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Pre- and In-season Stock Allocation at H&M Online

Master of Science Thesis in Supply Chain Management & Management and Economics of Innovation Programs'

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Abstract

Today the Swedish multinational retail-clothing company H&M mainly source products from production suppliers in Asia, resulting in extensive lead times. The time-consuming transportation and short fashion seasons and trends require H&M to produce to stock based on forecasts. H&M Online, which is the e-commerce company within the H&M group, are currently planning to source their largest online market Germany from two warehouses instead of only using one warehouse as of today. This will in theory shorten the critical lead time from 3-5 days to 1-2 days to all German e-commerce customers. The more decentralized logistics setup will on the other hand bring challenges when it comes to the allocation of stock between the two warehouses both before a season starts but also during an ongoing season. The purpose of the thesis is consequently to develop a pre-season stock allocation model and to come up with strategies for how to optimize the stock allocation during an ongoing season for the hypothetical warehouse network.

The pre-season allocation model and in-season allocation strategies are developed by combining theoretical insights from e-commerce, fashion forecasting and stock allocation literature with qualitative and quantitative findings from the case study at H&M Online. The developed model is mainly based on a statistical forecasting method, which estimates a future allocation split based on previously observed demand data last comparable season from the market that the warehouses supply, together with future sales targets for the upcoming season set by H&M's market experts. By testing and simulating the developed pre-season stock allocation model using historical demand data from the spring season of 2014 to estimate suitable stock allocation splits for the spring season of 2015, a total miss in sales of 7.4 percent at an aggregated level for all H&M Online's departments is achieved. Potential improvement areas for the model are identified. Due to the fashion e-commerce industry's many sources of future demand uncertainty and to shortcomings of the developed allocation model, stock allocation during ongoing season can and should be used. In-season stock allocation strategies suitable for H&M Online are usage of real-time demand data during season to update the stock allocation split between the warehouses but also different stock postponement and quick response strategies.

Key words: E-commerce, Fashion, Warehouse network, Stock allocation, E-tailer

Table of Contents

1. Introduction

This chapter presents the background to the examined problem, the purpose, research questions, expected outcomes of the research and finally project limitations.

1.1 Background

Today the Swedish multinational retail-clothing company H&M mainly have production suppliers in Asia, which results in time-consuming transportation of products. The long lead times and short fashion seasons and trends require H&M to produce to stock based on forecasts. In order for H&M to serve their Northern European e-commerce market, H&M currently use four warehouses, which are located in Borås (Sweden), Oslo (Norway), Poznan (Poland) and Great Britain. Norway and Great Britain are sourced with separate goods streams directly from suppliers. All products which are to be offered on H&M's largest e-commerce market Germany together with Austria, the Netherlands, Sweden, Denmark and Finland are on the other hand distributed via the warehouse in Poznan, which also by far is H&M Online's largest warehouse.

The provided customer service level is to a great extent dependent on H&M Online's ability to keep a constantly high product availability in stock and to offer its customers short lead times. A high product availability together with quick deliveries are proved to increase sales and remain competitive on the fashion e-commerce market. In order to increase the product availability and to be able to shorten its lead times to online customers, H&M are currently assessing the strategic logistics setup of the product flow from suppliers to customers on the German e-commerce market. More specifically, H&M are planning to source the e-commerce market of northern Germany from the warehouse in Poznan, while the southern part potentially is going to be supplied by a new warehouse in Slovakia. This potential strategic setup will in theory shorten the delivery time from 3-5 days to 1-2 days to all German e-commerce customers.

The more decentralized logistics setup will on the other hand bring challenges when it comes to product availability. The two warehouses will namely now supply two "markets" (northern and southern Germany) with differing and constantly changing customer demand, as is the characteristic of the fashion e-commerce industry. As the initial deliveries of products prior to a season starts are the largest shipments of the total merchandise volume sent to the warehouses, the stock allocation of products between the two warehouses before and during an ongoing season consequently have high strategic importance. Inaccurate initial/pre-season stock allocation will force an increase in inventory rebalancing during season, leading to costly added transports of products between the warehouses in order to avoid stockouts and not having the same product offering to all German online customers. Imprecise stock allocation of products during an ongoing season could further impair the customer offer and increase the need for costly "emergency" transports between the warehouses.

1.2 Purpose

The Master's thesis describes H&M Online's current and future potential logistics setup with focus on the product flow to the German e-commerce market. The purpose of the thesis is to develop a pre-season stock allocation model and to come up with strategies for how to optimize the stock allocation during an ongoing season between the warehouse in Poland and the hypothetical warehouse in Slovakia.

1.3 Research questions

The thesis aims to answer two main research questions through both a theoretical and an empirical approach:

- How can a fashion e-tailer, like H&M Online, develop a pre-season stock allocation model to allocate products between warehouses to ensure high stock availability?
- How can a fashion e-tailer, like H&M Online, strategically configure the in-season stock allocation to flexibly adapt to variations in customer demand?

1.4 Expected outcome

Expected outcome of the thesis are conclusions for how H&M Online can allocate products between the warehouse in Poland and the potential warehouse in Slovakia, both before a season starts and during a season. More specifically, a pre-season stock allocation model will be developed for H&M Online and also ideas or strategies for how to allocate stock between the two warehouses during an ongoing season. The conclusions will be adjusted for the fashion industry. The results will furthermore provide ideas and approaches for future strategic pre- and in-season stock allocation decisions for fashion e-tailers.

1.5 Limitations

The Master's thesis report is limited to the German e-commerce market supplied by the warehouse in Poland and a hypothetical warehouse in Slovakia. The developed pre-season stock allocation model also has to be relatively easy to use and understand since H&M Online will need to implement it quite soon. The company is in other words not looking for a complex model or a "black box" solution.

2. Methodology

This chapter presents and discusses the process of the thesis. Initially, the chapter presents the research process and the general methodology that was used. More detailed information is then introduced for each part of the research process. The chapter ends with a discussion about the reliability and validity of the study.

2.1 The research method

The project was carried out according to the process presented below in Figure 2.1. First off, the problem presented by H&M was analyzed and a problem definition was formed in order to create the main objectives and limitations of the thesis. Thereafter the research questions were formulated based upon the defined problem. In order to deepen the knowledge in the field and to partly answer the research questions, a theoretical study was then conducted. Data collection was also carried out in parallel with the theoretical study, The Master's thesis is namely based upon an extensive case study, where the collected data is of both qualitative and quantitative nature. The collected data was then analyzed, evaluated and compared with theory in order to create a pre-season stock allocation model and in-season stock allocation strategies. Several pre-season stock allocation models were developed and in parallel tested through simulations in order to get a reliable and satisfactory final model. Finally, conclusions were made.

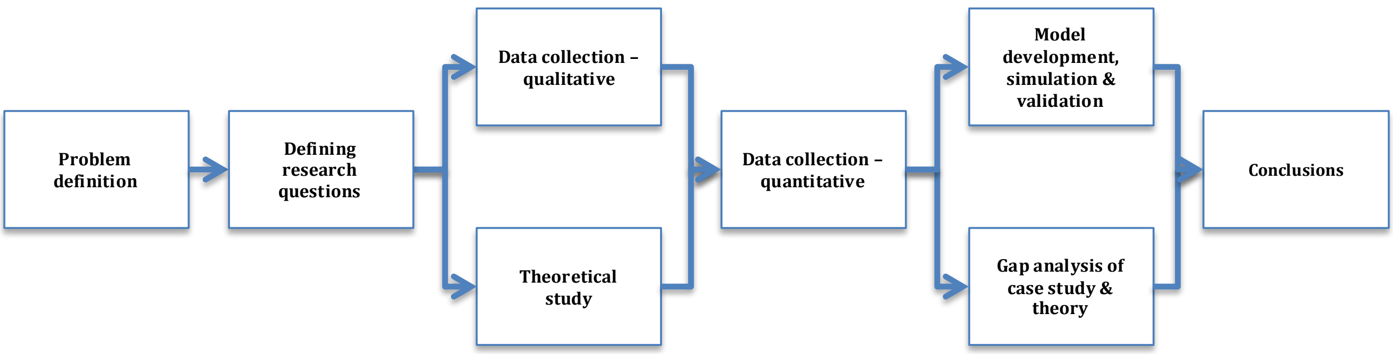

Figure 2.1 The research process.

2.2 Theoretical framework

The initial focus of the theoretical research was to gain knowledge within general areas of the fashion e-commerce industry, especially from the perspective of logistics. Further research was then carried out with more specific focus on sales forecasting and stock allocation. Ultimately, the purpose was to create an extensive knowledge base to rely on.

To create the theoretical framework textbooks, articles and online resources were used. The sources were evaluated on the basis of origin in terms of university, titles of the authors and publishing year. The references were further investigated to eliminate possible misinterpretations and to strengthen the validity of the sources. (Bryman & Bell, 2015)

2.3 Research design

This report is a product of an in depth case study at H&M Online. The case study is most accurately described as a typical case study, where the researchers explore a phenomenon by exemplifying it through a case within an organization. A case study gives the opportunity to study the case in more detail and provides a deeper understanding of an object of interest. The nature of the study is to combine both qualitative and quantitative methods as well as to include theory concerning fashion e-commerce and stock allocation. Mixing both a qualitative and a quantitative approach provides a better understanding of the research problem than if any of the methods had been used alone. Furthermore, this approach enables the researchers to triangulate and approach the problems from different angels in order to achieve better validity. (Bryman & Bell, 2015)

2.4 Empirical study

The empirical data collection was initially a qualitative study with the purpose to understand the organization in general and to map the current state. The data was collected through open interviews with the supervisor at the company and followed by semi-structured interviews with other employees within the logistics, purchasing and sales department at H&M Online (See References for the interviewee list). In general, the interviews were made face-to-face with a few exceptions of telephone meetings. The choice of semi-structured interviews was made because it enables the interviewer to be flexible and it also gives the freedom of the interviewees to discuss and explain their reasoning. Also, it allows the interviewers to prepare questions and guidelines to establish a base and a structure in the interviews. When the mapping of the current state was finished, the interviewees were asked to verify their contribution to the case study, consequently verifying and giving the case additional creditability (Bryman & Bell, 2015). Furthermore, secondary data such as internal documents were also used to map the current state.

The quantitative part of the empirical study consists mainly of numerical data and was collected at the company through internal documents. The data consists of sales statistics, return data, sales targets, stock levels etc. Verification of the data was made by several employees to enhance the creditability (Bryman & Bell, 2015).

2.5 Gap analysis and stock allocation modelling

Both the collected qualitative and quantitative data together with theoretical insights were used to create a pre-season stock allocation model and in-season stock allocation strategies. The creation of the pre-season allocation model was of an iterative approach, where the authors added functions to the model as the work proceeded. The model was initially built in a small scale but was designed to be expanded and to handle larger quantities of data. The researchers used Microsoft Excel in the creation of the model.

2.6 Simulation and validation of the pre-season stock allocation model

Simulation involves the construction of an artificial environment in which relevant information and data can be generated (Kothari, 2004). In this particular H&M-case, demand data from the spring seasons of 2014 and 2015 were used in several simulation rounds. By putting the demand data from 2014 in the models, projected stock allocation splits were created for 2015. The forecasts were then compared with the actual demand of the spring season of 2015. According to Kothari (2004) simulation permits the researcher to observe a system under controlled conditions and is useful when building models for understanding future conditions. Furthermore, a higher creditability can be obtained. In order to validate the developed allocation model the results of the simulation were compared with optimal allocation splits, calculated using the known actual demand split between the markets that the two warehouses supplied during the spring season of 2015.

2.7 Sampling of interviewees

It was early on decided that it was desired to get in contact with several individuals throughout the supply chain at H&M Online in order to understand the operations of H&M Online. Snowball sampling was used to select the right persons for interviews, i.e. recommendation from the supervisor at H&M and other employees. The intention with "snowball strategy" is to identify the most suitable person to interview (Flick, 2009). Validity was obtained through cross checking of the gathered data with other interviewees.

2.8 Reliability and validity

To assess and establish quality of a study Bryman and Bell (2015) point out the importance of ensuring reliability and validity. This particular study is partly based on several qualitative interviews that influence the reliability of the study since it is hard to replicate and freeze a social setting and circumstances at a given time. In order to engage this issue of external reliability all interviews have been recorded and transcribed. The internal reliability has been reached through the presence of both interviewers during all interviews. This to make sure that there was an agreement on what was discussed and to avoid misinterpretations. Furthermore, the meetings were discussed and summarized afterwards in order to highlight the main takeaways.

Validity is a generic term for different kinds of validity, but generally refers to whether a study of a concept or phenomenon corresponds to the actual concept or phenomenon. Focus is to ensure as high validity as possible since its importance speaks for itself – without validity any conclusion become less trustworthy. (Bryman & Bell, 2015) A triangulation method of sources is used to ensure the validity of this study, both during the collection of data as well as combining empirical findings with theoretical concepts.

3. Theoretical framework

This chapter presents the theoretical framework that the study is based on. It includes a description of the characteristics of the fashion e-commerce industry, demand forecasting and theory about stock allocation models and strategies.

3.1 The fashion e-commerce industry

“Fashion” is the word used to describe trends which affirm themselves in a spontaneous way each given moment. Thus, the concept includes not only the clothing industry but also other sectors, such as shoes, jewelry and accessories. (Blumer, 1969) The fashion industry has during the recent years become increasingly complex and dynamic. In this industry, competition is fierce (Newman & Cullen, 2002). The dramatic shift from mass fashion into segmented fashion, the advent of new technology, and the nature of sourcing and supply chain decision which are increasingly global are just some examples that have contributed to this complexity. Moreover, consumers’ purchase attitude is everyday more influenced by the “complete shopping experience” provided at the point of sale, i.e. the contact point between the supply chain and the consumer. (Danziger, 2006) A higher awareness for brand also influences the requirements for aligning the operations throughout the supply chain to fit the characteristics of the brand and its positioning (Moore & Birtwistle, 2004). Thus, one can argue that the fashion industry is synonymous with rapid change and, as a result, the likelihood of succeeding in the fashion industry is largely determined by an organization’s flexibility and responsiveness (Christopher et al., 2004).

The pervasive nature of the world wide web in the "connected world" is undeniable. From the first click in the morning to access our e-mail to the final "shut down" of the evening we are continually engaged with the online community. As follows, the connected world has become a significant part of individuals’ daily lives and has therefore also transformed consumers' shopping habits. (Hayes et al., 2007) Consequently, the retailing industry landscape has dynamically changed over the last decades and entered into the online era. Online shopping is now adopted by a huge number of consumers and the most popular sector is the constantly evolving fashion industry. Also, the growth of social networks, such as Facebook, Twitter, Google+ etc., has provided opportunities for fashion e-tailers to communicate with customers online and has transformed these platforms into transactional sites. (Zhang et al., 2015) The number of consumers shopping online and the amount they spend will, according to Vignali and Reid (2014), continue to increase for several years to come within the fashion industry. Moreover, a prominent characteristic in the e-commerce fashion industry is the high return rate of products. The rate can, according to Min et al. (2008), be as high as 30 percent for some categories of products. This is especially true for businesses exploiting the business model “Find-Try-Buy”. The main reasons to why products are returned are refunds, exchanges for other products and quality issues (Stock et al., 2006).

3.1.1 Development of the global e-commerce fashion industry

During the last 20 years the fashion e-commerce industry has experienced a lot of change due to pressure from a number of external factors such as globalization, increase of customer requirements and new technology. These external factors will be further described below followed by recent trends identified in the fashion industry.

In order to sustain and enhance its competitive advantage the fashion industry has needed to reduce its cost base. The main outcome of this has been to buy and move the production of products to developing nations, where the labor cost is significantly lower. Furthermore, the globalization also impacts the retailing part of the company as well as the production – i.e. products are sourced offshore and sold worldwide. A result of this is substantially longer lead times, and causes replenishment of products to be very difficult in the fast moving fashion industry. Moreover, it is not only the distance that causes long lead-times in global sourcing. It is also the delays and variability at both ends of the supply chain as well as the import/export procedures in between. (Christopher et al., 2004)

A strong ongoing change in the industry is an evolvement from mass fashion into segmented fashion (Sekozawa et al., 2010). Customer tastes change dynamically and their expectations vary (Brittistoni et al., 2013). Thus, companies are forced to meet the customer on both a product and service level. An effect of this is a greater variety of products and more frequent design changes. (Chan F.T.S. & Chan H.K., 2010)

Moreover, technology has enabled a massive flow of information throughout the industry. Hence, customer requirements have increased due to instant knowledge of brands and new trends. The capability to take business decisions has at the same time also improved, from retailers to manufactures, through sharing of data and knowledge in real-time. (D'Amico et al., 2013) The above explained external factors have resulted in an industry characterized by rapid change and have forced organizations to become responsive and flexible (De Felice et al., 2013).

Recent trends identified in the fashion industry are vertical integration and outsourcing, agile supply chains and quick response-systems. Within the fashion industry, companies increase their vertical integration in an attempt to increase efficiency, eliminate intermediaries and better understand customer needs. (Marchegiani et al., 2012) However, some companies also choose to outsource all production in an effort to enhance competitive advantage (Grant, 2013). Also, retailers and manufacturers have identified that collaboration leads to quicker product development, production and distribution, as well as higher profits. This approach has therefore been intensified in the industry. (Marchegiani et al., 2012) Moreover, according to Iannone et al. (2013) and Battista and Schiraldi (2013), an agile organization within an agile supply chain performs better than conventional organizational structures and forecast driven supply chains, which might not be capable of meeting the difficulties of the fashion e-commerce industry. In order to become more responsive to customer demand fashion companies have adopted different quick response policies. They have in other words enhanced abilities to quickly scale up or down to be able to respond to consumer preferences throughout the supply chain (Au & Chan, 2002; Choi, 2006). A quick response-system enables manufactures to adjust production of various colors, styles and sizes during the season. Hence, a higher responsiveness can partly substitute or support forecasting in an environment of high uncertainty (Nenni et al., 2013).

