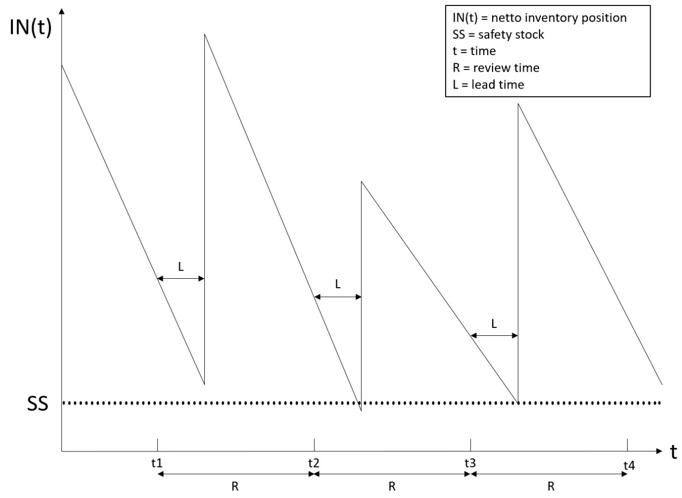


Figure 3.8: Replenishment policy MediaMarkt

The mathematical formulation of the store order quantity in units can be found in Equation 3.1. The store orders the forecasted demand D at store i of product x during the review interval R_i and lead time L_i plus the necessary safety stock $ss_{t,t+L_{x,i}}$ or commercial shelf value $U_{x,i}$ minus the current inventory position $IP_{t,x,i}$. The commercial shelf value, called the minimum fill by the company, is an imposed minimum amount of products on the shelves to make the shelves look fuller. Fuller shelves look more appealing and can result in extra sales according to the company. 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.

$$Q_{store} = max[\left\lceil D^{forecast,x,i}_{t,t+R_i+L_i} + max[ss_{t,t+L_{x,i}}, U_{x,i}] - IP_{t,x,i} \right\rceil, 0] \tag{3.1}$$

The DC order quantity is calculated similarly. The forecasted demand for the DC is the combined demand of all n stores in the product DC lead time $L_{x,DC}$ plus the DC review time $R_{x,DC}$. In addition, since online customers are also served from the DC, this demand is also added. The DC order quantity calculation in units is given in Equation 3.2.

$$Q_{DC} = max[\left\lceil \sum_{i=1}^{n} D^{forecast,x,i}_{t,t+R_{x,DC}+L_{x,DC}} + D^{forecast,x,online}_{t,R_{x,DC}+L_{x,DC}} + ss_{t,x,DC} - IP_{t,x,DC} \right\rceil, 0] \tag{3.2}$$

The safety stock is calculated with the formula given in Equation 3.3, where k is the safety factor and σ_L is the standard deviation of the forecast error during the lead time.

$$ss = k\sigma_L \tag{3.3}$$

Since the forecast errors are assumed to be normally distributed, k can be obtained by taking the inverse of the standard normal distribution Φ^{-1} (mean 0, standard deviation 1) of the service level α as is shown in Equation 3.4. According to the documentation, the service level is defined as the fill rate, the fraction of demand directly satisfied from the shelf.

$$k = \Phi^{-1}(P_2) \tag{3.4}$$

From order quantity calculation formulas given in Equation 3.1 and Equation 3.2, we can observe the following. The replenishment policy solely focuses on inventory minimization during the review interval plus the lead time. Although this yields inventory savings, order quantities can become low if there are short review periods and lead times. This is in line with the findings in section 3.2, showing that order quantities are generally small. A low Q_{store} leads to inefficient picking operations as explained in section 3.2 and, therefore, high warehousing costs. In addition, low Q_{DC} leads to mixed pallets, resulting in higher inbound operation costs as sorting requires more effort. Moreover, it is harder for the supplier to reach economic loads, pressuring them to increase their prices.

The estimation for the standard deviation in the safety stock calculation in Equation 3.3 is based on the forecast error during the lead time. This is in line with research that shows that 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 (Barrow & Kourentzes, 2016; Van Donselaar & Broekmeulen, 2014). Nevertheless, the standard deviation is estimated during the lead time while a periodic review inventory policy is used. Instead, the standard deviation should be calculated during the review interval plus the lead time.

Furthermore, the commercial shelf value is a strange concept. Currently, the commercial shelf value is used as a safety stock. Safety stock allows the company to guarantee a certain service level by storing extra inventory to compensate for fluctuations in demand. Although these safety stocks increase the average stock levels in the stores, it does not guarantee that this is the minimum amount of products on the shelves. In many instances, demand can be higher than expected. As a result, inventory from the safety stock is sold and the inventory level drops below the commercial shelf value that is used as the safety stock.

3.4 Demand forecast methods

The demand forecast is made on the product-location level. This means that a demand forecast is created for each SKU at each store. This is a weekly forecast based on 16 different forecast methods. The best method is chosen based on past performance on the historical sales data. The forecasting methods are summarized in Appendix A.

Currently, no accurate data is available to determine the forecast's performance. Consequently, we are unable to make a reasonable estimation of the forecast bias. Nevertheless, the order proposal data shows that only 16% of the supplier order proposals are used without manual interference. This indicates that the forecast in its current form is not helpful for the company. Forecast & replenishment employees explain that interference is needed since lead time inputs for the forecast are incorrect. The lead time inputs are the supplier-to-warehouse lead times that are used in the replenishment policy as mentioned in section 3.3. This is analyzed in more detail in section 3.6.

3.5 Demand analysis

The data used in the demand analysis are the weekly product sales at each location, including the online sales over the period 31-1-11-2020 till 31-11-2021. The data is transformed, cleaned and analyzed in Python 3.9.

3.5.1 Data cleaning

The resulting dataset contains approximately 800,000 product-location combinations. The dataset must be reduced to reduce the computational load required for the analysis. However, the dataset must still be a good representation of the product portfolio. Hence, it is chosen to filter out the products currently not in the active assortment, which means that they are not being replenished from a supplier. From these unique products, 5,000 are random uniformly sampled, which leads to 73,000 product-location combinations.

Furthermore, the sales must be corrected for promotional influences to get a clear insight into the actual demand distributions. The actual sales are corrected based on the estimated promotional impact given as a percentage of the increase in sales. The resulting dataset is the weekly corrected product-location sales. We find the correction is not entirely accurate since the correction results in several weeks of negative demand. Consequently, this negative demand is altered to zero. Also, there are many product-location combinations with low demand. As a result, these products have many weekly sales of zero. This results in missing values within the dataset that are not considered when making calculations. However, changing these values to zero would not be correct either, as some products are introduced later in the year and therefore have missing values in the first weeks of the dataset. Consequently, it is chosen to mark a product as introduced if demand is observed in a week. The weekly sales value is set to zero if no demand is observed after this week. Although this would provide a better insight into the actual demand statistics, the average demand might be overestimated since a product can be introduced before it observes demand.

3.5.2 Demand analysis

Since our goal is to gain insight into the demand statistics of the products, it is chosen to calculate the statistics based on the average of the values found at each location for that product. The following average statistics are calculated: mean, standard deviation and coefficient of variation (CV).

It is found that there are many slow-movers within the assortment. Approximately 96% of the assortment has an average mean weekly demand smaller than one over all the product-location combinations. Furthermore, only 0.1% has an average product-location demand larger than 8. Nevertheless, these products are probably essential for the company since they make up 17% of the total sales volume.

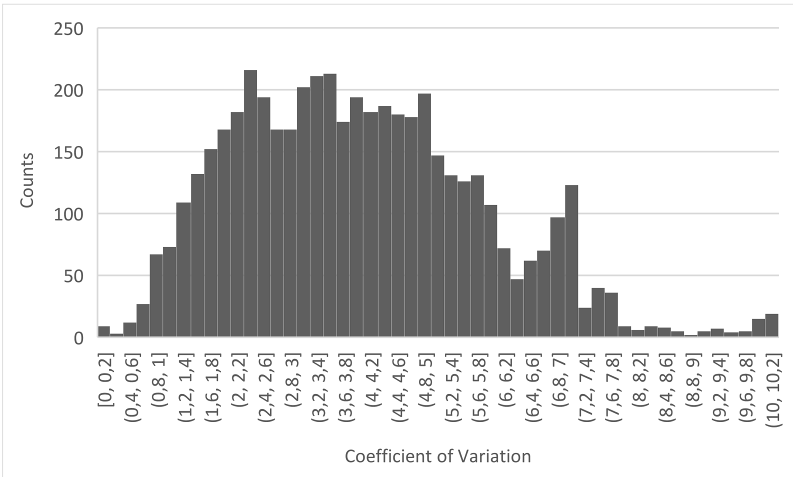


Figure 3.9: Coefficient of Variation distribution products

Also, the observed demand variability can range widely as the minimum, and maximum CV interval lies between 0 and 10.2. Nevertheless, the most significant proportion of products has a CV between 1 and 5, as seen from Figure 3.9. This can mainly be attributed to the slow movers since the products with an average demand larger than 1 show a different picture, as seen in Figure 3.10.

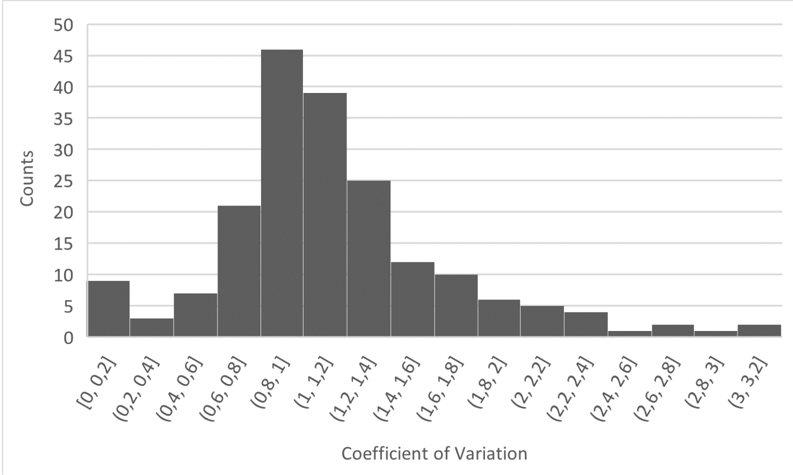


Figure 3.10: Coefficient of Variation without slow-movers

It can be concluded that MediaMarkt has a product portfolio with a wide range of demand characteristics. Within the assortment, there are many slow-movers; however, the fast-movers make up a large proportion of the total sales.

