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Analysis of uncoordinated versus coordinated inventory control

Master Thesis at Duni Group

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Preface

We would like to begin this master thesis with an acknowledgement of all the individuals who have helped us carry out this project. The completion of the master thesis would not have been possible without the help and support from both representatives at *Duni Group* and the *Faculty of engineering - Production Management.*

We would like to extend an extra thank you to our supervisor at Duni, Wiktor Hjelm. We are very grateful for the support and guidance throughout the project as he always contributed with challenging questions and knowledge about the company that led the project forward.

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Lastly, we would like to show our appreciation to friends and family who have supported us by proofreading and general support.

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Mirja Björning & Johanna Rådemar

Summary

This master thesis has been completed at the *Faculty of Engineering, Production Management* in collaboration with the company *Duni Group.* The overall objective has been to provide guidance to Duni and analyze how they should control their inventory at each node in their new supply chain set up. The purpose was to determine appropriate reorder points for each location in Duni's new supply chain setups using appropriate uncoordinated and coordinated inventory control methods. Furthermore, Duni seek guidance on how the inventory control would be affected by changing location of their central warehouse or implementing a consolidation point.

The master thesis used a problem-solving research approach, which was divided into two phases. The purpose with *phase 1* was to thoroughly understand Duni and create the future relevant scenarios. *Phase 2* focused on solving the identified problem, which was conducted according to a six-step generic approach for operation research projects. Two mathematical models were needed - an *analytical model* and a *simulation model*. The analytical model was chosen by performing a literature review of existing models and discussions with the supervisor at the Faculty of Engineering. The simulation model was provided by the Faculty of Engineering.

The result showed that the most appropriate inventory method to determine reorder points for Duni was coordinated inventory control. This since that method best fulfilled the objective to meet end customer service requirements with as little inventory as possible. However, the benefits with reducing inventory levels and hence tied up capital could not be explicitly determined due to the fact that none of the chosen models actually meet target fill rate for all items. Regarding the scenario of changed location of the CWH, the result showed that stock should be reallocated when lead times change. However, no significant reduction in inventory levels could be determined. Regarding the scenario with a consolidation point, the result seemed to indicate that if the batch size is very small compared to the batch sizes Duni uses today, the model will obtain better fill rates while still maintaining the same inventory levels.

As the models seemed to have problems in fulfilling the target fill rate, further research could be to investigate if there exist other distributions, for instance gamma distribution, that would be more suitable to apply when the demand has such high coefficient of variation of demand as seen in this thesis project.

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CHAPTER 1

INTRODUCTION

This chapter begins with introducing the reader to the background of the master thesis and an overall introduction of the case company. Thereafter, the problem identification is presented followed by specific research questions and the purpose. Lastly, delimitations of this master thesis are discussed.

1.1 Background

The importance of efficient inventory control of supply chains has increased during the last decades. Efficient inventory control can contribute to improve the competitiveness of a company, where the objective is to minimize the total cost for purchasing and holding inventory while simultaneously meeting customer requirements (Axsäter, 2003). Furthermore, the growing e-commerce and omni-channel distribution have increased the need to efficiently control inventory levels. The growing online sales often means that warehouses must be able to distribute their products in multiple channels, which includes both direct deliveries to customers and replenishment of stock in downstream warehouses (Berling, Johansson & Marklund, 2020). In many cases, the different channels have different demands, expectations and service requirements. This creates a need among companies to find an efficiency inventory control solution (Berling et al., 2020).

There are different approaches that can be used when optimizing a company's control of inventory throughout the supply chain, such as *uncoordinated* and *coordinated* inventory control. Broadly described, uncoordinated control refers to optimization of inventory without regard to the interdependence between inventories in the supply chain while coordinated control takes this interdependence into account (Axsäter, 2015).

This master thesis intends to investigate potential advantages of using coordinated control at the Swedish company Duni Group's supply chain with upstream demand. Duni is facing large changes regarding their global supply chain, where improvements of inventory control are necessary. New research and technology have provided new opportunities for firms to coordinate their inventory control yet the methods to apply efficient control of inventory in practice can be challenging (Axsäter, 2015). The question of investigating benefits of coordinated inventory control before implementing it in practice has thus been discussed at Duni, which is the main reason for conducting this master thesis.

1.2 Company description

Duni operates within the industrial sector that supplies tabletop concepts i.e. napkins, table covers, candles and meal packaging. The products are mainly single-use, low-valued products and available in more than 40 markets across the world (Duni, 2020a). Within this industry, Duni is the market leading company in Northern Europe with 2,500 employees across 24 countries and had a turnover of 1588 MSEK in 2019 (Duni, 2019). The headquarter is located in Malmö, with production sites in Sweden, Germany, Poland, New Zealand and Thailand. Duni produces their own products as well as sells and distributes outsourced products. The company strives to create products that evokes a pleasant and positive atmosphere for every occasion where food and drink is offered, something Duni themselves denominates as Goodfoodmood® (Duni, 2020a).

Duni's products are divided into two brands, Duni and Biopak. While Biopak is a relatively new part of the Duni organization, the Duni brand instead represents the company's business area where they have years of experience. Biopak was acquired in 2018 and was launched in Europe 2019. The brand has a strong focus on environmentally friendly meal packages, which are produced from recycled materials (Duni, 2020b). The different brands are further presented in *Figure 1.1.*

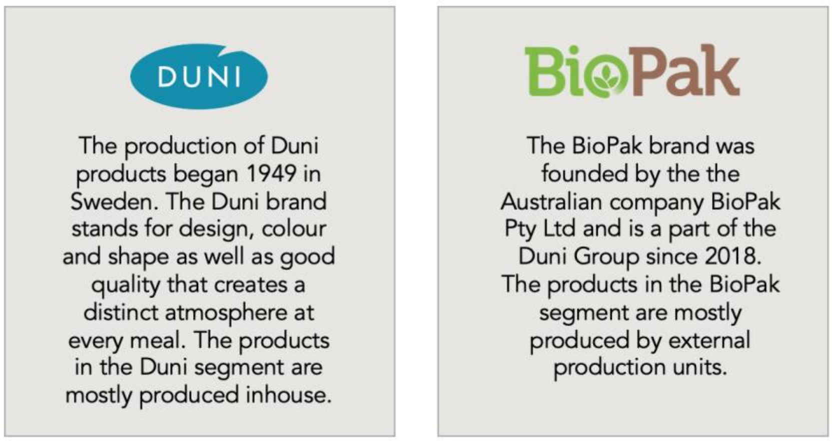

Figure 1.1. Short explanation of Duni and BioPak. Adapted from (Duni, 2020b).

The company sells their products Business to Business (B2B), which means that their end customer mainly consists of stores, wholesalers and restaurants (Duni, 2020b). Both brands are distributed globally in six regions *NorthEast*, *Central*, *West*, *South*, *Rest of World.* More precisely, as seen in *Table 1.1,* the regions include:

Table 1.1. Regions where Duni distributes both brands and corresponding sales data.

Region	**Countries**	**Total sales volume 2019 [€mn]**
NorthEast	Northern and Eastern Europe including Russia.	90
Central	Germany, Austria and Switzerland.	211
West	The Netherlands, Belgium, Luxembourg, UK and Ireland.	86
South	France, Spain and Italy.	53
Rest of World	All sales outside Europe, where the largest regions are Australia, New Zealand, Thailand and Singapore.	94

1.2.1 Outsourced production at Duni

This master thesis focuses on Duni's outsourced production, which is products from the Duni brand as well as BioPak. An illustration of Duni's organizational structure is demonstrated in *Figure 1.2.* The department of outsourced production is a sub-department within the operations department. A reconstruction of the operations department was implemented approximately a year ago, where the outsourced production department was established (Hjelm, 2020).

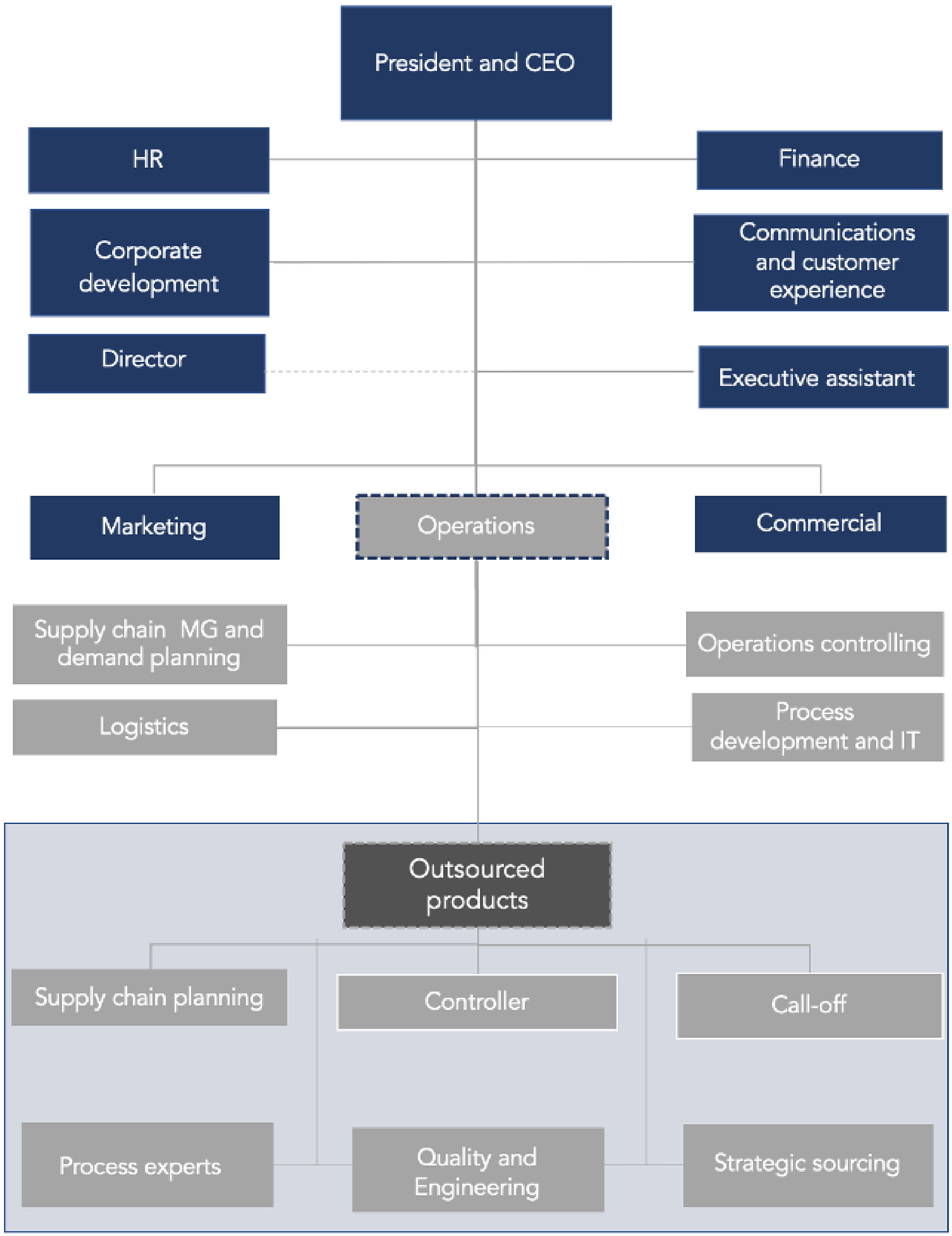

Figure 1.2. Organizational chart of Duni Group.

In recent years, Duni has increased its share of outsourced products that has allowed the company to be more flexible and reduce the need for investments in new facilities and production lines that need maintenance (Hjelm, 2020). The company's outsourced products have grown due to several acquisitions, such as BioPak, and now represent about 40% of the company's revenue (Duni, 2020b). Today, Duni sources approximately 2000 different items, which can be grouped into five main commodities - *Plastic, Wood, Paper*, *Bagasse* and *Candle & led* (Winter, 2020). These products are sourced from both Asia and Europe and distributed globally. As the outsourced production is a relatively new and growing area for Duni, the company has faced several challenges within this business area. This has put additional requirements on their supply chain.

1.2.2 The supply chain for outsourced production

An illustration of Duni's supply chain for outsourced products is illustrated in *Figure 1.3*. As seen in the figure, their supply chain consists of suppliers in Asia and Europe that deliver their products to a warehouse in Germany or directly to the warehouse in Sweden. From these warehouses, the products are either distributed directly to the end customer or distributed through their distribution centers located in Europe before being sent to the end customer. A product can thus be delivered via different routes in the supply chain.

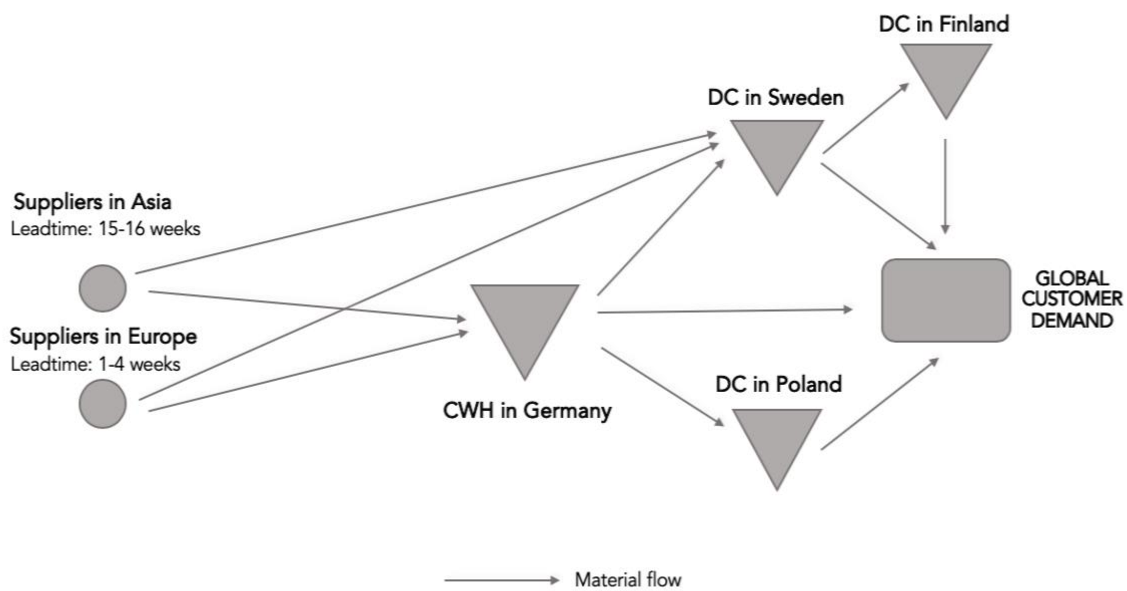

Figure 1.3. The supply chain for sourced products at Duni Group.

1.3 Problem identification

The supply chain for outsourced production has faced several challenges due to increased volume of sourced products. First of all, one of the challenges is, according to Duni, that the suppliers in Asia can be rather immature when it comes to production planning. These suppliers only produce when they have received an actual purchase order (PO), even though Duni desires that their suppliers instead would be able to produce against a forecast. This causes both longer lead times and challenges with maintaining an efficient replenishment process. However, Duni believes that by modifying the size of the purchase orders, stock levels can be reduced, and inventory control improved.

Secondly, Duni has for a long time prioritized transporting full containers instead of having low inventory levels in their warehouses. The main reason for this is the low product value relative the transportation cost. Full containers have been the focus, even though this might lead to purchasing larger volumes than customers actually demand. Hence, control of inventory levels has not been prioritized at Duni, which have resulted in too high inventory levels and excessive costs. In addition, the issue with high inventory levels has become an even more discussed topic during the COVID-19 pandemic, as the company is currently experiencing that several of the warehouses are reaching its maximum capacity (Hjelm, 2020).

Due to the two mentioned challenges in combination with growing volumes sourced from Asia, Duni has identified a need for improvement of their currently used supply chain set up. The long-term goal of a transformation is to improve the structure and the inventory control in the company's supply chain in order to better meet global demand and reduce unnecessary costs. In the new supply chain, the current problem with excessive amounts of stock in their inventory will not be overlooked. In order to handle the situation with holding excessive inventory, Duni seeks to investigate if new methods can be used to improve their inventory control. More specifically, the company questions if a coordinated control method can provide improvements compared to the type of uncoordinated control method applied today. Their uncoordinated inventory control used today means that each inventory location in their supply chain is controlled and optimized independently, disregarding the inventory levels at other locations (Axsäter, 2015).

1.3.1 Research questions

Duni have identified a need for transforming their existing supply chain set up. Exactly how the new supply chain set up will look like is not yet fully decided. The company thus aims to understand the potential benefits of using coordinated control in future supply chain set up. The purpose of this master thesis is not to provide guidance on which new supply chain set up that is best suited for Duni, but rather an indication of how the company's inventory control can be affected by investigating various future supply chain set up scenarios.

The main scenario consists of a simplification and modification of the company's existing supply chain to a simpler divergent structure. It is this scenario that lays the foundation for the two sub-scenarios, which will be investigated by performing a sensitivity analysis of the main scenario. By performing the sensitivity analysis, guidance of how the achieved service requirements and stock levels would be affected by adjusting different factors such as lead time and batch size can be provided. A detailed explanation of each scenario will be presented in chapter 3.

Duni is currently using a multi stage inventory system controlled by a policy similar to a (R,Q) policy, where the same policy also will be assumed for the future scenarios. In a (R,Q) policy, a batch quantity (Q) is ordered when the inventory position[1] decreases to or below the reorder point level (R) (Axsäter, 2015). Each new supply chain scenario will have a similar divergent supply chain structure as illustrated in *Figure 1.4*, with one central warehouse with N-number of

[1] *Inventory position = stock on hand + outstanding order - backorders.*

distribution centers. In each setup, the central warehouse (CWH) will for each item have a specified lead time (L_{CWH}) from suppliers in Asia and Europe, a reorder point (R_{CWH}) and an order quantity (Q_{CWH}) for each product. Similarly, the distribution centers (DC) will also have reorder points policies with fixed order quantities. Additionally, the DCs will have required fill rates targets (S_i) in order to fulfil customer service requirements. The company owns the CWH as well as the DCs, which means that they from a control perspective have a centralized supply chain.

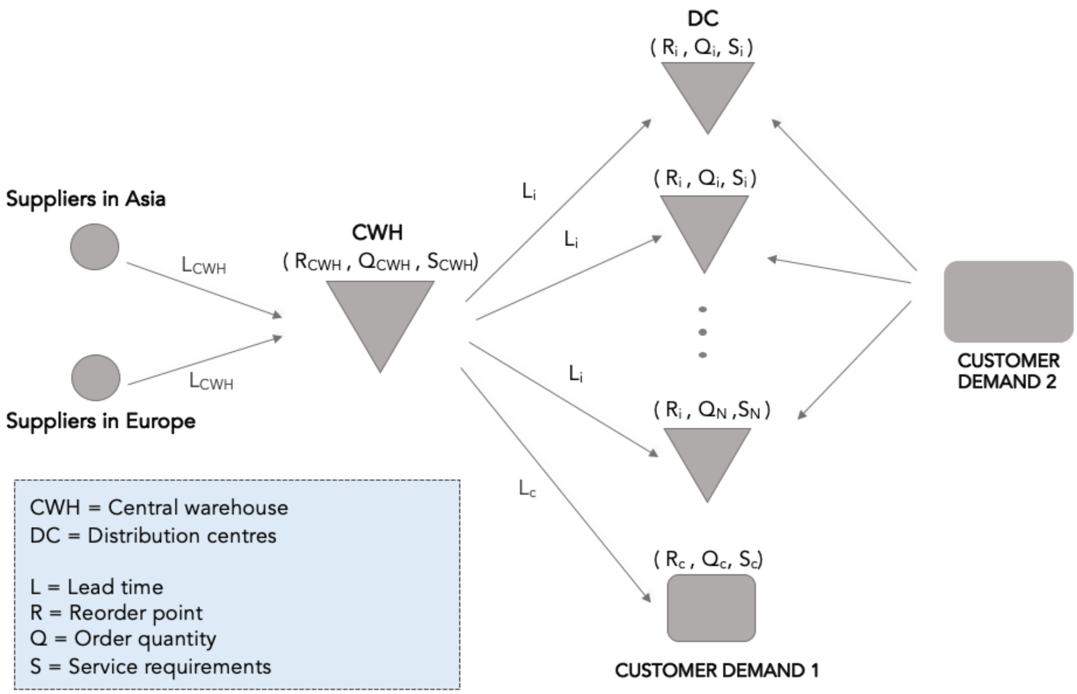

Figure 1.4. The new supply chain setup for sourced products at Duni Group.

The objective is to find an inventory control method that minimizes their average inventory levels and tied up capital, while still meeting customer service requirements. A deeper analysis is required to determine the timing and order sizes, meaning *when* to order and the quantity of *how much* to order. However, as this thesis assumes fixed order quantities the main focus is to determine when to order and thus how much inventory should be kept at each node in the new supply chain in order to fulfill their service targets. Hence, the identified challenge for Duni is to understand how to determine appropriate reorder points (R) in the various new supply chain scenarios and thereby appropriate average inventory levels.