3.1.2 Challenges in the fashion e-commerce industry

A big challenge for fashion companies is products' demand characteristics (Lee, 2002). The products often exhibit short life-cycles due to the fact that products are designed to capture a certain moment and thus only is sellable in a short period of time, measured in months or even weeks. The short selling season is a result of the highly competitive fashion market, where it is of great essence to constantly refresh the product assortment in order to meet customers' demand. This has resulted in an extended number of seasons for retailers where entire product ranges frequently are replaced. (Soni & Kodali, 2010)

The demand of fashion products is, as stated earlier, associated with a lot of uncertainty. Customers' buying decisions are namely very impulsive where buying decisions very often are made at the point of sale. This is also true for web shops where customers click around and often buy products spontaneously. Meaning that, the customer, when confronted with the product is stimulated to buy it. It is therefore, at that specific point, a critical need for stock availability. The demand for these products is also rarely linear or stable. The demand is effected by numerous different factors, for instance weather, films, sport stars, pop stars etc. Hence, the demand is characterized by high volatility which makes it difficult to forecast. This is amplified by the tremendous product variety, which makes the demand highly fragmented. (Nenni et al., 2013)

Moreover, the large variance in demand in combination with a high number of stock keeping units (SKU) results in low volume of sales per SKU (Gutgeld & Beyer, 1995). In addition, the demand for SKUs within the same product line can vary significantly. Demand is in other words very hard to predict, even on an aggregated level. (Abernathy et al., 2000)

3.1.3 Critical lead-times in the fashion e-commerce industry

One way to cope with uncertainty is to improve the quality of the forecast. However, with the volatility of demand and the short life-cycles present in the fashion industry precise forecasts are difficult to create. Another way is to decrease lead-times within the supply chain, which can enable a more agile approach and decrease the uncertainty. There are three critical lead-times that are crucial for success in fashion markets; time-to-market, time-to-serve and time-to-react. (Christopher et al., 2004)

Since the fashion market is characterized by short life-cycles, the ability to quickly spot trends and translate them into products as quick as possible has become a criterion for success (time-to-market). Being slow to market has two outcomes. First, a major miss in sales opportunity is likely to occur. Secondly, due to the late market entrance the demand will start to fall and the supplier might end up with obsolete stock. The result of a late entry to market is depicted in Figure 3.1.

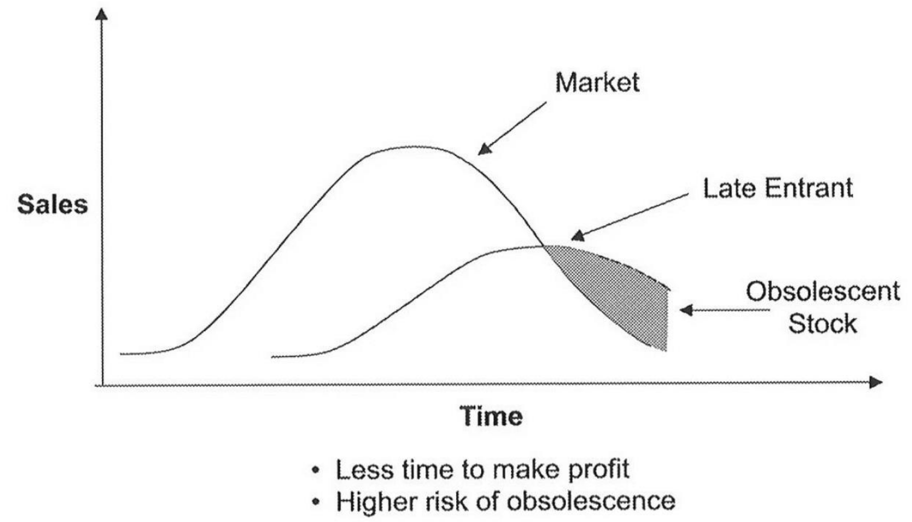

Figure 3.1 Result of late entry to market (Christopher et al., 2004).

Traditionally retailers place orders on suppliers a long time prior to the season starts (time-to-serve), which can be around nine to twelve months. Obviously this is problematic in a chaotic environment, which the fashion industry is. The risk for both obsolescence and stockouts is high as well as the significant inventory carrying cost incurred in the supply chain. This is a result of the underpinning philosophy of cost-minimization, which is present in the industry. The main costs, which are minimized, are production and shipping costs. However, the total cost of the supply chain stretches even further, down to cost of obsolescence, forced mark-downs and inventory carrying costs. (Christopher et al., 2004)

Finally, time-to-react has become a centerpiece in how to tackle the fast moving environment and to become more responsive. Organizations are typically slow in recognizing changes in the "real demand". Real demand is what customers are requesting right now, hour-by-hour or day-by-day. Clearly, there are some major contradictions in achieving this success factor. The underlying problem is that the time it takes to source materials, convert them into products and move them to the market place is far longer than what the customer often is prepared to wait. This gap of time is termed the "lead-time gap" and is the difference between the logistic lead time and the customer order cycle time. In general, this gap is filled with forecast based inventory to ensure product availability when the customer demands it. (Rushton et al., 2014)

3.2 Stock allocation of products

Stock allocation represents a retailer's last chance to meet customer demand, ensuring that products are at the right place, at the right time and for the right price. At stake are sales, profit margins and customer loyalty. In today's fast moving and uncertain fashion market where companies are fighting for market share, a carefully laid merchandising and stock assortment plan with allocation strategies that are just as pensive is vital for success. Retailers usually put the most effort into planning based upon last year's data. A truly optimized stock allocation is driven by demand potential rather than historical sales alone. Thus, a smart stock allocation is a combination of push and pull strategies. (Buxton, 2015) This section describes the push and pull concept, centralized vs. decentralized warehousing, inventory rebalancing and inventory pooling.

3.2.1 Push and pull

Design of logistics and inventory decisions is affected by the nature of demand and limitations of the supply chain. There are two main approaches, which literature often refers to, in how to handle the demand and uncertainties; *push* and *pull*. The *push* approach is when inventory is based upon the expectation of demand, which includes both known demand in the form of existing orders and forecasted demand. These forecasts are usually based on historical sales data. Difficulties arise when there is either a higher or lower demand than forecasted. The result is lost revenues from missed opportunities or higher inventory carrying and product obsolescence costs. The *pull* approach is based upon actual known customer demand, i.e. responding directly to customer purchases. The pull approach requires quick reactions to sudden changes in the market place and is useful when there are uncertainties in the demand requirements or order cycle time. (Rushton et al., 2014)

3.2.2 Centralized vs. decentralized warehousing

A distribution system consists of a certain number of warehouses. Distribution systems consisting of several warehouses on a local level is known as a high level of decentralization. There are mainly two advantages with this setup. Firstly, decentralization gives closeness to customers, which is important for products requiring short delivery time. Secondly, distribution costs are minimized, which can be advantageous when customers buy frequently and in small quantities. (Melachrinoudis, 2007)

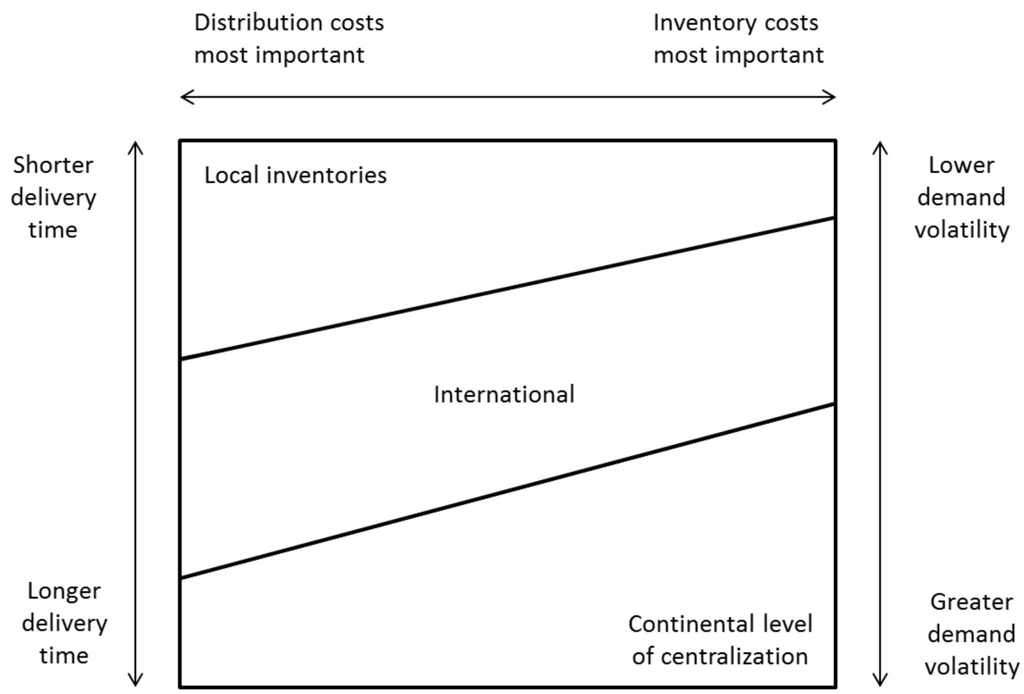

Figure 3.2 Tradeoffs between centralized and decentralized warehousing (Harrison & Van Hoek, 2008).

Systems with few warehouses are known as centralized. Centralization of warehouses has the potential of economies of scale and low holding costs. Moreover, centralization gives reduced risk of cascading effects, obsolescence, less total warehouse space needed and minimization of non-value adding activities. Also, according to Melachrinoudis (2007), the customer service level can be higher for the centralized setup, as it is easier to control products in stock and the stock availability is higher. On the other hand, the opposite is argued since a centralized warehouse can result in longer distance to customers and thus a lower service level if the transports are not fast and efficient enough (Ballou, 2004).

Additionally, inventory velocity can be increased due to warehouse consolidation (Melachrinoudis, 2007). The tradeoffs between centralized and decentralized warehousing is depicted in Figure 3.2.

3.2.3 Inventory rebalancing

An e-tailer encounters two decisions when having several warehouses; initial allocation of products prior to the selling season starts and, depending on the match of forecasted demand and actual demand, stock allocation during an ongoing season to rebalance the inventories between the warehouses (Agrawal, 2003). In the event of stockouts at a warehouse, the replenishment or rebalancing using a nearby warehouse may result in substantial improvements for the service performance of the e-tailer. Such shipments between warehouses are called (emergency) lateral transshipments. (Axsäter, 1990) In order to minimize costs in form of emergency transshipments, lost sales and low customer service level, a proactive inventory balancing is vital. Due to the availability of real-time sales data, such decisions regarding inventory balancing can be taken at the right time before a situation of stockouts is reached. (Agrawal, 2003)

3.2.4 Virtual pooling of inventory

Another way of minimizing lost sales due to an unbalanced inventory between warehouses is virtual pooling of inventory. Anupindi et al. (2001) define the concept as sharing of inventory between several warehouses so shortages of products at one warehouse can be satisfied from surplus at another. In many cases e-tailers assign customers to a selected warehouse depending on the location of the customer in order to fulfill sufficient customer orders. The basic idea of virtual pooling is that e-tailers can fulfill their customer demands even though the assigned warehouse is out of stock. Retailers with good IT infrastructure have the possibility to fulfill the customer order by delivering the particular product from another warehouse if needed. A well-functioning IT system enables the creation of a shipment from another warehouse with the selected product in stock, i.e. showing the customer the stock availability from more than one warehouse. However, delivering the product from another warehouse than the optimal one is not an ideal solution, as stated in the earlier section. The transportation and handling costs increase and the service level decreases in terms of longer delivery time.

An e-tailer therefore wants to avoid this situation by allocating products right from the beginning but virtual pooling gives some flexibility to the system if implemented. (Chhaochhria, 2007)

3.3 Pre-season stock allocation

For retailers with products characterized by short life cycles and high demand uncertainty, the initial stock allocation of products between warehouses can have significant strategic importance. This is especially true for fashion retailers such as H&M and Zara who introduce thousands of new articles each year. In addition, the initial shipment for the season is for many retailers the largest shipment. There is a high correlation between the quality of the initial shipment and the profitability of a product throughout its life cycle (Garro, 2011). Furthermore, the initial allocation is often the most challenging one, as the demand uncertainty is maximal. As the season proceeds more and more sales data is collected and demand patterns are better understood (See section 3.4). However, at that point poor initial allocation decisions might be too late to overcome. (Gallien et al., 2015)

Proper initial inventory management, which helps to balance supply and demand when allocating products between warehouses, is heavily dependent on accurate forecasts of future demand for the markets that the warehouses supply. A good pre-season forecasting method or strategy can help to avoid under- or overstocking during season, which further affects other critical operations of the whole supply chain, such as production planning, achieving high customer service level, pricing etc. (Liu et al., 2013) The following sections first describe the main characteristics which needs to be considered in the design of a sales forecasting system for the fashion industry. Thereafter will different sales forecasting models and strategies be presented and evaluated from the perspective of the fashion industry.

3.3.1 Forecasting demand in the fashion industry

Several papers in literature have examined the effects of forecasting on supply chains. In general, for companies using a push flow supply chain, sales forecasting is proved to have a substantial impact for the supply chain management. Researches have also demonstrated that reductions in forecast errors lead to improvements in supply chain performance, by for instance reducing the notorious bullwhip effect. (Bayraktar et al., 2008; Fildes & Kingsman, 2010; Zhao, Xie & Leung, 2002; Lee, Padmanabhan & Whang, 1997) Below follows the main characteristics which needs to be taken into account when constructing a forecasting model or strategy for the fashion industry.

One of the most important features of the forecasting system is the forecast horizon – the longer the horizon, the more data for the supply chain to work with, but the higher are often the errors of the forecast. Different forecasting methods have to be used according to the considered horizon. (Thomassey, 2014)

Another main characteristic which should be taken in account when designing a sales forecasting system for the fashion industry is the products' life cycles. When considering a product's life cycle in general it is often composed of four phases: a launch, a rise, a maturation and a decline phase. However, the life cycles of products in the fashion industry are very often quite short, as also was discussed in section 3.1. Especially compared with their long supply processes. (Choi, 2007; Nenni, 2013) Due to the high variety of products within a typical fashion retailer firm, there are big differences in terms of products' life cycles. It would therefore be too simplistic to assume that all of them have the same "behavior" and consequently can be forecasted using the same method. Apparel products should therefore be differentiated according to the nature of the items. Three common groupings of items are: (Thomassey, 2014)

- Basic items – sold throughout the year (e.g. denims) or each year (e.g. basic white T-shirt)
- Fashion/New items – sold punctually during a short period and generally not replenished during season
- Best selling items – sold each year with slight modifications in line with present fashion trends and could be replenished during season

"Basic items" and "best selling items" are, in terms of forecasting, commonly considered in the sales forecasting system, while "fashion/new items" often are forecasted outside of the traditional forecasting process and has specific forecasts. This is especially true for "fast fashion" brands, such as Zara. (Thomassey, 2014; Caro & Gallien, 2010)

Next to the many differences in the products' life cycles, the product variety is heavily increased and complicated by the many styles, colors and sizes that each product or article is offered in. This further aggravates the management of stock keeping units and consequently also the forecasting design. (Liu et al., 2013) This huge variety, a changing reference for each collection and short life cycles require the fashion industry companies to aggregate the sales data in order to create functioning forecasting methods. Selection of the right level and the right criteria for the aggregation is then the main concern. Classification methods include both quantitative and qualitative approaches. However, most companies prefer to aggregate their sales data according to their internally used hierarchical classification of the topology of products. (Correa, 2007) An example of a common aggregation by topology of products is depicted below in Figure 3.3:

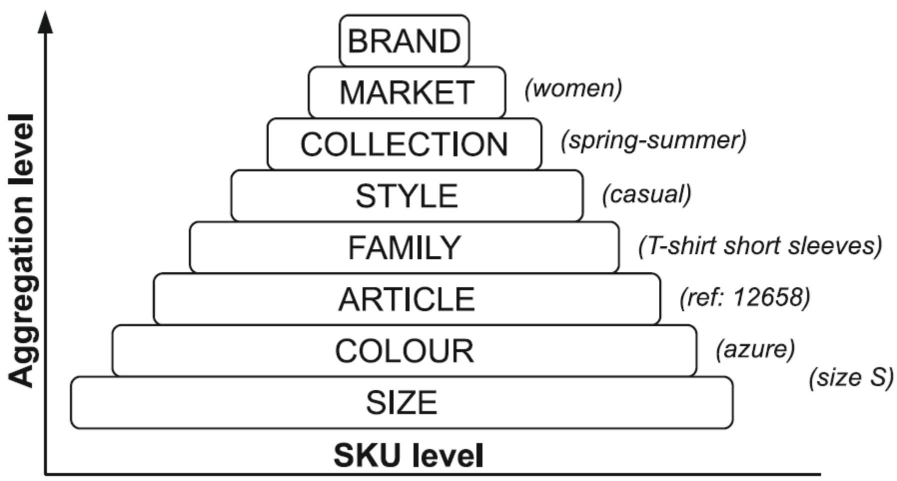

Figure 3.3 Data aggregation by topology of products (Thomassey, 2014).