3.5.3 Correlation

The correlation between stores is analyzed. Demand correlation determines the relation between the demand patterns. As correlation can impact the amount of safety stock needed in a system (Zinn, Levy & Bowersox, 1989), it is necessary to check whether demands are independent. The Pearson correlation coefficient is computed between all stores, which deliver correlation matrices for all products. In addition, the average Pearson correlation of store demands is calculated. Figure 3.11 shows the distribution of the average correlation coefficients. We observe that approximately 71% of the products observe low correlation ($-0.3 < \rho < 0.3$), 23% observe moderate correlation ($0.3 < \rho < 0.5$) and 6% strong correlation ($\rho > 0.5$). Only one product has a moderate negative correlation ($\rho - 0.4$). Although the actual demand does not show abnormal patterns, this product is considered an outlier.

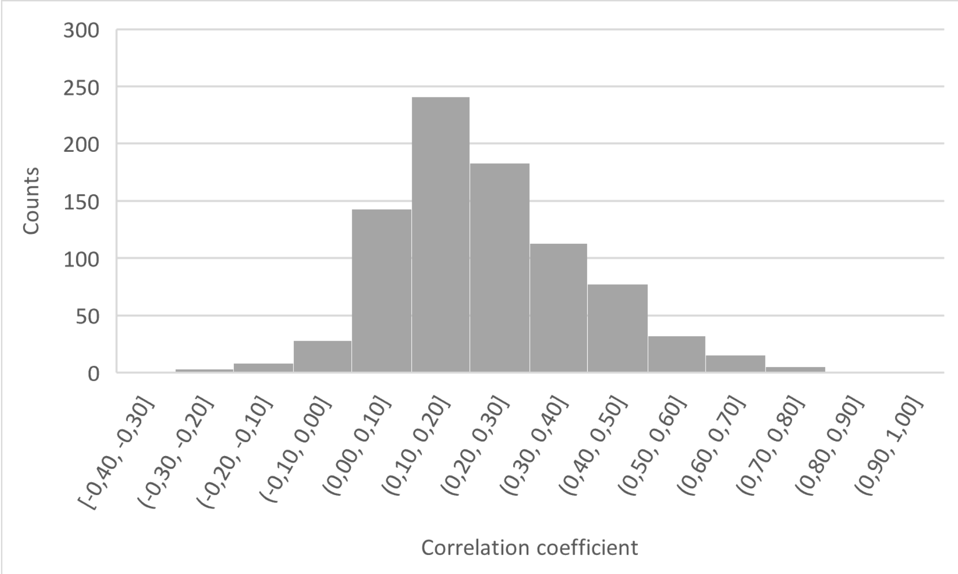


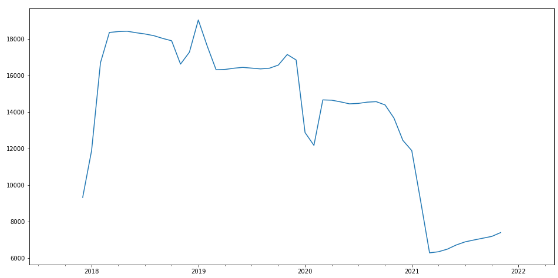
Figure 3.11: Distribution average correlation coefficients

It can be concluded that there are many products with correlation. Logically, this should be incorporated into the ordering decisions.

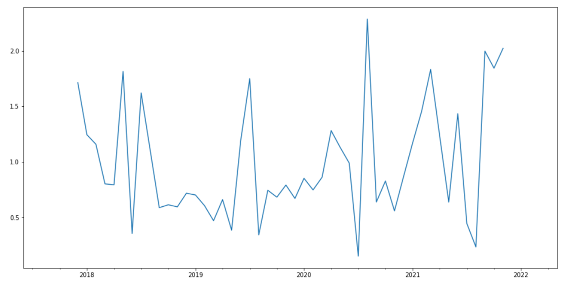
3.5.4 Seasonality

Seasonality analysis is performed to investigate if there is time-varying demand. Sales over a more extended period are necessary to find the seasonal influences. Therefore, it is chosen to use the product group monthly total sales from 1-6-2017 to 1-6-2022. Product group data is preferred over individual product data as it increases reliability. A product group is composed of multiple related products with the same characteristics. I.E. product group 'LCD-TV' is formed of all LCD-TV products. Products within the group are assumed to have similar trends and seasonality characteristics. Hence, the seasonal patterns from the product groups give the most accurate representation of the seasonal influences.

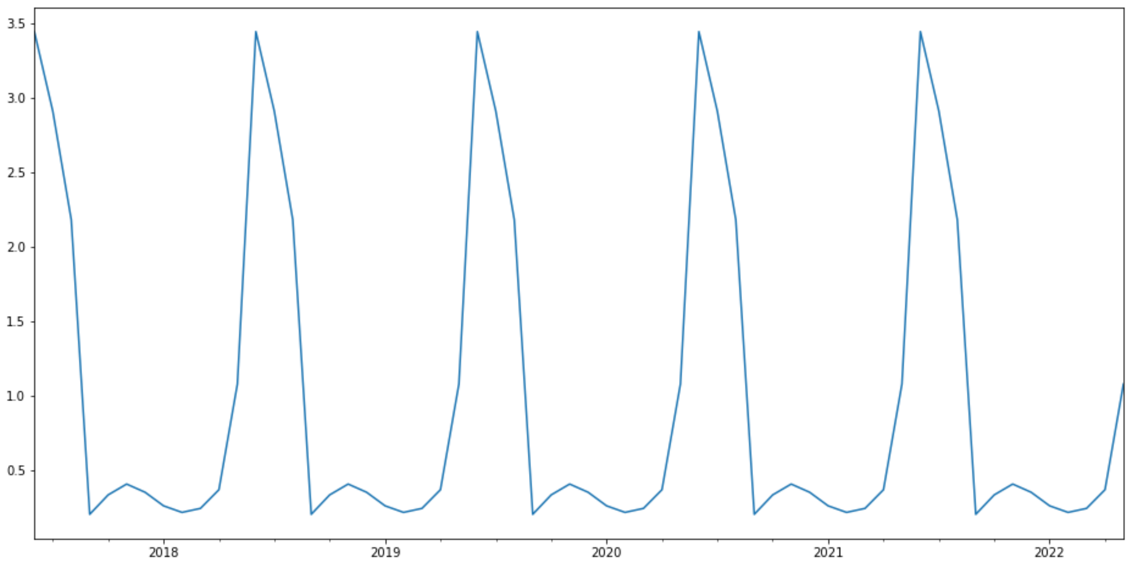
The monthly sales are time series that can be decomposed to analyse the trend and seasonality of the sales. The data is decomposed with the *seasonal_ decompose* package in Python 3.9 (*Seasonal decompose package*, n.d.). This allows for identifying the seasons and their impact on the number of sales. Furthermore, an autocorrelation calculation on the time series is performed to see if the correlation at each lag k is significant. I.E. the product group 'SDA luchtbehandeling' is a product group that includes household airconditioning systems.



(a) Trend



(b) Residuals



(c) Seasonality

Figure 3.12: Seasonal decomposition

The result of decomposing the sales in the trend (a), residual (b), and seasonality (c) can be seen in Figure 3.12.

These graphs show that there is a strong seasonal influence in the summer, which is logical since most people buy air conditioning systems in the summer. The peak sales month for this product group is July, while October to March can be seen as the low season. The autocorrelation is plotted to verify the conclusions in Figure 3.13.

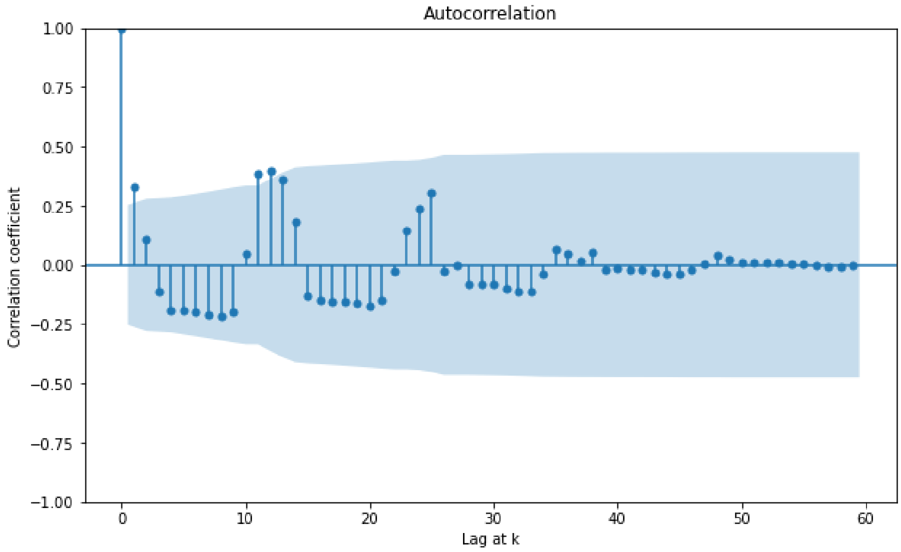


Figure 3.13: Autocorrelation plot

The shade represents the 95% confidence interval. From the graph, it can be seen that the seasonality periods 11 and 12 are statistically significant. In other words, the season appears every year. We find seasonality for several product groups. However, most product groups do not observe time-varying demand.

3.6 Supplier lead time

The lead time to the central warehouse is analyzed based on the order and warehouse inbound data in the period 12-11-2019 to 23-7-2022. The order issue date and planned delivery date can be retrieved from the order data. The inbound warehouse data provides the actual order delivery date. These values allow for calculating the (actual) lead times to the central warehouse per supplier.

3.6.1 Data cleaning

The orders that do not have a delivery date in the warehouse inbound data are deleted from the dataset. Also, the data with a delivery date earlier than the order issue date are deleted. Furthermore, multiple orders appear to have a planned delivery date of 1-1-2099; logically, these are removed as well. Finally, suppliers that have delivered less than three orders are eliminated as they are deemed irrelevant.