To conclude, the overall objective with this master thesis is to provide guidance to Duni and analyze how they should control their inventory at each node in the new supply chain set up. Two important research questions are then:

- *How to set appropriate reorder points at CWH and at each DC in their new supply chain setups to meet the predetermined fill rates with as little inventory as possible?*

- *Which effects; benefits and drawbacks can be identified when comparing uncoordinated and coordinated inventory control of their new supply chain set up?*

1.4 Purpose

The purpose of this master thesis is to:

1) Determine appropriate reorder points for each location in Duni's new supply chain setups using appropriate (i) uncoordinated and (ii) coordinated inventory control methods. The objective is to meet end customer service requirements with as little inventory as possible.

2) Identify the benefits and challenges with the two different inventory control methods and determine which method that is the best one for the case company.

3) Given the most suitable inventory control method for Duni, perform a sensitivity analysis to provide guidance of how the inventory control might be affected if the supply chain structure changes.

1.5 Delimitations

The scope and delimitations of the master thesis have been discussed and formulated together with both the case company and the supervisor Johan Marklund at the Faculty of Engineering, division of Production Management at Lund University. This section will present the general delimitations for the scope of the thesis project.

As previously mentioned, this thesis will be limited to the supply chain of Duni's outsourced production. The total supply chain for outsourced products at Duni includes the flow from suppliers to the wholesalers which sell the products to end customers. However, the wholesalers will not be considered in this project since Duni cannot control their inventory levels. The scope of this master thesis has also been delimited to focus on the European demand since that is where Duni sells most of their products today. Hence, all other flows outside this have been disregarded.

Furthermore, the scenarios to be investigated are fictitious. This means that the scenarios are built on various simplifying assumptions regarding lead times and order quantities. It is also assumed that the main scenario constitutes the foundation for the other scenarios, which means that the two sub-scenarios do not receive equal weight in the analysis. Thus, not as many simulations have been performed for the two sub-scenarios as for the main scenario.

A large part of the methodology of this master thesis has been to collect the right data, run an analytical model and perform simulations. To be able to conduct the master thesis within the time frame not all 2000 sourced items could be analyzed. Instead, a small set of test items from the company's product assortment was used. This selection has been conducted together with Duni and is further explained in *section 3.3*.

Moreover, the area of uncoordinated and coordinated inventory control contains many different models for how to optimize the inventory system. In this master thesis, only one uncoordinated and one uncoordinated method was used. This limitation was necessary in order to carry out the project within the given time frame and also that only one model was necessary to use in order to fulfill the purpose of the master thesis. The most suitable model that was selected is discussed and presented in the literature review in *section 4.8* and *section 4.9.*

Lastly, some assumptions were made to the collected data used as input in the analytical model. These assumptions have been made due to simplification reasons and are presented in *Chapter 5.*

1.6 Target Group

The target group of this master thesis is the management of outsourced production at Duni and master students at Lund University, Faculty of Engineering. This means that the reader is expected to have basic understanding of inventory control and concepts within the area of supply chain management.

CHAPTER 2

METHODOLOGY

This chapter presents the methodology used in this master thesis. The methodology has been divided into two main phases - phase 1 and phase 2, where each phase is explained in the following chapter. Lastly, the objectivity, validity and reliability of the master thesis is discussed.

2.1 The scientific approach

In order to fulfil the purpose of this master thesis, a suitable scientific approach needs to be chosen. When the research question has been formulated and a clear purpose is defined, an appropriate method should make it possible to answer the research question and thus fulfil the purpose (Skärvad & Lundahl, 2016).

Overall, this master thesis used a *problem solving* research approach. According to theory, this approach aims to find a solution to an identified problem (Skärvad & Lundahl, 2016). This thesis aimed to solve an identified problem within the area of inventory control at Duni. Hence, this research approach was appropriate to use for this project. However, in order to create a thorough foundation for the problem solving research, the methodology for this thesis has been divided into two main phases - *phase 1* and *phase 2.* The purpose with *phase 1* was to thoroughly understand Duni and create relevant future scenarios. *Phase 2* focused on solving the identified problem, which was conducted according to a six-step generic approach for operation research projects. Each phase will be further explained in the following sections.

2.2 Phase 1

Phase 1 consisted of getting to know the company Duni, understanding the problem of outsourced production and laying the foundation for which scenarios that would be further analyzed. The following sections will explain how this was done for this master thesis. In *section 2.2.1,* the choice of applying a descriptive study will be motivated. Thereafter, in *section 2.2.2,* the difference of collecting data either quantitative or qualitative will be discussed as well as which method was best suited for this project. Finally, a discussion of using primary or secondary data will be presented in *section 2.2.3*.

2.2.1 Descriptive study

The main purpose in a descriptive study is to describe and understand a studied system more thoroughly (Skärvad & Lundahl, 2016). This approach is appropriate to use when the researcher desires to gain an in-depth understanding of a specific topic but not explain any relations between variables (Skärvad & Lundahl, 2016; Björklund & Paulsson, 2012). In this master thesis, the initial step consists of describing, mapping and understanding Duni's supply chain and processes. Hence, a descriptive study was appropriate to use in *phase 1*.

A thorough understanding and description of the company's existing supply chain was necessary to lay the foundation for the modifications that would represent the various supply chain scenarios.

The objective with *phase 1* included creating scenarios for different new setups that aligned with the company's current resources and capacities. Additionally, as Duni has over 2000 items in their outsourced product portfolio the descriptive phase also involved understanding the product portfolio in order to later decide which items would represent a suitable sample group.

2.2.2 Quantitative and qualitative studies

Depending on which data that is desired, the study can be either quantitative or qualitative (Höst, Regnell & Runeson, 2006). A quantitative study entails collecting information that can be measured numerically i.e. number, weight or proportion. Surveys or mathematical models are usually more suitable to apply when using a quantitative study. However, everything cannot be measured numerically which sometimes makes qualitative studies more appropriate to use (Höst, Regnell & Runeson, 2006). Hence, a qualitative study can be used when the researcher desires to gain a deeper understanding of a specific problem or situation. Qualitative data primarily consists of words and descriptions that contain many details (Höst, Regnell & Runeson, 2006, p.30). A common way of collecting the data is through interviews within a defined scope. The difference between a qualitative and quantitative study is thus determined by how the data is collected (Björklund & Paulsson, 2012).

In order to succeed with the descriptive study, an appropriate method for collecting data was required. In *phase 1* of the thesis, the collected data come from interviews, which in turn defines the first phase as qualitative. The qualitative data gained from the interviews at the company was not only needed in order to describe the supply chain, but also to identify and specify problems at Duni. Furthermore, this data was needed in order to build a foundation for *phase 2*.

2.2.3 Primary and secondary data

As stated by Höst, Regnell and Runeson (2006), data can either be primary or secondary. Primary data is defined as the data collected with the purpose of the current research project in mind. The advantage of using primary data is that it can be seen as less biased and is thereby often preferred. On the contrary, secondary data is defined as data gathered with another purpose in mind than the purpose of the current study. Since this information might be biased towards that purpose it is important to ensure that the information is still accurate to use in the study at hand. As an example, the information gained through literature reviews are secondary data, where it is important to assure that the information is used correctly for the sake of the current study (Björklund and Paulsson, 2012).

The data gathered through interviews at Duni was defined as primary data. Additionally, the demand data collected from the company’s database was also defined as primary data since it was obtained for the same purpose as for this master thesis project. However, it should be mentioned that some complementary information has been gathered through web pages such as Lubsearch[2] and presentations provided by the company. This information is secondary data and was used to describe general facts about the company or conduct the literature study. It should be highlighted that all used secondary data from Lubsearch have been peer reviewed or confirmed as credible with the supervisor at the faculty of engineering.

[2] *Lubsearch is a search service at Lund University that collects the university's resources.*

2.3 Phase 2

After a thorough foundation had been created in *phase 1*, *phase 2* of this thesis was initiated. The problem to be solved was an inventory control problem, which belongs to the field of operational research (OR). Thus, the second phase of this master thesis was conducted according to a six step generic approach for OR projects which was adapted from Hillier and Lieberman (2012). OR should "*be applied to problems that concerns how to conduct and coordinate the operations within the organization"* (Hillier and Lieberman, 2012, p.2). The approach can be summarized in six major steps, which are presented in *Table 2.1*. The various steps were thereafter modified to suit this particular master thesis, where the modification is presented in the next section.

Table 2.1. Description of the six major steps in operation research [3]

Step 1: Define the problem of interest and gather relevant data.
This step includes formulating a well-defined problem with clear objectives, limitations, time limits and alternative courses of action. This also involves aligning with the case company's expectations and requirements. The OR study aims to find the solution that is optimal for the whole firm, rather than optimize each part of the firm individually. Furthermore, data gathering usually constitutes a time-consuming element in OR studies since OR requires a lot of data in order to understand the problem as well as formulating the mathematical model. (Hillier & Lieberman, 2012, p.7-10)
Step 2: Formulate a mathematical model to represent the problem.
When the problem has been identified and data is gathered, the next step is to reformulate it to be suitable for analysis. In an OR project this typically means constructing a mathematical model that corresponds to the defined problem. This includes determining relevant decision variables ($x_1, x_2, \dots, x_n$), where n represents the number of quantifiable decisions to be made. Thereafter, the objective function, meaning the quantitative measure of performance, is expressed by these decision variables. Restrictions of the objective functions are defined as constraints. However, deciding correct values can be difficult due to challenges in data gathering. Therefore, it is crucial to perform a proper sensitivity analysis and examine how the approximated values may affect the solution. (Hillier & Lieberman, 2012, p.10-13)
Step 3: Develop a computer-based procedure for deriving solutions to the problem from the model.
The next step is to develop a method for deriving solutions to the identified problem from the model. This step can be simplified if existing standard algorithms can be used on computers that already have available software packages. However, it is worth mentioning that the identified solutions will only be optimal with regard to the used model. In order to formulate the mathematical model, some simplification of reality is required. Thus, there is no guarantee that the formulated model completely reflects reality. That being said, it is important to emphasize that if the model is well designed and tested, the solution should be a good solution for the real

[3] *These steps are adapted from Hillier & Lieberman (2012, p.7-21)*

system. This means that the solution can provide a guidance of course of action on how to handle the real problem. (Hillier & Lieberman, 2012, p.14-16)

Step 4: Test the model and refine it as needed.

As stated above, the formulated model is a simplification of reality. This implies that there is a risk that some relevant factors have been incorrectly estimated or some interrelationships have not been included. Hence, in order to ensure that the model renders a valid result, the model needs to be tested and corrected. Major bugs need to be removed until the model can be reliably used. This process is called model validation, where the aim is to increase the validity of the model. The validation process may differ depending on the defined problem and usage of the model. (Hillier & Lieberman, 2012, p.16-18)

Step 5: Prepare for the ongoing application of the model as prescribed by management.

In this step, the model is prepared for implementation. A well-documented system for applying the model determined by the management is installed. This contains both the model, solution procedure and operation process for implementation. (Hillier & Lieberman, 2012, p.18-20)

Step 6: Implementation.

The final step is implementation. It is vital to make sure that model solutions are correctly translated into the operation procedures. The implementation relies on cooperation between management and the OR researchers. (Hillier & Lieberman, 2012, p.20-21)

2.3.1 Practical work process in this master thesis project

The general six step approach within OR research adapted from Hillier and Lieberman (2012) was described in the previous section. In this section, these general steps were modified to suit this master thesis and hence represent the practical approach. The six general steps were modified to:

1. Define the problem of interest and gather relevant data.
2. Selection of test items.
3. Select suitable mathematical (analytical and simulation) models.
4. Test and refine the model.
5. Sensitivity analysis of the main scenario.
6. Discussion of results.

2.3.1.1 Define the problem of interest and gather relevant data

The problem defined in *phase 1* was based on qualitative data. However, as this master thesis intended to apply a mathematical model, quantitative input data was needed. Hence, the focus in this step was to gather numerical data and the quantitative study was justified. The numerical data was collected by the case company for the same purpose as for this project. The data could therefore be seen as accurate, unbiased and categorized as primary data. The data needed as input to the mathematical model can be summarized as:

- *Sales data* between 2019-01-01 to 2019-12-31.
- *Mean* and *standard deviation* of customer demand for each item and DC.
- *Lead times* from suppliers in Asia and Europe to the CWH for each item.
- *Transport time* between CWH and DCs for each item.
- Internal demand, meaning the *order quantities* for each item demanded from the CWH.
- Target fill rates, meaning the *service requirements* for each item and DC.

2.3.1.2 Selection of test items

In order to make the thesis project feasible within the time frame a number of test items were selected. There are various approaches that can be used when selecting a sample for analysis, where Bryman and Bell (2011) highlight two general approaches - *probability sample* or *non-probability sample.* The former refers to when the sample is selected by a random selection method, which means that each item in the total population has a known probability of being chosen. This approach minimizes the sampling error. Examples of random selection methods are simple random sample, systematic sample or stratified random sampling. Non-probability sample is the opposite of probability sample, which means that no random selection method is used. This implies that some items have a higher probability of being chosen than others. (Bryman & Bell, 2011, p.179)

In this master thesis project, a non-random selection method was used. Duni required some predetermined factors that needed to be taken into consideration when selecting test items for this master thesis. Hence, a random method could not be used since that would risk choosing items that were not of importance for this project. Duni uses an internal classification of their products divided into five groups. A number of test items were thereafter selected in each group based on predetermined requirements. A deeper explanation of the selection of test items will be presented and motivated in chapter 3.

2.3.1.3 Select suitable mathematical models

As this master thesis project would not develop a new model, step 2 and step 3 in the general six step approach presented in *Table 2.1* is outside the scope of this project. Instead, this step included setting appropriate requirements for the mathematical models and thereafter choosing existing models that fulfilled the requirements. These requirements were determined based on interviews and dialogs with Duni and the supervisor at Lund University.

Two mathematical models were needed - an *analytical model* and a *simulation model*. The analytical model was chosen by performing a literature review of existing models and discussions with the supervisor at the Faculty of Engineering, Production Management. The literature review and selection of a suitable analytical model will be further discussed in *section 4.8* and *4.9.*

Based on the dialogs and interviews, the requirements were defined as follows:

- The model must be able to handle (R,Q)-policies at all stock points.
- The model must be easy to apply in a real-life inventory system.
- The model must be applicable to a divergent distribution system with one central warehouse and N non-identical downstream warehouses

- The model must be able to handle upstream demand, meaning direct supply from CWH to end customer.

2.3.1.4 Test and refine the model

After the analytical model had been selected, the next step was to test and refine the model. As a substantial time has been devoted to collecting and cleaning large amounts of data, there is a risk that there may be an error somewhere due to the human factor. Therefore, this step was a vital part of the project for the results to be accurate. The testing and redefining of the model was performed using the following approach:

1. Clean data to fit the input parameters of the analytical model.
2. Analyze the input data and select a suitable demand distribution.
3. Run the analytical model.
4. Use the output from the analytical model and verify the model by simulations in the simulation model.
5. Evaluation of the standard deviation of the fill rate.
6. Refine input parameters and perform step 1-5 if needed.

2.3.1.5 Sensitivity analysis of the main scenario

Step 5 and 6 from the generic six steps in an OR project presented in *Table 2.1* was also outside the scope of this master thesis. Instead, these steps were modified to a sensitivity analysis of the main scenario. As previously stated, Duni seek guidance on how to control their inventory at each node in different future scenarios. By adjusting input parameters in both the analytical model and simulation model, such as lead time and order quantities, the various sub-scenarios could be simulated.

2.3.1.6 Discussion of results

The final step included comparing the scenarios relative to each other. The objective of this step was to compare the output from each scenario and examine both benefits, drawbacks, similarities and differences. Lastly, the final step of the methodology was to analyze main findings and answer the research questions.

2.4 Objectivity, Reliability and Validity

Regardless of what phase, the objectivity, reliability and validity of the thesis should be considered. These terms are important to achieve in order to ensure high quality of the master thesis. The following section will hence discuss these terms and how it has been achieved in this project.

2.4.1 Objectivity

When conducting theoretical research, objectivity is important to take into consideration for the credibility of the master thesis. Objectivity may include aspects such as correct reproduction of data, clearly distinguishing between facts and values, impartiality and completeness. However, if total objectivity cannot be achieved, the researcher should clearly and openly present all assumptions. (Skärvad & Lundahl, 2016)

The main objective of this master thesis was to investigate advantages of coordinated control in different future scenarios. As these scenarios are fictitious, it should be emphasized that the focus was to recommend a direction for the future inventory control method rather than hundred percent correct values of reorder points and optimization of inventory levels. This means that simplifications have been made in order to be able to simulate the different scenarios within the given time frame. Therefore, in order to achieve objectivity, all assumptions that affected the results have been clearly stated throughout the master thesis. Furthermore, as the obtained results are based on simulations from a well-tested mathematical simulation model, the results are not affected by any own opinions of the researchers.

2.4.2 Reliability

According to Skärvad and Lundahl (2016, p.110), the term reliability refers to that the research and its result should not be affected by the individual researchers nor external circumstances. A reliable result should be the same if the test will be performed once again. Karlsson (2010, p.25) states that these aspects may be difficult to fulfil and instead highlights the importance of enabling the reader to easily follow the written text and chain of logic. This should result in the reader being able to draw the same conclusions as well as understand how the conclusions were reached.

In order to achieve reliability in this master thesis, two aspects have been taken into considerations. Firstly, the simulations have been performed in what is referred to as steady state. The simulation time has also been chosen to be the longest possible for each item in order to ensure that all possible outcomes were taken into consideration. Secondly, the chain of logic in the report highlighted by Karlsson (2010), has been achieved by constantly explaining simplifications and underlying assumptions.

2.4.3 Validity

In a qualitative research, validity refers to the absence of measurement errors. The term can be divided into *internal validity* and *external validity*. The internal validity refers to whether the research actually measures what is intended to be measured, while the external validity means that the result should be valid in a similar context outside the study (Karlsson, 2010, p.25).

In OR studies, one vital aspect is the model validation, which refers to that the model should represent the real process correctly. By ensuring that the model is valid, it is reasonable to assume that the model is an accurate representation of reality and thus fulfils the intended purpose (Laguna & Marklund, 2013). However, when developing a new model, there is a risk that it contains bugs that need to be fixed. Such as parameters that have been incorrectly estimated or interrelationships that have been forgotten to include (Hillier & Lieberman, 2012). Therefore, the model must be thoroughly tested before it is used in practice. The model chosen in this master thesis have been carefully tested in previous research at *The Faculty of Engineering, Department of Production Management*. Furthermore, the model's assumptions seemed after careful evaluation suitable to apply on Dunis fictious supply chain. Thereby, both the validity of the model can be seen as fulfilled.

Furthermore, Hiller and Lieberman (2012) highlights the importance of validation and correction of input data for the model. All collected data used in the mathematical model was based on extracted data from Duni's own ERP system. Hence, it can also be considered as validated as the ERP system is assumed to have valid and accurate data. However, it should be kept in mind that the examined systems are fictitious, which means that real data is assumed to be applicable to the fictitious scenarios. This was discussed with representatives from Duni who confirmed that this did not significantly affect the result as the purpose was to provide direction of potential future scenarios, rather than exact values of the results.

CHAPTER 3

CONSTRUCTED SCENARIOS AND SELECTION OF TEST ITEMS

This chapter begins with presenting the three constructed scenarios, which consist of one main scenario and two sub-scenarios. Thereafter, the process of selection of test items is presented, where the predetermined requirements for selection of test items is discussed.

3.1 Scenarios

One main scenario and two sub-scenarios were created in this master thesis. As previously stated, the reason for investigating different supply chain scenarios was that Duni has not fully decided how the future supply chain set up should be constructed. In order to align the created scenarios with Duni strategic direction, the scenarios have been created based on interviews and dialogs with employees and management at Duni.

As Duni strived to coordinate the structure of their existing supply chain, the *main scenario* represented a simplified and modified version of the company's current supply chain set up with a simpler divergent structure. This is referred to as *the main scenario*. Additionally, Duni seek guidance in how the coordinated system would be affected if modifications in the supply chain set up were performed. These modifications were illustrated by creating two different sub-scenarios, *Sub-scenario 1* and *Sub-scenario 2*. Each scenario will be further explained in this chapter.

3.1.1 The main scenario

The supply chain in the *main scenario* with a divergent structure is illustrated in *Figure 3.1*. The suppliers are located in both Asia and Europe, which delivers to the CWH located in Germany. From there, the CWH can supply directly to end customers or to DCs located in various places in Europe. In this scenario, a comparison was conducted of the fill rates and inventory levels that were rendered by using either uncoordinated or coordinated control, while still meeting the predetermined service requirements.