The most suitable level to aggregate on depends on the type of demand forecast method. Forecasts based on for instance time series techniques often use historical demand data from the "family" level as data from several years back then is needed. Data on the SKU- or size-level is in that particular case not possible since historical data won't be available for most of the articles or products. Forecasts made on a lower aggregation level is on the other hand often more accurate given that historical demand data is available. (Thomassey, 2014)

A fourth important feature which has to be considered for every time series analysis is the effect of seasonality. Its impact on sales forecasting has been thoroughly studied in literature (Chatfield, 2013; Franses, 1996; Hylleberg 1992). Seasonal variation in the fashion industry is however special since some items are much more sensitive to seasonality than others. Take for instance the difference in seasonal variation between common underpants and short sleeve T-shirts, as depicted in Figure 3.4. Underpants are not very sensitive to seasonal variations while short sleeve T-shirts exhibit much more periodic fluctuations with sales peaks during the summer periods. The effects of seasonality should consequently be more or less integrated in the forecasting method depending on a certain cloth's sensitivity to seasonal variations. (Thomassey, 2014)

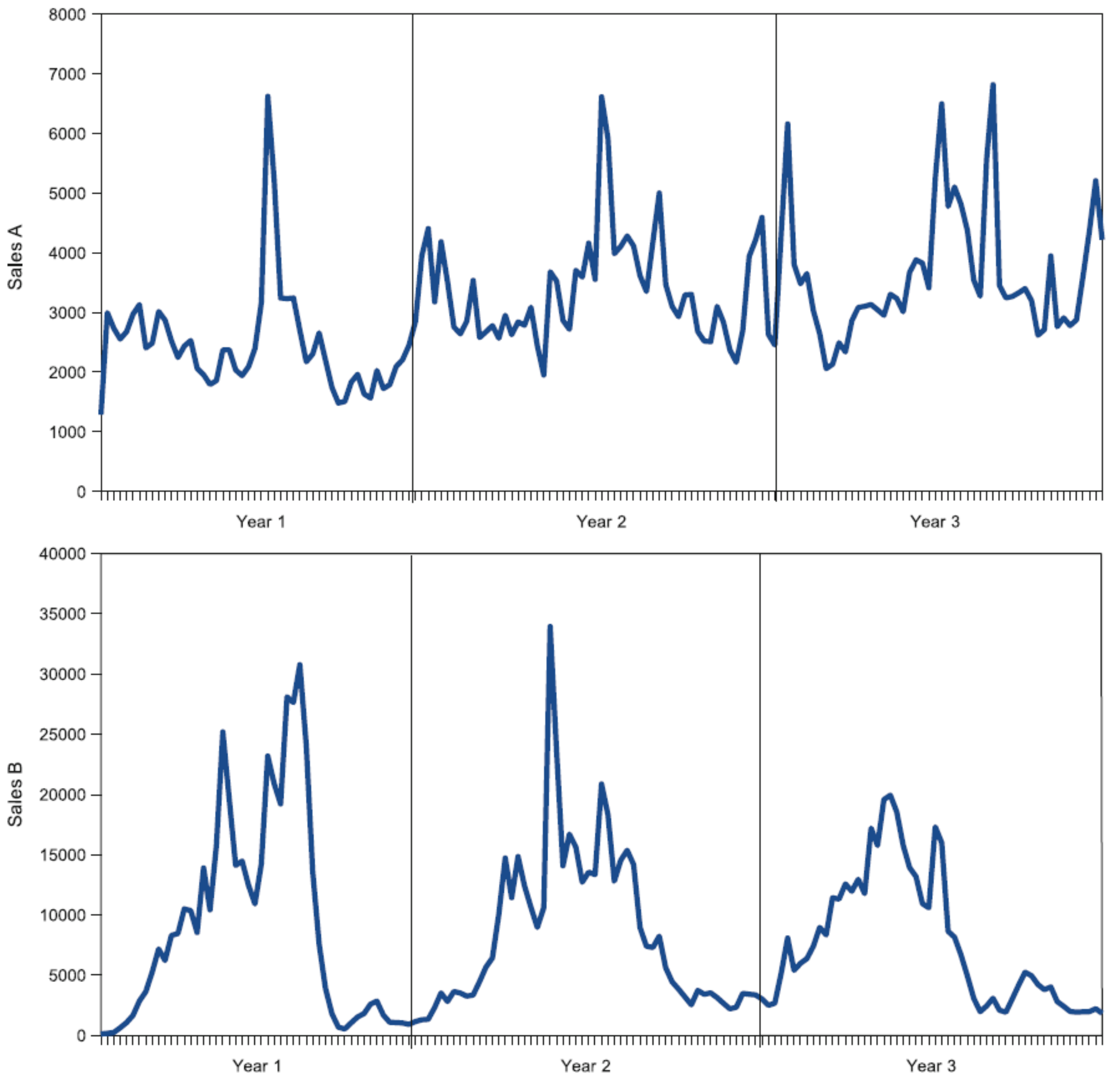

Figure 3.4 Seasonal variation of common underpants' (A) and short sleeve T-shirts' (B) sales (Thomassey, 2014).

A fifth characteristic which should be taken into account when designing a sales forecasting system for the fashion industry is the use of historical sales data. It is vast and often used as the historical demand data input in sales forecasting. However, it is not demand data. It is rather the portion of the demand that the e-tailer is able to capture by projecting demand and allocating products accordingly. This captured demand can be very different from actual or true demand in situations where stockouts "decide" what is available or not. The initial sales data, during the first couple of weeks, has a lower possibility to be affected by stockouts. Consequently, initial sales data gives a more accurate picture of the real demand. (Garro, 2011) For instance, consider a product that sells evenly throughout a ten-weeks period. If supplies of that product run out at the end of the eighth week, it is logical to assume that the retailer could have sold 25 percent more than they had available. (Hammond et al., 1994) There are different methods to estimate true demand which can be read more about in the articles written by Jain, Rudi and Wang (2014), Nahmias (1994) and Caine and Plaut (1976). Fashion companies often also have clearance sale at the end of the season in order to free inventory space for new products the upcoming season. The demand data from clearance sale weeks is however not considered as true demand but is instead a result of poor demand forecasting creating excess inventory. (Hammond et al., 1994)

Several factors or variables have a large impact on the sales in the apparel market and make the sales very fluctuated. These factors are often called explanatory variables and are in some cases uncontrolled and in some cases even unknown. Some of the variables affect customers' purchasing power/decisions and others drive traffic to the stores (both physical and online stores). Identification and quantification of the factors' impact on demand is often very difficult to control. (Nenni, 2013) Figure 3.5 describes a non-exhaustive list of variables which often is considered by marketing experts for their impact on purchasing decisions and/or store traffic. (Little, 1998) When constructing the forecast, practitioners have to be aware of the explanatory variables as they are essential to model the apparel sales. The ones with the highest impacts should also be integrated if possible. As the explanatory variables are many it won't be possible to create an exhaustive list. Data for some variables are neither not always available such as competitor and weather data and consequently cannot be a part of the forecasting model. (Thomassey, 2010)

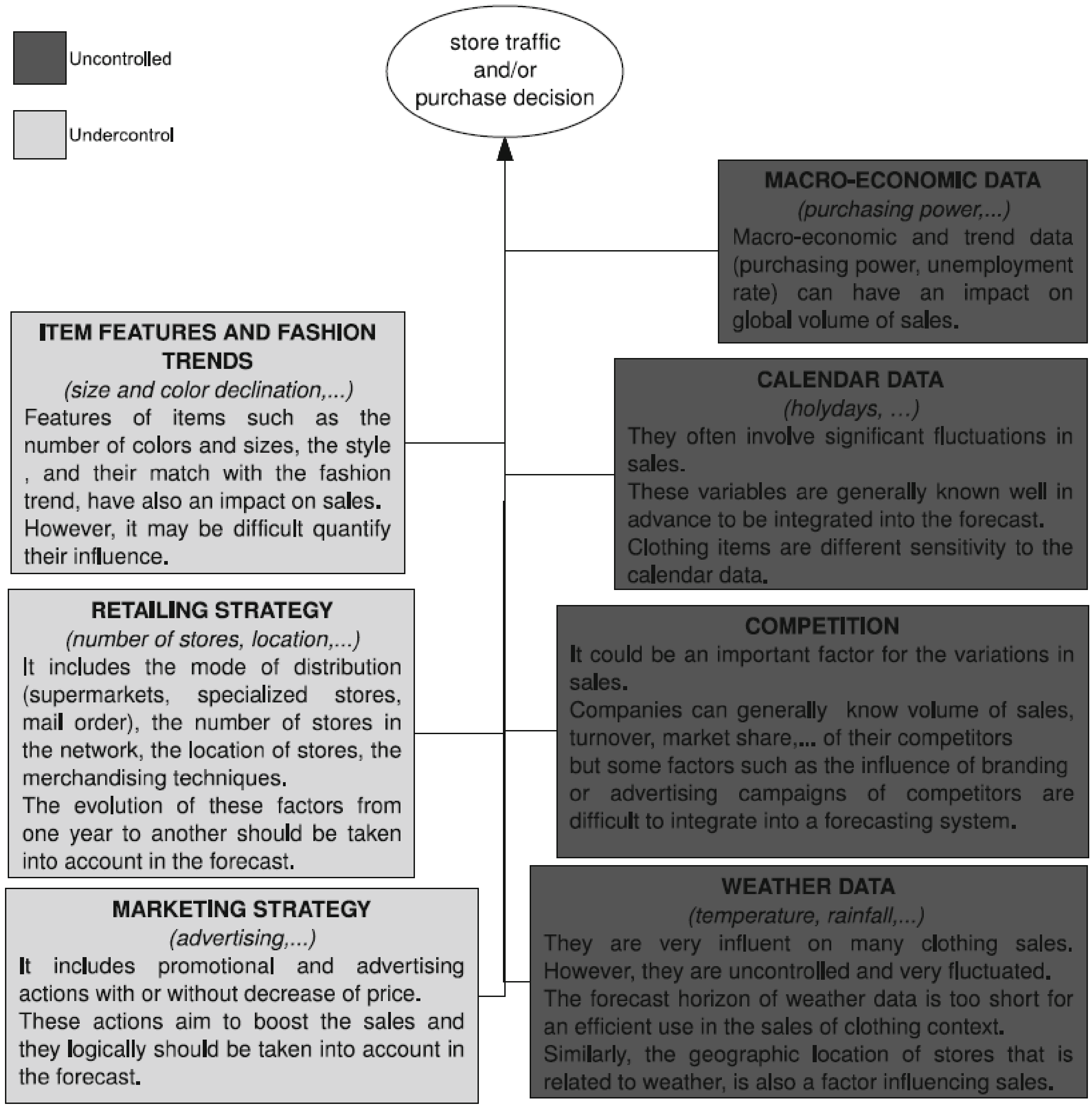

Figure 3.5 Exogenous variables related to the sales of apparel items (Little, 1998).

3.3.2 Forecasting methods for the fashion industry

Forecasting methods for the fashion retailing industry can, according to Liu et al.'s (2013) literature review, be divided into statistical fashion sales forecasting methods, artificial intelligence (AI) fashion sales forecasting methods and hybrid methods for fashion sales forecasting. These three types and their advantages and drawbacks are conceptually described below.

3.3.2.1 Statistical fashion sales forecasting methods

Fashion sales forecasting has traditionally been done through the usage of statistical methods, i.e. times series forecasting methods. Different statistical methods have been used through the years and include linear regression, moving average, weighted average, exponential smoothing (used when a trend is present but not linear), exponential smoothing with trend, double exponential smoothing, and so forth. (Liu et al., 2013) According to Box et al. (2008), statistical time series analysis tools such as ARIMA (Autoregressive integrated moving average) is also often used in sales forecasting as they are easy to implement and time-efficient in terms of run time. Thomassey et al. (2003) use item grouping to study sales forecasting accuracy for new products and find that more product families and pertinent grouping criteria should be used to improve the forecasting precision. The methods mentioned above together with other pure statistical forecasting models have been implemented in different areas and they have provided satisfactory results. However, their precision heavily depends on the field of application and as the fashion industry is quite unique in terms of demand pattern, there are some issues with this type of forecasting technique. (Thomassey, 2014)

Even though being widely used due to ease-of-use and relatively short calculation time, statistical methods have some shortcomings from the perspective of the fashion industry. First of all, it requires expert knowledge to choose the right statistical methods. Secondly, apparel sales are affected by several variables such as seasonal variations, fashion trends, and other sometimes stochastic factors (as explained in section 3.3.1), implying that a pure statistical method might fail in its forecasting. (Liu et al., 2013) Most of the time series forecasting methods also require larger historical data sets from several seasons back in time and are often also limited to linear structures. (Thomassey, 2014)

3.3.2.2 AI and hybrid fashion sales forecasting methods

In order to improve the fashion retail forecasting AI based methods have been developed in parallel with the strong improvement in computer technology. AI methods can derive arbitrarily nonlinear relationships directly from a data set, which makes them more accurate compared to statistical forecasting methods. Commonly employed methods in literature are artificial neural network (ANN) models and “fuzzy logic models” and they are the first ones used for fashion sales forecasting. Both models show satisfactory results and can be read more about in literature. (Liu et al., 2013) However, both models are also time consuming due to the fact that they are utilizing gradient-based learning algorithms. Extreme learning machine (ELM) based models have therefore been developed which are faster. These models are on the other hand quite unstable since they can produce different results in each different run using the exact same variables. (Choi, Hui & Yu, 2011)

Both statistical and AI based methods have advantages and drawbacks which are more or less suitable for fashion sales forecasting. Consequently, various hybrid models have been established to exploit the strengths of different methods. They are therefore considered to be more suitable also to fashion sales forecasting compared to pure statistical and AI methods. Hybrid models which are studied in the fashion forecasting literature often integrate or combine the fuzzy model, ANN and ELM with statistical methods. These different hybrid models can be read more about in literature. (Liu et al., 2013)

3.3.2.3 Forecasting methods applicable for the fashion industry

Based on the main characteristics which needs to be taken into account when designing a sales forecasting system for the fashion industry (as described in section 3.3.1) and the above described forecasting techniques, the perspective on applications and real-world implementation in the fashion industry is briefly touched upon below.

The two main categories of item types to be forecasted are existing items and new items (as explained in section 3.3.1). Prediction of new items is more difficult due to lack of historical demand data. There are not too many articles that have been exploring new item forecasting in the fashion industry but one of them is Thomassey, Happiette and Castelain (2003), who argue for an item classification approach. Zara instead tries to identify a comparable item sold last season which is similar to the new item and thereafter forecasts the demand for the new item by mainly using the comparable item's historical demand data (Gallien et al., 2015). Despite the many developed advanced forecasting methods available in literature, few of them actually are used in today's fashion industry. That is especially true for advanced forecasting methods implemented in commercial software. The main reason is that practitioners want and need to keep control of their forecasts. Companies often do not want to let a "black box" be in charge of the forecasting as it is such a crucial operation. Due to this understanding- and interpretation-issue apparel firms often develop and implement their own customized forecasting systems, which generally achieve acceptable results. (Thomassey, 2013)

3.4 In-season stock allocation strategies

The fashion industry is dynamic, as mentioned several times before, and is highly affected by the ever-changing market trend and consumer needs. As fashion retailers and e-tailers face a high level of demand uncertainty from multiple sources pre-season forecasts have a high risk of being wrong. As a result fashion e-tailers need to conduct demand forecasts for their products in response to real-time requests by customers during season. By using more real-time data and quick response fashion e-tailers can optimally rebalance or adjust inventory in the warehouses during the ongoing seasons, which is referred to as "in-season stock allocation". (Choi et al., 2014) This section describes different in-season stock allocation strategies.

3.4.1 In-season demand data

In an article, written by Fisher and Raman (1996), analyzing a major skiwear firm, the authors conclude that observing a portion of demand in season improves the forecast accuracy. This improvement is illustrated in Figure 3.6 and 3.7. They also observe that a quick response to the in-season sales data increases the profits and reduces the costs of stockouts and excess inventory, see section 3.4.3.

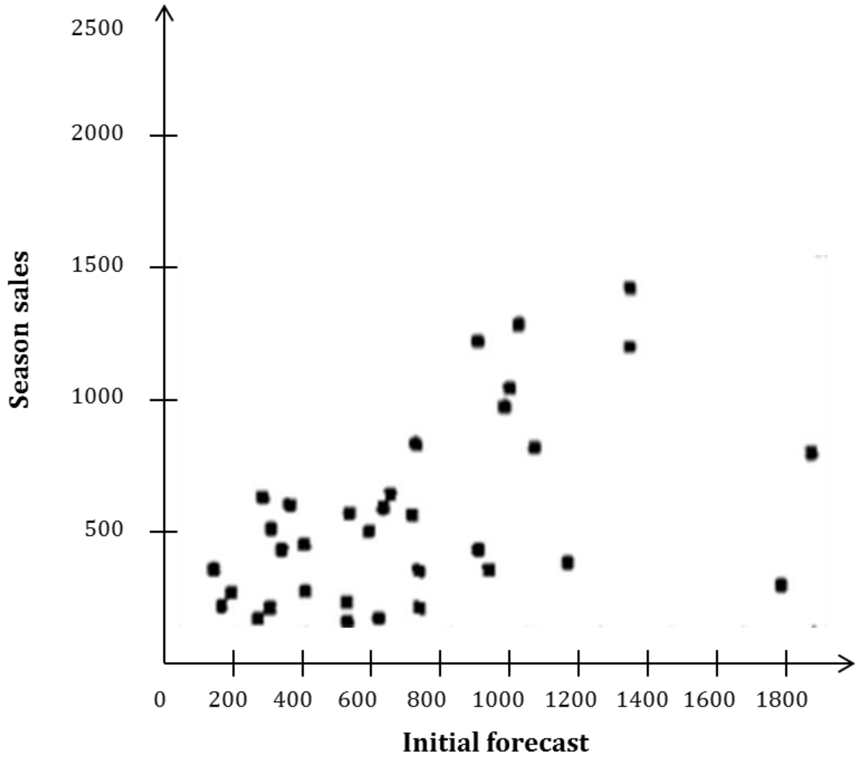

Figure 3.6 Season sales versus initial forecast (Fisher & Raman, 1996).