3.6.2 Supplier lead time analysis

From the order data and inbound warehouse data, the following can be calculated. First, 'planned lead time', which is the difference between the order issue date and the planned delivery date. Second is the actual lead time, which is the difference between the order issue date and the actual delivery date. Third, the delay is defined as the actual lead time minus the planned lead time. Negative values are altered to zero as these represent orders delivered before the planned delivery date and are, therefore, not delayed. From these values, the following statistics per supplier are collected: mean planned lead time, standard deviation planned lead time, mean actual lead time, standard deviation actual lead time, mean delay, and standard deviation delay. The average values for all suppliers are shown in Table 3.1.

Table 3.1: Supplier statistics

Average	Value (days)
Mean planned lead time	11.975
Std planned lead time	14.942
Mean actual lead time	21.958
Std actual lead time	22.808
Mean delay	11.068
Std delay	16.864

It can be observed that the actual lead times are highly variable. This shows that replenishment is not performed at regular intervals. Moreover, delays are common as well, causing uncertainty in the system. Further analysis revealed two types of orders: replenishment and planned. Replenishment orders are regular orders generated by the system according to the replenishment logic given in section 3.3. Planned orders are manually created or altered existing orders. The lead times of these orders are often different from the replenishment orders. Hence, we should differentiate between these two types in the analysis. Since this analysis aims to get an indication of the supplier performance under regular replenishment, it is chosen to solely analyze the replenishment orders. The replenishment orders are found by selecting the orders with a planned order lead time as the input lead time the system uses in its calculations. The revised average statistics can be found in Table 3.2.

Table 3.2: Revised average supplier statistics

Average	Value (days)
Mean planned lead time	4.327
Std planned lead time	0.0
Mean actual lead time	14.578
Std actual lead time	13.087
Mean Delay	10.297
Std Delay	13.052

This shows a different picture than Table 3.1. The order and actual lead time are considerably shorter than in Table 3.1. Nevertheless, the standard deviation of the actual lead time is still high compared to the mean actual lead time. There are certainly opportunities to improve supplier reliability.

Chapter 4

Solution Design

This thesis aims to provide a framework that guides the company in selecting the right distribution strategy. We show that different business environments require different distribution strategies. Three distribution strategies are considered that are widely used in practice: TW, Pre-C, and Post-C. For these strategies, an effective inventory control policy is proposed that can be easily implemented in practice. In addition, the warehousing costs are considered in determining the appropriate inventory control policy such that high warehousing costs can be avoided.

First, section 4.1 describes the general setting for which the solution design is applicable. The setting should apply to OWMR systems that sell consumer electronics. Second, section 4.2 describes the considered distribution strategies in detail and proposes effective inventory control policies for these strategies. Third, section 4.3 outlines distinct scenarios and factors that influence the preference for a distribution strategy. Last, section 4.4 proposes the DSP framework and the DSS decision tree based on the findings in section 4.3.

Furthermore, this Chapter uses the notation as in Table 4.1.

Table 4.1: Notation

Notation	Meaning
σ_j	Standard deviation demand at location j
μ_j	Yearly demand rate at location j
$D_{j,x}$	Stochastic demand during x periods at location j
IP_j	Inventory position at location j
Q_j	Order quantity at location j
K_y	Order setup costs for strategy y
h	holding costs per time unit
P_2	Fill rate
S_j	Echelon order-up-to level of stockpoint j after allocation
L_j	Lead time to location j
R	Review period
z_j	Echelon inventory position of stockpoint j before allocation
ρ_{ji}	the demand correlation between stockpoint j and i
p_j	Rationing fraction for stockpoint j
$E[OS_y]$	Expected order size for strategy y
hc_y	handling costs per unit for strategy y
TH_y	Total annual handling costs for strategy y

4.1 Setting

Consider a supply chain with one central warehouse and N retailers. Stochastic demand is observed at the retailers and at the warehouse in the form of online customers. Supplier lead times are stochastic as well. Inventory replenishment of the warehouse and retailers are controlled centrally based on central information of all stock levels throughout the system. In this system, holding costs are equal at all stock points. This is a reasonable assumption since the storage cost, such as storage space rent, is often fixed. Therefore, it is not directly influencing the cost of keeping stock. Hence, the holding costs are not dependent on where the stock is stored. Demand that cannot be met with stock on hand is backordered. In the case of backorders, penalty costs are incurred to compensate for factors that negatively affect the organization. Furthermore, the system's objective is to achieve a target service level at a minimum cost. This service level is defined as the fill rate: the specified fraction (P_2) of demand to be satisfied directly from available inventory.

The inventory can be positioned at both the retailer and in the warehouse. The products ordered are from an external supplier that is assumed to have unlimited capacity. Management can distribute the orders through three different distribution strategies to the desired stock points: TW, Pre-C, and Post-C.

4.2 Distribution Strategies and Inventory Control

This section describes the considered distribution strategies and proposes an inventory control policy for the respective distribution strategy. First, the TW strategy is considered in subsection 4.2.1. Then, the Pre-C strategy. Last, is the Post-C strategy.

4.2.1 TW

Under a TW strategy, the central warehouse is used as an intermediary stock point that supplies the retailers upon order. The retailers order from the warehouse if their stock level is too low. Upon demand, products are retrieved in the warehouse by order picking. This order is consolidated with other orders with the same destination so economical transportation loads can be achieved. After consolidation, the orders are shipped to the retailers and put into their storage. The warehouse orders from external suppliers if their stock level is too low. Upon order arrival in the warehouse, the products are checked, sorted and stored in the warehouse.

We propose to control the ordering decision of the central warehouse and stores under the TW strategy by an echelon periodic review order-up-to (R,s,S)-policy. An echelon stock policy is chosen instead of an installation stock policy. Echelon inventory policies incorporate downstream stock information in their replenishment decision. Incorporating this information can yield savings in inventory costs compared to installation policies that solely make ordering decisions based on the information of a single stock point. Hence, an echelon stock policy generally requires less stock to be held at more upper stock points in the system (Axsäter & Rosling, 1993).

In addition, an order-up-to-level S is proposed so that small and frequent ordering can be avoided. The inventory level is reviewed in specific intervals since ordering decisions in a retail supply chain are generally periodically reviewed (van der Vlist, 2007).

In order to estimate the reorder level of the (R,s,S)-policy under stochastic discrete demand and a target service level, it is necessary to approximate the demand probability distribution by a theoretical distribution. We propose to find the theoretical distribution by the two-moment approximation by Adan, van Eenige and Resing (1995), as it is a simple but effective fitting procedure .

First, the mean μ_t and standard deviation σ_t of the historic demand per period is calculated. Then, using Equation 4.1, the theoretical probability distribution is determined. The binomial distribution is selected when $-1 < a < 0$, the Poisson distribution when $a = 0$, the negative binomial distribution when $0 < a < 1$, and the geometric distribution when $a \geq 1$. For the determination of the exact parameter values we refer to Adan et al. (1995).

$$a = \frac{\sigma^2/\mu - 1}{\mu} \tag{4.1}$$

Using the formula of Zheng and Federgruen (1991) to approximate the inventory position probability distribution of the (R,s,S)-policy, the theoretical demand distribution, and the generic expression for the fill rate P_2 in Equation 4.2, it is possible to find the right reorder level for a given target service level with a simple search procedure.

$$P_2 = 1 - \frac{E[\{D_{j,R+L} - IP_j\}^+] - E[\{D_{j,L}) - IP_j\}^+]}{D_{j,R}} \tag{4.2}$$

These steps can be performed with the the DoBr tool. The DoBr tool is an Excel file with functions coded in VBA to calculate several Key Performance Indicators (KPIs) for multiple inventory policies. For the implementation of the DoBr tool we refer to Broekmeulen and Van Donselaar (2015).

Furthermore, stochastic lead times can be included by calculating the mean and variance of D_R, D_L, and D_{L+R} using the equations given in Appendix B.

The order-up-to level S is equal to the MOQ minus 1 since discrete demand is observed. We estimate the MOQ with the EOQ formula given in Equation 4.3. Note that a larger MOQ inflates the actual fill rate if the reorder level remains equal since replenishment is performed less frequently. As a result, a larger MOQ leads to a reduced reorder level for a given target service level. This is accounted for into the DoBr tool.

For the stores, these steps can be performed directly. However, for the central warehouse, the warehouse echelon lead time should be used instead to make the calculation. The warehouse echelon lead time is defined as the lead time between the retailers and the warehouse plus the lead time between the warehouse and its supplier. In addition, the aggregate demand and aggregate standard deviation should be used as input.

Since shortages at the warehouse can lead to a lower service level at the retailers, an inflated service level should be used. However, safety stock and service level optimization is not part of this research and therefore is left out of scope. This research assumes that the inflated probability of non-stock outs by Van Donselaar (1990) as target fill rate for the central warehouse, will yield satisfactory results. This inflated fill rate is given in Equation 4.4.

$$EOQ = \sqrt{\frac{2K_{TW}\mu}{h}} \tag{4.3}$$

$$Inflated\ P_2 = \frac{1}{3} + \frac{2}{3}P_2 \tag{4.4}$$

4.2.2 Pre-C

Under a Pre-C strategy, orders are centrally placed at external suppliers. Upon order, the goods are allocated to their final destination. Based on this allocation, the goods are sorted on pallets and shipped to the central warehouse. Upon arrival at the warehouse, the pallets are combined with other pallets with similar destinations and sent to the retailers. Since the goods are already sorted and allocated, the process is relatively fast and does not require much handling.

The Pre-C strategy's ordering decisions are comparable to the direct delivery system as the allocation is performed at the supplier. We propose to control the system with a periodic review order-up-to-level (R,S)-policy. Order setup costs are not taken into account since the expensive warehouse processes, such as order picking, are now outsourced to the supplier. As a result, we focus on inventory minimization during the replenishment interval. Solving $IP(\tau)$ in equation Equation 4.2 for a given fill rate, we can find the optimal echelon order-up-to level S_j^* for a stock point j. Note that the lead time is now the time from ordering at the supplier till delivery at the stores. Again, for the demand probability distribution, the two-moment approximation can be used (Adan et al., 1995). The system-wide echelon order-up-to level S_0^* can be found by the summation of all S_j^*.