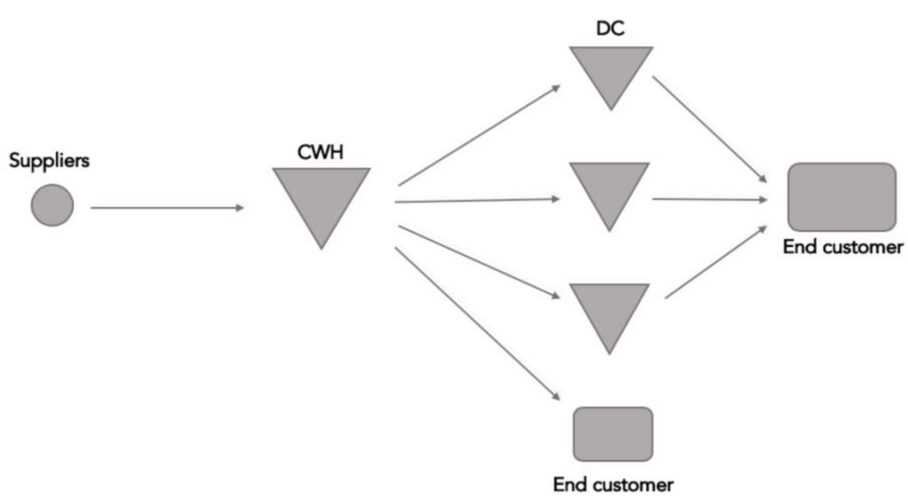

Figure 3.1. The main scenario.

3.1.2 Sub-scenario 1 - Change of batch sizes

Sub-scenario 1 was a minor modification of *the main scenario* and is illustrated in *Figure 3.2*. An internal discussion at Duni regarding a consolidation point has been brought up in order to utilize full containers and reduce unnecessary inventory. The company believes that a consolidation point can provide opportunities to reduce the batch sizes sent from the suppliers to the CWH. This may also provide opportunities to reduce cost of shipment and tied up capital in terms of held inventory. However, this may be at the price of increased complexity in their supply chain and investment cost to build the consolidation point.

The consolidation point was simulated by using the same supply chain structure as in the main scenario but with reduced batch sizes between suppliers and the CWH. In reality, a consolidation point would slightly increase the lead time from the suppliers to the CWH with one or two days. However, to be able to provide distinct results only the order size factor was changed. The reduction of batch sizes was first divided by two and then by a quarter. Additionally, the batch size was adjusted to be the number of items that was equal to one pallet. Hence, three different batch sizes were simulated in sub-scenario 1. The results from this scenario were used to provide guidance on how adjustment of batch sizes might affect Duni's inventory control.

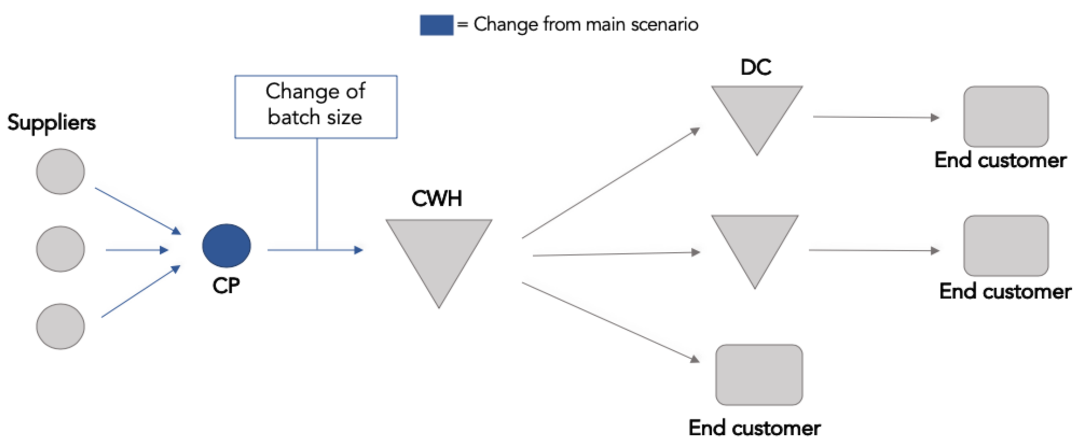

Figure 3.2. Sub-scenario 1.

3.1.3 Sub-scenario 2 - Change of lead times

As Duni sources large volumes from Asia, the company has also discussed the opportunities of a new location of the CWH, closer to the suppliers. Hence, Duni seek guidance on how the inventory levels would change if a CWH would be located in Asia, instead of Germany. The new location was simulated by using the same supply chain structure as in the main scenario but with changes in lead times between the nodes. More precisely, by decreasing the lead time from the suppliers to the CWH to 2-3 days and increasing the lead time from the CWH to the DCs to 14-90[4]. This is illustrated in *Figure 3.3*.

[4] *For detailed lead times between CWH to DCs, please see Appendix B.*

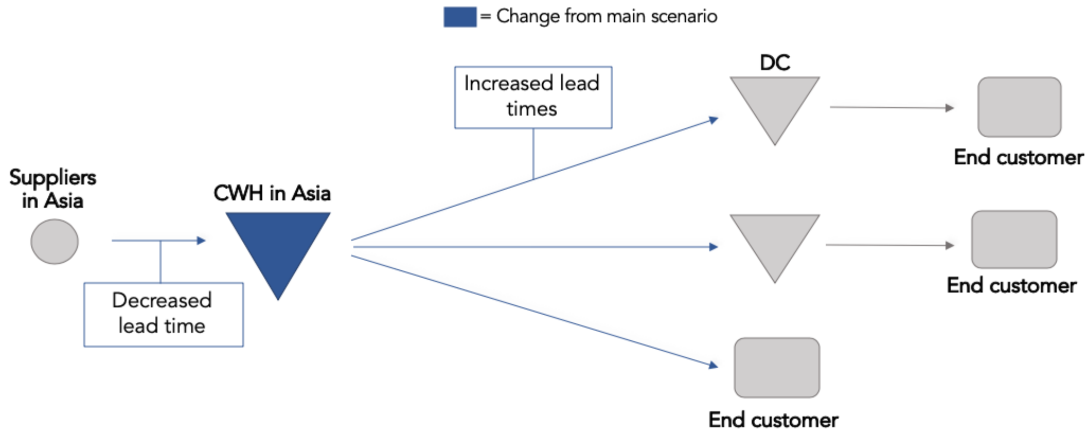

Figure 3.3. Sub-scenario 2.

3.2 Selection of test items

As stated in the methodology, the selection of test items was performed in collaboration with Duni. In order to present how the selection of test items was performed, the company's classification first needs to be explained.

The company has divided their product portfolio into six classification segments: A, B, C, D, N and O items. The classification is based on two factors: number of order lines as well as share of contribution margin. A-items are those items who have the largest sales volume as well as the largest contribution margin. B to D-items follow the same reasoning but with decreased sales volume and contribution margin. N-items are articles newer than one year and O-items are obsolete items with incomplete master data. The segmentation model is further illustrated in *Figure 3.4.*

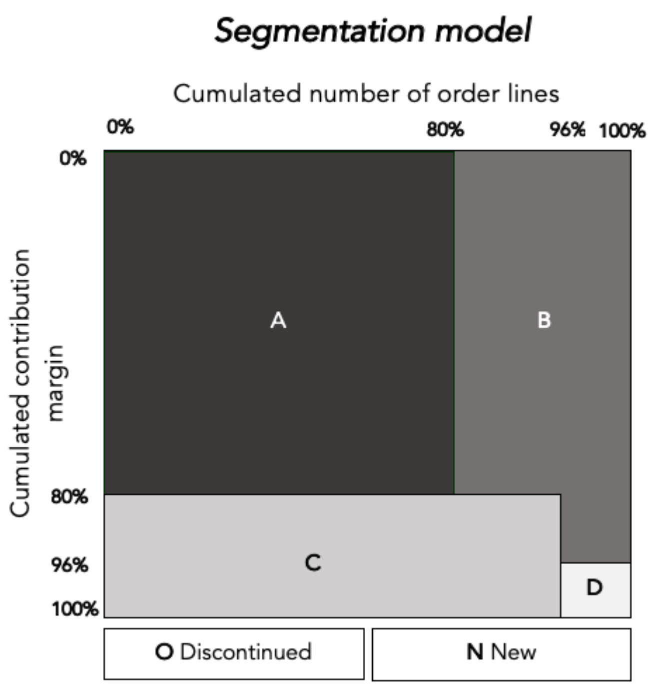

Figure 3.4. Definitions of classifications adapted from Duni.

In this master thesis, D-items and O-items were excluded. The O-items were determined to be excluded from the beginning of the thesis project since those articles are not currently sold at Duni. D-items were first expected to be included. However, as data were collected it became apparent that these items often contained incomplete data with fewer than 10 observations during the year of 2019. Therefore, the decision was made to exclude these items as well. To summarize, the classifications that were deemed relevant for this thesis were thus A, B, C and N items.

All items within a classification have an assigned target service level. A-items has a target service level of 96%, B-items 94%, C-items 92% and D-items 90%. As N-items are new products, these items have not yet received a set service level. However, it was considered suitable for the N-items to have a lower service level compared to the other items. Hence, the service level for these items was determined to 88% in this thesis.

There were various aspects to consider when selecting test items. In each of the classification groups A, B, C and N, five items were selected based on predetermined requirements for each group. These requirements are stated in *Table 3*.1. By selecting five items from each of the four categories the total sample size was decided to be limited to 20 items. Due to the limited time frame as well as the number of scenarios, which contained time consuming calculations and simulations, the total size of 20 seemed appropriate. The total list of selected items is provided in *Appendix B.*

Table 3.1. Requirements for test items.

Requirement	Explanation
1. The items needed to be relevant for Duni, meaning, the items with the largest contribution margin in each category.	The test items were selected in collaboration with the company, which was the reason why a non-random selection method was used. Contribution margin is defined as the revenues minus variables costs divided by revenues. The items were ranked in a decreasing order, with regards to largest contribution margin.
2. There must exist sales data for the year 2019	There must exist at least data of 10 sales opportunities for it to be considered as enough data.
3. The item must be make-to-stock items	Make-to-stock items are items that are manufactured based on a forecasted demand and then placed to be stored as stock.
4. Active supplier	The supplier must be an active supplier, which means that the supplier currently supplies the company with products.
5. The chosen items must represent different values of lead times, order quantities and customer demand.	From an inventory control perspective factors such as demand, lead time, costs and service requirement affects the decision regarding level of inventory. This means that items with similar values of these factors will according to theory be controlled in the same way. Hence, items with different values were needed. If more than two items within the same classification had similar order quantity and lead time a new item were chosen.

A list of the selected items can be found in *Appendix B* along with the associated classification, article description, supplier, lead times, batch quantities and target fill rate.

3.2.1 Selection of test items for each sub-scenario

All 20 test items were used in the main scenario in this master thesis. However, for the two sub-scenarios, only 8 items were selected in order to fit the project within the set time frame. The explanation for selecting the items in each sub-scenario is stated in *Table 3.2* and the detailed list of the selected items for each sub scenario can be found in *Appendix B*.

Table 3.2. Test items in each sub-scenario.

Scenario	Explanation
Sub-scenario 1	Two items within each classification were selected based on batch size, lead time and experienced demand. If simulation time were considered to be too long, a new item within this classification were selected.
Sub-scenario 2	Two items within each classification were selected based on the condition that the supplier needed to be located in Asia, lead time and experienced demand. If simulation time were considered to be too long, a new item within this classification were selected.

CHAPTER 4

THEORETICAL FRAMEWORK

In this chapter, the theoretical framework used in this master thesis is presented. The reader will be given a general background of inventory management, uncoordinated and coordinated control followed by a literature review of existing methods. Lastly, the method chosen for this master thesis will be presented.

4.1 Overview of theoretical framework

The objective with the following sections is to present the theoretical background that is used in this master thesis. In order for the reader to easily follow and understand the presented theory, an illustration of the structure of the theoretical framework is introduced in *Figure 4.1*.

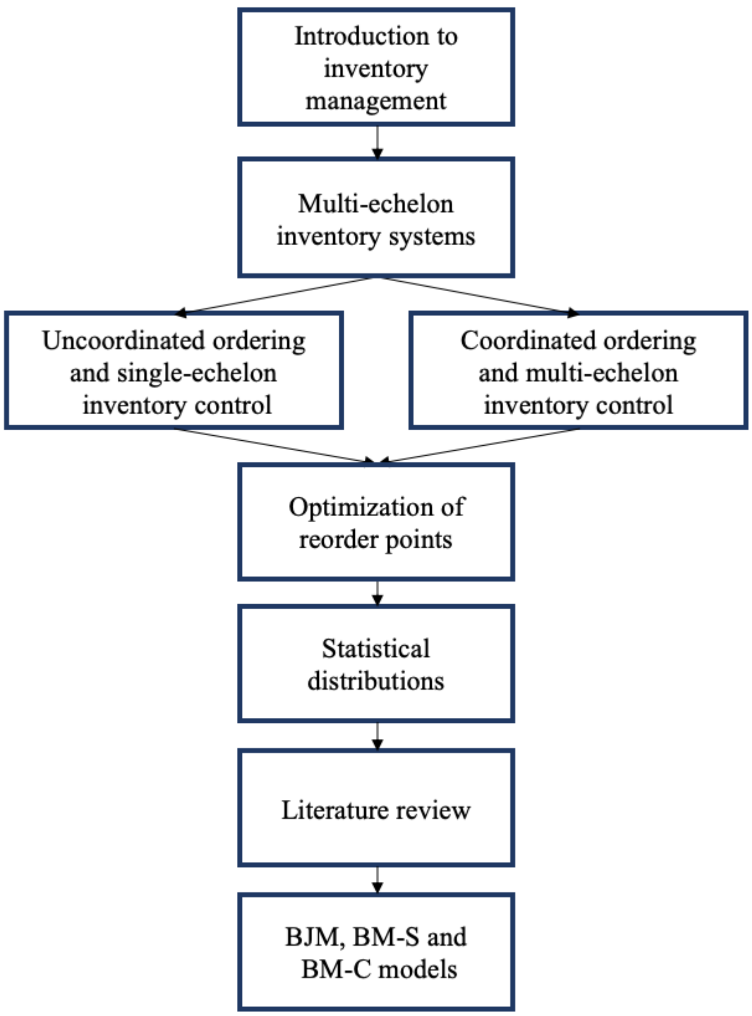

Figure 4.1. Structure of theoretical framework.

4.2 Introduction to inventory management

Inventory management (IM) plays a vital role in all types of product-based companies (Riad, Elgammal & Elzanfaly, 2018). The purpose of IM is to supervise and control flow of material from suppliers to warehouses and further to the end customers (Axsäter, 2015). As IM often extends over several business areas such as sales, purchasing and supply chain planning, the main objective is to balance and align the internal goals of these business areas (Axsäter, 2015; de Vires, 2020). A certain level of inventory is required to be able to meet customer demand and hedge against uncertainties in the supply chain. On the contrary, reduction in inventories levels will free up cash that can be used elsewhere in the company (Axsäter, 2015). This trade-off is also highlighted by Kiesmüller (2009), who emphasizes that transport managers often focus on utilizing full trucks while inventory managers aim to minimize stock. This trade-off implies the importance of having efficient inventory management.

When analyzing supply chain systems, different types of inventory control methods can be used. With a suitable method to control inventory, theory indicates that companies are able to reduce their inventory level while still being able to meet customer demand (Axsäter, 2015). Small percentage of reductions in inventory cost can also result in large increase of profits for companies (Nagaraju, Ramakrishna Rao, Narayanan & Pandian, 2016). Minimization of total inventory and thus corresponding costs is one of the foremost actions that increases net revenues in supply chains today (Nagaraju et al., 2016). Hence, efficient inventory control of the supply chain is an important aspect for firms to take into account when seeking for opportunities to increase profit.

The objective with inventory control is to determine the timing and order sizes, meaning *when* to order and *how much* to order. In order to make a decision regarding this, different factors should be considered such as various costs, expected demand and inventory situation. (Axsäter, 2015)

4.3 Multi-echelon inventory systems

Study the system illustrated in *Figure 4.2*. The supply chain has a divergent structure which consists of one central warehouse and N number of distribution centers. This supply chain network with multiple warehouses is defined as a multi-echelon inventory system (Axsäter, 2015). More precisely, when the system consists of two echelons, it can be referred to as a two-level inventory system where inventories can be held at each node (Axsäter, 2015; Hausman & Erkip, 1994).

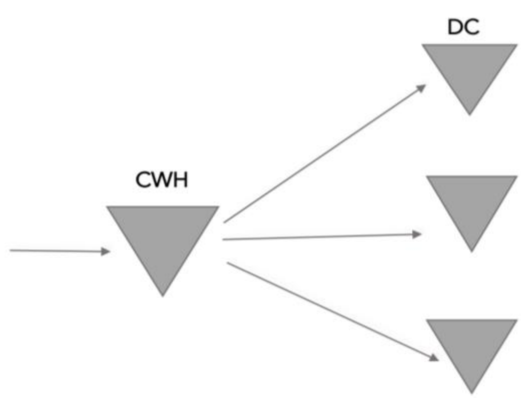

Figure 4.2. Two-level inventory system.

A multi-echelon inventory system can be controlled with various methods, which previously in this master thesis have been referred to as uncoordinated and coordinated inventory control. From now on, the term uncoordinated control will be referred to as *single-echelon* inventory control, as the system is reviewed as a collection of independent single-echelon systems. In the same way, the term coordinated control will be referred to as *multi-echelon* inventory control. These new terms are further described in the next sections.

4.4 Single-echelon inventory control

A single echelon system is general distinguished by two features (Axsäter, 2015, p.43):

1) Various items can be controlled independently.
2) The items are stored at a single location.

This means that when using a single-echelon inventory control method each node is considered as an independent inventory location. Each node is holding inventory, where the inventory control is optimized independently based on the demand that occurs at that location. This implies that the individual node that hold stock in the system are sub-optimized as the interrelations between the nodes are neglected.

If orders of different items need coordination, the first feature presented above cannot be fulfilled. In addition, if the items are distributed over large distances or geographical regions it may be more suitable to use a multi-echelon control method (Axsäter, 2015, p.46).

4.5 Multi-echelon inventory control

In contrast to a single-echelon inventory control method, multi-echelon inventory control includes the interdependence between the nodes in the network. This enables a coordinated control of inventory decisions for the total system. Hence, the total cost and inventory levels of the entire system can be optimized simultaneously. It should be noted that multi-echelon inventory control may be more complicated to model and use in practice compared to uncoordinated single-echelon inventory control. However, as the inventories held at each echelon in a real-life system will affect each other there are still incentives to use coordinated control. (Axsäter, 2015; Hausman & Erkip, 1994).

4.5.1 Multi-echelon system with upstream demand

The two-level inventory system presented in *Figure 4.2* laid the foundation for the inventory system analyzed in this master thesis. The CWH must however be able to satisfy both end customers as well as replenish orders to the downstream warehouses. The direct deliveries to the end customer will from now on be referred to as *upstream demand,* where an example of a multi-echelon inventory system with upstream demand is illustrated in *Figure 4.3.* As seen in the figure, a part of the stock in CWH may be reserved for upstream demand.

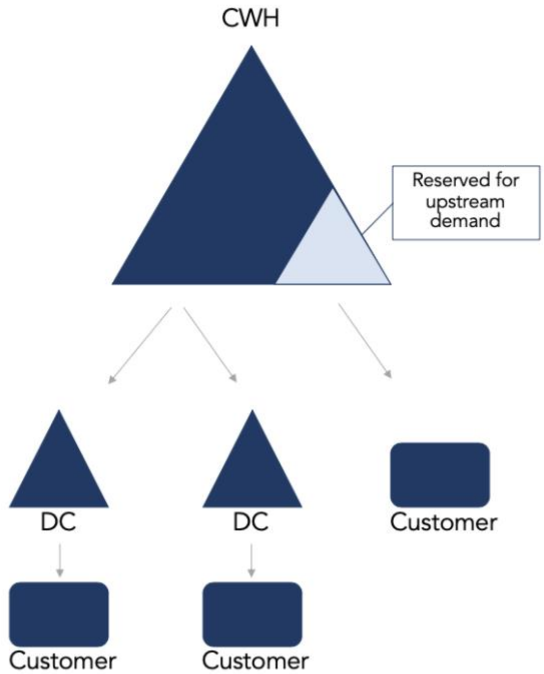

Figure 4.3. A multi-echelon inventory system with upstream demand.

In multi-echelon inventory systems without upstream demand, stock is generally pushed downstream towards the DCs and thus closer to end customers. In that kind of system, the CWH has no predetermined target service requirement towards the DCs. Instead, the DCs have a predetermined target service requirement towards the end customer which usually renders a lower fill rate at the CWH. However, when modeling a multi-echelon inventory system with upstream demand, the CWH reserves a part of the stock for upstream demand, which also have a predetermined service requirement. The upstream demand at the CWH has higher priority than the orders towards the DCs, which is handled by using a critical order policy. This order policy means that if the stock at the warehouse is less than or equal to the critical level, the upstream demand is satisfied while the downstream demand is backordered. (Berling et al., 2020)

4.6 Optimization of reorder points

Optimization of the reorder points in a multi-echelon inventory system can be performed with different methods. Stated by Axsäter (2015), one way is to optimize the reorder points under fill rate constraints while another method can be to optimize against costs, such as holding costs as well as backorder or shortage cost. Furthermore, optimizing a multi-echelon inventory system can be rather complex. One option is thus to simplify the system by decomposing the multi-echelon system into several single-echelon inventory systems (Hausman & Erkip, 1994). By doing so, the optimization of reorder points can be facilitated.

Before a detailed explanation of how the optimization of reorder points can be performed some general understanding of ordering systems is needed. The following sections will therefore present general concepts and important terms that are necessary to understand. A general understanding of the basic concepts is required in order to be able to determine which inventory control method that is appropriate to use in this master thesis.