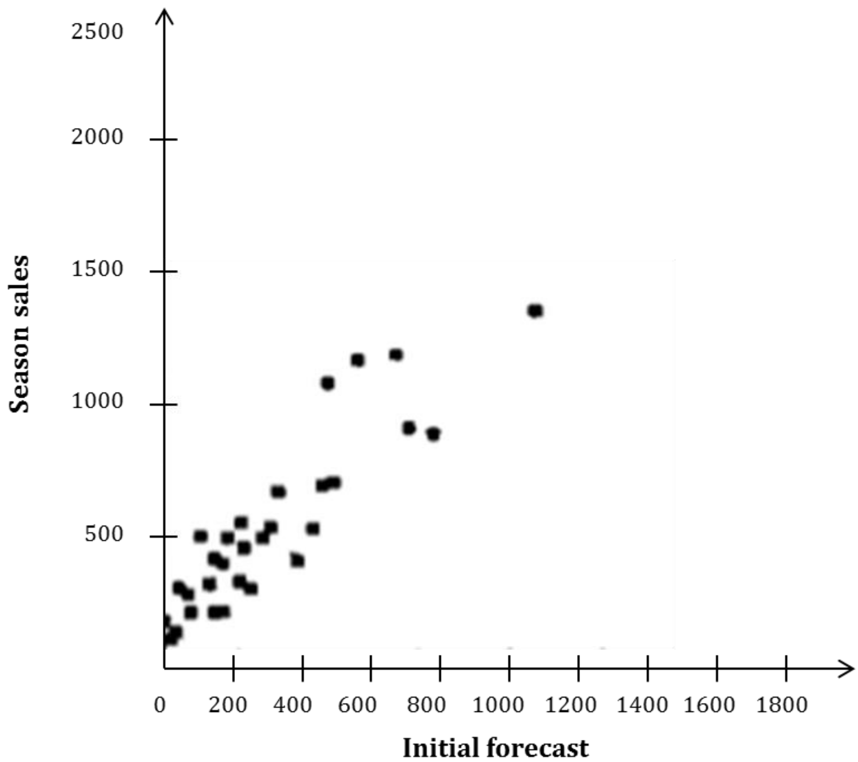

Figure 3.7 Season sales versus revised forecast based on first 20 percent of demand (Fisher & Raman, 1996).

3.4.2 The challenge of short-term forecasting

The forecast horizon is, as explained in section 3.3.1, one of the most important features of the forecasting system and according to Liu et al. (2013), the described forecasting methods in section 3.3.2 are suitable for middle- and long-term forecasting. Short-term and very short-term forecasting (such as real-time based forecasting) have on the other hand not been as widely studied in literature as middle- and long-term forecasting. Given the nature of the fashion industry, this sort of relatively shorter forecasting is crucial for in-season stock allocation and other supply chain-related operations. Liu et al. (2013) argue that speedy statistical models combined with a fuzzy logic based model into some kind of hybrid can be suitable for real-world implementation of a very short-term sales forecasting system. There are however also other strategies, besides forecasting and the use of in-season demand data, for coping with the issue of short-term forecasting and in-season stock allocation – see below.

3.4.3 Postponement of stock allocation

Postponement is a strategy intended to maximize possible benefits and minimize risk and uncertainties by delaying further decisions until the last possible moment. The logic behind postponement is that risk and uncertainty costs are tied to the differentiation (place, form and time) of goods that occurs during manufacturing and logistics operations. To the extent that parts of the manufacturing and logistics operations can be postponed until final customer commitments have been obtained, the risk and uncertainty of those operations can thus be reduced or eliminated. The concept of logistics postponement is to maintain a certain amount of anticipatory inventory at one or several strategic locations. It consequently means to postpone changes in inventory location downstream in the supply chain to the latest possible point. (Pagh & Cooper, 1998; Grant, 2013)

In order to optimize stock allocation and postponement one must truly understand the products' lifecycles, especially for products with short lifecycles. Some fashion products just have approximately six- to eight-weeks lifecycle and the inventory often arrives at the retailer's warehouse in only one delivery. Even though an initial allocation logic has been used in advance to determine which warehouse has the best chance of selling the products at full price, retailers should give themselves some wiggle room. When it is possible retailers should therefore use a postponement strategy. Collecting sales data during some weeks will give the retailers and e-tailers knowledge about how well the initial allocation is working. To postpone some inventory instead of pushing it all at once enables retailers to adjust the result of the initial stock allocation model, taking into account shifts in buying behaviors and demand patterns from what was predicted. To allocate products based on demand is highly appropriate as it is costly to move products between warehouses. Once stock is in the wrong place its more likely to be marked down while other warehouses lose out on sales. (Buxton, 2015)

3.4.4 Quick response

Quick response is a strategy that enables fashion retailers and e-tailers to postpone the ordering decision and improve the initial demand forecast based on more accurate market information. Using quick response, they can react quickly to market preference changes, by shortening production lead times and adopting efficient inventory replenishment policies (Choi and Sethi, 2010). As an example, Zara are one of the pioneers in the fast fashion retailing industry and is able to offer trendy fashion products from conceptual design to ready-to-sell merchandise in just two weeks' time. The firm has in other words been able to substantially cut its lead times. In addition, Zara are capable of providing two replenishment shipments to each worldwide store every week. Zara also adopt both forecasting practices and optimization models to enhance and simplify the entire process. (Caro & Gallien, 2010)

4. Empirical information

In this chapter the empirical findings from the case study of H&M Online are presented. It consists of general background information about the firm, its products and more specific description of the logistics at H&M Online.

4.1 H&M Online background

The year 1998 H&M started to sell products in the Nordics over the Internet and have since then rapidly expanded in both sales volume and new markets. H&M Online are today present in 32 countries worldwide, see Figure 3.1.

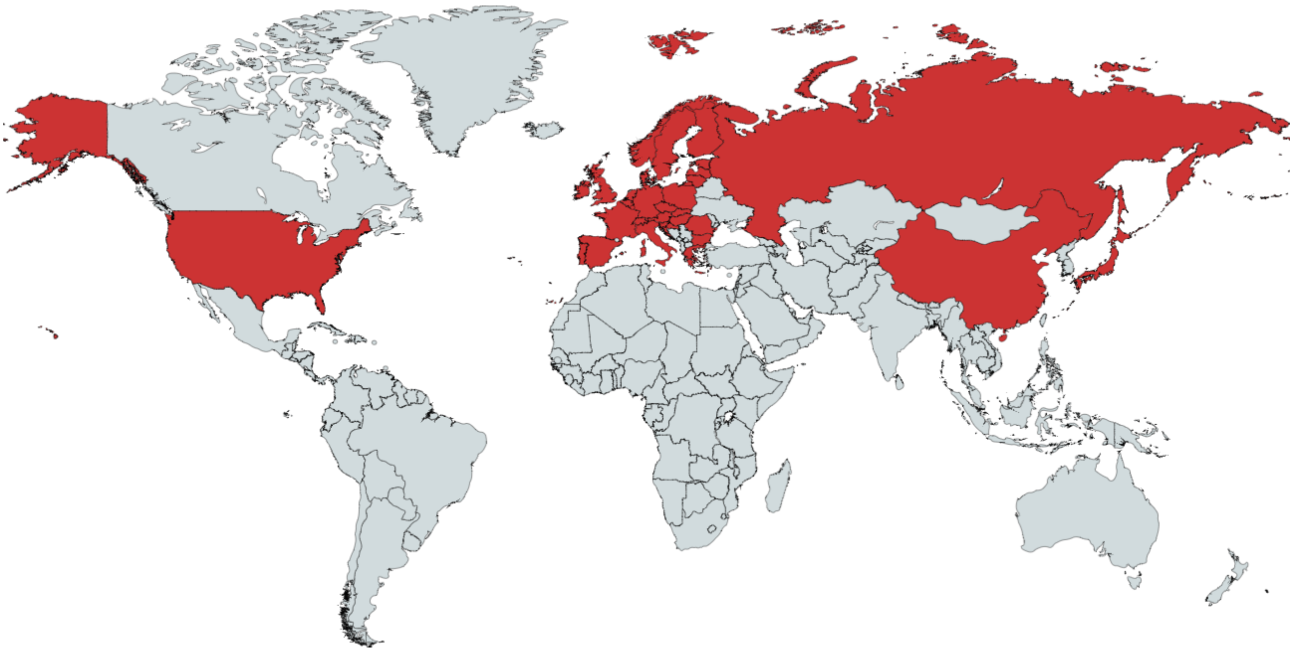

Figure 3.1 H&M Online's market presence.

H&M Online divide their 32 markets into different larger groups which they name "planning markets". The planning market of interest in this Master's thesis is the Central Europe planning market which consists of the markets Germany, Austria, the Netherlands, Sweden, Denmark and Finland. This planning market is sourced by a warehouse in Poznan, Poland through which all products are delivered from the suppliers. Products are mainly supplied by producers in Asia and Turkey, and thereafter transported to Poznan to be sold on the Central Europe planning market. The smaller local warehouse in Sweden is sourced by the major warehouse in Poznan.

Products offered in the different markets are more or less the same with few national specific products. The printed catalogue is also the same in all markets where it is offered. Moreover, H&M divide the year into two seasons, spring and fall. The spring season is set from December to July and the fall season runs from July to December. Prior to a season, H&M Online set a commercial plan. The commercial plan consists of different sales driving activities. The activities include especially catalogues, campaigns and assortment releases. H&M launch several different catalogues during a season, which also are presented on the website. The different catalogues are of different sizes where two of them, the main catalogue and midseason catalogue, display the majority of the articles. The main catalogue, which is released in the beginning of the season, includes around 30 percent of all articles during a season. The midseason catalogue displays about 20-25 percent and is released in the middle of a season. All products sold at H&M Online are linked to one or several activities, meaning that the products then will be displayed during these activities and consequently be part of an increased marketing towards customers. Products which have not been successful enough are often put on discount by the merchandisers. The discounts are often bigger at the end of each season, especially the last two weeks.

H&M's business concept is defined as "Fashion and quality at the best price in a sustainable way". The company ensures the best price by in-house design, no middlemen, large purchasing volumes, buying the right products from the right markets, efficient logistics and cost-consciousness in all parts of the organization. Another important element for H&M is sustainability where they devote considerable resources. (H&M, 2016)

4.1.1 Product hierarchy

H&M Online provide thousands of different products, which are organized according to Figure 3.2. First off, the products are divided into ten divisions, where one division represents one product category. H&M's product divisions are the following; Men, Ladies, Ladies selected, Ladies accessories and cosmetics, Boys, Girls, Baby, Divided, White room and Home. Further, these divisions contain on average five sections each, where one section equals one product line, i.e. customer style (e.g. sporty, suited etc.). One section is then separated into different departments, including different clothing categories such as pants, jackets, dresses etc. Each department contains several different models. Lastly, the products are differentiated into color and size. This decomposition represents H&M's product hierarchy. H&M Online offer approximately 80.000-100.000 SKUs during a season.

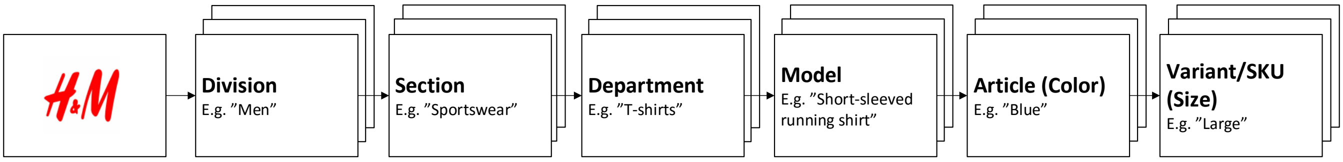

Figure 3.2 H&M's product hierarchy.

4.2 Supply chain overview from design to end customer

The supply chain serving H&M's ecommerce business is managed separately from the firm's physical retail store network. Before reaching the end customers products have been transferred through several processes adding more or less value to the final product delivery. An overview of H&M Online's current supply chain steps are depicted as a flow chart in Figure 3.3. More details about the different steps are described below the figure.

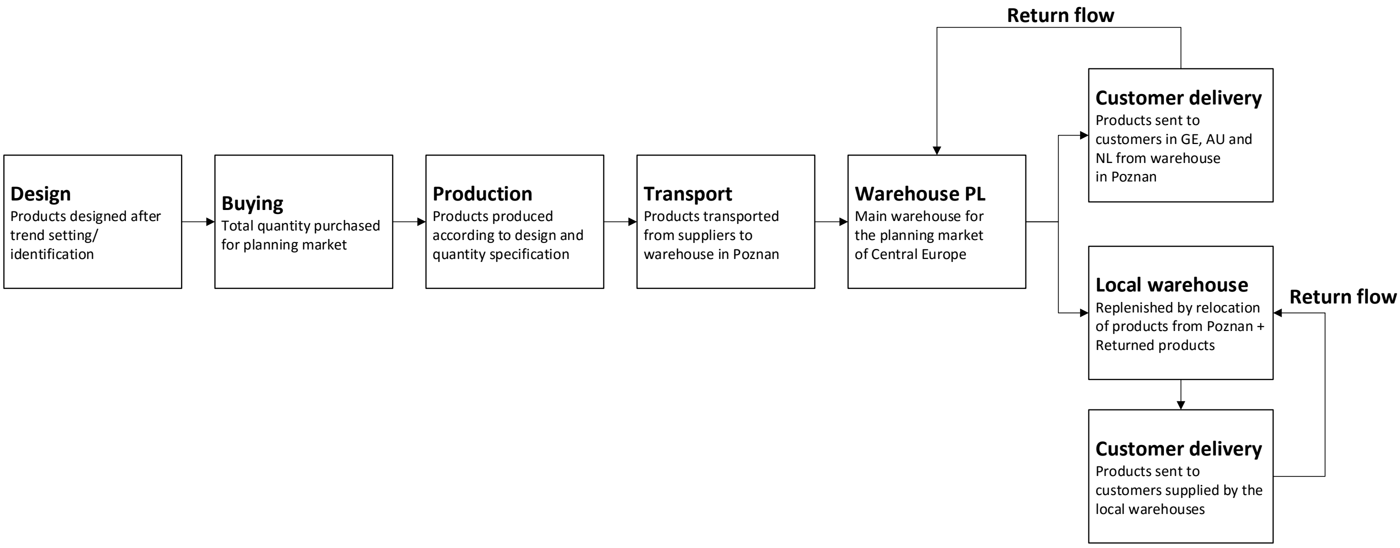

Figure 3.3 Overview of the current supply chain of Central Europe planning market.

4.2.1 Design and buying

Products sold at H&M are in a first stage designed for a specific season by designers who try to identify and/or set the upcoming trends. The collection design often starts one year ahead of the actual release. As products are continuously being designed, the buying office at H&M starts to analyze the garments and estimates a total quantity for each product to be sold at the different so called planning markets for the upcoming season. The reason to why the buying office quantifies the products to be sold for such a big region is due to the difficulty of forecasting the demand for smaller individual markets. Market experts also set sales targets per country, i.e. how much more will H&M Online be able to sell of all products in each country.

The quantification or forecast made by the buying department is mainly based on the commercial plan, historical sales data (when possible) and countries' economic situation. The initial forecasts are made on department level, meaning that the buying department determines the total quantity to be purchased for each specific department. Each department is then responsible for setting/forecasting the quantity for the models included in a specific department.

4.2.2 Production and transport

The production of the designed products is outsourced to suppliers of garments in mainly Asia and Turkey. Production lead time varies and can range between two weeks and six months depending on material and product complexity. Since the bulk of the products is produced in Asia (approximately 80 percent) lead time to Poznan is quite substantial with an average transportation time of six to eight weeks. The transportation time from suppliers in Turkey is around two to six days. A more detailed view of the logistic process is illustrated in Figure 3.4, showing the flow of goods from suppliers to end customers. As depicted in the figure the suppliers often produce a quantity of products that is not enough to entirely fill a whole container (Less than container load - LCL). The packages are therefore sent to a consolidation terminal close to a port, where containers are fully loaded with packages of garments from several different suppliers (Full container load - FCL). The containers are thereafter sorted and marked at the terminal according to the intended destination warehouse. The sorted containers are then loaded onto vessels and shipped to the port of Gdansk or Gdynia via Hamburg, from where the products are transported to the warehouse in Poznan.

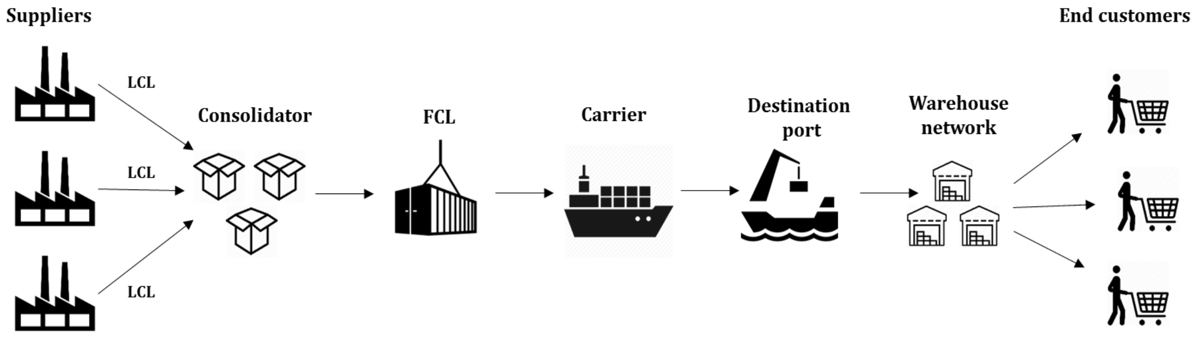

Figure 3.4 Logistic process from suppliers to end customers at H&M Online.