4.2.3 Post-C

Under a Post-C strategy, centralized ordering is performed based on the aggregate demand of the retail outlets. Upon order arrival at the warehouse, the products are allocated to the outlets based on an allocation rule. Then, based on this allocation, the order is sorted, consolidated with other incoming orders and shipped with other loads with identical destinations. Note that the pallets from the Post-C strategy are combined at the central warehouse with shipments from the Pre-C and TW strategy to achieve economic loads.

Since order setup costs are expected to be of less importance, it is chosen to control the system with (R,S)-policies. For the Post-C strategy we propose to find the system parameters with the approach developed by Van Der Heijden, Diks and De Kok (1999). They show that Equation 4.2 can be extended to a two-echelon system, assuming that the allocation parameters p_j are known. This results in Equation 4.5. Nevertheless, this is only possible under the balance assumption that states: *the allocation results into only nonnegative allocation quantities.*

$$P_2 = 1 - \frac{E[\{D_{j,L_j+R+L_0} + p_j D_{0,L_0} - S_j^*\}^+] - E[\{D_{j,L_j}) + p_j D_{0,L_0} - S_j^*\}^+]}{D_{j,R}} \tag{4.5}$$

where stock point 0 is the central warehouse. Again, for the demand distributions, the two-moment approximation of Adan et al. (1995) can be used. Then, Equation 4.5 can be solved using bisection if the allocation fractions p_j are known. The system-wide order order-up-to level S_0^* is obtained by the summation of all S_j.

For the calculation of the demand characteristics, we refer to Van Der Heijden et al. (1999). Since it can be expected that the approximations are better for S_j if the balance assumption is only violated slightly, it is chosen to choose the allocation fraction p_j such that the expected imbalance is minimized.

The allocation fraction p_j can be determined with the approach in Van Der Heijden, Diks and De Kok (1996). This approach takes $Var[z_j - S_j]$ as a surrogate expression for the imbalance and minimizes subject to $\sum p_j = 1$. For a detailed step-by-step guide we refer to Van Der Heijden et al. (1999).

4.3 Distribution strategy preference

This section discusses different factors and their influence on the preference for a distribution strategy. Based on a scenario, we determine how inventory should be positioned within the supply chain. Then, combined with the characteristics of the distribution strategy, we can determine the preferred strategy.

This section is structured as follows. First, we consider the scenario of level demand. Second, we analyze the preferred choice under different levels of demand variability. Third, the impact of lead time length and uncertainty on the preferred strategy is analyzed. Fourth, we propose the preferred distribution strategy under multiple levels of demand correlation. Last, several other factors that influence the preference for a distribution strategy are mentioned.

4.3.1 Level demand

We can say that constant demand is ideal from a supply chain management standpoint. The absence of uncertainty eliminates the need for safety stock in the system. Centralizing inventory does not result in risk-pooling benefits. As a result, supply chain managers should focus on cost reduction in handling and transportation.

Yan and Tang (2009) show that both Pre-C and Post-C perform significantly better under level demand ($CV \leq 0.2$). As a result, we propose to use a cross-dock strategy in these circumstances. Cross-docking the items will result in considerable savings in handling as it eliminates the expensive picking operations in the warehouse. The choice between a Pre-C and Post-C depends on the costs that can be saved through the Pre-C strategy. The Post-C strategy should be chosen if the Pre-C strategy will not generate considerable savings in handling costs.

The total yearly handling costs TH for the Pre-C and Post-C distribution strategies can be calculated with Equation 4.6 and Equation 4.7, respectively. The expected order size $E[OS]$ can easily be found if the order-up-to levels are known for the strategies. For the exact determination of $E[OS]$ we refer to Van Donselaar and Broekmeulen (2014). The formulas consist out of two components: 1) fixed order setup costs and 2) variable handling costs. The fixed order setup costs in Equation 4.6 represent the fee that the supplier charges to perform the sorting at their facility and the fixed inbound costs under the Pre-C strategy. The fixed order setup costs in Equation 4.7 include the fixed start-up costs of the sorting and inbound process of the Post-C strategy.

$$TH_{Pre-C} = \frac{\mu}{E[OS_{Pre-C}]}(K_{Pre-C}) + \mu * hc_{Pre-C} \tag{4.6}$$

$$TH_{Post-C} = \frac{\mu}{E[OS_{Post-C}]}(K_{Post-C}) + \mu * hc_{Post-C} \tag{4.7}$$

4.3.2 Probabilistic demand

To correct for demand uncertainty, safety stock is needed to achieve the target service level. Centralized inventory in a warehouse that supplies the stores allows for a critical advantage. By storing the safety stock centrally, the system-wide safety stock can be reduced. By combining the aggregate distributions, the standard deviations of the retailer are pooled. In other words, the product shortages experienced by one location are offset by the overages of another. Hence, a target service level can be achieved with a lower system-wide inventory than with multiple decentralized inventories. This is true since the standard deviation of the central warehouse is smaller than the summation of the individual store standard deviations, as is shown in Equation 4.8.

$$\sigma_{WH} = \sqrt{\sum_{j=1}^{n} \sigma_j^2} \tag{4.8}$$

The total percentage reduction in aggregate safety stock, also called Portfolio Effect (PE), can be calculated with Equation 4.9 (Tallon, 1993).

$$PE = 1 - \frac{\sigma_{WH}}{\sum_{j=1}^{n} \sigma_j} \tag{4.9}$$

Both the TW and Post-C strategy benefits from risk-pooling since the order-to-store allocation is performed at the warehouse. This late allocation pools the demand over the supplier-to-warehouse lead time, reducing the overall observed variability. The Pre-C does not have this benefit and therefore is only preferred in circumstances of level demand as mentioned in subsection 4.3.1.

Nevertheless, the Post-C strategy has been shown to outperform the TW strategy under moderate demand variability ($0.2 < CV \leq 1.0$) (Yan & Tang, 2009). The considerable savings can be explained by the significant difference in handling costs. As a result, we propose to use the Post-C strategy under moderate demand variability.

However, research by Dogru (2006) has shown that the balance assumption does not yield satisfactory results under higher levels of demand variability $CV > 1.0$. These high uncertainty levels cause an imbalance in the system. In general, imbalance occurs if a big demand occurs at one store while there is little demand in the other store, and there is not enough stock available at the central warehouse to balance the inventories again. Since the Post-C strategy operates under the balance assumption (see subsection 4.2.3), large imbalances can cause stock-outs and rationing inventory at the warehouse should be preferred. As a result, in case of high demand variability ($CV > 1.0$), we propose to use the TW strategy.

4.3.3 Lead time length

From the inventory control methods in section 4.2, it can be easily shown that the amount of inventory necessary within the system increases in the supplier lead time. However, since the TW and Post-C strategies benefit from lead time risk-pooling, they are affected less than the Pre-C strategy. Yan and Tang (2009) show that under low supplier lead time ($L_0 \leq 3$ days) the Pre-C strategy can outperform the TW and Post-C strategy. A short lead time mitigates the positive effect of pooling the demand variabilities. As a result, inventory centralization does not lead to significant inventory savings. Therefore, we propose to use a cross-dock strategy under low supplier lead time $L_0 \leq 3$ days. Again, the choice between a Pre-C and Post-C strategy depends on the costs that can be saved through the Pre-C strategy. The Post-C strategy should be chosen if the Pre-C strategy will not generate considerable savings in operational costs.

On the other hand, for longer lead times, the Pre-C strategy should be avoided. We propose to use a Post-C or TW strategy for supplier lead times larger $L_0 > 3$. In these circumstances, risk-pooling could provide benefits. The choice between the TW and Post-C strategy depends on the amount of variability observed. As described in subsection 4.3.2, under moderate or low demand variability $CV \leq 1.0$, the Post-C performs well. Therefore, we propose to use a Post-C strategy if the supplier lead time is longer than $L_0 > 3$ days and the product observes moderate variability $CV \leq 1.0$. For a supplier lead time $L_0 > 3$ days and high demand variability $CV > 1.0$, we propose that a TW strategy should be selected.

This interaction between supplier lead time, demand variability, and distribution strategy preference is visualized in Figure 4.1.

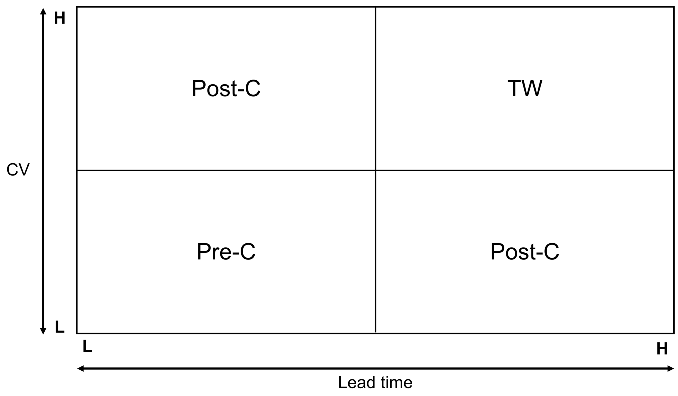


Figure 4.1: Matching distribution strategies with demand uncertainty and supplier-to-warehouse lead time

4.3.4 Demand correlation between stores

Research has widely shown that organizations can benefit from the centralization of stocks. The magnitude of the benefit is affected by the correlation between demands at different locations (Tallon, 1993). Due to a positive demand correlation, the stores' demands do not cancel each other out anymore. This reduces the risk-pooling effect and, therefore, the positive impact of centralizing stock.

This can be mathematically illustrated by calculating the warehouse standard deviation with the demand correlation as in Equation 4.10, with σ_i & σ_j the standard deviation at store i & j, and ρ_{ji} the correlation coefficient of demand between the stores. This shows that the warehouse standard deviation increases in ρ. Therefore, the system-wide safety stock will increase if the demand correlation increases. As the correlation increases, the risk-pooling effect decreases. As a result, the potential benefit of inventory centralization is reduced.

$$\sigma_{WH} = \sqrt{\sum_{j=1}^{J} \sigma_j^2 + 2(\sum \sum_{j<i} \sigma_j \sigma_i \rho_{ji})} \tag{4.10}$$

Suppose the reduction of inventory by pooling the risks via an intermediary stock point does not outweigh the reduction in operations costs of a cross-dock strategy. In that case, the organization should distribute their products via a Pre-C or Post-C strategy. Research shows that the benefit of risk-pooling is almost eliminated above

$\rho > 0.5$ since the PE effect (Equation 4.9) is down approximately 80% with identical demands (Zinn et al., 1989). Therefore, we propose that in this situation, a cross-dock strategy should be used. Again, the preference of a Pre-C or Post-C depends on the savings in operational costs as explained in subsection 4.3.1.