4.6.1 Inventory position

Regardless of inventory control policy, the main objective for inventory control is to determine the timing and order sizes, meaning when to order and the quantity. This decision is based on the stock situation, different cost factors and customer demand. The stock situation is also referred to as inventory position, which is defined as the physical stock on hand plus the outstanding orders that have not yet arrived minus backorders which are orders placed by customers but not yet delivered[5] (Axsäter, 2015, p.46).

The ordering decision will be based on the inventory position. Furthermore, the costs associated with the inventory is based on the inventory level which only includes stock on hand and backorders. Backorders is defined as items that have been ordered but not yet delivered. (Axsäter, 2015, p.46)

4.6.2 Continuous or periodic review

An inventory control system can either be reviewed continuously or periodically. In the continuously reviewed system, a new order is triggered as soon as the inventory position decreases under a certain level. The time it takes from the order is placed until it is delivered is defined as the lead time. This lead time not only refers to time in production or transport time but also includes time aspects such as administrative work, inspections or preparation time. In contrast to the continuous review, a periodically reviewed system is reviewed at a given moment in time. The time gap between these review points is generally constant, where the time interval between the reviews is defined as a review period. (Axsäter, 2015, p.47)

Axsäter (2015) points out that both methods have benefits and drawbacks, where it may be important for the company to understand the impact of using a particular method for data collection. Collecting data in a continuous review usually means more detailed data that reduces the need for safety stock but also implies that more data needs to be saved and stored. In practice, it is common to use continuous review on items with low demand. The periodic review system is instead desired when a company aims to coordinate orders for different items and is more appropriate to use on items with high demand. This kind of review also reduces the amount of inspections that is needed for collecting data and thus decreases costs of inspections. However, as the time between the reviews in a periodic reviewed system decreases to a very short period, it becomes similar to a continuous review system. (Axsäter, 2015, p.47)

4.6.3 (R,Q) order policy

In inventory control two common types of inventory control policies[6] are (R,Q) policy and (s,S) policy (Axsäter, 2015). As seen in *Figure 4.4,* in the (R,Q) policy a batch quantity (Q) is ordered when the inventory position decreases to or below the reorder point level (R). It might sometimes be required to order more than one Q to obtain an inventory position higher than R, which implies that the policy also can be referred to as (R, nQ). If the system is reviewed continuously or if the batch quantity is equal to 1, one will reach the exact inventory position of the reorder point.

[5] *Inventory position = Stock on hand + outstanding orders – backorders.*

[6] *An inventory control policy refers to when the replenishment of an order should take place.*

However, if the system is reviewed periodically or if Q is greater than one unit the inventory position can be below the reorder point R. (Axsäter, 2015, p. 48-50)

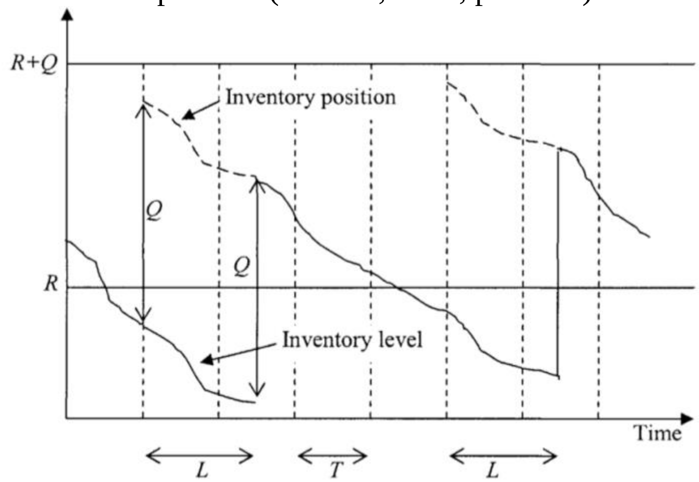

Figure 4.4. Illustration of (R,Q)-policy. Adapted from Axsäter (2015)

4.6.4 (s, S) order policy

In the (s,S) policy, see *Figure 4.5,* the reorder point is defined as s. The policy means that when the inventory position decreases to or under the reorder point, an order up to the maximum level S is ordered. If the order is placed exactly when the reorder point is needed, the (s, S) policy is equivalent to the (R,Q) policy. (Axsäter, 2015, p.49)

There is also a variation of the (s, S) policy, which can be called the S-policy. This policy will place an order as long as there exists a period demand. It means that an order up to S is placed independently of the inventory position. By introducing the notation s = S-1, the S-policy can be defined as (S-1, S) policy. (Axsäter, 2015, p.49)

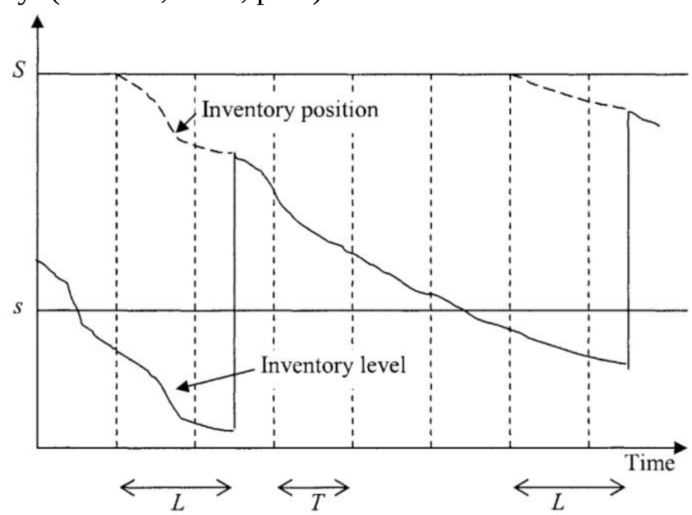

Figure 4.5. Illustration of (s,S)-policy. Adapted from Axsäter (2015).

4.6.5 Service levels

A suitable reorder point will be based on one of three predetermined conditions: service level, specific shortage cost or a given backorder cost. In real life, it is often easier to determine desired service level than the associated shortage or backorder costs. According to theory provided by Axsäter (2015, p.94), service levels can be defined in different ways where the authors highlight three types of service levels: *probability of no stockout per order cycle* (S_1), *the fraction of demand that can be satisfied immediately from stock on hand* (S_2) and *the fraction of time with positive stock on hand* (S_3). Regardless of how it is determined, it is important that the service level is clearly defined and interpreted similarly throughout the company. The service level used in this thesis project is the *fraction of demand that can be satisfied immediately from stock on hand* (S_2), which from now on will be referred to as the *fill rate*. (Axsäter, 2015, p.94-95)

4.7 Statistical distributions

In order to approximate the demand, a statistical distribution is needed. In reality, demand is nearly always discrete which refers to the fact that every customer demands an integer number of units (Axsäter, 2015, p.129). When the demand is relatively low it is suitable to use a discrete demand model. However, if the demand is fairly high over a time period, it may be more convenient to consider the demand to be continuous (Axsäter, 2015, p.85).

Analysis of demand data is needed to approximate the real demand of the items in the system. Modelling a multi-echelon inventory system that faces stochastic demand can be very challenging, which means that the demand data often is approximated with a suitable statistical distribution. There are various distributions that can be used to approximate discrete or continuous demands. The following sections will present theory regarding some of the commonly used demand distributions models and when they are appropriate to apply.

4.7.1 Coefficient of variation

The measure coefficient of variation is defined in this thesis as the ratio between the mean and variance, see *Equation 1*.

$$\frac{\sigma^2}{\mu} \tag{1}$$

4.7.2 Discrete demand model - Compound Poisson distributed demand

Axsäter (2015, p.77) states that a common assumption to make in a stochastic inventory model is that the cumulative demand[7] follows a nondecreasing stochastic process with stationary and mutually independent increments. Those processes can be assumed to be a sequence of compound Poisson processes. In contrast to the Poisson distribution, the compound Poisson distribution allows customers to order more than on item at the same time.

In a compound Poisson process, customers arrive according to a Poisson process with a mean arrival rate (λ). Hence, the probability of k customer arriving during a set time interval (t) can be expressed as *Equation 2*.

$$P(k) = \frac{\lambda t^k}{k!} e^{-\lambda t}, \qquad k = 0, 1, 2, \ldots \tag{2}$$

[7] *The cumulative demand is in this thesis defined as the combination of the total demand for a specific item.*

The size of a customer order J is a stochastic variable, where the distribution of J is referred to as the compounding distribution. This variable is independent of other customer order sizes and the distribution of the customer arrivals. The probability of the demand size j (j =1, 2, …) is denoted as f_j. Furthermore, define:

f_j^k = The probability that k customers will demand a total of j units
D(*t*) = The stochastic demand under the time interval *t*

Given that no customers will order zero items, meaning f_0^0=1, and that $f_j^1 = f_j$, f_j^k can be determined from *Equation 3,* which represents a recursive convolution.

$$f_j^k = \sum_{i=k-1}^{j-1} f_i^{k-1} f_{j-i}\, , k = 2,3,4 \ldots \qquad (3)$$

By combining *(2)* and (*3)*, the probability that the demand during the time interval t equals the demand size j units can be expressed as P(D(t) = j), which is seen in *Equation 4*: (Axsäter, 2015)

$$P(D\,(t) = j) = \sum_{k=0}^{k} \underbrace{\frac{(\lambda_i t)^k\, e^{-\lambda t}}{k!}}_{\text{P(k customers arrive)}} \cdot \underbrace{f_j^k}_{\text{P(customers demand j units)}} \qquad (4)$$

The average demand per time unit is defined as μ and the standard deviation of the same demand is denoted as σ. These can be obtained by using *Equation 5 and 5*:

$$\mu = \lambda \sum_{j=1}^{\infty} j \cdot f_j = \lambda\, E[J] \qquad (5)$$

$$\sigma^2 = \lambda \sum_{j=1}^{\infty} j^2 \cdot f_j = \lambda\, E[J^2] \qquad (6)$$

For a more thorough description, see Axsäter (2015, p. 77-80).

4.7.3 Continuous demand model - Normal distributed demand

When the demand is high, it is more appropriate to model the demand by a continuous distribution where the normal distribution is suitable to use. The central limit theorem states that under general conditions a sum of independent random variables will have the approximation of a normal distribution. In several situations the demand is represented from multiple independent customers, which makes it reasonable to approximate demand by normal distribution. In addition, if the time period for a process is long enough, it is reasonable to assume that the discrete demand from a compound Poisson process can be approximated to a normal distribution. Furthermore, the normal distribution is commonly used due to its simplicity and because computations are often quite fast. (Axsäter, p.85, 2015).

However, there are drawbacks of using a normal distribution. There is a probability for negative values of the demand when the mean is small compared to the standard deviation. This may be a problem if the normal distribution is used to model the lead time demand, since this cannot be negative. Hence, some outcomes might only be approximately true if using the normal distribution, even though they are exactly true for compound Poisson demand. When using the normal distribution, the mean and standard deviation can be obtained from *Equation 7.* (Axsäter, 2015)

$$\mu' = \mu \cdot L \qquad (7)$$
$$\sigma' = \sigma \cdot \sqrt{L}$$

Given the mean (μ´) and standard deviation (σ´) of the demand during a set time period, one can fit a specific normal distribution by using the standardized normal distribution with a mean equal to zero and standard deviation equal to one. The standardized normal distribution has the density function presented in *Equation 8* and distribution function presented in *Equation 9.* (Axsäter, 2015)

$$\varphi\,(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}\,, [-\infty < x < \infty] \qquad (8)$$

$$\Phi\,(x) = \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi}} e^{-\frac{u^2}{2}}\, du \qquad (9)$$

For a more thorough description, see Axsäter (2015, p. 85-86).

4.8 Literature review of multi-echelon inventory control models

Today, there exists a large number of multi-echelon models that can be used when analyzing inventory systems. To be able to choose the most appropriate model for this master thesis, a literature review of existing multi-echelon inventory control was needed. The purpose of the literature study is to present existing models to the reader and find the model that meets the predetermined requirements presented in *section 2.3.1.3*. It should be noted that academia comprises many developed models that are not covered in this literature review, in order to solely present most relevant models for this particular study. The goal is to provide the reader with a broad definition for some existing alternatives, rather than to explain each specific assumption behind each individual model.

Different exact methods for optimization have been developed over the years. Axsäter (1993) published an exact evaluation method for continuous review (R,Q) policies in a two-level inventory system with identical retailers. Axsäter's method was later further developed by Forsberg (1996), who published an exact evaluation method of two-level inventory systems with N number of non-identical retailers[8] with Poisson demand. Later, another exact method was presented by Axsäter (2000), which also studied a two-echelon inventory system with N number of non-identical retailers. The assumption in this method is similar to the assumptions presented

[8] *In this master thesis retailer is a synonym to DC.*

by Forsberg (1996)[9], but the difference was that the retailers faced an independent compound Poisson demand instead. If the customer can order more than one unit at the same time, the assumption of compound Poisson demand is a more suitable assumption compared to Poisson demand. The exact model developed by Axsäter (2000) performs well for small systems but often becomes too computationally complicated to apply for large systems.

Several approximation methods have also been developed, such as Andersson, Axsäter and Marklund (1998) and Andersson and Marklund (2000). These models use a decomposition approach and focus on minimizing holding costs and backorder costs in a one-warehouse N retailer system based on a predetermined backorder cost per unit and time unit at the retailers. Andersson et. al (1998) approximated the stochastic lead times to the retailers with the correct average and introduced backorder cost β_i[10] as a means to coordinate the system. β_i for i=1,2,…N is determined through an iterative procedure that can be quite time consuming. This approximation made it possible to optimize the multi-echelon system by decomposing the system into N + 1 single-echelon systems. The method was later generalized by Andersson and Marklund (2000) to a system with non-identical retailers and complete deliveries. However, none of the introduced models takes fill-rate constraints into consideration. Furthermore, all these models assume that the exact distribution of demand at the CWH can be determined, which in reality is challenging to obtain (Berling & Marklund, 2014).

The presented models that use a decomposition approach have a close relationship with the approximation model developed by Marklund and Berling (2013). This model assumes a compound Poisson demand at the retailer and optimizes the reorder points while still meeting predetermined customer demands. The presented model focuses on slow-moving items with irregular and lumpy demand and is thus a suitable model for demand with a coefficient of variation greater than 1.

In an article published by Marklund and Berling (2014), the researchers stated that even if several exact and approximation methods exist, few models are used in practice. The main reasons are that the models are often based on restrictive assumptions and are computationally challenging to apply in practice. Due to the limitations of the previously presented models, Marklund and Berling (2014) developed a model where the researcher assumed a one-warehouse N-retailer system with centralized control, fixed order quantities and assumed adjusted normal demand. This model is computationally easy to apply, where the objective is to minimize the inventory cost of the whole system while still meeting end customer service requirements. Furthermore, the model can use real data from companies (Marklund & Berling, 2014). Hence, as seen in *Table 4.1*, this model fulfils almost every predetermined requirement.

[9] *See Forsberg (1996) for detailed presentation of model assumptions.*

[10] *An order that cannot be fulfilled at the current time due to shortage in the warehouse.*

Table 4.1 Requirements for model selection.

Requirement	**Fulfilled l**
The model must be able to handle a (R,Q)-policy.	✓
The model must be able to optimize while still meeting predetermined customer demand.	✓
The model must be easy to apply in a real-life inventory system, work in large systems and applicable on real life data.	✓
The model must be applicable on a one-warehouse N-retailer system.	✓
The model must assume fixed order quantities.	✓
The model must be able to handle upstream demand.	✕

However, as seen in *Table 4.1,* there is still one predetermined requirement that none of the presented models fulfills. The upstream demand supplied directly from CWH to the end customer is an aspect that none of the discussed models take into consideration that so far has been introduced to the reader. In a working paper by Berling, Johansson and Marklund (2020) - *"Controlling Inventories in Omni-Channel Distribution Systems with Variable Customer Order Sizes"* - the authors investigate three different methods to optimize an inventory system with upstream demand. Based on the predetermined requirements presented in *Table 4.1,* all three models seemed appropriate candidates to use in this thesis. In the next section, a comparison of the models will be performed in order to determine which was most suitable for this master thesis.

4.9 BJM, BM-S and BM-C

Berling et al. (2020) investigates three heuristics, which they refer to as the BJM, BM-S and BM-C. These models represent different ways of optimizing inventory control in a multi-echelon inventory distribution system with upstream demand. The presented work by Berling et al. (2020) is related to earlier published work by Axsäter et al. (2007) and the approximation's methods presented by Berling and Marklund (2013; 2014). In the work provided by Axsäter et al. (2007), the researchers suggest a *separate stock policy* controlling a one warehouse N retailer system, where the CWH also faces direct upstream demand. The model they investigate assumes compound Poisson demand distribution, first-come-first-served allocation, (R,Q) policy and complete backordering at all locations. To deal with the upstream demand at the CWH an artificial DC that replenish stock from the CWH with an (S-1, S) policy and a transportation time of zero is introduced. It can be compared to a separate stock at the CWH that only is used to serve the direct demand. However, the separate stock heuristic presented by Axsäter et al. (2007) minimizing the total holding and backorder cost and does not perform well in systems with fill rate constrains and large variance in order sizes. The reason is that the separate stock level, that is used for direct demand, tends to be overestimated due to that the policy treats the artificial retailer the same as a regular retailer. Thereby, the method does not take the total inventory level at the CWH into account but only the reserved inventory level. (Berling et al., 2020)

Instead of the separate stock policy, Berling et al. (2020) introduces a *combined stock policy,* which can be explained as a critical level policy where backorders are served in a first-come-first-served sequence. This policy determines the critical stock level S that is needed to fulfil the fill rate for upstream demand, given the reorder point at the CWH. The combined stock policy may be used with different methods. The policy was integrated the approximation methods presented by Berling and Marklund (2013; 2014). The incentive for this was that these approximation methods is computationally simple to implement in practice, performs well and are broad enough to apply on systems with continuous review (R,Q) policies and varying order sizes. The method provided by Berling and Marklund (2013) approximates the demand with compound Poisson demand, while Berling and Marklund (2014) suggest adjusted normal demand. Both use an induced backorder cost technique for decomposing the inventory system into N + 1 single echelon systems. (Berling et al., 2020).

The induced backorder costs need to be determined with another approach when using the combined stock policy, where two methods exists: *the naïve* and *the iterative*. The iterative method is used in the BJM heuristic, while the naïve is used in the BM-C and the BM-S heuristics (Berling et al., 2020). To summarize and further clarify what distinguishes the three heuristics and their assumptions, please see *Figure 4.6.*

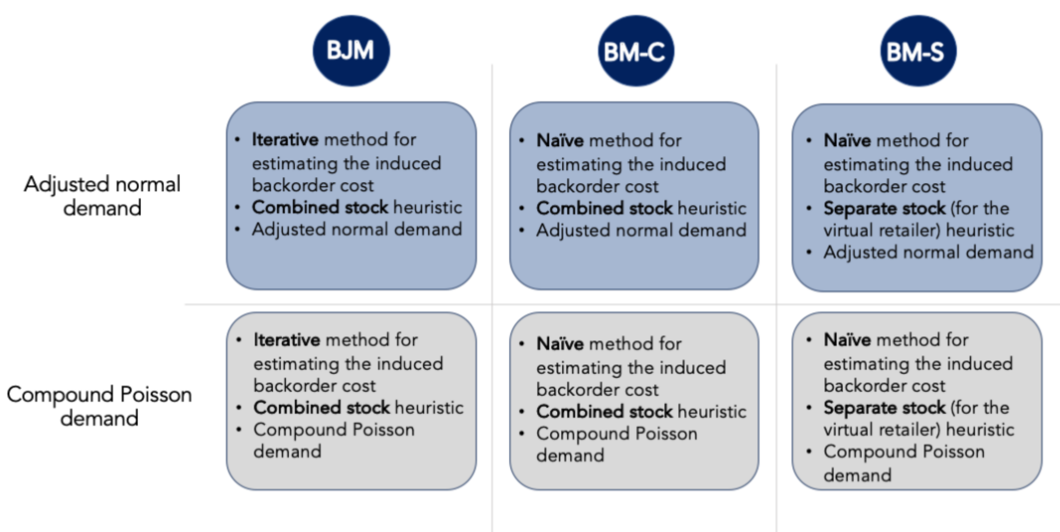

Figure 4.6. Illustration of the difference between the versions of the model adapted from Berling, Marklund and Johansson (2020).

The numerical study performed by Berling et al. (2020) showed that BJM performed best in terms of achieving target fill rate with lowest possible inventory. The BM-C performed second best with regards to achieving the target fill rates but with an increased level of inventory compared to the BJM model. These two heuristic models use the *combined stock policy* while the BM-S model uses the *separate stock policy*, which had an inferior performance compared to the two other heuristics. Based on this, it was decided that the *combined stock policy* that was most suitable to apply in this master thesis as well, and the BM-S model was excluded. Which of the BM-C and BJM model that was most suitable for this master thesis remained to be investigated and is further discussed in the following section.

4.10 Assumptions made in the BJM and the BM-C heuristics

In this section the assumptions made in the BJM and BM-C heuristics will be stated. If further details are desired, we refer to Berling et al. (2020) as well as the papers by Berling and Marklund (2013; 2014). The notation used in the heuristics are summarized in *Table 4.2*.