4.2.3 Warehousing and replenishment

The warehouse center in Poznan gets daily deliveries from suppliers and some percentages of each procurement order is controlled during a quality inspection procedure in the warehouse. Products arrive in Poznan in boxes where each box only contains one type of SKU/variant from a specific supplier. Once inside the warehouse boxes are stored in a buffer storage area before being allocated to the other local warehouses in the Central Europe planning market or being picked and sent to customers in Austria and Germany.

The product flow to the warehouse in Poland is a push flow where garments, as described above, are produced to stock and supposed to cover the demand for the planning market of Central Europe. 50-60 percent of the total seasonal products arrive in Poznan at the beginning of a specific season, as the first catalogue is released. The remaining garments arrive during the rest of the season, especially right before the mid-season catalogue is released. Some products are only delivered from suppliers once while other products have several deliveries throughout the season. The total bought quantity from suppliers is in the latter case split into several deliveries and spread out during the season.

The local warehouse in Borås is, as mentioned before, part of the planning market of Central Europe and is consequently sourced by the warehouse in Poznan. It takes around six business days for garments to be picked and packed in the Poznan, transported to Borås and being sellable for customers on the website.

4.2.4 Future hypothetical warehouse network setup

As H&M Online grow rapidly throughout Europe, the warehouse setup needs to grow with it in order to secure inventory. H&M Online are planning to build a new warehouse in Slovakia to support the growing demand and to relieve the operations of the warehouse in Poznan (see hypothetical warehouse setup in Figure 3.5). Another reason is to spread the risks, as placing all inventory under the same roof can be risky in the event of an accident. The reason to why the new warehouse will be located in Slovakia is mainly due to operational costs. In the future warehouse setup the warehouses in Poland and Slovakia will share the responsibility of supplying the growing German market, which also happens to be H&M's largest market. Using two warehouses will also enable H&M to reach a crucial goal of theirs, delivering products to all customers within 1-2 days in Germany. The local warehouse in Sweden will still be supplied by the warehouse in Poznan and it will also deliver products to Norwegian e-commerce customers. Moreover, the warehouse in Slovakia will take over the responsibility of serving customers in Austria.

Figure 3.5 Hypothetical warehouse setup for the planning market of Central Europe.

4.2.5 Distribution to end customers and returns flow

As previously stated, the material or product flow to the warehouses is a push flow since products are produced to stock. The decoupling occurs first when a customer places an order on different product variants or SKUs. As each order is customized, the product flow from the warehouse to the customer can be seen as a pull flow. Products are in other words picked to assemble a specific customized order and then delivered to the customer.

Sales statistics from 2015 are presented in Figure 3.6 below, showing the distribution of sold pieces per market included in the planning market of Central Europe. Sales and return data from 2014-2015 for all H&M Online's SKUs are presented in Appendix 1.

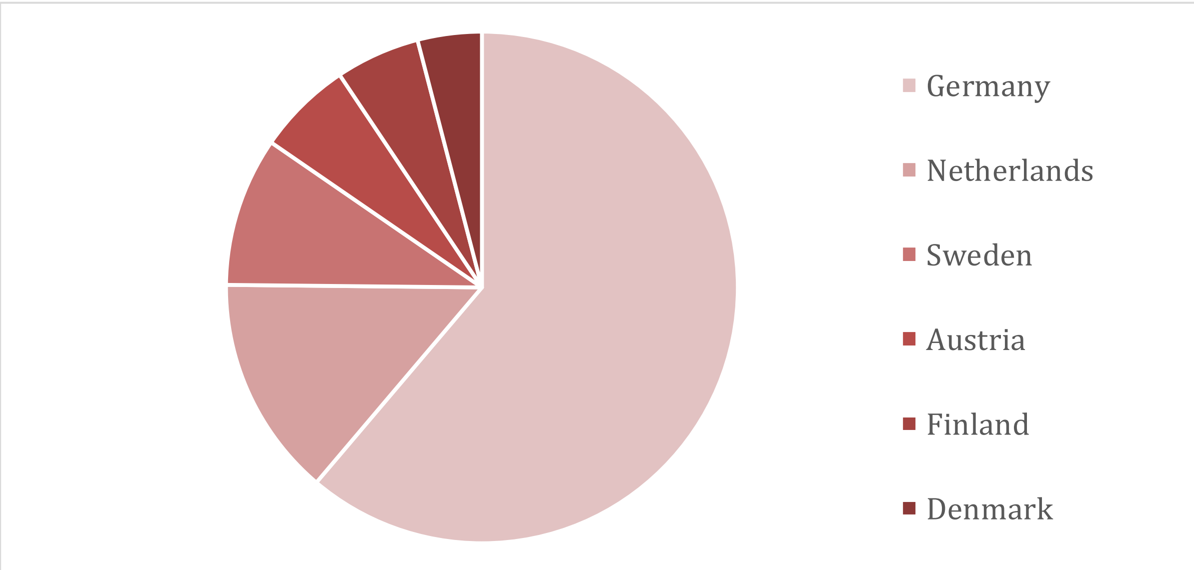

Figure 3.6 Distribution of sold pieces on the Central Europe planning market 2015.

The delivery time and price for a certain customer order differ between H&M's various online markets but normally ranges between 3-5 days for the Central Europe planning market, see Figure 3.7.

	Germany	Austria	Netherlands	Sweden	Denmark	Finland
Standard delivery	3-5 days 4.90 EUR	3-5 days 5.75 EUR	3-5 days 4.90 EUR	3-5 days 39.90 SEK	3-5 days 44.90 DKK	3-5 days 8.00 EUR
Return	Free	1.00 EUR	1.00 EUR	36.90 SEK	40.50 DKK	Free

Figure 3.7 Delivery times, delivery prices and return prices for the Central Europe planning market 2016.

The reverse logistic process is initiated by an online customer choosing to return its products to H&M. This push-based flow of products is quite common as H&M Online's business model "Find-Try-Buy" encourages its customers to return bought garments. As the return flow is substantial for the e-tailer it accounts for a large part of the replenishment of the warehouses. Returned products are currently sent to the warehouse it was delivered from, where the garments are repacked and sold again after being approved in a quality inspection. The return statistics for the markets included in the Central Europe planning market are shown in Figure 3.8.

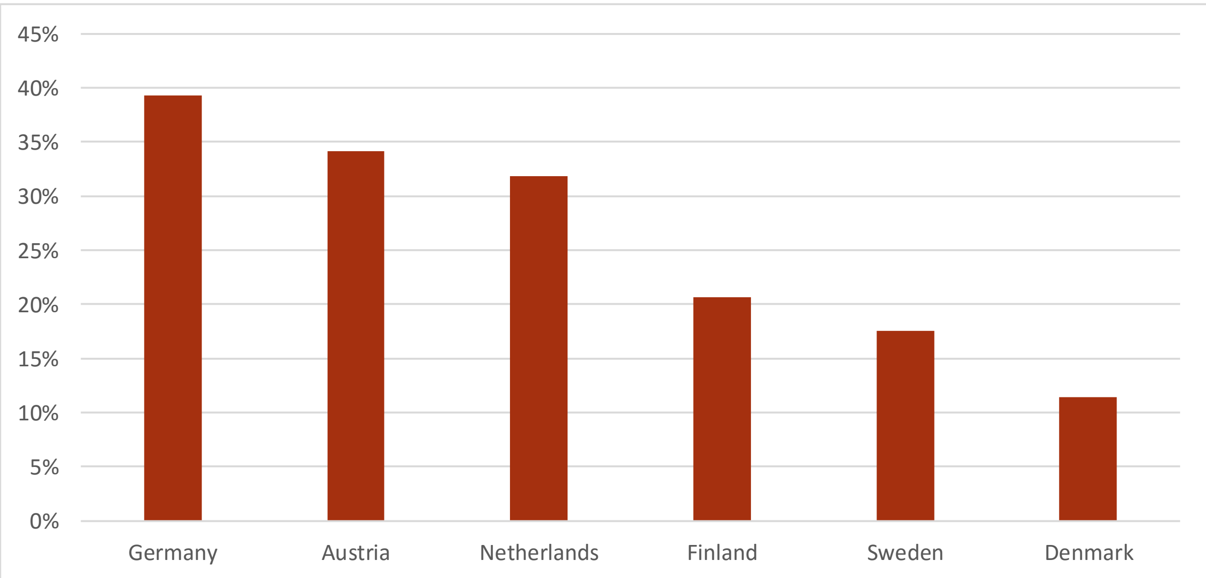

Figure 3.8. Return statistics for markets in the Central Europe planning market 2015.

4.3 Shopping at H&M Online

Customers on all markets that H&M Online are present in have the possibility to buy products through the website or by phone. All product types available for purchase at the online store are displayed for the customer at H&M's homepage. This initial view has no information regarding availability on color- or size-level. The color- and size-level availability are instead displayed first in the model specific view (see Figure 3.9). Products out of stock are not displayed on the web shop and cannot consequently be bought by online customers.

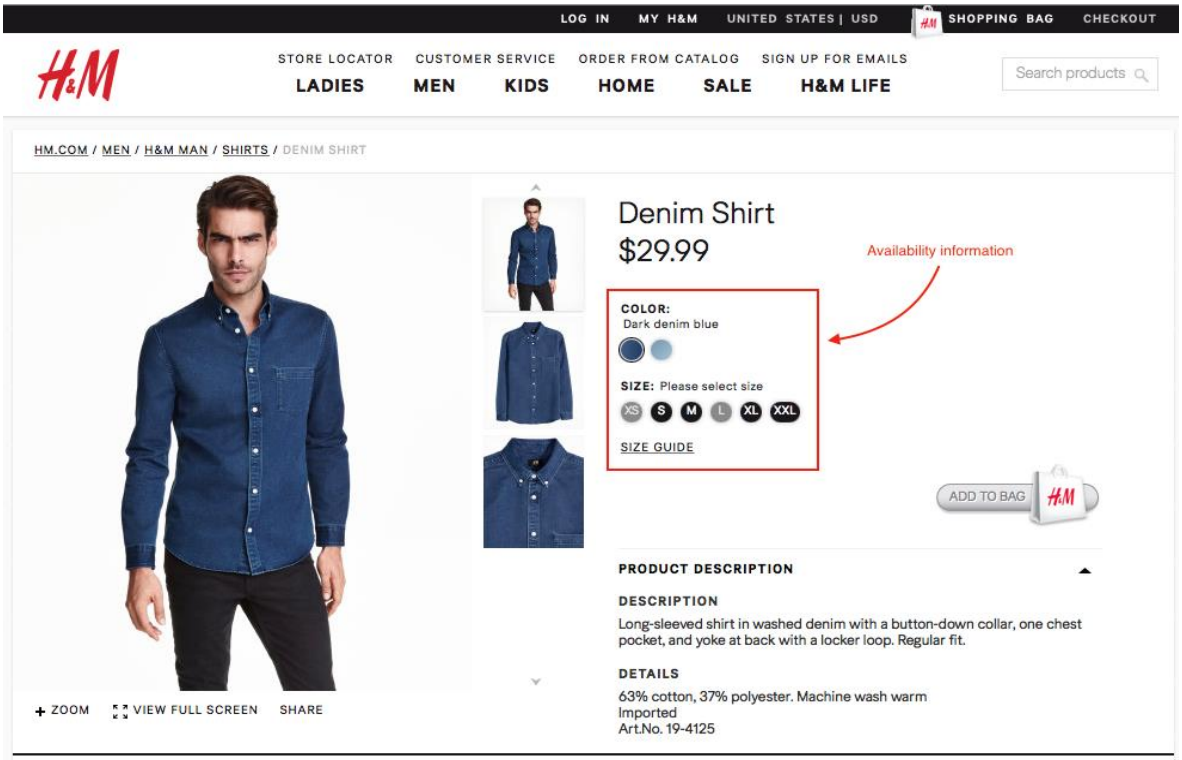

Figure 3.9 Model specific view.

As customers continuously find products to buy, he or she places them into a virtual shopping bag. Here information about the chosen products are presented as a list (quantity, color, size and availability). In the next step, which is the checkout, the customer enters personal details, makes a delivery choice and selects payment method. Finally, the customer confirms or accepts the order and an order confirmation is presented and sent to the customer. An overview of the online customer order process is presented in Figure 3.10.

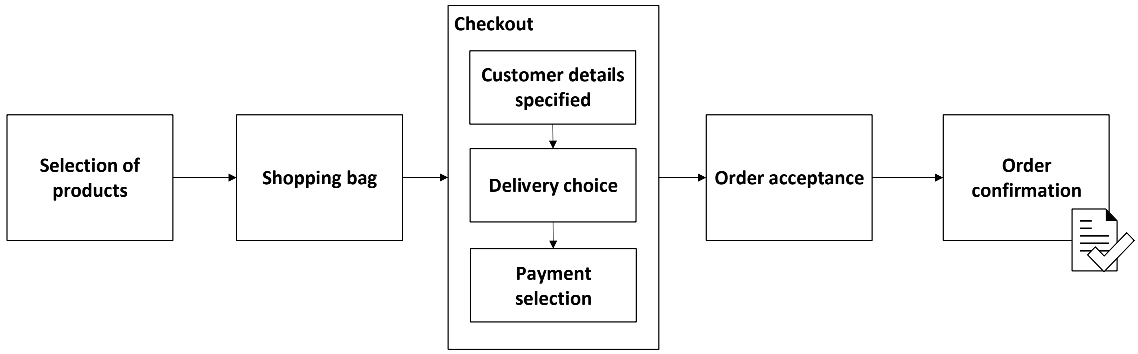

Figure 3.10 Online customer order process at H&M Online.

4.3.1 Sales process

Behind the scenes of the customer view of the purchase there is a back-end setup, which bring in the logistic to the purchase. The back-end setup is presented in Figure 3.11, displaying the customer order flow and the two variables that steers the purchase; ATP-check (Available to promise) and validation. These variables are used throughout the process and determine what can be bought on the website and corresponding delivery terms. One example is presented in Figure 3.11, where the ATP gives information on which sizes that are available for purchase.

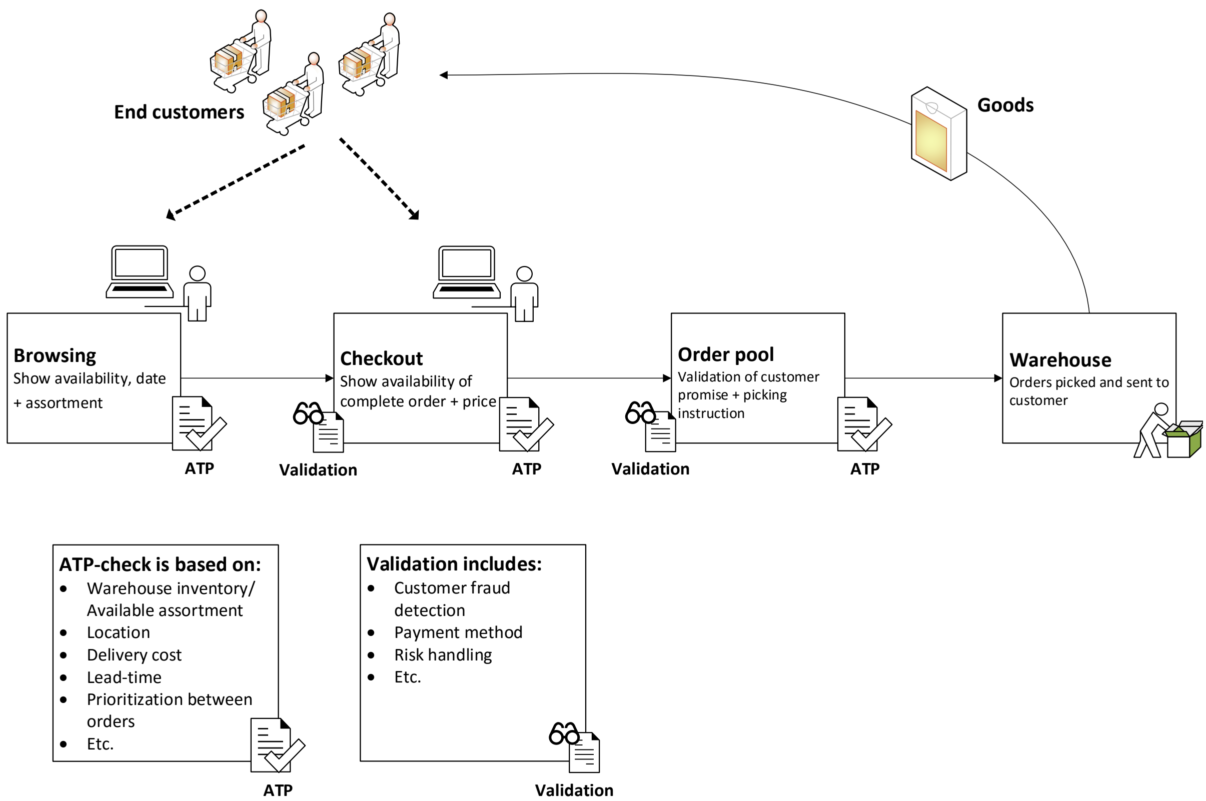

Figure 3.11 Sales process - overview

The availability to promise (ATP) comprises warehouse data and a set of business rules (see Figure 3.11). The ATP execution decides what is shown for the customer at the website and also if it is possible to deliver the products to the customer. It is in other words crucial that the ATP information is correct in order to maximize sales and customer satisfaction. The validation consists of a number of business rules, which are applied to the customer order and determine whether it fulfills them and can complete the order. The order is thereafter transferred to the order pool where a final check and validation of the customer is performed. The order information is then sent to the warehouse and picked according to a FIFO-procedure before delivered to the customer.