If there are enough stores, $J > 30$, we can assume that the average Pearson correlation between retailers would provide a fair estimate of all the correlations. Hence, an average correlation of $\rho > 0.5$ can be used as a decision criterium. If $J < 30$, one should calculate the portfolio effect using Equation 4.10 and Equation 4.9. The smaller the portfolio effect, the increased preference for one of the cross-dock strategies.

4.3.5 Additional decision factors

Additional decision factors that should be taken into account when making distribution strategy decisions are mentioned in this section. The impact of these factors could be different depending on the company. Nevertheless, they can be critical in determining the appropriate distribution strategy.

Supplier reliability

For cross-dock strategies, supplier reliability is of great importance. As the cross-dock carries no inventory, product availability can only be achieved if an order arrives in timely fashion. Compensating for lead time uncertainty or not delivering in full can result in high store safety stocks. Since stores often have limited backroom capacity, these situations should be avoided. In addition, delayed deliveries complicate the cross-dock management that is already complicated by itself. Therefore, for unreliable supplier that have high lead time uncertainty or incomplete deliveries, we propose to use a TW strategy.

Popularity

The popularity of a product can be expressed as the system-wide demand. This popularity can determine the cross-dock strategy efficiency. Higher popularity increases order quantities that lead to more efficient cross-dock operations (Vogt, 2010). Sorting of lower order quantities can take more time, therefore reducing the Post-C efficiency.

For the Pre-C strategy, products are sorted at the supplier level. Hence, suppliers will charge relatively high fees since their sorting process becomes inefficient or they will not accept the order since it is hard for them to achieve economical loads. As a result, products with low popularity, I.E. slow-movers, are not suited for one of the cross-dock strategies. Therefore, for those products we propose to use a TW strategy.

Total cubic movement

Total cubic movement refers to the total volume of a product that is moved through the central warehouse: *total cubic movement = demand * product volume*. Literature argues that assigning a product with high cubic movement to a cross-dock strategy would relatively save a lot of space in the warehouse and therefore saves inventory costs (Li et al., 2008; Benrqya et al., 2020). We argue that the opposite is true. Stores are often constrained by space. There is limited capacity on the shelves and in the backroom. Under the cross-dock strategies, the stores observe longer lead times. Hence, the stock-levels are generally higher. In addition, high volume products are harder to distribute under the Post-C strategy as manually sorting requires more effort, therefore decreasing the strategy efficiency. Therefore, for products with high total cubic movement, we propose to use a TW strategy.

Value

For products with low value, handling costs can be critical to achieve good product margins. The handling costs are relatively high compared to the holding costs. Therefore, supply chain managers should aim at distributing these products in the most efficient manner. For products with low value we propose to use one of the cross-dock strategies as they require minimal handling throughout the supply chain.

4.4 DSP-framework

This section proposes the distribution strategy preference (DSP) framework of all factors that should be included when selecting the right distribution strategy for a product. We summarize their influence on the distribution strategy preference. For a more detailed explanation we refer to section 4.3. Furthermore, we propose the distribution strategy selection (DSS) decision tree that selects an distribution strategy from an inventory control perspective. This allows supply chain managers for quick distribution strategy selection while keeping the other factors in mind.

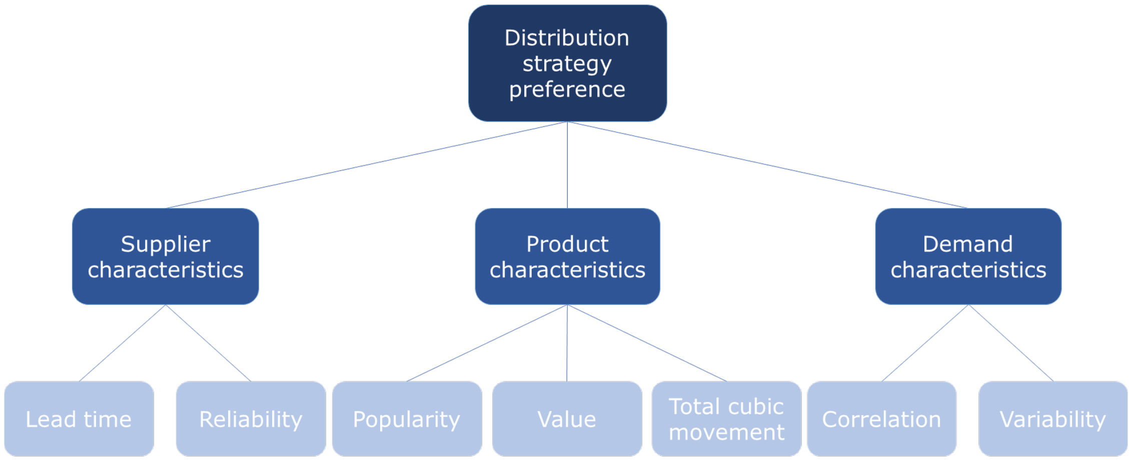


Figure 4.2: DSP-framework

The DSP framework can be found in Figure 4.2. We summarize the influence of the factors.

Supplier characteristics

Lead time: Short lead times reduce the lead time risk-pooling effect. As a result, centralization of inventory does not result into inventory savings. As cross-dock strategies require minimal handling, they should be preferred under short lead time.

Reliability: There is a lot of interdependence in the chain under cross-dock strategies. Compensating for lead time uncertainty or incomplete deliveries with safety stocks in the stores is undesirable. Therefore, under low supplier reliability, a TW strategy should be preferred.

Product characteristics

Popularity: Low popularity can decrease the cross-dock operational efficiency. Therefore, for products with low popularity, I.E. slow-movers, a TW strategy should be used instead.

Value: For low value products, handling costs are relatively high. Therefore, the focus should be on handling costs minimization. Consequently, a cross-dock strategy should be preferred.

Total cubic movement: cross-dock strategies result in longer store lead times. Therefore, stock-levels in the stores are generally higher. As stores are often constrained by space, products with a high total cubic movement should be distributed with a TW strategy.

Demand characteristics

Demand correlation: the demand correlation between stores decreases the risk-pooling effect. As a result, the potential benefit of inventory centralization is reduced. Therefore, under higher levels of demand correlation, one should choose one of the cross-dock strategies.

Demand variability: as demand variability increases, the risk pooling effect increases as well. Therefore, the Pre-C strategy should only be used under low levels of demand variability. Post-C outperforms the TW strategy under moderate levels of variability. However, under high levels of variability, the balance assumption is violated more seriously. Hence, one should choose the TW strategy under high uncertainty.

4.4.1 DSS decision tree

We propose to use this decision tree to allow for quick distribution strategy selection. Using this decision tree would allow supply chain managers to choose the right distribution strategy for the product quickly. It offers a high probability that the right distribution strategy is chosen from an inventory control perspective. The decision tree can be found in Figure 4.3

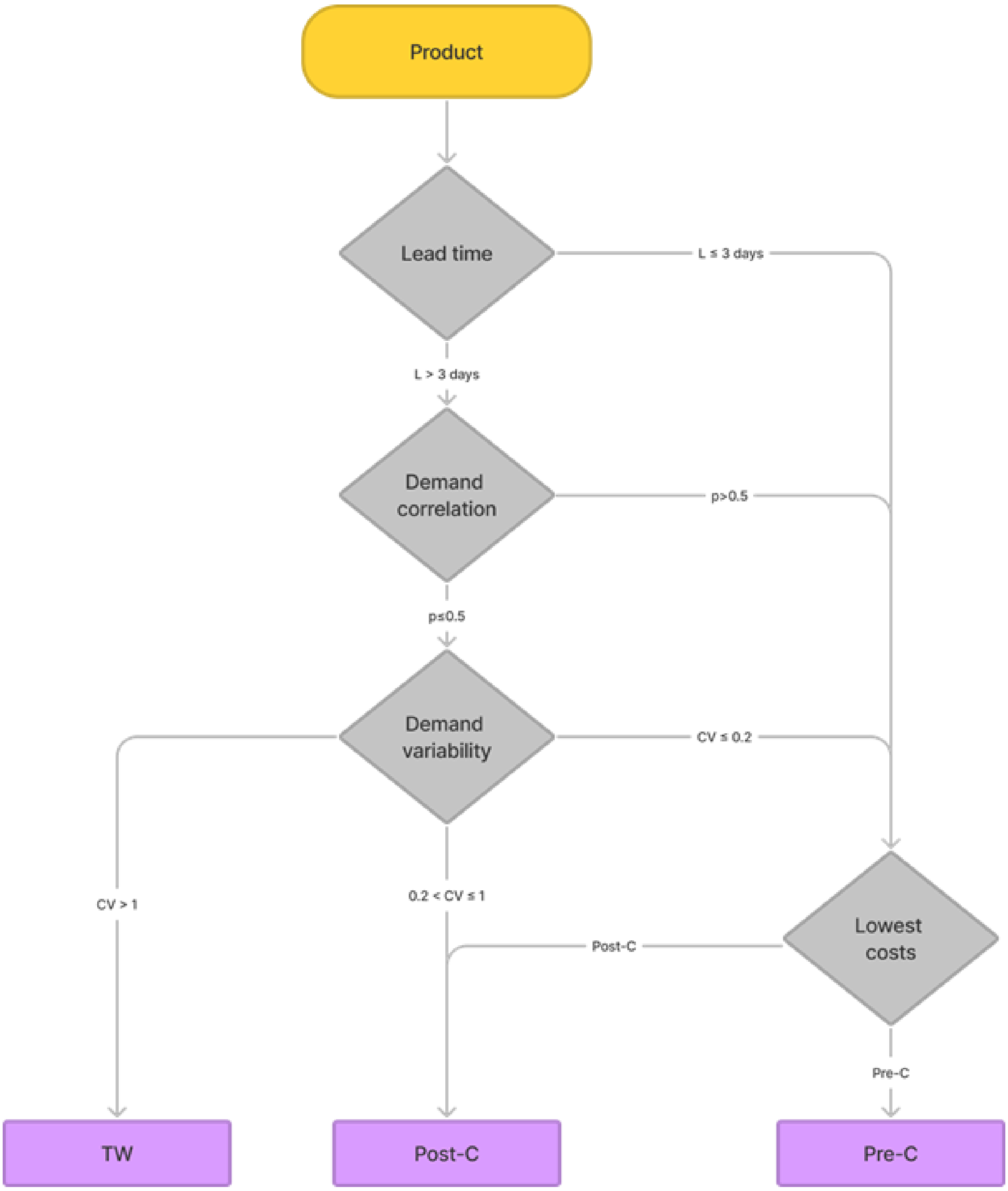


Figure 4.3: DSS-decision tree

Lead time is chosen as primary factor as it dictates the magnitude of the risk-pooling effect. Products that have a supplier lead time shorter than 3 days are eligible for one of the cross-dock strategies. The operational costs under those strategies should be compared to make a definitive choice between the two strategies. This could be done with Equation 4.6 and Equation 4.7. Then, demand correlation is reviewed as it also affects the degree of risk-pooling. Products that have high demand correlation ($\rho > 0.5$) between stores should be cross-docked. Again, the operational costs of this product should be compared for the two strategies. Last, demand variability should be analyzed. Products with a high CV value ($CV > 1$)

should be distributed according to the TW strategy, products with moderate CV ($0.2 < CV \leq 1$) according to the Post-C, and the operational costs should be compared for products with low CV ($CV \leq 0.2$). For detailed explanation of the decision criteria, we refer back to the previous section.