Table 4.2. Notations used. Adapted from Berling, Johansson & Marklund (2020).

Denotation	Short explanation
IP_i	Inventory position at node i (i=0,1,...,N,N+1)
IL_0	Inventory level of the general stock at the CWH
IL_{N+1}	Inventory level of the stock reserved for the virtual DC at the CWH
IL_{CWH}	Total Inventory level at the CWH ($IL_{CWH}=IL_0+IL_{N+1}$)
IL_i	Inventory level at the DC i (i=1,..., N)
h_i	Holding cost at DC I per unit and time unit
γ_{N+1}	Expected fill rate for the upstream demand at the CWH
γ_i	Expected fill rate at the DCs.
μ_{N+1}	The expected demand at CWH generated by the virtual DC
μ_i	The expected demand at CWH generated by the DCs
μ_0	The total expected demand at the CWH. $\mu_0 = \sum_{i=1}^{N+1} \mu_i$
R_0	The reorder point for the general stock at the CWH.
S	The critical reservation level of the combined stock at the CWH which is equivalent to the base stock level at the virtual DC.
R_{CW}	The reorder point for the combined stock at the CWH.

	($R_{CW} = R_0 + S$)
Q_0	The order quantity placed from the CWH to the suppliers
R_i	The reorder points at the DCs
R	(R_1, R_2, ..., R_N)
Q_i	Order quantity placed from the DCs to the CWH.
z+	Max (z,0)
z-	Max (-z, 0)

The objective is to minimize the expected total cost per time unit (TC) by optimizing the reorder points and the critical reservation level, with regards to the predetermined fill rate constraints. This objective function is formulated and presented in *Equation 10*.

$$\begin{aligned} \min\ TC(R_0, S, \boldsymbol{R}) &= h_0 E[IL^+_{\mathrm{CW}}] + \sum_{i=1}^{N} h_i E[IL_i^+] \\ \text{s.t. } \gamma_{N+1}(R_0, S) &\geq \gamma^*_{N+1} \\ \gamma_i(R_0, R_i) &\geq \gamma^*_i \quad \forall\, i = 1, \ldots, N. \end{aligned} \tag{10}$$

4.10.1 Assumptions regarding upstream demand and lead times

The upstream demand is handled in the models by using a virtual DC, which reserves stock at the CWH. More precisely, the stock at the CWH is divided into two parts where one stock serves the direct upstream demand (index N+1) and one stock replenishes to the DCs (index 0), including the virtual DC. The transportation time from the CWH to the virtual DC is set to zero as the virtual DC is integrated with the CWH. (Berling et al., 2020)

The models are based on certain assumptions regarding lead times and transportation time. The lead time from the suppliers into the CWH (L_0) and the transportation time from the CWH to the DCs (l_i) are assumed to be constant and positive. The lead time from the CWH to the DC (L_i) is on the other hand stochastic, which is a consequence of stock outs that causes delay at the CWH. (Berling et al., 2020)

4.10.2 Assumptions regarding stock policies and order size

The CWH and DCs use continuous review installation stock (R,Q) policies to replenish their inventory. As presented in the theory, this means that a batch quantity (Q) is ordered when the inventory position decreases to or below the reorder point level (R). The objective is to optimize the reorder points for predetermined order quantities. (Berling et al., 2020)

The order quantities are assumed to be fixed and will not be optimized. According to Berling et al. (2020), this is motivated by the fact that using deterministic lot sizing methods in a stochastic environment have been proven to have a small impact on the expected cost, given that the reorder points are adjusted adequately. Furthermore, the choice of order quantities is in practice often limited or adjusted to fit the size of the load carriers or package sizes.

The virtual DC replenishes stock from the CWH using a continuous (S-1, S). The base stock level (S) is equivalent to a critical reservation level for the combined stock in the CWH. This is the stock level that meets the target fill rate for the upstream demand at the CWH given the warehouse reorder point (R_0). All orders that cannot be satisfied are backordered using the first-come-first-served principle (FCFS). (Berling et al., 2020)

4.10.3 Assumptions regarding the induced backorder cost

The costs that the models take into account are the holding costs per unit and time unit at the CWH for the general stock (h_0) and the stock reserved for the virtual DC (h_{N+1}). All DCs and the virtual DC are operating under target fill rate constraints. If the CWH are unable to deliver units to the DCs, the induced backorder cost (β_i) occurs. For example, the cost of holding extra safety stock or cost associated with shortage at the DCs. The induced backorder cost at the CWH is estimated using the weighted average of all the induced backorder costs at the DCs, based on each DCs contribution of the total demand. In the specific case with upstream demand, this includes both the induced backorder cost at the DCs (β_i for i =1,..., N) and the induced backorder cost at the virtual DC (β_{N+1}). (Berling et al., 2020)

The induced backorder cost associated with the virtual DC requires a different approach than for the regular DCs due to the fact that the transportation time is set to zero. To estimate the induced backorder cost at the virtual DC two different methods is preferable. One which Berling et al. (2020) refers to as the *naïve method* and one the *iterative method*.

The *naïve method* is used in the BM-C model and sets the induced backorder cost associated with the virtual DC (β_{N+1}) equal to the backorder cost per time unit for the direct demand. The naïve method tends to overestimate the correct value for β_{N+1}, which may lead to a higher value of R_0 that renders excessive stock at the CWH. (Berling et al., 2020)

The *iterative method* is used in the BJM model. This method attempts to find a better estimation of β_{N+1} by applying more computational work. More precisely, the procedure is initiated with the naïve estimate βN+1 and an iterative search procedure is used to determine a lower estimate of the induced backorder cost at the virtual DC. Thus, the difference between these methods is how the induced backorder cost at the virtual DC is calculated. (Berling et al., 2020)

In this thesis the BM-C heuristic with the naïve method was chosen to be the most suitable model for Duni. This is further motivated in chapter 5.

4.10.4 Assumptions regarding the demand at the CWH

The demand at the CWH can be estimated using standard distributions but with the correct mean and variance. The guidelines of which demand distribution to use is summarized in *Table 4.3* and is adapted from Berling et al. (2020).

Table 4.3. Guidelines for the most appropriate demand distribution to use at the CWH.

Coefficient of variation (σ^2 / μ)	Distribution
$\sigma^2 / \mu > 1$	Negative binomial distribution
$\sigma^2 / \mu = 1$	Discrete approximation of the normal distribution
$\sigma^2 / \mu < 1$	Discrete approximation of the gamma distribution

Berling and Marklund (2014) concludes that applying the approximation approach in *Table 4.3* works very well, using standard deviations with the correct mean and variance. Thus, the demand at the CWH was approximated by fitting distributions to the correct mean and variance according to *Table 4.3*.

4.10.5 Assumptions regarding the reorder point at the CWH

The reorder point at the CWH can be calculated by minimizing the expected holding cost and induced backorder cost per time unit. As the formula for minimizing the costs is, according Berling et al. (2020), convex the optimal reorder point (R_0*) can be rendered by searching for the maximum.

4.10.6 Assumptions regarding the demand for each DC

To be able to estimate the demand at each DC the lead time from the CWH to the DCs first needs to be determined. In these models, the stochastic lead time is approximated by an estimation of its mean. According to Berling and Marklund (2014) this is done by applying Little's law, see *Equation 17*, where Trp_i is the transportation time from the CWH to DC_i and $E(W_0)$ is the average delay caused by shortage at the CWH.

$$\overline{L_i} = Trp_i + E(W_0) \tag{17}$$

Thus, the standard deviation of the lead time is estimated by setting the lead time variability to zero. The demand at the DCs which occurring during the estimated lead time ($\overline{L_\iota}(R_0)$) are defined as:

$$\mu_{D_i(L_i)} = \mu_i \bar{L}_i \tag{18}$$

$$\sigma_{D_i(L_i)} = \sqrt{\sigma_i^2 \bar{L}_i} \tag{19}$$

4.10.7 Assumptions regarding the reorder point at each DC

When the demand for each DC has been determined, the system is decomposed into N coordinated single-staged systems. The system is optimized using methods for single-echelon systems, where the objective is to find the smallest reorder point (R_i) for each inventory location *i* that satisfies the target fill rate with minimum inventory. The fill rate can thereafter be determined using either the assumption of compound Poisson demand or normal demand.

A problem that appears when the normal distribution is used is the underlying assumption that all customer order sizes are equal to one. This implies that in the normal demand model an order is triggered when the inventory position is exactly equal to the reorder point. Hence, a problem appears when the customer order size is greater than one since an undershoot of the reorder point will appear. This means that replenishment of orders will be performed even though the inventory position is below R_i. (Berling and Marklund, 2014)

To compensate for undershooting, Berling and Marklund (2014) consider methods for adjusting the reorder points. This is referred to as adjusted normal distribution. This has proven to be a good approximation for the normally distributed demand, as long as the probability for the negative demand is low. The greater the variance of the experienced demand is, the greater the probability for negative demand become.

In previous research conducted by Berling et al. (2020), the compound Poisson distribution rendered betters results in terms of achieved fill rate if the coefficient of variation of the demand experienced at the DCs was greater than one. However, the compound Poisson distribution requires more computational work. The adjusted normal distribution is computationally simpler but may be questionable for highly variable demand were the normal distribution have a large probability for large realizations.

4.10.8 Assumptions regarding the reorder point at the virtual DC

The critical reservation level S can be determined by using the combined stock heuristic. Furthermore, each heuristic can use either compound Poisson demand or adjusted normal demand to find the optimal reorder point for the virtual DC.

CHAPTER 5

ANALYSIS OF INPUT DATA FOR THE ANALYTICAL MODEL

The purpose of this chapter is to provide the reader with an understanding of how the theoretical framework has been applied in practice. First, an introduction of the generic work approach is introduced. Thereafter, a thorough explanation of how the collected data was used in the analytical model will be provided.

5.1 Generic work approach

Applying a multi-echelon inventory control method in practice can be both complex and challenging. In this thesis, a computer-based system was used to perform these calculations, which are based on mathematical models. Thus, for those readers who are more interested in understanding the generic work approach, a general and simplified description of how the theoretical approach is applied in practice is briefly explained in *Figure 5.1*.

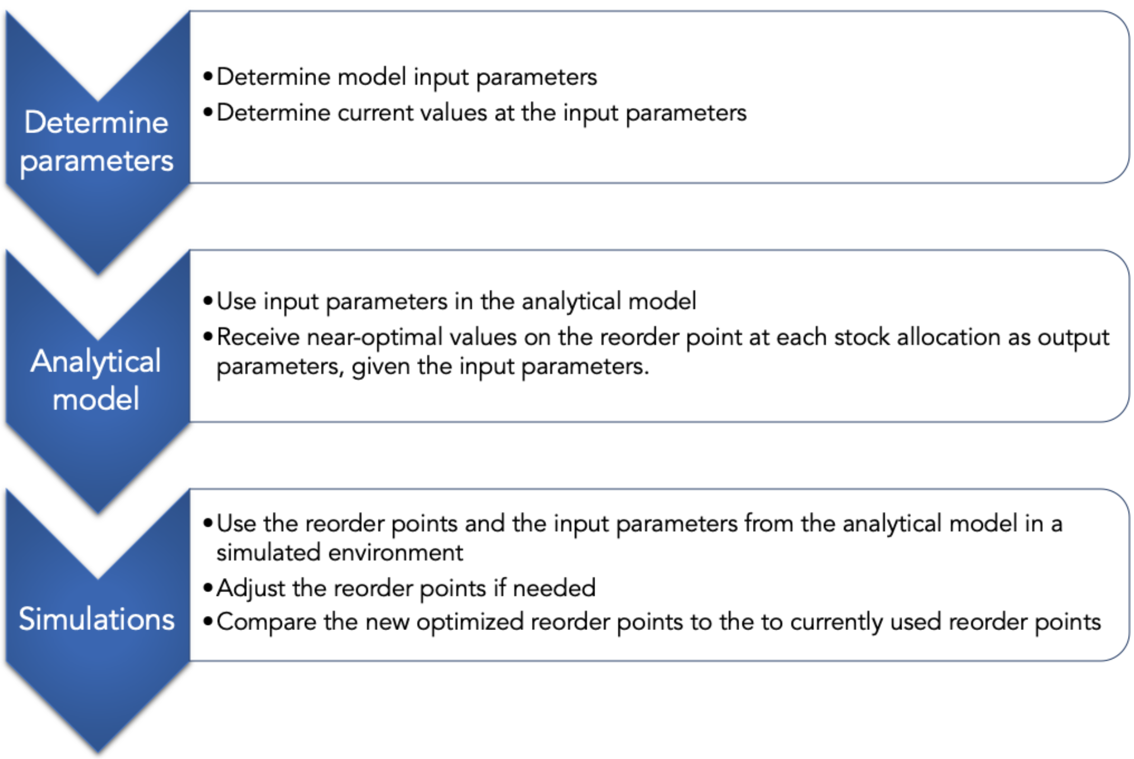

Figure 5.1. How theory is applied in practice to receive the optimal reorder points for each stock location.

The first step was to determine input parameters, such as lead times, batch quantities and the demand distributions. Consider the supply chain illustrated in *Figure 5.2*, which represents a multi-echelon inventory system with upstream demand and the data that needed to be collected. The data was provided from Duni's ERP system and can be summarized as:

- The daily sales volumes for 2019 from 2019-01-01 to 2019-12-31
- Order placed on daily bases by the downstream warehouses for the same time period as above
- Orders sent from the CWH to the downstream warehouses for the same time period as above
- The share of direct sales from the CWH
- Target fill rates for all items
- Transportation time from supplier to the central warehouse
- Transportation time from CWH to the downstream warehouses

The time units were chosen to be one day since the sales data available was aggregated on daily bases.

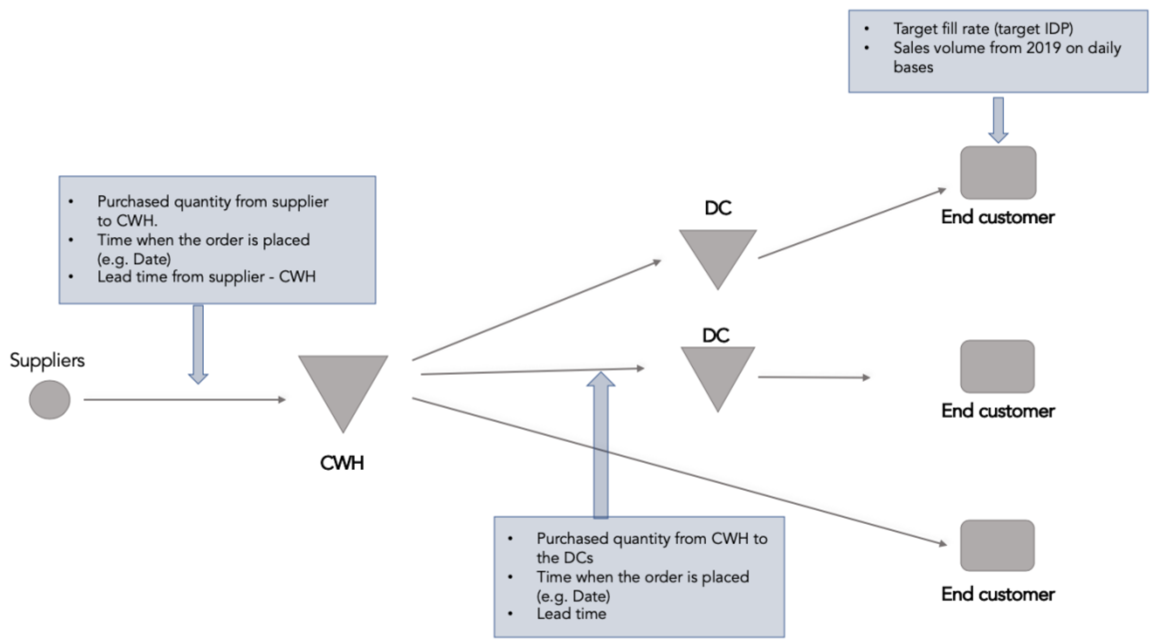

Figure 5.2. Required data.

5.2 BM-C model applied in this master thesis

Section 4.9 presented the general assumptions regarding the model. This section intends to justify why these assumptions represents an adequate approximation of the fictious system to be studied. Furthermore, this section will in general terms explain how calculations were performed on the collected data to fit it to the BM-C heuristics. If data were missing, assumptions were needed to be done, which also will be discussed in the following sections.

5.2.1 Assumptions regarding upstream demand and lead times

In the *main scenario* and *sub-scenario 1*, the lead times from the suppliers to the CWH (L_0) was assumed to be fixed and the same as in Duni's currently used supply chain. These lead times were provided from Duni's ERP system and varied between 14-90 days, for details see *Appendix B*. Using the same lead times as Duni has in their current supply chain was reasonable as the stock locations corresponds to the same locations in both systems. However, in *sub-scenario 2, n*ew lead times were used as the stock locations was assumed to change.

The lead time from the CWH to the DCs in the fictious supply chain was set equal to the calculated lead times (l_i), which consists of two parts - the transportation time and the average delay due to shortages at the CWH. The transportation time was estimated based on interviews with representatives at Duni and is summarized in *Table 5.1.* The average delay was approximated in the model using a suitable distribution.

Table 5.1. The internal transportation time from the CWH to the downstream DCs.

To DC	DC 1	DC 2	DC 3
From Germany	3 days	2 days	2 days

The transportation time to the virtual DC was set to zero in the fictious supply chain, which is logical as the stock in is assumed to be located at the same location as the general stock.

5.2.2 Assumptions regarding stock policies and order size

All locations in the fictious supply chain was assumed to use an (R, Q) policy for replenishment of inventory. Duni currently applies a policy similar to a (R, Q) policy, which made the assumption regarding a (R, Q) policy suitable to adapt in the fictious system as well. However, the chosen model is based on the assumption that the order quantities are fixed, which is not aligned with the real system Duni has today where order quantities may vary. Nevertheless, the assumption of fixed order quantities was appropriate in the fictious system to be studied as Duni strives for a simplification of their supply chain structure. The BM-C heuristic was decided to be a feasible model to apply on Duni's fictious supply chain due to the fact that the fictious supply chain has a rather simple, divergent structure which uses a (R, Q) policy.

The order sizes (Q_0) for each item in the current set up, sent from the supplier to the CWH, was also assumed fixed. As Duni today are generally sourcing an almost fixed minimum order quantity per item from the supplier, the assumption of fixed order quantities between supplier and CWH corresponds to an appropriate approximation. These order sizes were provided by Duni and can be found for each item in *Appendix B.* The order quantity varied between 9-5250 units. The Q_0 for each item was used in the fictious supply chain.

The order sizes sent from the CWH to the DCs (Q_i) in the current supply chain were not accessible and thereby needed to be estimated. Q_i for the fictious supply chain was calculated using the real average shipped quantity during the time period of 2019. If data were missing for one specific item and DC, it was assumed to have the same quantity as shipped to the other DCs. A brief analysis of rounding up the internal quantity to full or half full pallets were performed for each item. For the majority of the items however, the average quantity shipped was very far off from a full or half pallet. Hence, the decision was made that only the average shipped quantity should be used in the fictious supply chain set up as Q_i.

5.2.3 Assumption regarding the induced backorder cost

In this master thesis, the holding cost was set to 1 per time unit in the fictious supply chain. As the heuristics optimizes the reorder point against fill rate constraints and not cost, the holding cost did not need to be known.

As explained in *section 4.9* the difference between the BJM and BM-C heuristics is their way of estimating the induced backorder cost at the virtual retailer. In the paper by Berling et al. (2020), the BJM heuristic had a superior performance compared to the BM-C model. This since the heuristic were able to find a β_{N+1} that rendered the minimum stock while still achieving the target fill rates. The initial choice of heuristic for this thesis was the BJM model using the iterative method for estimating β_{N+1} with the use of adjusted normal demand. However, the model was not able to achieve the target fill rate for the selected test items. This was due to a high variability of the customer demand and thereby a large probability of negative realizations when using the normal demand approximation. Thus, the BM-C heuristic, using the naïve method to estimate β_{N+1} and adjusted normal demand, were tested and rendered better achieved fill rate. Due to the superior performance of the BM-C heuristic in this project, the naïve method was chosen to estimate the induced backorder cost at the virtual retailer.

5.2.4 Assumption regarding the demand at the CWH

Since Duni strives for a simpler supply chain structure not all DCs has been included in the fictious supply chain. Hence, the demand in the fictious supply chain was based on the experienced demand from Duni's current supply chain but only included the demand from the selected DCs.

In the BM-C heuristic there are three different standard distributions that are available to model the real demand, negative binomial, normal distribution and gamma distribution. The guidelines for which one that is most suitable to apply in different situation is provided in *Table 4.3* in *section 4.10.4*. To be able to use the guidelines the mean, variance and coefficient of variation first needed to be calculated. This was done with the approach described in *section 4.10.4,* using the average sales volume for the time period 2019-0101 to 2019-12-31 at the selected DCs. When a negative sale value occurred, these were assumed to be returned items and replaced with a value of zero. The negative values were few and of low value and hence this simplification has a minor effect on the result.