4.4 Product life cycles

The different products offered by H&M act differently throughout their life cycles in terms of sales and returns. Most of the products have shorter life cycles with substantial variation in demand from week to week. In Figure 3.12, 3.13 and 3.14 the demand of three different products are illustrated showing their sales and returns per week. As can be seen the three different products, "Cajsa", "MAXI leggings" and "Linda Blazer", have different sales and returns distribution throughout the season and different life cycle lengths. This is the typical case when comparing the demand of H&M Online's products.

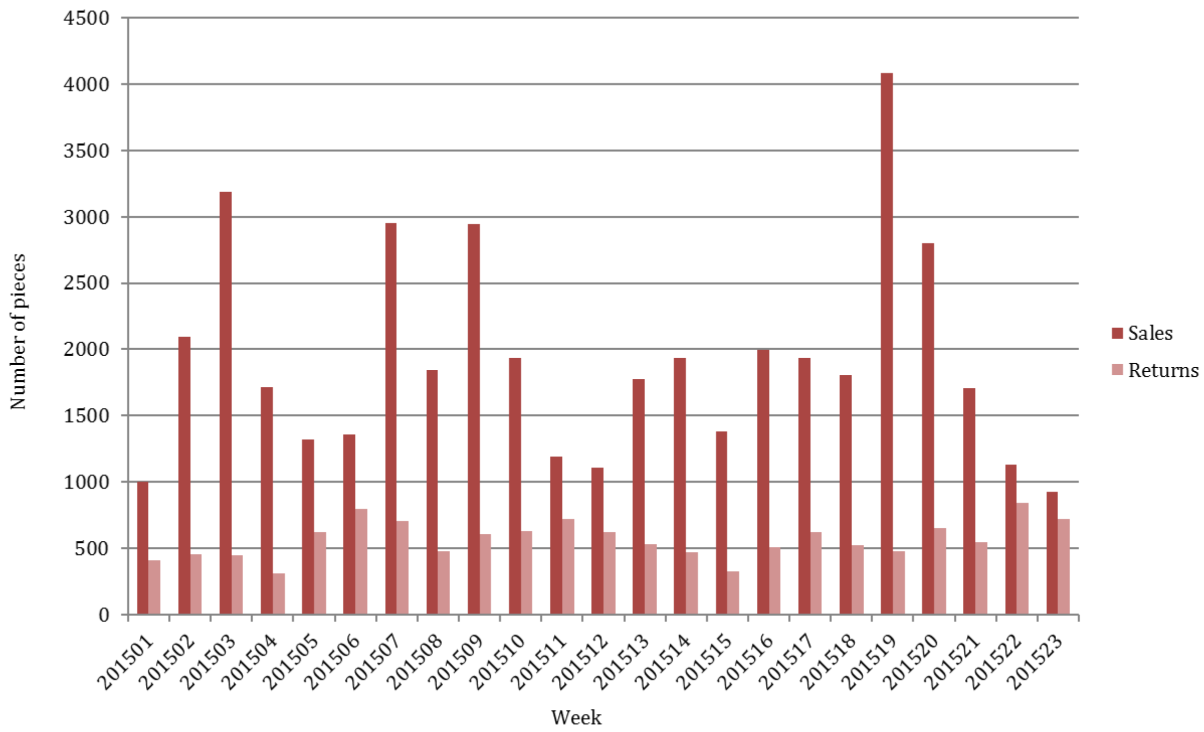

Figure 3.12 Sales and returns week 1-23 for product "Cajsa".

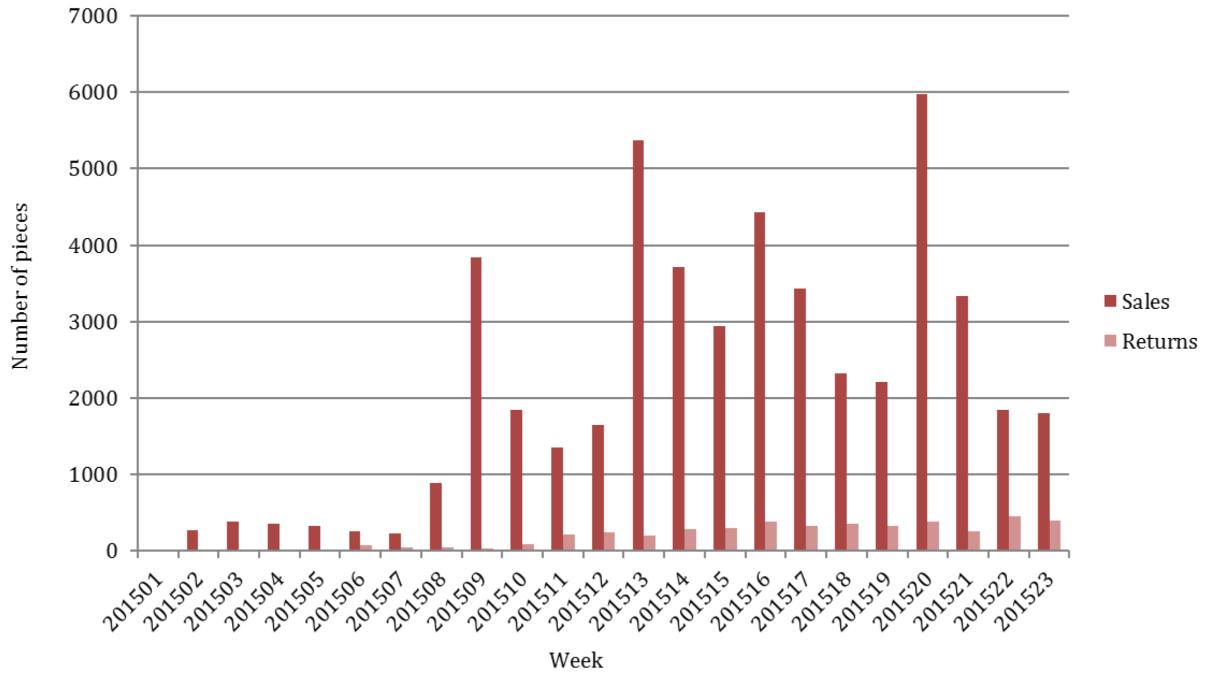

Figure 3.13 Sales and returns week 1-23 for product "MAXI leggings".

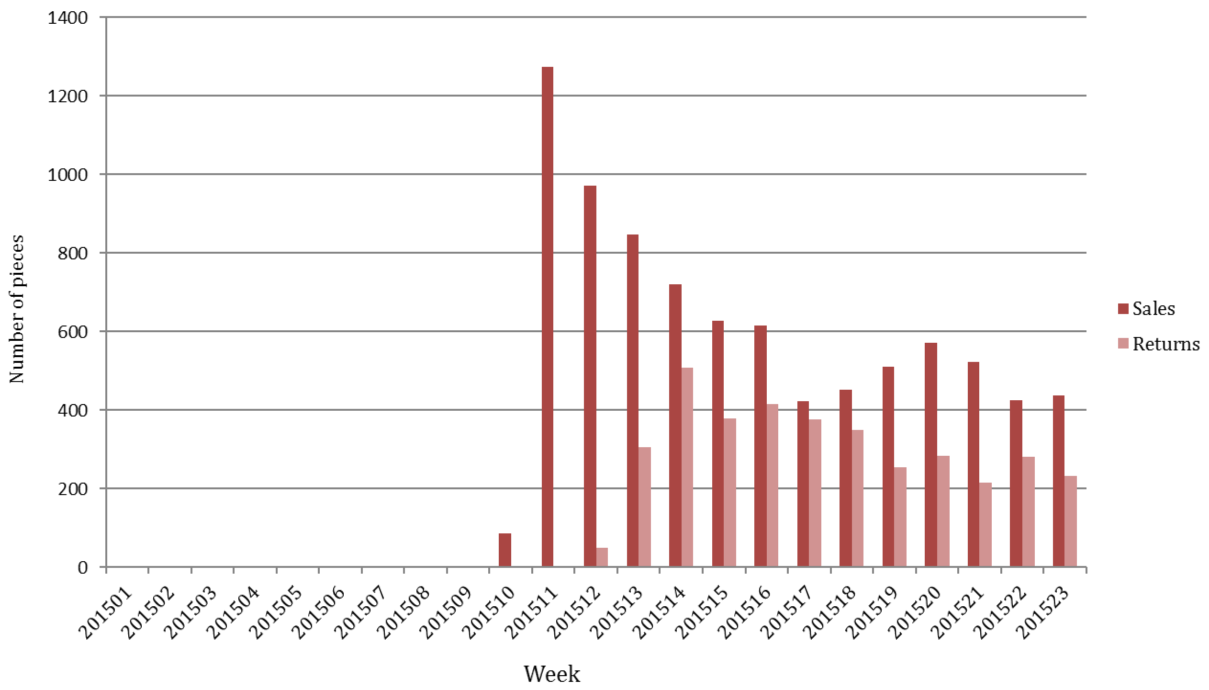

Figure 3.14 Sales and returns week 1-23 for product "Linda Blazer".

Some products live longer than one season and some just a couple of weeks. As H&M compete in the fast fashion industry, most of their product assortment is replaced each season. Approximately 25 percent of all products reoccur the following comparable season. Also, H&M Online are more often offering smaller quantities of “unique” collections – for instance the Versace-collection. The sales of these collections are very difficult to forecast, which aggravates the pre- and in-season allocation of inventory between the different warehouses. The life cycles of the products are further impacted by the different sales driving activities set in the commercial plan. Depending on how many times a certain product is linked to a catalogue, campaign and/or an assortment release, it will be more or less exposed to potential customers. Other variables such as weather, discounts, display on the webpage etc. also affect the product life cycle and make it more stochastic in nature.

5. Analysis

The analysis combines the case study findings with the theoretical framework to develop a pre-season stock allocation model and in-season stock allocation strategies for H&M Online.

As can be seen in this case study of H&M Online, the e-commerce company encounters challenges representative for the fashion e-commerce industry. Their products exhibit short life cycles and the majority of them are replaced each season. Further, the number of catalogue releases and unique collections increase for each year and result in a high and growing product variation. There has in other words been an obvious development from mass fashion to segmented fashion also for H&M (Sekozawa et al., 2010) and as a result lower demand per SKU in general (Gutgeld & Beyer, 1995). These mentioned challenges make demand forecasting and consequently also stock allocation highly uncertain also for H&M Online (Abernathy et al., 2000).

Furthermore, H&M Online's global supply chain creates a long “time-to-serve” lead time which, according to Christopher et al. (2004), is problematic in such a fast changing environment as the fashion e-commerce market is. It affects H&M’s ability to react to changes in real demand, and thus creates a lead-time gap between them and their customers (Rushton et al., 2014). H&M's business idea builds upon a push philosophy and is therefore not armed to be very responsive. However, in this push mentality an accurate stock allocation could, according to Buxton (2015), minimize the lead-time gap. Precise pre- and in-season stock allocation would enable H&M to become more responsive and meet the ever changing customer demand in a more flexible way, ensuring products at the right place, at the right time and for the right price. Furthermore, this is something that is especially vital for an e-tailer where customers’ purchase attitudes are highly impulsive and influenced by the complete shopping experience, which is provided at the contact point between the supply chain and the customer (Danziger, 2006). These factors make the supply chain very exposed and critical for success in the competitive fashion industry.

5.1 Pre-season stock allocation model

The pre-season stock allocation model developed for H&M Online's future warehouse setup in Germany is presented in the formula below. The model consists, on a high level, of three parts; historical sales, returns and future sales targets. The outcome of the model is how much of the stock that should be directed or allocated to each of the warehouses before the season starts. Moreover, the model uses aggregated demand data on department level, leading to that all color- and size-variants of products included in a certain department will have the same allocation split between the warehouses. The choice of forecasting method and variables of the model are explained and motivated in section 5.1.1.

$$All\%_{WH1}^{T} = \frac{Sales_{WH1}^{T-1} - Returns_{WH1}^{T-1}}{Sales_{Tot}^{T-1} - Returns_{Tot}^{T-1}} \text{x} \frac{TargetIndex_{WH1}^{T}}{TargetIndex_{Tot}^{T}}$$

$$All\%_{WH2}^{T} = 1 - All\%_{WH1}^{T}$$

- $All\%_{WH1}^{T}$ = Allocation split next comparable season for warehouse 1
- $All\%_{WH2}^{T}$ = Allocation split next comparable season for warehouse 2
- $Sales_{WH1}^{T-1}$ = Historical sales data the last comparable season for the markets supplied by warehouse 1 (Includes returned products which are resold)
- $Returns_{WH1}^{T-1}$ = Returns data the last comparable season for the markets supplied by warehouse 1
- $Sales_{Tot}^{T-1}$ = Historical sales data the last comparable season for the markets supplied by warehouse 1 and warehouse 2 (Includes returned products which are resold)
- $Returns_{Tot}^{T-1}$ = Historical returns data the last comparable season for the markets supplied by warehouse 1 and warehouse 2
- $TargetIndex_{WH1}^{T}$ = Sales target for the markets supplied by warehouse 1 as an index-number compared to last year's sales (Index 110 = +10 percent sales increase compared to last year)
- $TargetIndex_{Tot}^{T}$ = Sales target for all markets supplied by warehouse 1 and 2 as an index-number compared to last year's sales (Index 110 = +10 percent sales increase compared to last year)

5.1.1 Development and choice of the model

The developed pre-season stock allocation model uses, as shown above, a statistical time-series forecasting approach, i.e. it estimates a future allocation split based on previously observed demand data. Even though this type of time-series forecasting has shortcomings, which Liu et al. (2013) and Thomassey (2013) mention when used in fashion-related settings, the ease of use and its time-efficient characteristics are very important factors for H&M Online. The e-commerce company is not looking for a complex allocation model or a "black box" solution but a model which is easy to understand and implement while providing satisfactory results. A statistical time-series forecasting method is therefore preferred in this particular case.

The pre-season stock allocation model considers the last comparable season's demand data as input together with a sales target for the upcoming season. Demand data for all weeks of the last comparable season is however not included in the model. The last two weeks of the period are namely omitted and in line with the recommendations of Hammond et al. (1994). Clearance sale namely occurs during these weeks at H&M Online and does not represent true demand data. Return rates are, as seen in chapter 4. Empirical information, quite high at H&M Online and therefore also an important part of the pre-season allocation model. The returned products can namely, not surprisingly, be offered and sold to customers again, which has to be accounted for in the model.

The third main part or input of the model is the future sales targets for the markets that the warehouses supply. This target is set by market experts at H&M Online on a country level; i.e. how much more will a specific country be able to sell next comparable season compared to last season on an aggregated or total level. The target is mainly based on historical sales data, countries' economic situation and the commercial plan set by H&M. It therefore partly captures some of the explanatory variables explained by Little (1998) in Figure 3.5, such as macro-economic data and marketing strategy, on an aggregated level. Thomassey (2012) further argues for the importance of being aware of the explanatory variables and integrating the ones with the highest impact in the forecasting model. The inclusion of the future sales target variable in the allocation model is an attempt to achieve this.

As stated in section 5.1, the pre-season stock allocation model uses aggregated sales data on department level, leading to that all color- and size-variants of products included in a particular department will have the same allocation split between the warehouses. Selection of the right criteria and right level of aggregation can be done in both quantitative and qualitative ways. However, most companies prefer to aggregate their sales data according to their internally used hierarchical classification of the topology of products, according to Correa (2007). This is also in line with what H&M Online prefers as it makes the model easier to use. Furthermore, the most suitable level to aggregate sales data on depends on the type of sales forecast method, according to Thomassey (2014). Since a statistical forecasting method, which is used in this particular case, needs historical demand data the “family” level is most appropriate (see Figure 3.3). This is due to the fact that a major part of H&M Online’s collection is replaced next comparable season and consequently does not have historical demand data. The aggregation level “family” from Figure 3.3 is equal to department level at H&M.

5.1.2 Simulation, results and validation of the model

In order to test and validate the pre-season stock allocation model a simulation is conducted as a first step. The simulation uses the demand data from the spring season of 2014 to project the allocation split for the spring season of 2015. How well the estimated allocation split manages to capture actual sales during the spring season of 2015 is then analyzed. The results from the simulation is thereafter, in a second step, compared with the optimal allocation splits, which are calculated using the known actual sales split during the spring season of 2015. The two steps or parts are described more in detail below.

5.1.2.1 Part I – Simulation of the model

As the future warehouse setup still is hypothetical, no demand data is available. To construct a real case similar to the hypothetical warehouse setup with two markets supplied by two different warehouses and to test the pre-season stock allocation model, the six existing markets within the planning market Central Europe are divided into two markets. The first market (market 1), consisting of Sweden, Finland, Denmark, the

Netherlands and Austria, is supplied by warehouse 1. The second market (market 2) is represented by Germany and is supplied by warehouse 2 (see Figure 5.1).