Chapter 5

Case Study

In the previous Chapter, we constructed a solution that should be applicable to a one-warehouse-multiple retailer system that sells a variety of consumer electronics. This Chapter is designed to validate the solution design and to test the practical relevance of the solution. The solution design is validated with a case study at Media-Markt Saturn. The solution design was constructed to solve two challenges: 1) choosing the right distribution strategy for the product and 2) high inventory-related costs due to small and frequent ordering. Therefore, we show the impact of the provided solution on these two subjects.

The Chapter is structured as follows: First, section 5.1 implements the DSS decision tree on the existing product portfolio and compares the distribution strategy outcomes to the current situation. Second, section 5.2 proves the design choices by varying variables and analyzing their impact on the distribution strategy's costs. Last, section 5.3 compares the the order quantities under the current and newly developed replenishment policy for the TW strategy.

The results are computed with Python 3.9 and the DoBr tool (Broekmeulen & Van Donselaar, 2015).

5.1 DSS implementation

This section implements the DSS decision tree based on the existing product portfolio. For this portfolio the demand characteristics and supplier lead time information is computed from company data.

For each product, the average Pearson correlation is computed based on the weekly product-location sales. The average correlation is the average of all location combination correlations. Products that are solely sold online do not have inter-location correlations. Since the distribution strategy for these products can be compared to a direct-delivery system and not one of the distribution strategies in question, they are eliminated from the dataset. Furthermore, the supplier lead time length and variability are computed and linked to the remaining products. Products with unknown lead time are dropped from the dataset. The mean demand and standard deviation of the demand are computed such that the CV value can be calculated. The resulting dataset consists of approximately 3000 unique products with the given average correlation, lead time and CV value. Since there is not accurate operational cost data avaialalbe for the Pre-C strategy, it is assumed that the operational costs under the Pre-C strategy are lower. This is a reasonable assumption since the Pre-C strategy requires even less handling than the Post-C strategy. The Pre-C strategy should never be chosen if the operational costs are higher.

A distribution strategy is selected based on the framework. The results can be found in Table 5.1. Based on these results 87% of the products would qualify for a TW strategy, 5% for a Pre-C strategy and 8% for a Post-C strategy. There are many products with high demand variability and therefore would not qualify for the Post-C strategy. However, the sales volume shows a different picture. Approximately 30% of the sales volume should be distributed according to the Post-C strategy. This is in line with the findings in Chapter 3, where we found that moderate and fast-movers (average demand per store > 1 unit/week) generally have a lower CV value.

Table 5.1: Percentage of products vs criteria

Criteria	Percentage of all products	Percentage of moderate and high demand products
$L_0 < 3$ days	1.19	0.54
$\rho > 0.5$	3.83	5.36
$CV > 1$	86.62	34.05
$0.2 < CV \leq 1.0$	8.35	60.05
$CV \leq 0.2$	0	0

Looking at the products with moderate and high demand (average demand per store

> 1 unit/week), the results show a different picture. 60% Should now be distributed according to the Post-C strategy and only 34% with the TW strategy.

The results show that the conditions under which the strategy should be used, are strict. This is in line with literature as the Pre-C strategy is more sensitive to uncertainty in the supply chain. The TW strategy still seems to be suitable for most of the products in the retail consumer electronics industry. However, most products that have moderate or high demand are eligible for the Post-C strategy as they observe less demand uncertainty.

5.2 Decision criteria

This section is designed to prove the design choices out of the DSS decision tree and explore new results that cannot be examined directly from analytical solutions. In the numerical experiments, we set default values for a product that are based on average values. Then, one particular factor is analyzed by varying its value. Consequently, we can see the impact of that specific factor. In the experiments, we consider the inventory holding costs, that are a fixed percentage of the value of the product, and handling costs. We have assumed that the handling costs per piece hc_y for each distribution strategy are: $hc_{Pre-C} < hc_{Post-C} < hc_{TW}$. The handling costs for the Pre-C is estimated on company projections, the other handling costs are estimated with company data.

Since we were unable to estimate the out-of-stock costs due to imbalances, these were not taken into account. As a result, the Post-C strategy is likely to perform better under high uncertainty than it would in practice.

5.2.1 Lead time

We varied the supplier lead time to the warehouse from 0 to 3 weeks. The average annual costs are shown in Figure 5.1

From the Figure, it can be seen that all strategies profit from short supplier lead time. This is logical since less stock is necessary within the system. Nevertheless, the supplier lead time impacts the Pre-C strategy the most. The TW and Post-C strategy are able to pool the observed variability over the lead time. Hence, they benefit from risk-pooling. With shorter lead time, the Pre-C strategy is able

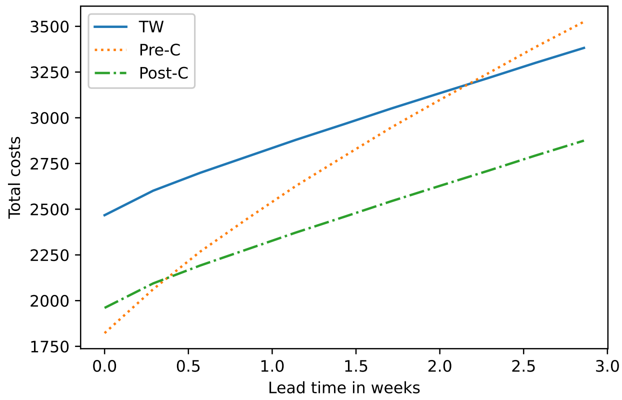


Figure 5.1: Expected annual costs vs outside lead time

to outperform the Post-C strategy. As lead time increases, the TW and Post-C strategy will outperform the Pre-C strategy. This is in line with our design choices that state that the Pre-C strategy should be chosen under short supplier lead time.

5.2.2 Demand correlation

We varied the demand correlation ρ from 0.0 to 1.0 with intervals of 0.1. The average annual costs are shown in Figure 5.2.

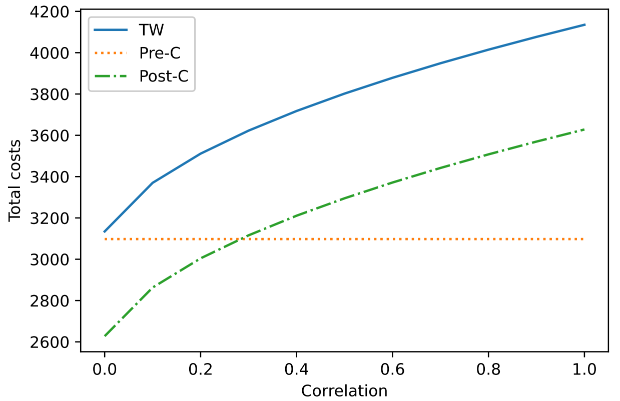


Figure 5.2: Expected annual costs vs demand correlation

In Figure 5.2, the costs for both the TW and Post-C strategy increase as the correlation increases. The costs for Pre-C remains constant. With low correlation, the cost for distributing the product with the Post-C strategy is lower than for the TW and Pre-C strategies. However, as the correlation increases, the benefit of risk-pooling for the TW and Post-C strategy decreases. As a result, the Pre-C strategy becomes increasingly preferable since it has lower handling costs. We can conclude that the

Pre-C strategy is always preferable if the correlation coefficient higher than $\rho > 0.5$. This is in line with our design choices that state that a cross-dock strategy should be chosen under high demand correlation.

5.2.3 Coefficient of Variation

The demand variability in the form of the coefficient of variation is varied between 0 and 2. The results are shown in Figure 5.3.

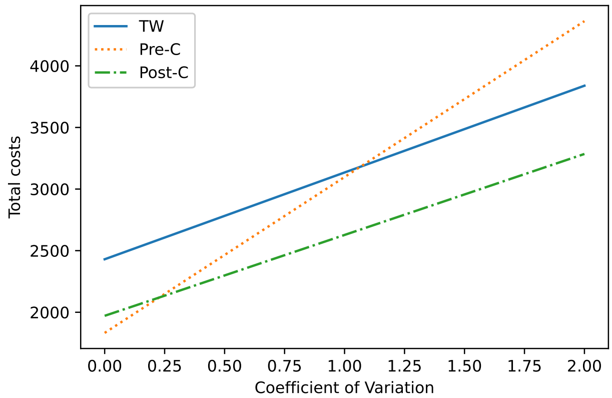


Figure 5.3: Expected annual costs vs CV

The costs for all distribution strategies increase as the demand variability increases. With lower variability, the average costs for the Pre-C strategy are the lowest. Nevertheless, with higher variability, Pre-C becomes most expensive. Low variability decreases the advantage of risk-pooling and therefore supports the advantage of lower handling costs that both Pre-C and Post-C enjoy. However, since the difference in handling costs is considerable, the cross-over point between the strategies is relatively late. Post-C is clearly outperforming the other strategies, also under higher levels of uncertainty. The actual costs for this strategy will be higher in practice since the costs resulting from imbalance situations are not taken into account in these calculations.