5.2.5 Assumptions regarding the reorder point at the CWH

The mean, variance and coefficient of variation of the demand appearing at the CWH can be found for each item in *Appendix G* and varied from 24-350. Since the coefficient of variation was very high, the negative binomial distribution was chosen as standard distribution in accordance with the guidelines provided in *Table 4.3*.

5.2.6 Assumptions regarding the demand for each DC

The demand in the fictious supply chain was based on experienced demand from Duni's current supply chain but only included the experienced demand from the selected DCs.

In the BM-C heuristic there are two standard distributions that are available to model the experienced demand at the DCs, the adjusted normal distribution and compound Poisson distribution. The distribution that was most suitable to apply was based on the mean, variance and coefficient of variation of the demand experienced at the selected DCs. To calculate these parameters the average sale volume from the time period 2019-0101 to 2019-12-31 were used, where the mean and variance were calculated using the mean and variance function in Excel. The coefficients of variation were then calculated using (1). When a negative sale value occurred, these were assumed to be returned items and replaced with a value of zero. The negative values were few and of low value, hence this simplification has a minor effect on the result.

5.2.7 Assumption regarding the reorder point at each DC

The mean, variance and coefficient of variation of the demand appearing at the DCs can be found for each item in *Appendix G*. As the coefficient of variation were significantly greater than one for the majority of items, the compound Poisson distribution were initially selected. However, the calculation of the near optimal reorder point using compound Poisson distribution took roughly 3-6 weeks per item. This extremely long calculation time were not practically feasible due to the time frame of this project. Hence, the adjusted normal distribution was instead selected to approximate the demand at the DCs since it only took 1-3 minutes.

As the coefficient of variation of the demand appearing at the virtual DC was very high it is important to emphasize the high probability of negative demand that may render inferior performance in terms of achieved fill rates. This may thus affect the validity of the model. However, the choice of adjusted normal distribution can be motivated by two arguments. First, it was the only statistical distribution available in the BM-C model that was practical feasible within the given time frame. Secondly, the purpose of this thesis was to compare uncoordinated versus coordinated inventory control in the fictious supply chain rather than generate exact reorder points. For this purpose, it is acceptable if the heuristic would not be able to render reorder points which *exactly* achieved the target fill rate.

5.2.8 Assumption regarding the reorder point at the virtual DC

The upstream demand in the fictious supply chain was based on the experienced demand from Duni's current supply chain. It only included the experienced demand from the CWH for items that was sent directly to the end customers. To calculate the near optimal reorder point for the virtual DC the average sales volume during the time period 2019-0101 to 2019-12-31 were used. The mean and variance function were thereafter calculated in Excel. The coefficients of variation were then calculated using (1).

The mean, variance and coefficient of variation can be found for each item in *Appendix G* and varied between 12,8-1246,8. The coefficient of variation was, similar to the DCs, high and the adjusted normal distribution were selected based on the same argument mentioned in *section 5.3.7*.

CHAPTER 6

SIMULATION MODEL

The purpose of this chapter is to provide the reader with a general overview of the used simulation model. The goal is that the reader should get a basic understanding of how the simulations was performed.

6.1 The simulation model

The simulation model used in this master thesis is referred to as ExtendSim 9.2 and is developed by Imagine That Inc. ExtendSim is a software that can be used for any type of simulations as well as building, running and analyzing different models for complex systems (ExtendSim, 2020). The following section intends to present the general simulation approach used in this master thesis, where a snapshot of the model is seen in *Figure 6.1*.

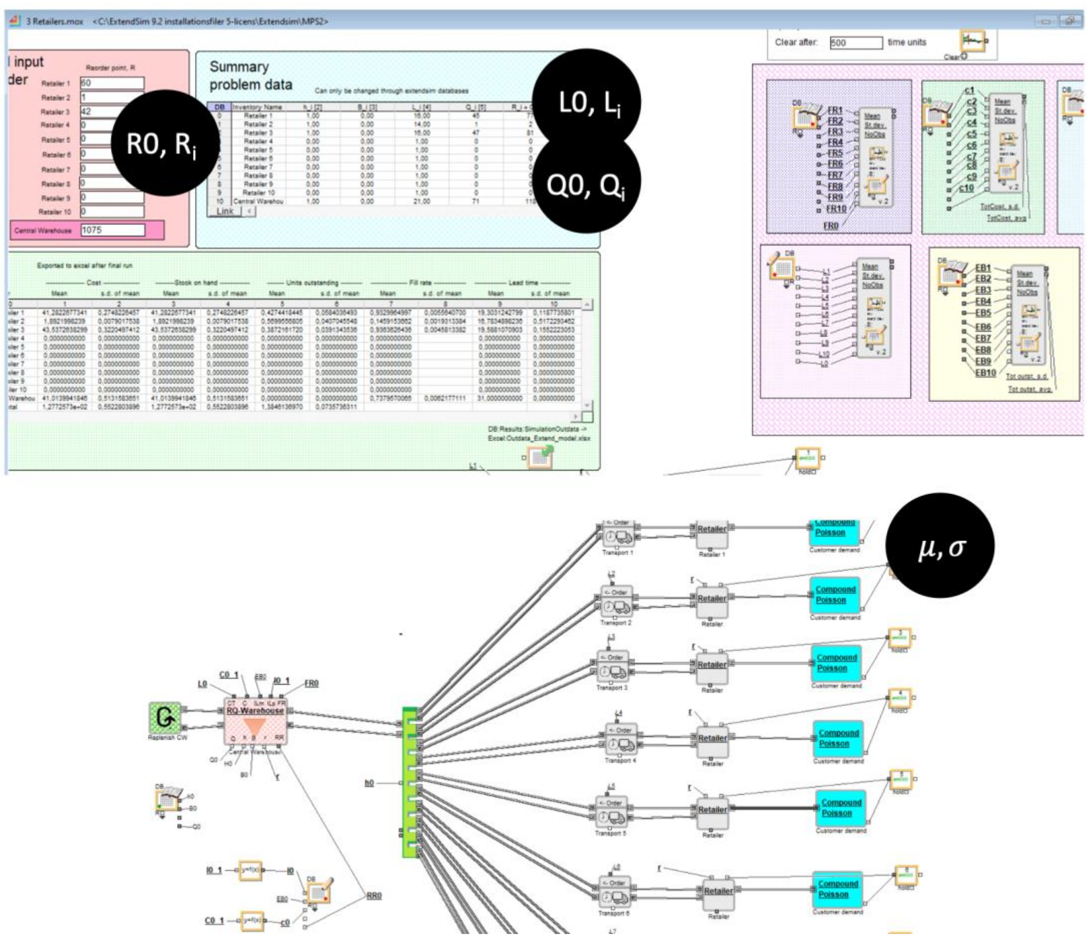

Figure 6.1. Snapshot of the simulation model.

The model had previously been applied in similar research conducted at *The Faculty of Engineering – Production Management* at *Lund University.* Hence, the model used in this master thesis is built and developed model at the department of *Production Management.* This meant that no new model was needed to be built. The validity of the simulation model can be considered as high as it is developed at a prominent research institute, where the model has been used in similar research where it was carefully validated and verified. This means that no change in the model logic needed to be made. The only action needed was to use new input values. Furthermore, the system represented a good approximation of the supply chain that Duni strives for in the future.

6.2 Simulation approach

The simulation model consists of different blocks, such as input blocks and output blocks. In the input blocks, the same data as for the analytical model was used but with addition of the new, obtained reorder points from the analytical model. All 20 items were simulated twice in the main scenario. First using the reorder point rendered from the analytical model with the uncoordinated the single echelon method and secondly, the reorder points obtained from the analytical model using the multi-echelon method. In the sub-scenarios, the eight selected items were simulated once using the multi-echelon method.

The output block consisted of *achieved fill rate* and corresponding *average stock on hand* at each location in the supply chain. These values were exported to an Excel-sheet and are presented in the result and analysis.

The supply chain system in the model consisted of one CWH and a number of DCs. There were 10 possible DCs available to use but only 3 to 4 DCs have been used in this project. More precisely, only the required number of DCs that were needed for each specific item were connected in the simulation model. Furthermore, one DC was determined to handle the upstream demand and hence represented the virtual DC. In this master thesis the virtual DC was represented by DCs number one. The transportation time for the virtual DC from the CWH was set to zero and the order quantity to one.

6.2.1 Simulation time

When simulating, it was important that the simulation time was long enough to reach steady state. The number of simulation runs were set to 30, which means that each item went through 30 independent simulation runs. At the end of each run, the simulation model gathered the result regarding the studied parameters. When each item had been simulated, the mean and standard deviation was determined as an average of the results from all 30 runs.

Each item has been simulated with a simulation time, which was determined based on what is referred to as the *warmup time*, *run time* and *number of blocks.* The total simulation time in the model was determined based on the supervisor recommendation and instructions. By first calculating the expected time of one order cycle using *Equation 21* and thereafter multiply (21) with 3 the warmup time could be determined.

Order cycle = Order quantity / Mean customer demand at each DC (21)

The run time was set to 300 order cycles. The total simulation time was determined from *Equation 22*:

$$\textit{Simulation end time} = \textit{Warmup time} + \textit{Run time} \qquad (22)$$

This approach means that each item can have varying simulation end times since it is dependent on the order cycle at each DC. In order to ensure that the simulation takes all possible outcomes into consideration, the longest simulation end time for that specific item where used in the simulations.

CHAPTER 7

RESULT AND ANALYSIS

The following chapters begin with reminding the reader of the purpose of this master thesis. Thereafter, the result and analysis from the main scenario will be presented, followed by the two sub-scenarios. In all scenarios, the main focus will be on achieved fill rate as well as the rendered average stock on hand.

7.1 Structure of results and analysis

The purpose of this master thesis was to determine appropriate reorder points for each location in the created supply chain setups using appropriate uncoordinated and coordinated inventory control methods. The objective was to meet the end customer service requirements with as little inventory as possible. Additionally, this project strived to identify the benefits and challenges with the two different inventory control methods and determine which method was most suitable for Duni. To be able to fulfil the purpose, two research questions were formulated:

1. *How to set appropriate reorder points at CWH and at each DC in their new supply chain setups to meet the predetermined fill rates with as little inventory as possible?*

2. *Which effects; benefits and drawbacks can be identified when comparing uncoordinated and coordinated inventory control of their new supply chain set up?*

To be able to answer the two research questions, this master thesis contained one main scenario and two sub-scenarios, where the results from the simulations will be presented according to that structure. Furthermore, what distinguished each scenario is summarized below.

The main scenario - Divergent structure
- Expected fill rates - single-*echelon vs multi-echelon inventory control*
- Expected stock on hand - *single-echelon vs multi-echelon inventory control*
- Further observations

Sub-scenario 1 - Consolidation point
- Adjusted batch sizes

Sub-scenario 2 - Changed location of CWH
- Adjusted lead times

Since the costs are not known in this master thesis, the focus of analysis is on achieved fill rates and average stock on hand for each item. It should also be noted that the interesting aspect to analyze is the relative values between the inventory control methods as well as the main findings from each scenario. The result will mainly be illustrated in figures and tables, but detailed numbers can be found in *Appendix* D.

7.2 The main scenario

Characteristics of the main scenario in *Figure 7.1*:

- Divergent structure.
- The same lead time as Duni has today between each node.
- The same order quantity as Duni has today between supplier and CWH.
- Average values of the internal shipment quantity between CWH and DCs.

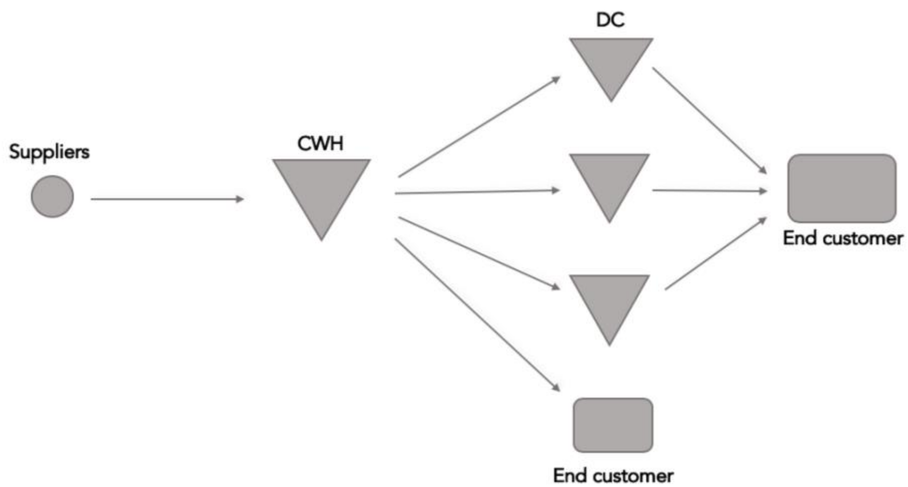

Figure 7.1. Reminder of the main scenario presented in chapter 3.

7.2.1 Expected fill rates - *Single-echelon versus multi-echelon*

This section presents and compares the result from the two different inventory control methods, meaning the uncoordinated single-echelon method versus the coordinated multi-echelon control method. The results regarding achieved fill rates from the main scenario, using the BM-C model, is presented in *Table 7.1.* The values in the table represents the deviation from the target fill rate, meaning *the achieved fill rate* from the simulations minus *the target fill rate.* Hence, a negative value means that the target fill rate is not achieved and a positive that the target fill rate is exceeded. The desired deviation is zero since it means that the model neither underestimates nor overestimates the fill rate. However, as the rendered near optimal reorder points are discrete, the target fill rate will never be fulfilled exactly. This means that a small positive value is the best one can hope for. The reorder points obtained in each inventory control model, rendered from the analytical model, can be found in *Appendix D.*

Table 7.1. Summary of deviation from target fill rate, including all DCs as well as the CWH//virtual DC.

Measurement	Single-echelon	Multi-echelon
Mean deviation	-9,39%	-3,19%
Mean absolute deviation	12,59%	4,12%
St.d of fill rate (average)	0,15%	0,39%
Greatest positive deviation	12,00%	9,18%
Greatest negative deviation	-61%	-25%

Studying the *mean deviation* presented in *Table 7.1,* it can clearly be seen that the multi-echelon inventory control method renders fill rates that are closer to the target fill rate compared to the uncoordinated single-echelon approach. These values indicate that multi-echelon is the preferred method in regard to achieving target fill rate. It can also be seen that the mean deviation for both methods are negative, which means that the target fill rate is not achieved. This is obviously not desirable as it may lead to disappointed customers. On the other hand, if the achieved fill rate greatly exceeds the target fill rate, it might indicate that Duni holds an excessive amount of stock. This is also undesirable since it increases the tied-up capital.

The mean deviation is calculated using the average deviation from the target fill rate at all DC and at the CWH[11]. This means that the measured fill rates for some DCs might exceed the target fill rate, while in other cases it might not achieve the desired fill rate. Hence, the actual mean deviation from the target fill rate might be evened out by one another. It might therefore be more interesting to study the *mean absolute deviation*, which better captures the "actual" deviation from the target fill rate regardless of the greatest positive and negative deviation from the target fill rate. Comparing the mean absolute deviation from the two methods, the result again indicates that the multi-echelon inventory control method performs better compared to uncoordinated the single-echelon approach. More precisely, the multi-echelon inventory method renders a fill rate of 8.47 percentages points closer to target fill rate than the single-echelon method.

The average of the *standard deviations* (st.d) of the fill rate generated from the simulations was, for both methods, below 1%. Based on previous research, a st.d lower than 1% is assumed to be acceptable and strengthens the credibility of the results. This since a low st.d means that the obtained result does not vary much from the mean, while a higher deviation indicates that the result can differ greatly from the estimated mean value. The difference in st.d between the two inventory methods is only 0.24 percentages points, which is considered too minor to further analyze.

The *greatest positive* and *negative deviation* illustrates the extreme deviations. For the uncoordinated single-echelon inventory control method these extreme values are very high, meaning that the model in some cases greatly exceeds the target fill rate and in others fail to a large extent to achieve the target fill rate. Even though the multi-echelon inventory control model has quite large extreme values as well, they are smaller compared to the single-echelon inventory

[11] *For the multi-echelon inventory method, the fill rate at the virtual DC is included as well.*

control method. This as well, implies that the multi-echelon inventory control method has a better performance than single-echelon inventory control method.

The values presented in *Table 7.1* represents an average of all items, without separating upstream demand and replenishment to DCs. It is of interest to examine the result in regard to this breakdown as well, which is performed in the following section.

7.2.1.1 Expected fill rates at DCs – *Single-echelon versus Multi-echelon*

If only analyzing the expected fill rates for each inventory control method at the DCs, the performance at the CWH as well as the virtual DC is excluded. The result is presented in *Table 7.2* and *Figure 7.2.*

As seen in the table, the *mean deviation* of the achieved target fill rate is a negative value for both the single-echelon inventory control method and the multi-echelon inventory control method. The single-echelon inventory model significantly undershoots the target fill rate with a mean deviation of -17,44%, while the multi-echelon method also undershoots, but to a smaller extent, with a mean value of -3,89%. Hence, the overall goal of meeting the predetermined fill rates are to a greater extent achieved using the multi-echelon inventory model. This since the result clearly shows that the multi-echelon inventory control method performs better as the deviation is closer to zero. This can also be seen by only studying the *mean absolute deviation.*

Table 7.2. Summary of the deviation from target fill rate, only including the DCs.

Measurement	Single-echelon	Multi-echelon
Mean deviation	-17,44%	-3,89%
Mean absolute deviation	14,28%	4,20%
Greatest positive deviation	1,27%	9,18%
Greatest negative deviation	-61%	-25%

As seen in *Figure 7.2,* the target fill rate undershoots in the majority of the test items regardless of inventory control method. The fact that both methods undershoots the target fill rate for many items can be explained by the use of the adjusted normal distribution as an approximation of the end customer demand. The normal distribution assumes continuous demand and disregards the fact that the customers in reality often order more than one unit at the same time. Thus, the inventory control methods using the adjusted normal distribution have difficulties with reaching target fill rate as the order size increases.

Furthermore, as discussed in section 5.2, the model’s performance is also affected by the high coefficient of variation of end customer demand and hence the large probability of negative demand. This can also explain why the model have difficulties with reaching target fill rates.

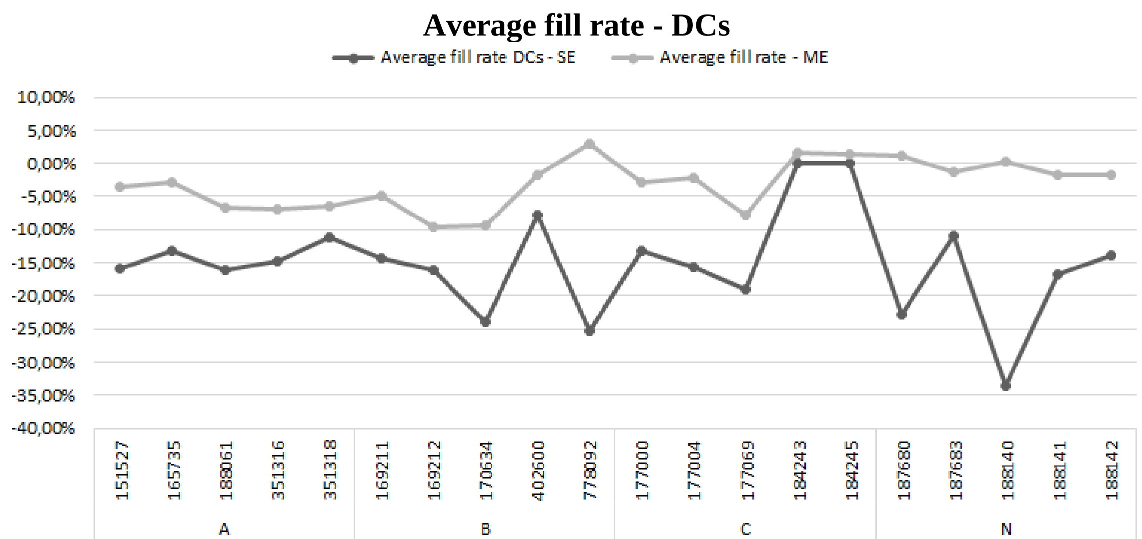

Figure 7.2. The average deviation from the target fill rate for each item, only including the DCs.

By using the same values as in *Figure 7.2* but instead sorting by increasing mean customer order sizes, the challenge of achieving target fill rate with normal approximation for increasing order sizes is further indicated, see *Figure 7.3*. The negative trend lines indicate that increasing customer order sizes is linked to inferior performance in reaching the target fill rate for the multi-echelon method, while it is a bit vaguer for the single-echelon inventory method. Since the fill rate is defined as the fraction of demand that can be satisfied immediately from stock on hand, it is reasonable that increased batch sizes result in increased undershooting. This can be explained by the fact that when the order sizes are larger than one there is a probability of the inventory level decreasing below the reorder point before a replenishment is done. Hence, as the mean order size increases so does the expected undershooting.