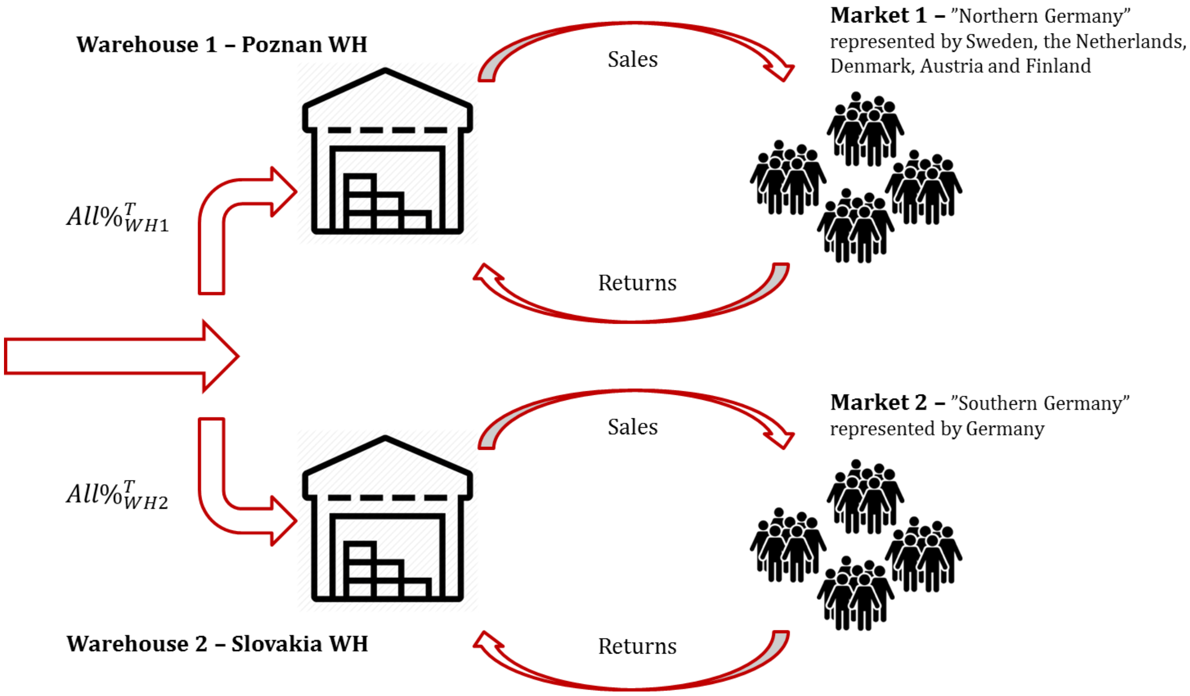

Figure 5.1 Visualization of the simulation.

By using the demand data from the spring season of 2014 for these two hypothetical markets pre-season stock allocation splits are calculated for warehouse 1 and 2, using the pre-season stock allocation model. An estimated sales split (referred to as "Estimated sales" in Figure 5.2 below) can then be calculated using the allocation split for each market. The sales split is later compared with the actual sales during the spring season of 2015 on the two markets. This simulation shows how much sales are impacted by the change from one to two warehouses, depending on which pre-season allocation split that is used. The simulation structure and result for a selected number of SKUs or variants in department 1111 can be studied in Figure 5.2.

Variant ID	OrderedPCS	Bought WH1	Bought WH2	Sellable WH1	Sellable WH2	Actual Sales WH1	Actual Sales WH2	Estimated Sales WH1	Estimated Sales WH2
105151	2423	956	1467	1163	1571	1043	1559	1043	1559
105152	966	381	585	463	627	775	1315	463	627
105153	6496	2562	3934	3116	4214	1986	4688	1986	4214
105154	1766	697	1069	848	1145	1206	2343	848	1145
105155	4109	1621	2488	1972	2665	1961	2512	1961	2512
105156	7224	2849	4375	3466	4686	2624	5627	2624	4686
105157	9176	3619	5557	4402	5953	3202	6873	3202	5953
105158	1370	540	830	657	889	830	866	657	866
105159	1385	546	839	664	899	531	808	531	808
105160	3241	1278	1963	1555	2103	1741	1824	1555	1824
105161	928	366	562	445	602	655	467	445	467
105162	924	364	560	443	600	1101	1420	443	600
105163	446	176	270	214	289	1154	909	214	289
105164	970	383	587	466	629	706	347	466	347
105165	473	187	286	227	306	884	957	227	306
105166	943	372	571	453	612	1249	1318	453	612
105167	910	359	551	437	590	365	634	365	590
105168	923	364	559	443	599	444	614	443	599
105169	1122	443	679	539	727	657	642	539	642

Figure 5.2 Simulation results from the pre-season stock allocation model for a selected number of variants in department 1111.

- $All\%_{WH1}^{T}$ = Allocation split next comparable season for warehouse 1 (In this particular example ≈ 39%)
- $All\%_{WH2}^{T}$ = Allocation split next comparable season for warehouse 1 (In this particular example ≈ 61%)
- $OrderedPCS$ = Total ordered quantity from supplier
- $Bought\ WH1 = OrderedPCS * All\%_{WH1}^{T}$
- $Bought\ WH2 = OrderedPCS * All\%_{WH2}^{T}$
- $Sellable\ WH1 = Bought\ WH1 * (1 + Avg\ return\ rate\ for\ dep.1111)$
- $Sellable\ WH2 = Bought\ WH2 * (1 + Avg\ return\ rate\ for\ dep.1111)$
- $Actual\ sales\ WH1 =$ The actual sales for warehouse 1 on market 1
- $Actual\ sales\ WH2 =$ The actual sales for warehouse 2 on market 2
- $Estimated\ sales\ WH1 =$ The quantity sold from warehouse 1 using the allocation split from the pre-season stock allocation model (Constraint: Cannot exceed $Actual\ sales\ WH1$)
- $Estimated\ sales\ WH2 =$ The quantity sold from warehouse 2 using the allocation split from the pre-season stock allocation model (Constraint: Cannot exceed $Actual\ sales\ WH2$)

As can be seen in Figure 5.2 the estimated sales sometimes differ from actual sales. This represents missed sales due to an inaccurate stock allocation split between the two warehouses. The total miss in sales running the simulation for all H&M Online's departments in season 1 using the above described pre-season allocation model ends up to 7.4 percent. Simulation results for all departments are presented in Appendix 2.

5.1.2.2 Part II – Validation of the simulation results

The optimized stock allocation is based upon the same logic as the simulation structure above but here instead of using the calculated stock allocation split from the pre-season stock allocation model we optimize the stock allocation split. When knowing the actual sales split of the spring season of 2015 it is possible to optimize the stock allocation split. By altering the stock allocation split it is namely possible to minimize the miss in sales. Technically, this is conducted by using the application "Solver" in Microsoft Excel. In Figure 5.3 the optimization result is presented for the same selected number of variants in department 1111 as in section 5.1.2.1. The optimal allocation split for department 1111 is approximately 33/67 percent in this particular example.

Variant ID	OrderedPCS	Bought WH1	Bought WH2	Sellable WH1	Sellable WH2	Actual Sales WH1	Actual Sales WH2	Estimated Sales WH1	Estimated Sales WH2
105151	2423	791	1632	962	1749	1043	1559	962	1559
105152	966	315	651	383	697	775	1315	383	697
105153	6496	2120	4376	2578	4688	1986	4688	1986	4688
105154	1766	576	1190	701	1274	1206	2343	701	1274
105155	4109	1341	2768	1631	2965	1961	2512	1631	2512
105156	7224	2357	4867	2867	5213	2624	5627	2624	5213
105157	9176	2994	6182	3642	6622	3202	6873	3202	6622
105158	1370	447	923	544	989	830	866	544	866
105159	1385	452	933	550	1000	531	808	531	808
105160	3241	1057	2184	1286	2339	1741	1824	1286	1824
105161	928	303	625	368	670	655	467	368	467
105162	924	301	623	367	667	1101	1420	367	667
105163	446	146	300	177	322	1154	909	177	322
105164	970	316	654	385	700	706	347	385	347
105165	473	154	319	188	341	884	957	188	341
105166	943	308	635	374	681	1249	1318	374	681
105167	910	297	613	361	657	365	634	361	634
105168	923	301	622	366	666	444	614	366	614
105169	1122	366	756	445	810	657	642	445	642

	$All\%^T_{WH1}$	$All\%^T_{WH2}$
Changing cells	33%	67%

Figure 5.3 Optimized stock allocation for a selected number of variants in department 1111.

As seen in Figure 5.3, the optimized allocation split for department 1111 differs from the calculated allocation split of the pre-season stock allocation model (39/61 percent vs. 33/67 percent). When knowing the actual sales split of the spring season of 2015, the optimized allocation split had been preferred. The total miss in sales during the spring season of 2015 using the above described optimized allocation approach ends up to 5.5 percent for all departments over the whole season. The allocation results for all departments using the optimal allocation approach are presented in Appendix 3.

5.1.3 Potential improvements of the model

The developed pre-season stock allocation model is, in line with H&M's preferences, a rather comprehensible and implementable tool to allocate products between warehouses before a season begins. However, the ease-of-use and time limitation result in some potential improvement areas for the model which are touched upon below.

To start with, the choice of a statistical forecasting method can be questioned. Liu et al. (2013) and Thomassey (2014) argue for instance that statistical forecasting methods have shortcomings, such as limitations to linear structures, requirements of expert knowledge and larger historical data sets, when used in fashion-related settings. In order to improve fashion retail forecasting AI based methods and hybrids of AI and time-series techniques have been developed in parallel with the strong improvement in computer technology. The hybrid methods try to combine advantages of statistical and AI based forecasting methods in order to cope with the unique characteristics of the fashion industry (Liu et al., 2013). It is of course impossible to state which method H&M Online should use since the methods have not been tested and validated using H&M's demand data. However, it still remains as a potential improvement area as other more sophisticated methods have provided more satisfactory results in literature compared to simpler statistical forecasting models. A second smaller potential improvement of the developed pre-season allocation model would, according to Thomassey (2014), be to use demand data from more comparable seasons than just the last one.

A third potential improvement of the pre-season allocation model would be to use actual or true demand data as input data. As Garro (2011) explains it historical sales data is the portion of the demand that the e-tailer is able to capture. This captured demand can be very different from true demand in situations where stockouts "decide" what is available or not. True demand can on the other hand be difficult for H&M Online to estimate as the e-commerce company only displays products on the website when they are in stock. There are however different methods of estimating lost sales due to stockouts, which can be further studied in the articles written by Jain, Rudi and Wang (2014), Nahmias (1994) and Caine and Plaut (1976). Another way to partly measure lost sales due to poor allocation of products between warehouses is to implement virtual pooling of inventory. Product availability from more than one warehouse will then be displayed on the website, making it possible to measure the number of times customers were not supplied by their assigned warehouses. (Anupindi et al., 2001)

Furthermore, the model can potentially be improved by integrating the explanatory variables in a more exhaustive way than just incorporating few of them in a single sales target-variable. Fashion trends is one important factor which preferably should be included as it has high impact on demand (Thomassey, 2010). Other explanatory variables such as competitor and weather data are on the other hand very difficult to predict why they consequently cannot be part of the forecasting model.

A fifth potential improvement area of the pre-season allocation model is in the choice of aggregation level. The developed model uses aggregated sales data on department level, leading to that all color- and size-variants of products included in a particular department will have the same allocation split between the warehouses. Thomassey (2014) on the other hand argues that forecasts made on a lower aggregation level often are more accurate. Since approximately 25 percent of H&M's product line reoccurs the following comparable season, historical demand data on product level is available for at least 25 percent of the products. Allocation can consequently be made on product level for one fourth of all products. Thomassey (2014) and Thomassey, Happiette and Castelain (2003) further argue that due to the high variety of products within a typical fashion retailer firm, there are big differences in terms of products' life cycles, which also has been seen at H&M Online. Apparel products should therefore be differentiated or grouped according to the nature of the items. Common groupings of items are basic items, new items and best selling items. The remaining 75 percent of H&M's products that do not reoccur the next comparable season could hypothetically therefore be grouped accordingly within each department. Allocation models using different forecasting methods could then be used for each group. For new items with high demand uncertainty the fast fashion company Zara for instance tries to identify a comparable item sold last season which is similar to the new item. Zara thereafter forecasts the demand for the new item by mainly using the comparable item's historical demand data. (Gallien et al., 2015)

A final potential improvement area of the model is related to the aspect of demand fluctuation over time during a season, i.e. seasonal variation or seasonality. Given that the forecasted demand over the whole season is accurate seasonality would only cause stockouts for certain products. It would namely be the products that have several deliveries from suppliers. Seasonality will on the other hand not cause any stockouts when products only have one delivery and that delivery occurs prior to the season begins. When a product has several deliveries a situation can namely arise where a company receives products after a peak in demand and not before. The result is stockouts until the next delivery arrives. The effects of seasonality should consequently be more or less integrated in the stock allocation model depending on a certain cloth's sensitivity to seasonal variations and the number of deliveries from suppliers (Thomassey, 2014).

5.2 In-season stock allocation strategy

The developed pre-season stock allocation model has areas of improvement, as explained above. The calculated allocation split also has a risk of being wrong due to the multiple sources of future demand uncertainty (Choi et al., 2014). As a result e-tailers need, according to Choi et al. (2014), to conduct demand forecasts for their products in response to real-time demand data and rebalance or adjust inventory during season in line with this data. Firms need to use more real-time data during season and quick response strategies to become more customer responsive and to close the lead-time gap between the supply chain and the customers (Rushton et al., 2014). The following sections analyze how H&M Online through different approaches can improve the stock allocation during an ongoing season.

5.2.1 In-season demand data

Technology has enabled e-tailers to collect and analyze huge amounts of data, among other real-time demand data during season (D'Amico et al., 2013). H&M Online could hypothetically therefore improve the stock allocation by adjusting the initial stock allocation split using a portion of the demand data collected during an ongoing season.

The idea is that real-time demand data during an ongoing season would give a better indication of what customers want compared to the historical demand data from last comparable season. This would be in line with Fisher and Raman (1996) who argue that observing and using a portion of the demand in a season can improve the forecast accuracy. By applying this insight to the case of H&M Online this would more practically imply a rebalancing of the stock between Poznan and Slovakia by 1) changing the stock allocation split of deliveries from suppliers arriving during season or 2) using transshipments between the warehouses during season. As products at H&M are delivered to the warehouses different amount of times (Some products are only delivered from suppliers once while others have several deliveries) the strategies will be adapted accordingly. The stock allocation split for products, which are delivered to H&M several times during season can be revised and updated before reaching the warehouses. This would in practice imply that the incoming deliveries are redirected to fulfill the updated allocation split. The redirection could hypothetically be done at the suppliers' facilities in Asia and Turkey or at the harbors in Hamburg, Gdansk and/or Gdynia. For products delivered only once a rebalancing approach using transshipments between the warehouses should be applied. The objective is, according to Agrawal (2003), to take proactive decisions regarding transshipments before a situation of stockouts is reached. The transshipments should be well planned and preferably consolidated to reduce the cost related to emergency transshipments.

However, in order to take such proactive decisions and update the stock allocation split one must preferably be able to predict the future using short-term or very short-term forecasting methods, i.e. real-time or in-season based forecasting. This is something that has not been widely studied in literature (Liu et al., 2013). Nevertheless, this type of shorter forecasting method is crucial for in-season stock allocation for H&M Online, given the nature of the fashion industry. There are however also other strategies for coping with the issues of short-term forecasting and in-season stock allocation for H&M Online – see below.

5.2.2 Postponement

A way for H&M Online to reduce uncertainty of the pre-season stock allocation forecast or model and to make in-season stock allocation easier is by using a postponement strategy, i.e. by delaying stock allocation decisions until more demand information is gathered (Pagh & Cooper, 1998; Buxton, 2015). Holding back some anticipatory inventory in the warehouses of, for instance, Hamburg, Gdansk and/or Gdynia would give H&M Online some wiggle room for updating and changing the stock allocation split before allocating products to the warehouses in Poland and Slovakia. A second postponement alternative is to over allocate certain products to the Polish warehouse in Poznan and thereafter, depending on the in-season demand in southern Germany, replenish the warehouse in Slovakia. This could be especially interesting for products with very high demand uncertainty. Even though an initial stock allocation between the two warehouses will be used, a postponement of some of the stock enables H&M Online to take decision in a later stage when real-time data is collected, consequently becoming more pull based.

5.2.3 Quick response

In order to react to the market preferences during season before it is too late H&M Online could establish a quick response strategy. Quick response is enabled mainly by shortening lead times within the supply chain or through efficient replenishment policies (Choi and Sethi, 2010). H&M's supply chain strategy is however highly impacted by their business idea of being cost efficient, which directly is reflected in their operational lead times. The collection design (time-to-market) often starts one year ahead of the actual release. This is partly due to the fact that the major part of all products are produced in Asia. In addition, the transportation lead times also are substantial (time-to-serve). As a result, their time-to-react to customers' preferences is long. A substantial shortening of these lead times is contradictory to H&M's overall supply chain strategy and business idea and is therefore probably difficult to fully implement. Nevertheless, shortening the lead-times throughout the supply chain would make H&M Online more responsive. H&M's cost-minimization philosophy mainly minimizes the costs of production and shipping and partly neglects the total cost of the supply chain. According to Christopher et al. (2004), the supply chain costs include more than production and shipping but also costs related to obsolescence, forced mark-downs and inventory carrying. Iannone et al. (2013), Caro & Gallien (2010) and Battista and Schiraldi (2013) also claim that an agile supply chain performs better than conventional forecast driven supply chains and is more capable of meeting the difficulties of the fashion e-commerce industry.

6. Conclusions and discussion

This chapter will present and discuss the conclusions and findings of the study in relation to the purpose and research questions.