5.2.4 Holding costs

The holding costs are varied as well to check the influence of the product value. The holding costs are varied between 0 and 35 euros per year. The results are seen in Figure 5.4.

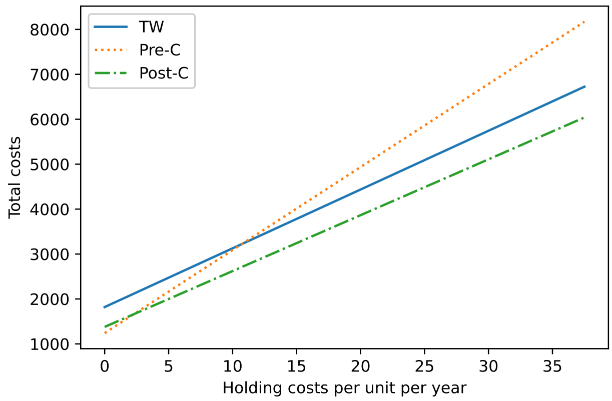


Figure 5.4: Expected annual costs vs holding costs

We observe that as the holding costs increase the benefit of lower handling costs is outweighed by the increasing holding costs. Therefore, for low-value products that have lower holding costs, it is more interesting to distribute via one of the cross-dock strategies as focusing on handling cost reduction is essential for performance. This is in line with our design choices. In addition, it can be seen that the TW and Post-C strategy hold less inventory than the Pre-C strategy for this product.

5.3 Economic order quantity

This section implements periodic review order-up-to policy (R,s,S) replenishment policy mentioned in subsection 4.2.1 for the TW strategy. Consequently, we demonstrate the effect on the inventory control performance compared to the currently used replenishment policy mentioned in section 3.3. We chose to implement the strategy for 16 products with different product values and demand rates. The product characteristics are given in Appendix C.

First, the annual holding costs are calculated by multiplying the holding costs percentage and the product value. Then, the order-setup costs are estimated based on company data and consist out of admin costs for order processing and order pick costs. For the warehouse order setup costs, storage (put-away) costs and inbound costs are used instead of the pick costs. Then, the economic order quantity (EOQ) is calculated with Equation 4.3. As this provides an order quantity in decimals, the costs of the order quantities around this decimal number must be compared. The order quantity with the lowest costs is chosen as the optimal order quantity.

The EOQ is compared with the order quantity according to the current replenishment policy. This is the forecasted demand during the lead time and review period. The EOQ should not be smaller than this quantity as this is the minimum amount of inventory necessary in the replenishment interval. Therefore, the EOQ is set equal to this quantity if it is smaller. The EOQs that are different from the current replenishment quantity are shown in Table 5.2. The complete results can be found in Appendix C.

Table 5.2: Current order quantity compared to EOQ

Product	Weekly average demand	Product value	Current Q_{store}	EOQ_{store}	≈ Weeks inventory	Current Q_{DC}	EOQ_{DC}
3	2.5217	25.50	3	6	2	92	92
5	0.7579	72.25	1	2	2	50	50
6	0.5385	46.75	1	2	3	40	40
8	0.3228	37.00	1	2	6	25	25
11	0.2037	31.00	1	2	9	19	19
13	0.1553	5.00	1	4	25	6604	6604
14	0.1522	10.00	1	3	19	19	23
15	0.1378	8.80	1	3	21	306	306

We find that order-up-to levels based on the EOQ could be interesting for the stores. Especially, the items that have low demand and low value benefit from implementing an EOQ. The holding costs for these products are relatively small compared to the order setup costs. As a result, ordering stock for several weeks could be beneficial. Since MediaMarkt's warehouse observes a much larger demand, holding costs are already significant. Therefore, cost minimization should be the focus to reduce inventory-related costs.

Certain order quantities may have additional appeal over the current EOQ. Often products are packaged in a box containing multiple pieces. The insensitivity of the total costs near the EOQ allows that these 'case-pack sizes' can be used if they are reasonably close to the EOQ (Silver et al., 2016). However, since the EOQs are generally small for MediaMarkt, these deviations could be large in percentages. Therefore, one should be careful when deviating from the EOQ.

The following time supplies are considered: 0.25, 0.5, 0.75, 1, 2, 3, 6, 9, and 12 months. Based on these time supplies, Table 5.3 shows the relation between weeks of supply and the demand value based on the EOQ. The demand value is the value of the product multiplied by the annual demand. These annual demand values are calculated with the approach described by Silver et al. (2016). MediaMarkt could use this as support for determining the desired inventory.

Table 5.3: Months in supply vs annual demand value

Annual demand value (DV)	Inventory in months
$9219 \leq DV < \infty$	0.25
$3073 \leq DV < 9219$	0.5
$1537 \leq DV < 3073$	0.75
$576 \leq DV < 1537$	1
$192 \leq DV < 576$	2
$64 \leq DV < 192$	3
$21 \leq DV < 64$	6
$11 \leq DV < 21$	9
$0 \leq DV < 11$	12

Chapter 6

Conclusions and Recommendations

This Chapter provides the conclusions and recommendations for this research. First, section 6.1 provides the main conclusions of this research. Second, section 6.2 recommendations for MediaMarkt. Last, section 6.3 includes the limitations within this research and provides directions for future research.

6.1 Conclusions

The main challenge was the development of an distribution strategy selection process. Currently, a structured approach for selecting the appropriate distribution strategy was missing. Consequently, sub-optimal strategies that cause reduced product availability and high supply chain costs are chosen. Furthermore, high warehousing costs arose from an inventory policy focused purely on inventory minimization without considering other operational cost factors. Therefore, the following two research assignments were stated:

1. *Design a decision support tool for selecting a distribution strategy to reduce costs and maintain product availability*
2. *Integrate warehouse cost factors into ordering decisions to reduce inventory and operational costs*

These assignments were divided into multiple research questions.

The distribution strategies dictate how inventory is positioned within the system. Therefore, we investigated the benefit of storing inventory centrally and the factors determining the magnitude of this advantage. Also, additional factors were analyzed as well.

1a. Which factors drive the advantage of inventory centralization?

The main benefit of inventory centralization is the risk-pooling effect. By storing the inventory centrally, the variabilities caused by demand fluctuations at different locations are combined. By combining the variabilities as an aggregate distribution, the standard deviations of the retailers are pooled. In other words, overages in one location offset product shortages in another. As a result, less system-wide safety stock is necessary. The three main factors that influence the magnitude of the risk-pooling effect are: 1) variability, 2) lead time, and 3) demand correlation. The larger the risk-pooling effect, the greater the potential benefit of inventory centralization

1b. Which factors drive distribution strategy performance?

The factors that determine the distribution strategy performance are the magnitude of risk-pooling and the handling costs for the respective strategy. For both the Pre-C and Post-C strategy handling costs are significantly lower since they eliminate expensive warehouse processes. Therefore, as the risk-pooling effect is small, one should consider choosing one of the cross-dock strategies. The risk-pooling effect is small under low variability, short lead time or high demand correlation.

Furthermore, the supplier reliability, product popularity, total cubic movement, and product value can be of significance as well. Therefore, these factors should be included into the distribution strategy selection process.

1c. How can the factors be integrated into a structured approach for selecting a distribution strategy?

The appropriate distribution strategy can be selected according to the DSP framework provided in section 4.4. The framework shows all factors that should be taken into account when deciding on the appropriate distribution strategy. In addition, the DSS decision tree in subsection 4.4.1 allows for quick distribution strategy selection purely from an inventory control perspective. It offers a high probability that the right distribution strategy is chosen. Combining both tools will allow supply chain managers to make a thoughtful distribution strategy choice.

The case study showed that cross-docking a significant proportion of the sales volume could be highly beneficial. Handling costs for these strategies are considerably lower than for the traditional warehouse strategy. Consequently, a TW strategy should be chosen only in cases where the reduction in holding costs by the risk-pooling effect is substantial. Nevertheless, many products observed substantial demand variability, especially slow-movers. Therefore, a traditional warehouse strategy could still be interesting for those products.

2a. Which processes are the main driver of warehouse operational costs?

It was found that the warehouse costs are driven predominantly by processes under the traditional warehouse strategy. The main contributors to the warehouse costs were inbound, pick, and storage processes. We expect pick and storage process efficiency to be improved by incorporating these into ordering decisions.

2b. What is the influence of ordering decisions on these processes' efficiency?

Larger order quantities would lead to fewer pick and storage tasks. As a result, more products are picked or stored at once. Less time is spent moving to the correct inventory location in the warehouse. As a result, process efficiency is improved, and warehouse costs are reduced.

2c. How can the newly developed ordering decisions be integrated into the existing replenishment policy?

These costs can be incorporated into the replenishment policy by introducing an order-up-to-level into the replenishment policy. This order-up-to-level is based on an economic order quantity. Instead of ordering the minimum inventory necessary, an order quantity is proposed that balances the order-setup costs with the holding costs.

The case study showed that implementing an economic order quantity could be especially interesting for store orders with low product value and low demand. Currently, the replenishment policy proposes small order quantities as demand is low during the replenishment interval. Consequently, the order-setup costs are relatively high compared to the holding costs. As a result, increasing order quantities can result in a reduction in the combined inventory and operational costs.

6.2 Recommendations MediaMarkt

Based on the findings of this research, we propose the following key recommendations for MediaMarkt:

The first recommendation is to allocate the order to the stores at the warehouse under the BBXD strategy. Currently, the orders are already allocated to the stores at the supplier. This makes the BBXD equivalent to the PAXD strategy from an inventory control perspective. Postponing the allocation reduces the system-wide safety stock since variabilities are pooled over the supplier-to-warehouse lead time. With this postponed allocation, the BBXD is similar to the Post-C strategy. The Post-C strategy showed strong performance despite long lead time and high variability. Therefore, a more significant proportion of the products can utilize reduced handling costs without increasing the holding costs significantly.

The second recommendation is to determine the supplier lead times accurately. The supplier lead times that are used by the software system are not equal to the found lead times in this thesis. As a result, the necessary inventory is calculated over the incorrect time period. This could cause significant overstock costs or could impact the service level considerably.