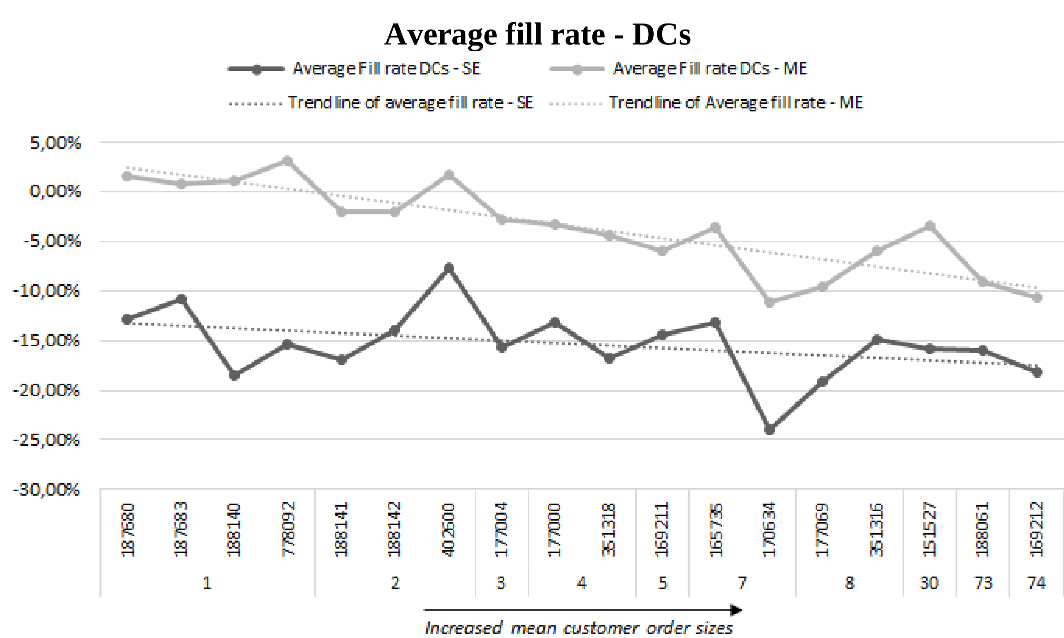

Figure 7.3. The average deviation from the target fill rate for each item sorted by increasing mean customer order sizes, only including the DCs.

7.2.1.2 Expected fill rates for upstream demand - *Single echelon versus Multi-echelon*

This section analyzes the expected fill rates for each inventory control method if only taking the upstream demand into consideration. In *Table 7.3,* the deviation from the target fill rate for each method is summarized.

It should be noted that the multi-echelon inventory control method uses two kinds of target fill rates at the CWH. One target fill rate for the upstream demand, which in this specific case is the same as the target fill rate for the end customer demand at the DCs. Additionally, there is one target fill rate for serving the DC's, which does not have any specific service requirement. The single-echelon inventory method, however, does not distinguish the upstream demand and the replenishment to the DCs from the CWH. Instead, the single-echelon inventory control method serves both from the same stock at the CWH.

Table 7.3. Summary of the deviation from target fill rate, only including upstream demand at the CWH.

Measurement	Single-echelon	Multi-echelon
Mean deviation	7,5%	-2,43%
Mean absolute deviation	7,5%	3,9%
Greatest positive deviation	12%	6,13%
Smallest deviation	4%	-11%

Studying *Table 7.3*, the *mean deviation* of target fill rate is positive for the single-echelon inventory control method but negative for the multi-echelon inventory control method. The single-echelon inventory control method appears to perform better in terms of achieving target fill rate as the mean deviation exceeds the target fill rate with 7.5%. This can be explained by the fact that in the single-echelon there is a tremendous amount of stock generated at the CWH, which in turn generates the high fill rates. This is further discussed in *section 7.2.2*, where the expected stock on hand is analyzed. However, even if the multi-echelon undershoots the target fill rate, it should be noted that the deviation from target fill rate actually is lower compared to the single-echelon method.

Comparing the *mean absolute deviation*, the multi-echelon inventory control method appears to be more appropriate since it only differs 3,9% from target fill rate while single-echelon differs 7,5%. However, by analyzing the patterns in *Figure 7.4*, it is clear that the result from the multi-echelon inventory control method varies considerably more compared to the result from the single-echelon method.

Figure 7.4 illustrates the average deviation from target fill rate for each item. As seen in the figure, the graph for single-echelon has a stair-like appearance. This is due to the fact that the single-echelon method generated a fill rate of 100% for all test items due to high stock levels at the CWH. As the target fill rate decreases according to the associated classifications, the difference between achieved fill rate and target fill rate increases, thus a stair-like pattern.

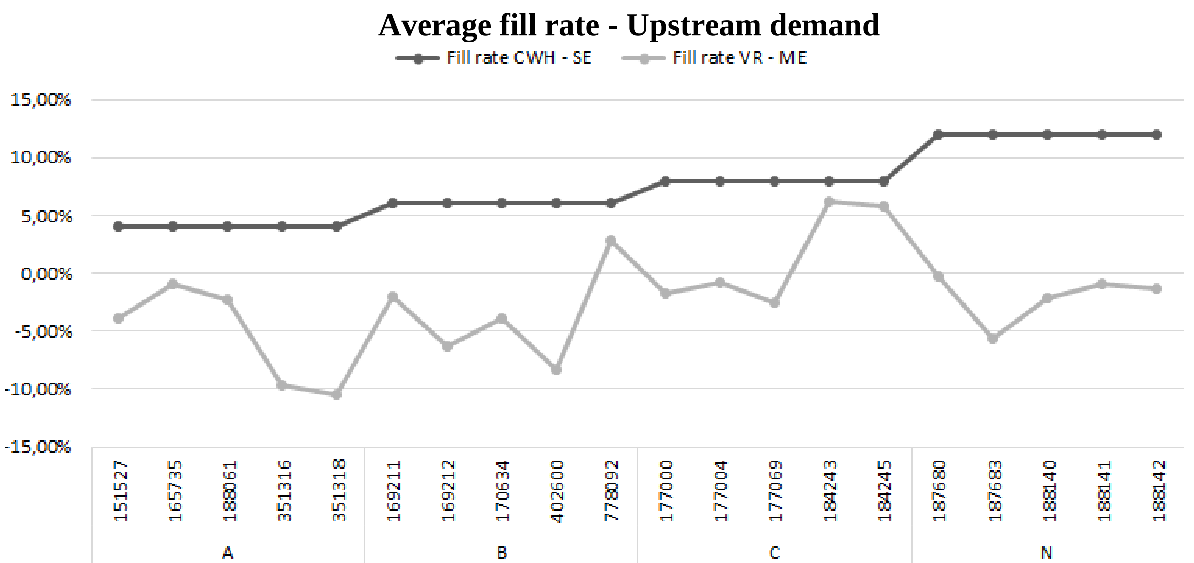

Figure 7.4. The average deviation from the target fill rate for each item, only including the upstream demand.

This result also shows that with an increasing customer order size there is an inferior performance, see *Figure 7.5.* As seen in the figure below, the trend line goes towards a lower achieved fill rate with increasing customer order sizes. This can reasonably be explained by the same argument as discussed in *section 5.2.* meaning the use of the adjusted normal distribution as an approximation of customer demand. As explained, the high coefficient of variation results in a large probability of negative demand which affects the model performance.

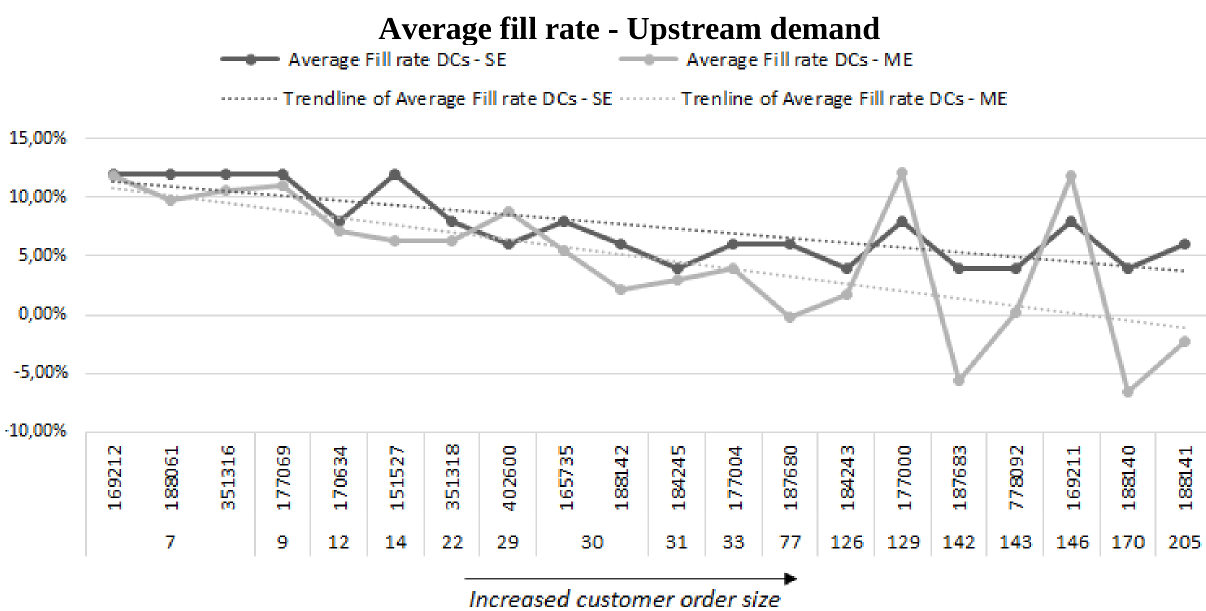

Figure 7.5. The average deviation from the target fill rate for each item, only including the upstream demand. Sorted by increased mean customer order size.

7.2.1.3 High share of upstream demand

Another interesting observation to highlight, which may have affected the model's performance was the large share of upstream demand compared to replenishment orders to downstream DCs. As illustrated in *Figure 7.6*[12], 19 of 20 items, meaning 95% of the analyzed items had a direct distribution of orders to the end customer of at least 40% of the total sales volume for that item. The high proportion of upstream demand is considerably higher compared to the test items examined in the research conducted by Berling et al. (2020).

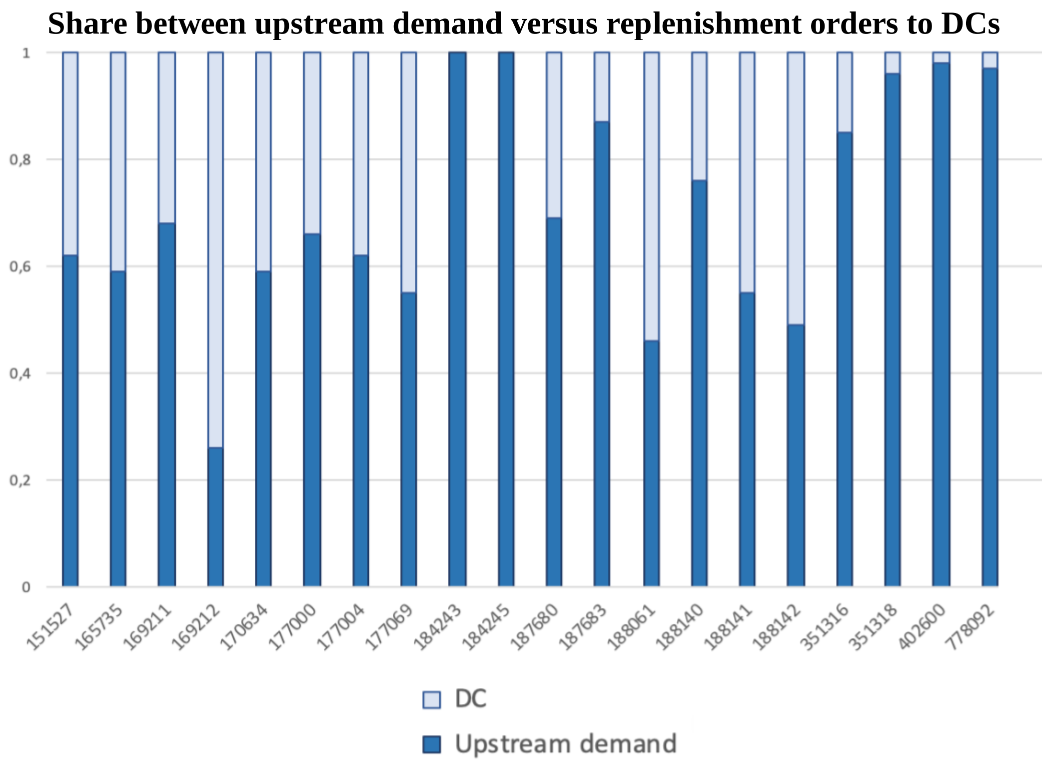

Figure 7.6. Share between upstream demand versus replenishment order to DCs.

In theory, when optimizing a system using a multi-echelon inventory control model the stock is usually pushed downstream towards the DCs. That leads to the achieved fill rate being lower at the CWH and higher at the DCs. This is reasonable since the purpose is to serve the end customer and hence stock is pushed downstream to enable a high fill rate at the warehouses closest to the customer. Thereby it is unnecessary to have a high fill rate constraint at the CWH since it will render high inventory levels.

However, when the upstream demand is added to a traditional multi-echelon model, a fill rate constraint is added to the CWH as well. As stated in the theory section regarding the BM-C model, the total stock at the CWH is split into two different parts, one which has a target fill rate towards direct upstream demand and one which has no fill rate constraint but only serves the DCs. When upstream demand is allowed, the result indicates that stock is no longer pushed downstream to the same extent and the total inventory level at the CWH reasonably becomes larger. As the fraction

[12] *For detailed numbers, please see Appendix G.*

of upstream demand in the multi-echelon model increases, the system moves towards a higher fill rate in the CWH, more similar to the result rendered from the uncoordinated single-echelon method. Hence, the improvements on the total system performance tends to decrease with an increased share of upstream demand. This is illustrated in *Figure 7.7.* The trend line in the multi-echelon model is not that steep, which can be explained by the fact that all items have a great share of upstream demand.

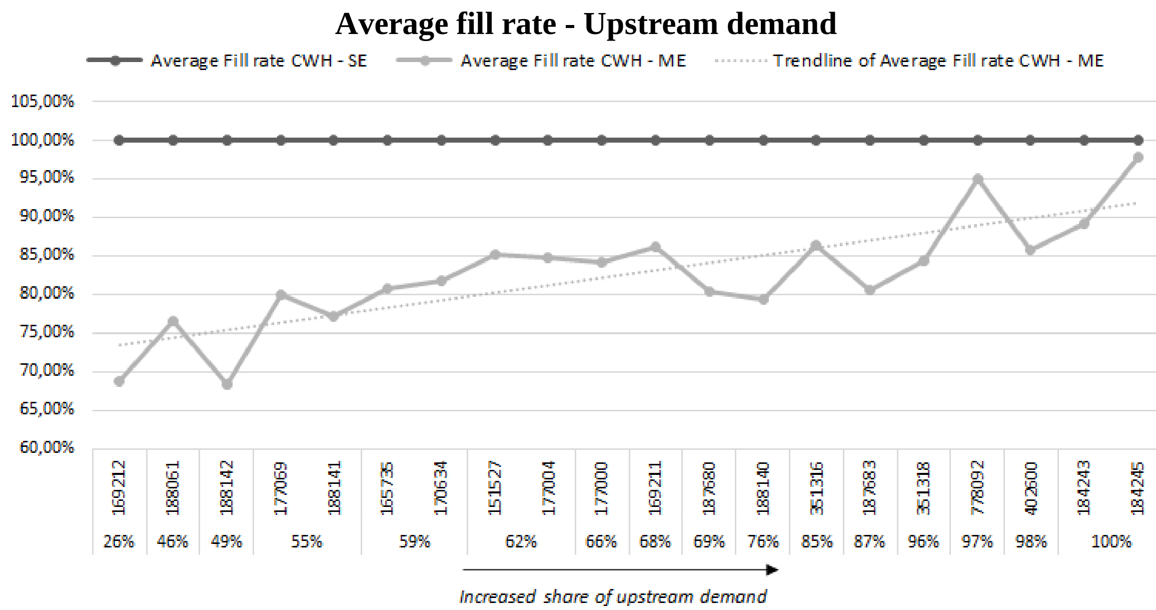

Figure 7.7. Average fill rate at the CWH of the total demand (including the upstream demand), sorted by increased upstream demand.

7.2.2 Expected stock on hand - *Single-echelon versus multi-echelon*

In this thesis, the average stock on hand is used instead of expected inventory holding cost since the latter factor is not known. Furthermore, the exact inventory levels are not the most interesting aspect, but rather the relative difference of how much stock is required for an uncoordinated versus a coordinated system.

In *Figure 7.8*, the total average generated stock on hand for the multi-echelon and single-echelon inventory control method is illustrated. It can be seen that the single-echelon control method generates larger total stock on hand compared to the multi-echelon inventory control method. Based on the theory presented, the result of higher total stock on hand in the single-echelon optimization is not surprising. However, that the stock levels optimized with single-echelon compared to multi-echelon exceeds as much as it does is quite unexpected.

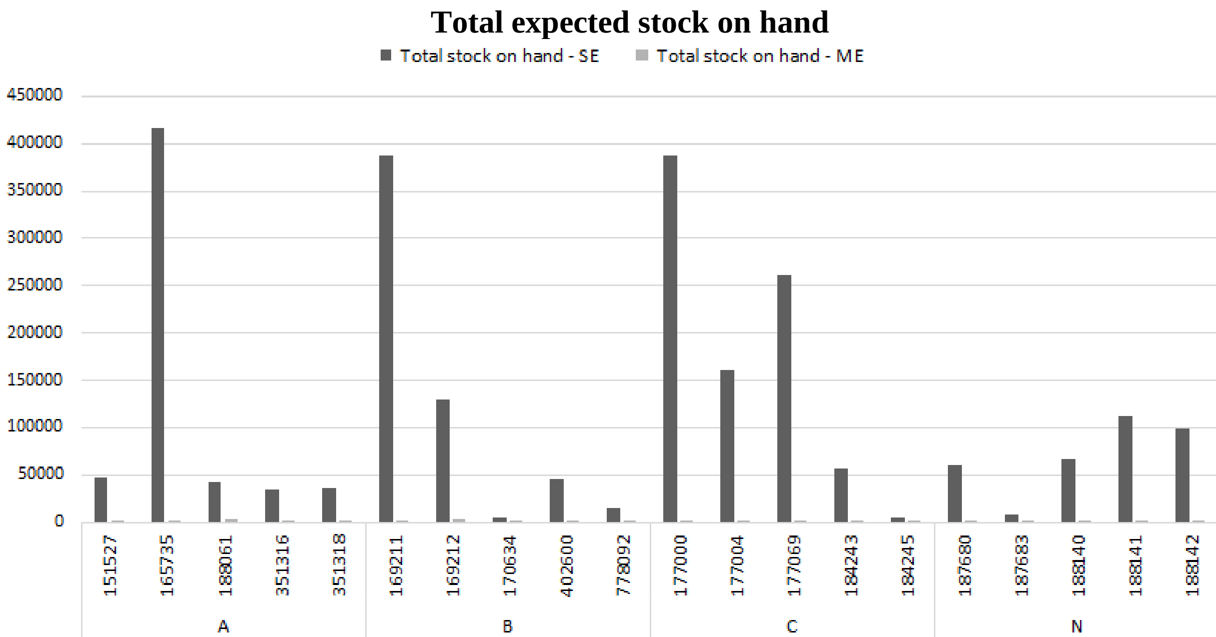

Figure 7.8. Total expected stock on hand sorted by classification.[13]

The distribution of where stock is located in the supply chain is also interesting to analyze. From the figure above, it was clear that the multi-echelon method lowers the stock levels significantly for all test items compared to the single-echelon inventory control method. However, it should be borne in mind that the multi-echelon often underestimated the overall target fill rate, which also indicates that the method partially underestimates the required stock levels.

The allocation of stock throughout the supply chain partly depends on the lead times. In the *main scenario*, there are notably long lead times between the suppliers and CWH (70-90 days) compared to the lead times between CWH and DCs or end customers (2-3 days). According to theory, this means that more stock should be kept at the CWH relative to the DCs. Studying the two circle-graphs in *Figure 7.9*, it is clear that both the single-echelon and the multi-echelon inventory control method keeps more stock at the CWH compared to stock at the DCs, which can be explained by the long lead times between suppliers and CWH. However, relative to each other, the figures also show that the stock is pushed downstream using a multi-echelon inventory model compared to the single-echelon model. This thus means that even in Duni's case, the theory that states that multi-echelon inventory controls tend to push stock downstream, seems to be correct in this case as well.

[13] *More detailed graphs of stock on hand levels, please see Appendix E.*

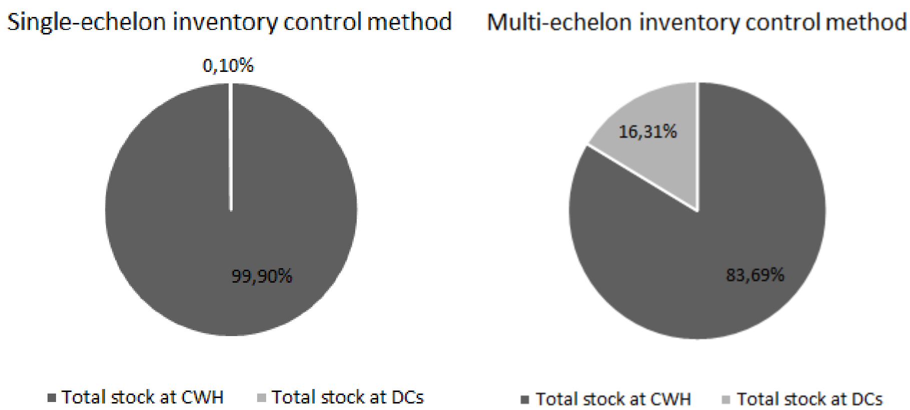

Figure 7.9. Share of total inventory at the CWH and at the DCs.