The pre-season stock allocation model developed for H&M Online's hypothetical future warehouse setup in Germany is presented in the formula below. The model is mainly based on a statistical forecasting method, which estimates a future allocation split based on previously observed demand data from the markets that the warehouses supply, together with future sales targets for the upcoming season set by H&M's market experts. The historical demand data, which is data from the last comparable season, is aggregated on department level, leading to that all color- and size-variants of products included in a certain department will have the same allocation split between the warehouses.

$$All\%_{WH1}^{T} = \frac{Sales_{WH1}^{T-1} - Returns_{WH1}^{T-1}}{Sales_{Tot}^{T-1} - Returns_{Tot}^{T-1}} \text{ x } \frac{TargetIndex_{WH1}^{T}}{TargetIndex_{Tot}^{T}}$$

$$All\%_{WH2}^{T} = 1 - All\%_{WH1}^{T}$$

The choice of a statistical time-series forecasting approach is motivated by H&M Online's preferences of having a model which is easy to use and implement as well as comprehensible with short calculation time. Clearance sale weeks are not part of the historical demand data input to better capture actual or true demand from last comparable season. The sales targets for the upcoming season is included in the model in an attempt to incorporate explanatory variables such as countries' purchasing power and H&M's marketing strategy the upcoming season. Demand data is aggregated on department level as it is convenient for H&M and in line with their preferences but also partly because approximately 75 percent of the collection is replaced next comparable season. This major part of the collection consequently does not have true historical demand data to use as input data to the stock allocation model.

By simulating the developed pre-season stock allocation model using historical demand data from the spring season of 2014 to estimate suitable stock allocation splits for the spring season of 2015, satisfactory results are achieved. It shows a total miss in sales of

7.4 percent at an aggregated level for all H&M Online's departments. This result is very close to the optimal one on department level which is 5.5 percent and calculated using an optimization model in Excel (Solver).

Potential improvement areas have been identified in order to enhance the precision of the projected pre-season stock allocation splits made by the allocation model. Firstly, more sophisticated forecasting methods would probably improve the model since statistical forecasting methods have shortcomings, such as limitations to linear structures, requirements of expert knowledge and larger historical data sets, when used in fashion-related settings. Secondly, demand data from more comparable seasons than just the last one would probably also have positive impacts on the model's results. True demand should preferably also be used as input data as historical demand data is the portion of the demand that the e-tailer is able to capture and not actual demand. Furthermore, the model can potentially be improved by integrating explanatory variables in a more exhaustive way than just incorporating few of them in a single sales target-variable. Fashion trends should for instance be included as it has high impact on demand. In addition, using historical demand data on product level when possible and adapting the allocation model and its forecasting methods for different groupings/classes of products would most likely improve the model even further. New items and basic items should for instance be allocated using different methods suitable for respective group's characteristics. A final potential improvement would be to more or less integrate the effects of seasonality in the stock allocation model, depending on products' sensitivity to seasonal variations and the number of deliveries from suppliers.

Due to the fashion e-commerce industry's many sources of future demand uncertainty and the mentioned shortcomings of the developed allocation model, in-season stock allocation can and should be used. There are different ways or approaches through which H&M Online optimally can allocate stock during an ongoing season between the warehouse in Poland and the hypothetical warehouse in Slovakia. One way would be to use real-time demand data during season to update the stock allocation split between the warehouses. The idea is that real-time demand data would give a better indication of what customers want compared to the historical demand data from last comparable season. The stock rebalancing could in practice be done by H&M Online by either 1) redirecting deliveries arriving from suppliers during season according to the updated allocation split or 2) using transshipments between the warehouses during season. However, in order to take such proactive decisions and update the stock allocation split one must preferably be able to predict the future using short-term or very short-term forecasting methods, i.e. real-time or in-season based forecasting. This is a difficult forecasting approach and something that has not been widely studied in literature. There are however also other strategies for coping with the issue of short-term forecasting and in-season stock allocation for H&M Online – postponement and quick response strategies. A stock postponement strategy for H&M Online would imply to delay stock allocation decisions until more demand information is gathered during an ongoing season. Holding back some anticipatory inventory in the warehouses of, for instance, Hamburg, Gdansk and/or Gdynia would give H&M Online some wiggle room for updating and changing the stock allocation split before allocating products to the warehouses in Poland and Slovakia. The e-commerce company's stock allocation decisions would in other words become more pull based. The quick response strategy is also pull based and relies on the idea of being highly responsive to customers' preferences by having short lead times within the supply chain and/or by having efficient replenishment policies. A substantial shortening of lead times is however contradictory to H&M's overall supply chain strategy and cost efficient-focused business idea and is therefore probably difficult to fully implement.

It should be noted that the pre-season stock allocation model developed for H&M Online is not a model that determines what quantity of products to be ordered from suppliers. The model's purpose is to decide where to allocate already bought products in a particular planning market. The responsibility of ordering products from suppliers lay in the hands of H&M's buying department, which is the cornerstone of the organization. An uninspected increase in total demand on all markets will consequently be impossible to capture with a stock allocation model since it does not determine the total quantity bought from suppliers. However, if the buying department manages to accurately estimate total demand on all markets but the demand differs substantially among the different markets, the allocation model has a crucial role of capturing these differences in order to avoid stockouts and emergency deliveries between warehouses.

The in-season stock balancing between the two warehouses for H&M Online should preferably be based on real-time in-season data. But how should H&M be organized in order to flexibly respond to changes in customer preferences and demand during an ongoing season? The fundamental question or issue probably is how much push versus pull based H&M should be. H&M's supply chain is currently mainly push based which is part of the company's success. Zara on the other hand is much more pull based which has made them very successful. As tradeoffs exist between the approaches the choice of which one to go for is much more about a particular firm's philosophy of how to do business than what the optimal supply chain approach is. Nevertheless, with the upcoming trends of much more segmented fashion, smaller collections within the fashion industry etc. H&M should configure its supply chain to be more responsive and agile where it is possible within the scope of their business philosophy. The stock allocation is one supply chain operation where this is possible to some extent. Even though the stock allocation is just one part of the pie it can be formed to minimize the lead-time gap and consequently make H&M Online more agile.

7. References

Theoretical framework

Abernathy, F. H., Dunlop, J. T., Hammond, J. H., & Weil, D., 2000. Retailing and supply chains in the information age. *Technology in society*, *22*(1), 5-31. ISO 690

Anupindi, R., Bassok, Y., & Zemel, E., 2001. A general framework for the study of decentralized distribution systems. *Manufacturing & Service Operations Management*, *3*(4), 349-368.

Au K.F., Chan N.Y., 2002. Quick response for Hong Kong clothing suppliers: a total system approach. Proceedings of the 13th Annual Conference of the Production and Operations Management Society, San Francisco, USA.

Axsater, S., Luleå University of Technology, Industrial Logistics, Department of Business Administration, Technology and Social Sciences & Business Administration and Industrial Engineering., 1990, "Modelling Emergency Lateral Transshipments in Inventory Systems", *Management Science,* vol. 36, no. 11, pp. 1329-1338.

Ballou, R.H., 2004, *Business logistics/supply chain management: planning, organizing, and controlling the supply chain,* 5.th edn, Pearson Prentice Hall, Upper Saddle River, N.J.

Battista, C., & Schiraldi, M. M., 2013. The logistic maturity model: Application to a fashion company. *International Journal of Engineering Business Management*, *5*.

Battistoni, E., Colladon, A.F. & Mercorelli, G., 2013. "Prominent Determinants of Consumer-Based Brand Equity", *International Journal of Engineering Business Management,* vol. 5, pp. 25.

Bayraktar, E., Koh, S. L., Gunasekaran, A., Sari, K., & Tatoglu, E., 2008. The role of forecasting on bullwhip effect for E-SCM applications. *International Journal of Production Economics*, *113*(1), 193-204.

Blumer, H., 1969. Fashion: From class differentiation to collective selection. *The Sociological Quarterly*, *10*(3), 275-291.

Box, G.E., Jenkins, G.M., Reinsel, G.C. and Ljung, G.M., 2015. *Time series analysis: forecasting and control.* John Wiley & Sons.

Buxton, M., 2016. Unlocking the Secrets to Allocation Success. Just Enough -Thought Leadership.

Caine, G. J., & Plaut, R. H., 1976. Optimal inventory policy when stockouts alter demand. *Naval Research Logistics Quarterly*, *23*(1), 1-13.

Caro, F., & Gallien, J., 2010. Inventory management of a fast-fashion retail network. *Operations Research*, *58*(2), 257-273.

Chan, F. T., & Chan, H. K., 2010. An AHP model for selection of suppliers in the fast changing fashion market. *The International Journal of Advanced Manufacturing Technology*, *51*(9-12), 1195-1207.

Chatfield, C., 2013. *The analysis of time series: an introduction.* CRC press.

Chhaochhria, P., 2007. *Inventory planning for low demand items in online retailing* (Doctoral dissertation, Massachusetts Institute of Technology).

Choi, T. M., 2006. Quick response in fashion supply chains with dual information updating. *Journal of industrial and management optimization*, *2*(3), 255.

Choi, T. M., 2007. Pre-season stocking and pricing decisions for fashion retailers with multiple information updating. *International journal of production economics*, *106*(1), 146-170.

Choi, T. & Sethi, S., 2010, "Innovative quick response programs: A review", *International Journal of Production Economics,* vol. 127, no. 1, pp. 1-12.

Choi, T. M., Hui, C. L. & Yu, Y., 2011. An intelligent fast sales forecasting model for fashion products. *Expert Systems with Applications*, *38*(6), 7373-7379.

Choi, T. M., Hui, C. L. & Yu, Y., 2014. *Intelligent Fashion Forecasting Systems: Models and Applications*. Springer.

Christopher, M., Lowson, R., & Peck, H., 2004. Creating agile supply chains in the fashion industry. *International Journal of Retail & Distribution Management*, *32*(8), 367-376.

Correa, J. R. 2007. *Optimization of a fast-response distribution network* (Doctoral dissertation, Massachusetts Institute of Technology).

D'Amico, S., Giustiniano, L., Nenni, M. E., & Pirolo, L., 2013. Product Lifecycle Management as a tool to create value in the fashion system. *International Journal of Engineering Business Management*, *5*.

Danziger, P., 2006. The Pop Equation: What Makes a Shop that Pops. Dearborn Trade Publishing, Chicago.

De Felice F., Petrillo A., Autorino C., 2013. Key success factors for organizational innovation in the fashion industry. *International Journal of Engineering Business Management,* 5.

Fildes, R., & Kingsman, B., 2011. Incorporating demand uncertainty and forecast error in supply chain planning models. *Journal of the Operational Research Society*, *62*(3), 483-500.

Fisher, M., & Raman, A., 1996. Reducing the cost of demand uncertainty through accurate response to early sales. *Operations research*, *44*(1), 87-99.

Franses, P. H., 1996. Recent advances in modelling seasonality. *Journal of economic surveys*, *10*(3), 299-345.

Gallien, J., Mersereau, A. J., Garro, A., Mora, A. D., & Vidal, M. N., 2015. Initial shipment decisions for new products at Zara. *Operations Research*, *63*(2), 269-286.

Garro, A., 2011. *New product demand forecasting and distribution optimization: a case study at Zara* (Doctoral dissertation, Massachusetts Institute of Technology).
Grant, R.M. 2013. *Contemporary strategy analysis,* 8., text edn, Wiley, Chichester, West Sussex.

Gutgeld, Y., & Beyer, D., 1995. Are you going out of fashion?. *The McKinsey Quarterly*, (3), 54-55.

Hammond, J. H., Obermeyer, W. R., & Raman, A., 1994. *Making supply meet demand in an uncertain world*. Boston: Graduate School of Business Administration, Harvard University.

Harrison, A., & Van Hoek, R. I., 2008. *Logistics management and strategy: competing through the supply chain*. Pearson Education.

Hayes, S., ebrary, I. & Ebrary., 2007. *Fashion online,* Emerald Group Publishing, Bradford, England.

Hylleberg, S., 1992. *Modelling seasonality*. Oxford University Press.

Iannone, R., Ingenito, A., Martino, G., Miranda, S., Pepe, C., & Riemma, S., 2013. Merchandise and replenishment planning optimisation for fashion retail. *International Journal of Engineering Business Management*, *5*.

Jain, A., Rudi, N., & Wang, T., 2014. Demand estimation and ordering under censoring: Stock-out timing is (almost) all you need. *Operations Research*, *63*(1), 134-150.

Lee, H. L., 2002. Aligning supply chain strategies with product uncertainties. *California management review*, *44*(3), 105-119.

Lee, H. L., Padmanabhan, V., & Whang, S., 1997. The bullwhip effect in supply chains. *MIT Sloan Management Review*, *38*(3), 93.

Little, J.D., 1998. Integrated measures of sales, merchandising, and distribution. *International Journal of Research in Marketing*, 15(5), pp.473-485.

Liu, N., Ren, S., Choi, T. M., Hui, C. L., & Ng, S. F., 2013. Sales forecasting for fashion retailing service industry: a review. *Mathematical Problems in Engineering*, *2013*.

Marchegiani, L., Giustiniano, L., Peruffo, E., & Pirolo, L., 2012. Revitalising the outsourcing discourse within the boundaries of firms debate. *Business Systems Review*, *1*(1), 157-177.

Melachrinoudis, E., & Min, H., 2007. Redesigning a warehouse network. *European Journal of Operational Research*, *176*(1), 210-229.

Min, H., Ko, C.S. and Ko, H.J., 2008. Managing product returns in customer-centric e-tail environments. *International Journal of Services Technology and Management, 9*(1), pp.51-70.

Moore, C. M., & Birtwistle, G., 2004. The Burberry business model: creating an international luxury fashion brand. *International Journal of Retail & Distribution Management*, *32*(8), 412-422.

Nahmias, S., 1994. Demand estimation in lost sales inventory systems. *Naval Research Logistics*, *41*(6), 739-758.

Nenni, M. E., Giustiniano, L., & Pirolo, L., 2013. Demand forecasting in the fashion industry: a review. *International Journal of Engineering Business Management*, *5*.

Newman, A. J., & Cullen, P., 2002. *Retailing: environment & operations*. Cengage Learning EMEA.

Pagh, J. D., & Cooper, M. C., 1998. Supply chain postponement and speculation strategies: how to choose the right strategy. *Journal of business logistics*, *19*(2), 13.

Rayman, D., Burns, D. J., & Nelson, C. N., 2011. Apparel product quality: Its nature and measurement. *Journal of Global Academy of Marketing*, *21*(1), 66-75.

Rushton, A., Croucher, P., & Baker, P., 2014. *The handbook of logistics and distribution management: Understanding the supply chain*. Kogan Page Publishers.

Sekozawa, T., Mitsuhashi, H., & Ozawa, Y., 2011. One-to-one recommendation system in apparel online shopping. *Electronics and Communications in Japan*, *94*(1), 51-60.

Soni, G., & Kodali, R., 2010. Internal benchmarking for assessment of supply chain performance. *Benchmarking: An International Journal*, *17*(1), 44-76.

Stock, J., Speh, T. and Shear, H., 2006. Managing product returns for competitive advantage. *MIT Sloan Management Review*, *48*(1), p.57.

Thomassey, S., 2010. Sales forecasts in clothing industry: The key success factor of the supply chain management. *International Journal of Production Economics*, *128*(2), 470-483.

Thomassey, S., 2014. Sales forecasting in apparel and fashion industry: a review. In *Intelligent Fashion Forecasting Systems: Models and Applications* (pp. 9-27). Springer Berlin Heidelberg.

Sébastien, T., Michel, H. and Jean-Marie, C., 2003. Mean-term textile sales forecasting using families and items classification. *Studies in Informatics and Control*, 12(1), pp.41-52.

Vignali, G. & Reid, L., 2014, "Analysing consumer motivation towards purchasing fashion online", *International Journal of Business and Globalisation,* vol. 13, no. 2, pp. 133-152.

Zhao, X., Xie, J., & Leung, J., 2002. The impact of forecasting model selection on the value of information sharing in a supply chain. *European Journal of Operational Research*, *142*(2), 321-344.

Zhang, M., Dai, X. & He, Z., 2015. "An empirical investigation of service recovery in e-retailing: An operations management perspective", *Journal of Service Theory and Practice,* vol. 25, no. 3, pp. 348.

Methodology

Bryman, A., & Bell, E., 2015. *Business research methods*. Oxford University Press, USA.

Flick, Uwe., 2009. *An introduction to qualitative research, fourth edition.* Sage Publications ltd, London

Kothari, C. R., 2004. *Research methodology: Methods and techniques*. New Age International.

Empirical information

Kantola, J. (2016, January 20) Head of Supply Chain (C. Adlarson & M. Holgersson, Interviewers)

Erneborn, U. (2016, February 8) Stock Controller (C. Adlarson & M. Holgersson, Interviewers)

Bengtsson, K. (2016, February 8) Stock Controller (C. Adlarson & M. Holgersson, Interviewers)

Lofter, F. (2016, February 16) Business Developer Logistics (M. Holgersson, Interviewers)

Hallmen, P. (2016, March 22) Project Manager - Global Online Expansion (C. Adlarson & M. Holgersson, Interviewers)

Johansson, T. (2016, March 22) Business Controller (C. Adlarson & M. Holgersson, Interviewers)

Internal documents from 2014-2016

H&M (2016). H&M's business concept. http://about.hm.com/en/About/facts-about-hm/about-hm/business-concept.html [2016-04-15]

Appendices

Appendix 1 – Sales and return data for Central Europe planning market

Confidential information

Appendix 2 – Simulation results for all departments

Confidential information

Appendix 3 – Allocation results using the optimal allocation approach

Confidential information