The third recommendation is only to use the PAXD strategy under strict conditions. The PAXD is sensitive to uncertainties in the system, especially since lead times are relatively long. Therefore, small uncertainties can cause stock-outs or high safety stocks in the stores. Also, the benefit in handling costs could be small since the supplier is likely to charge an extra fee for their extra processing tasks. Consequently, the PAXD should be solely utilized if uncertainty is small and benefits in handling costs are substantial.

The fourth recommendation is to implement order-up-to levels in the stores for slow-moving products with low value. These order-up-to levels could be based on the EOQ in order to reduce operational costs. 'Case-pack sizes' could be utilized instead of individual pieces if they are reasonably close to the EOQ. However, one should be careful when the EOQ is low, as this can result in more substantial cost differences.

The last recommendation is to revise the safety stock calculation. We found that the standard deviation is currently calculated over the lead time. However, since the company employs a periodic review inventory policy, the review period should also be included. Otherwise, the customer service level could be significantly affected. Moreover, the lead time uncertainty should also be included in the standard deviation since we found that the lead times are highly variable.

6.3 Limitations & directions for future research

This section describes the limitations of this research and directions for future research.

Firstly, we determined that the transportation costs were out of the scope of this research. Currently, the supplier pays the transportation costs to the warehouse; therefore, this does not directly influence the expenses for a specific distribution strategy. Nevertheless, it is harder for the PAXD strategy to reach economic loads as the products are already sorted at the supplier. Therefore, this could pressure the supplier to increase their prices and thus indirectly influence the appropriate choice for a distribution strategy. Future research could investigate the preferred choice for a distribution strategy while including transportation costs.

Secondly, promotional influences on the distribution strategy selection were not considered. Promotional influences likely have considerable effects on the distribution strategy choice as it changes the demand characteristics of the product. We expect especially demand correlation to be affected. Since MediaMarkt has multiple large promotions during the year, future research could investigate the effect of the promotions on the preferred distribution strategy choice.

Lastly, the extra penalty costs due to imbalance situations were not taken into account during the case-study. This is of significance since these imbalance situations can affect the performance of the Post-C strategy under high uncertainty. Future research could simulate the impact of the imbalance on the strategy its performance.

References

Adan, I., van Eenige, M. & Resing, J. (1995). Fitting Discrete Distributions on the First Two Moments. *Probability in the Engineering and Informational Sciences*, *9*(4), 623–632. doi: 10.1017/S0269964800004101

Apte, U. M. & Viswanathan, S. (2010, 11). Effective Cross Docking for Improving Distribution Efficiencies. *http://dx.doi.org/10.1080/713682769*, *3*(3), 291–302. doi: 10.1080/713682769

Axsäter, S. & Rosling, K. (1993). Installation vs. Echelon Stock Policies for Multilevel Inventory Control. *Management Science*.

Barrow, D. & Kourentzes, N. (2016). Distributions of forecasting errors of forecast combinations: implications for inventory management. *International Journal of Production Economics*, *177*, 24–33.

Benrqya, Y., Babai, M. Z., Estampe, D. & Vallespir, B. (2020, 6). Cross-docking or traditional warehousing: what is the right distribution strategy for your product? *International Journal of Physical Distribution and Logistics Management*, *50*(2), 255–285. doi: 10.1108/IJPDLM-03-2019-0091/FULL/PDF

Benrqya, Y., Estampe, D., Vallespir, B. & Zied Babai, M. (2014). Impact of Product Characteristics on Distribution Strategy Selection. *https://doi.org/10.1080/16258312.2014.11517350*, *15*(3), 38–50. doi: 10.1080/16258312.2014.11517350

Broekmeulen, R. & Van Donselaar, K. (2015). *Implementation DoBr 4.4. Eindhoven: Operations Management & Logistics.*

De Kok, A. (2012). *Analysis of stock control models for one location with one product, Lecture notes for the course Introduction Inventory Control.*

Dogru, M. (2006). *Optimal control of one-warehouse multi-retailer systems : an assessment of the balance assumption* (Doctoral dissertation, Eindhoven University of Technology). doi: 10.6100/IR601558

Handfield, R. B., Handfield, R. & Nichols Jr, E. L. (2002). *Supply chain redesign: Transforming supply chains into integrated value systems.* Ft Press.

Li, Z., Low, M. Y. H., Lim, Y. G. & Ma, B. (2008). Optimal decision-making on product ranking for crossdocking/warehousing operations. *IEEE International Conference on Industrial Informatics (INDIN)*, 871–876. doi: 10.1109/INDIN.2008.4618223

Mangan, J. & Christopher, M. (2005, 12). Management development and the supply chain manager of the future. *The International Journal of Logistics Management*, *16*(2), 178–191. doi: 10.1108/09574090510634494/FULL/XML

Nahmias, S. & Olsen, T. L. (2015). *Production and operations analysis.* Waveland Press.

Power, D. (2005). Supply chain management integration and implementation: A literature review. *Supply Chain Management*, *10*(4), 252–263. doi: 10.1108/13598540510612721/FULL/PDF

Seasonal decompose package. (n.d.). Retrieved from `https://www.statsmodels.org/dev/generated/statsmodels.tsa.seasonal.seasonal_decompose.html`

Silver, E. A., Pyke, D. F. & Thomas, D. J. (2016). *Inventory and Production Management in Supply Chains.* CRC Press. doi: 10.1201/9781315374406

Simchi-Levi, D., Kaminsky, P. & Simchi-Levi, E. (2008). *Designing and managing the supply chain : concepts, strategies, and case studies* (3rd ed. ed.). Boston: McGraw-Hill/Irwin.

Tallon, W. (1993). The impact of inventory centralization on aggregate safety stock: The variable supply lead time case. *Journal of Business Logistics*, *14*(1), 185.

Tompkins, J., White, J. & Bozer, Y. (1996). *Facility Planning* (2nd ed.). John Willey and Sons.

Van Der Heijden, Diks & De Kok. (1999). Inventory control in multi-echelon divergent systems with random lead times. *OR-Spektrum 1999 21:3*, *21*(3), 331–359. doi: 10.1007/S002910050093

Van Belle, J., Valckenaers, P. & Cattrysse, D. (2012, 12). Cross-docking: State of the art. *Omega*, *40*(6), 827–846. doi: 10.1016/J.OMEGA.2012.01.005

Van Der Heijden, M., Diks, E. & De Kok, A. (1996). Allocation policies in general multi-echelon distribution systems with (R,S) order-up-to-policies. *Memorandum COSOR*, *9623*.

van der Vlist, P. (2007). *Synchronizing the retail supply chain* (Unpublished doctoral dissertation). Erasmus Universiteit Rotterdam.

Van Donselaar, K. (1990). Integral stock norms in divergent with lot-sizes systems. *European Journal of Operational Research*, *45*, 70–84.

Van Donselaar, K. & Broekmeulen, R. (2014). *Stochastic inventory models for a* *single item at a single location.*

Vogt, J. J. (2010, 3). THE SUCCESSFUL CROSS-DOCK BASED SUPPLY CHAIN. *Journal of Business Logistics*, *31*(1), 99–119. doi: 10.1002/J.2158-1592.2010.TB00130.X

Yan, H. & Tang, S. l. (2009, 11). Pre-distribution and post-distribution cross-docking operations. *Transportation Research Part E: Logistics and Transportation Review*, *45*(6), 843–859. doi: 10.1016/J.TRE.2009.05.005

Zheng, Y.-S. & Federgruen, A. (1991, 8). Finding Optimal (s, S) Policies Is About As Simple As Evaluating a Single Policy. *https://doi.org/10.1287/opre.39.4.654*, *39*(4), 654–665. doi: 10.1287/OPRE.39.4.654

Zinn, W. ., Levy, M. . & Bowersox, D. J. (1989). Measuring The Effect OF Inventory Centralization/Decentralization on aggregate safety stock: the "square root law" revisted. *Journal of Business Logistics*(1).

Appendix A

Forecasting methods

Table A.1: Demand forecasting methods

Method
Moving average
Simple exponential smoothing
Exponential smoothing with trend
Exponential smoothing with seasonal indices
Naive season
Regression forecasting
Aggregate-level forecasting
Aggregate season model
Croston's method
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

Appendix B

Mean and variance under stochastic lead time

$$E[D_R] = RE[D_1] \tag{B.1}$$

$$E[D_{L+R}] = E[D_L] + RE[D_1] \tag{B.2}$$

$$E[D_L] = E[L] + E[D_1] \tag{B.3}$$

$$var[D_R] = Rvar[D_1] \tag{B.4}$$

$$var[D_{L+R}] = var[D_L] + Rvar[D_1] \tag{B.5}$$

$$var[D_L] = E[L] \cdot var[D_1] + E^2[D_1] \cdot var[L] \tag{B.6}$$

where D_x is the dumand during x periods, R the review period, and L the lead time. For the derivation of these formulas we refer to Broekmeulen and Van Donselaar (2015) and De Kok (2012).

Appendix C

Products R,s,S implementation

Table C.1: Products used for R,s,S implementation

Product	Mean weekly demand	Value
1	54.53	34
2	399.575	117.3
3	25.217	25.5
4	12.881	178.5
5	0.7579	72.25
6	0.5385	46.75
7	0.4106	102
8	0.3228	37
9	0.2561	72.25
10	0.25	2500
11	0.2037	31
12	0.158	102
13	0.1553	5
14	0.1522	10
15	0.1378	8.8
16	0.1048	200

Table C.2: Current order quantity compared to EOQ

Product	Weekly average demand	Product value	Current Q_{store}	EOQ_{store}	Weeks inventory	Current Q_{DC}	EOQ_{DC}
1	54.530	34.00	47	47	0	4839	4839
2	39.575	117.30	35	35	0	156	156
3	2.5217	25.50	3	6	2	92	92
4	1.2881	178.50	2	2	1	66	66
5	0.7579	72.25	1	2	2	50	50
6	0.5385	46.75	1	2	3	40	40
7	0.4106	102.00	1	1	2	32	32
8	0.3228	37.00	1	2	6	25	25
9	0.2561	72.25	1	1	3	20	20
10	0.2500	25000.00	1	1	4	13	13
11	0.2037	31.00	1	2	9	19	19
12	0.1580	102.00	1	1	6	31	31
13	0.1553	5.00	1	4	25	6604	6604
14	0.1522	10.00	1	3	19	19	23
15	0.1378	8.80	1	3	21	306	306
16	0.1048	200.00	1	1	9	17	17