7.2.2.1 Expected stock on hand at the DCs – *Single-echelon versus Multi-echelon*

By further breaking down the diagrams in *Figure 7.8* and *7.9* above, additional interesting findings have been observed. Although multi-echelon inventory control lowers the total average stock on hand the result in fact shows an increase of stock at the DCs when optimizing with multi-echelon inventory, see *Figure 7.10*. This means that the large increase of total stock in the system in the single-echelon method seems to be caused by a major increase of stock only at the CWH, not at the DCs.

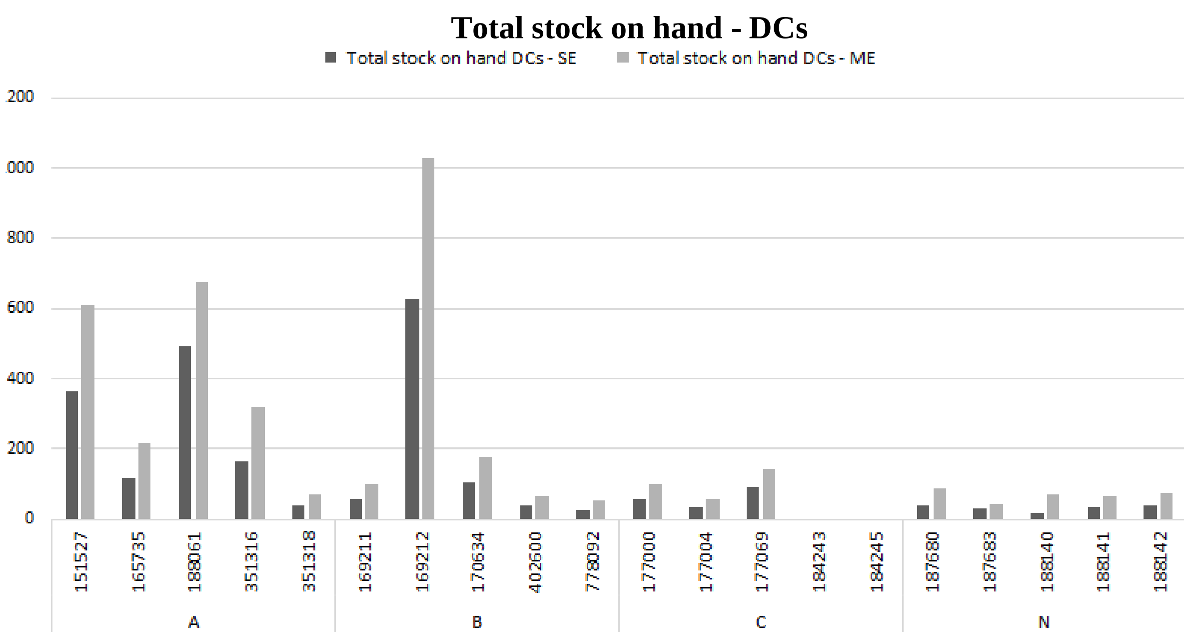

Figure 7.10. Inventory held at the DCs excluding the CWH and the virtual DC, sorted by classification.

7.2.2.2 Expected stock on hand at the CWH – *Single-echelon versus Multi-echelon*

The expected stock on hand at the CWH, comparing single versus multi-echelon, is illustrated in *Figure 7.11*. This is also a clear example of where in the supply chain the different methods choose to place stock. The single-echelon method places a great amount of stock at the CWH, while the multi-echelon inventory model pushes some stock downstream, towards the DC and can thereby manage to decrease the level of inventory in the whole system.

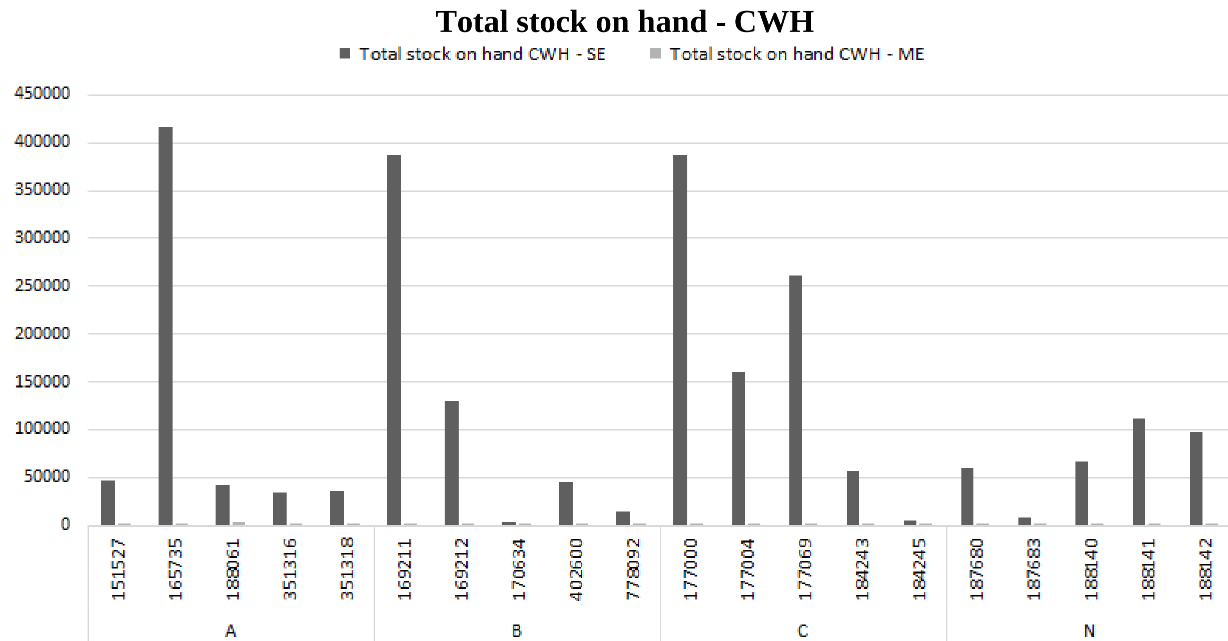

Figure 7.11. The total inventory held at the CWH exulting the DCs, sorted by classification.

7.2.3 Further observations

When analyzing the input data and running the analytical model, further observations were noted. As seen in the analysis of expected fill rate above, the achieved fill rate from the simulation model often deviated from the predetermined target fill rate when using the BM-C model. This is undesirable since one strives for a deviation close to zero. In the case study presented by Berling, Marklund and Johansson (2020), it was the BJM method using the compound Poisson distribution that rendered the best results in terms of achieved fill rate with as low inventory level as possible. Hence, this BJM model was tested in this project to see if the BJM model could render better results with regards to achieved fill rate. This model approximates demand using compound Poisson distribution and the iterative method to estimate the induced backorder cost.

Table 7.4 illustrates the comparison of the result from the BJM model and the BM-C model. Only two items were able to be compared since the run time of the analytical model, using compound Poisson, took roughly 3-6 weeks per item. Hence, more items were not able to fit within the time frame of this project.

Table 7.4. Results rendered from the simulations, comparing the BJM model and the BM-C model.

Item	Share of upstream demand	Deviation from target fill rate - upstream demand		Deviation from target fill rate - DCs		Total expected stock on hand	
		BJM	BM-C	BJM	BM-C	BJM	BM-C
778092	97%	-2,35%	2,78%	0,38%	3,04%	934	985
187680	69%	-6,41%	-0,23%	-2,33%	1,57%	233	276

In *Table 7.4* it can be seen that the BM-C model renders higher achieved fill rates compared to the BJM model but at a cost of slightly increased total average stock on hand. The increase of stock in the BM-C model is expected as the naïve method tends to overestimate the correct value of the induced backorder cost, which increases the total stock on hand.

In previous research by Berling et al. (2020) the share of upstream demand was maximum 40% of the total demand and the coefficient of variation varied between 5 to 20. The coefficient of variation for the simulated items in this thesis varied between 0,1 to 84,3. Thus the two test items presented in the model above have both higher upstream demand and coefficient of variation compared to the test items in the research paper (Berling et al. 2020). This may explain the inferior performance of the BJM model as it uses the iterative method for estimating the induced backorder cost at the virtual DC that tends to render a lower stock in the CWH.

7.2.3.1 High coefficient of variation

One possible reason why the used model not fulfilled target fill rate can be explained by the high coefficient of variation. Although the collected data only represented a small selection of the total product portfolio at the Duni, a general observation was that the coefficient of variation was considerably high for the majority of items and stock location. As seen in *Table 7.5,* only 40% of the analyzed demand flows had a coefficient of variation lower than 20, while 60% had a coefficient of variation higher than 20.

Table 7.5. Coefficient of variation above 20 including DC and virtual DC.

Coefficient of variation (σ^2 / μ)	Percentage
$\sigma^2 / \mu \geq 20$	60 %
$\sigma^2 / \mu \leq 20$	40 %

A more detailed illustration of all items and flows coefficient of variation is seen in *Figure 7.12*[14]. *Analyzing* all items, the coefficient of variation varied between values of 0,1 to 1246,87. However, the values of 1246,87 are an extreme value compared to the other values and was considered as an outlier. Disregarding this value, the coefficient of variation varied between 0,1 to 345.

[14] *For detailed values please see Appendix G*

Furthermore, based on the items selected for this master thesis, the data in the graph also indicates that A and B-items have a higher coefficient of variation compared to C and N-items.

Coefficient of variation for each item

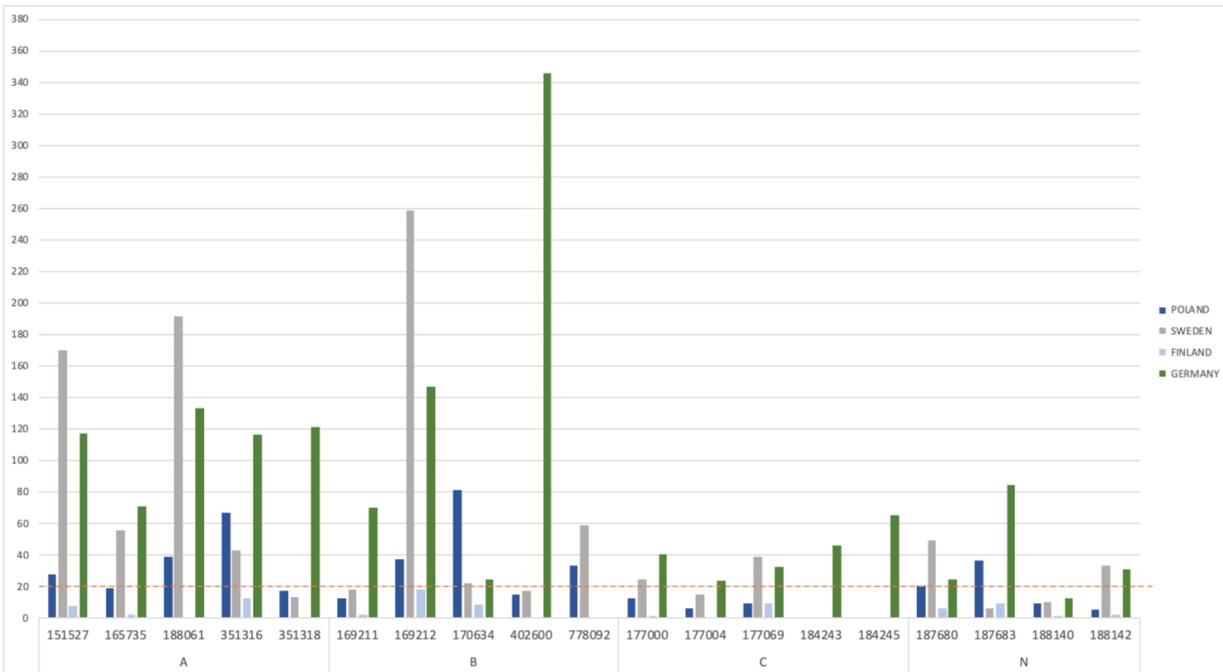

Figure 7.12. Coefficient of variation per item.

The high variation in order quantities places high demands on Duni's ability to control inventory. From an inventory planning perspective such high varieties of the coefficient of variation are not desired due to the difficulty of planning inventory levels according to expected demand and hedge against uncertainties. At the moment, Duni allows all customers to order whatever order quantities the customer desires but based on this finding, Duni should consider the possibilities of improved demand management. Although this is to some extent outside the scope of this master thesis, Duni should consider initiating a discussion both internal and with customers regarding for instance predetermined intervals of order quantities that the customer is allowed to order within.

7.3 Summary of comparison of single-echelon versus multi-echelon

The presented result from *the main scenario* implies that there are benefits and drawbacks with both inventory control methods. The result clearly indicates that there are opportunities to reduce inventory levels at Duni by applying coordinated, multi-echelon inventory control compared to uncoordinated, single-echelon control. In addition, the average absolute mean deviation from target fill rate was lower for multi-echelon, which also indicates further advantages of the control method. On the other hand, the result also shows that the higher proportion of upstream demand, the benefits of multi-echelon inventory control decrease. This means that if the proportion of upstream demand becomes too high, there are not as great incentives for Duni to apply coordinated inventory control.

Furthermore, the multi-echelon inventory control method seems too often undershoot the target fill rate, while the single-echelon inventory control method overestimated the fill rate. Too high fill rate indicates unnecessarily high inventory levels and high cost for tied up capital, which is not desirable. At the same time, it means that the customer's demand can be met consistently no matter when an order is placed. On the contrary, too low fill rate means that the inventory method underestimates the level of stock needed to meet customer demand, which in turn can lead to dissatisfied customers. This result thus indicates that there are advantages and disadvantages with both inventory control methods.

However, if another distribution than normal distribution or compound Poisson had been used to approximate customer demand, the benefits with multi-echelon might become more distinct. Regarding the practical applicability, the results suggests that another statistical demand approximation needs to be applied in order to make the method worth implementing in practice. The hypothesis is that if a better distribution approximation had been used, the multi-echelon inventory control method would have an even more superior result compared to single-echelon inventory control.

To summarize, based on the presented findings, the control method that seems most appropriate to apply at the Duni is coordinated, multi-echelon inventory control. However, none of the selected models seems to perform as good as desired, meaning that further research is needed to determine the most optimal model for Duni.

7.4 Sub-scenario 1

Characteristics of *sub-scenario 1*:

- Divergent structure
- The same lead time as the main scenario between CWH and DCs.
- *Changes in order quantities* between supplier and CWH due to consolidation point.
- The same average values the internal shipment as the main scenario between CWH and DCs.

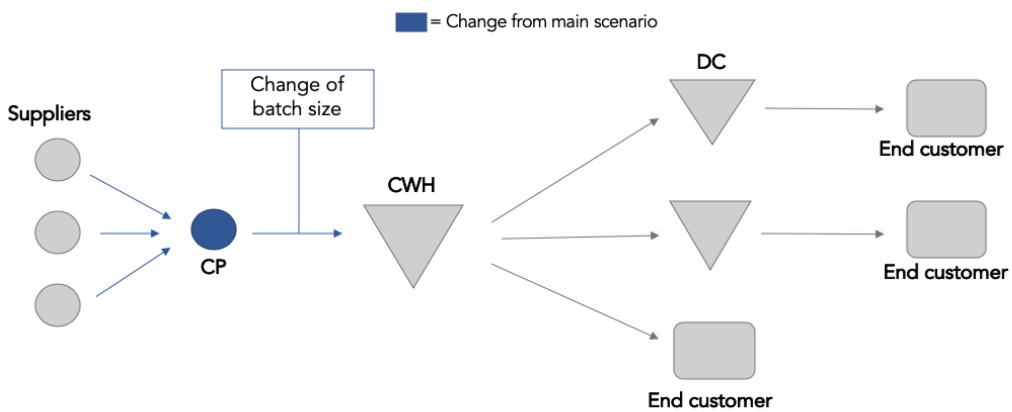

Figure 7.13. Reminder of sub-scenario 1 presented in chapter 3.

The analysis only includes the costs mentioned in the BM-C model and no other costs that may occur in the supply chain such as transportation or picking costs. As the fictitious supply chain is a simplification of Duni's currently used system, this analysis will not provide implications of how decreasing batch sizes would affect their current inventory control. The section will rather analyze how the performance of the model is affected as the batch sizes are adjusted.

7.4.1 Expected fill rates - *Decrease of order sizes*

A detailed result regarding the average deviation from the target fill rate for each item is tabulated in *Table 7.7.* As seen in the table, regardless of batch size the majority of the test items still seems to undershoot the target fill rate. Comparing the result from the main scenario with the result with ½ and ¼ batch size, the values indicate mixed results. The green boxes indicate an improvement compared to the main scenario, while a red box indicates a worsening. In the cases where there has been a worsening, the change in the model's performance to achieve fill rate seems to be so small compared to the main scenario that it can be assumed to have a minimal impact. The results are hence to varied to be able to make a clear conclusion.

Table 7.6. The average deviation from the target fill rate.

Classification	Art nbr	Main scenario	½ batch size	¼ batch size
A	151527	-3,62%	-3,61%	-3,54%
A	351318	-6,47%	-1,18%	-1,07%
B	402600	-1,67%	-1,85%	-1,99%
B	778092	2,95%	-0,30%	-0,94%
C	177000	-2,95%	-3,17%	-2,79%
C	177069	-7,87%	-7,77%	-8,42%
N	187680	1,12%	1,39%	1,35%
N	188142	-1,85%	0,16%	-2,03%

The *absolute mean deviation* for the eight selected items for sub-scenario 1 is presented in *Table 7.6*. Compared to the main scenario, there is no significant difference in the achieved fill rates when the batch sizes are reduced from the original size to ½ batch size and ¼ batch size. The largest difference between the main scenario and the two reduced batch sizes only corresponds to 1,13%, which is a relatively low improvement of the model's performance. This supports the finding that no clear conclusion can be made.

Table 7.7. The absolute mean deviation from the target fill rate for all items in sub-scenario 1.

Main Scenario	½ batch size	¼ batch size
3,56%	2,43%	2,77 %

7.4.2 Expected stock on hand - *Decrease of order sizes*

The expected stock on hand for sub-scenario 1 is presented in *Table 7.8*, as well as the values from the main scenario. As seen in the table, the average stock on hand for the whole system increases as the batch size decreases. Considering that the model improved its ability to fulfil target fill rate for some items, the increased stock is expected. The tabulated values also indicate that the core reason for the increase of stock in the sub-scenario is mainly due to item 351318. Overall, the obtained result does not show that any significant changes occurs in the model's performance when changing decreasing to 50% and 25% of the original order size. Thereby there exist no further interest in analyzing the upstream demand and the DC separately.

Table 7.8. The total expected stock on hand.

Classification	Art Nbr	Main scenario	½ batch size	¼ bath size
A	151527	1976	2011	1998
A	351318	1170	4465	4651
B	402600	1851	1807	1786
B	778092	585	397	861
C	177000	939	620	619
C	177069	681	664	660
N	187680	276	266	262
N	188142	314	363	305
Total		**7792**	**10592**	**11142**

7.4.3 Decrease of order sizes - *Batch size of one pallet*

The impact of a decreasing to half the size and one quarter size seems difficult to unambiguously define. The system as a whole improves the achieved fill rate by ~1%, with an increase of stock levels with almost 3000 units. However, this change is too small in order to confirm an improvement performance of the model.

After discussing main findings from sub-scenario 1 with representatives at Duni, it was requested to further investigate if sizes of one pallet could affect the model performance instead. Hence, the simulation was performed once again but with the batch size of each item corresponding to one pallet. The percentages size of the main scenario's batch size can be seen in *Table 7.9*. An interesting observation when using the size of one pallet is that all items, except 165735, significantly reduced their batch sizes.

Table 7.9. The number of items that is equal to one pallet, per item.

Classification	Art Nbr	Nbr of items per pallet	Percentages of main scenarios batch size [15]
A	188061	14	0,27%
A	165735	135	112,5%
B	169212	30	2,86%
B	402600	18	1,52%
C	177000	24	4,36%
C	177069	16	5,26%
N	188142	10	4%
N	186783	32	16%

7.4.3.1 Expected fill rates - Batch size of one pallet

Reducing the batch size to one pallet seems to result in an overall positive impact of the fill rate. For 6 of 8 items, the deviation from target fill rate was improved, see *Table 7.10*. Furthermore, if one instead only studies the fulfilled fill rate, 7 of 8 items improved the fill rate. This since item 186783 went from a negative value to a positive, even though the deviation from the target was larger.

Table 7.10. The average deviation from the target fill rate.

Classification	Art Nbr	Main scenario	One pallet batch size
A	188061	-6,77%	4,43%
A	165735	-3,60%	-3,74%
B	169212	-9,58%	-7,67%
B	402600	-1,67%	0,48%
C	177000	-2,95%	0,42%
C	177069	-7,87%	-6,24%
N	188142	-1,85%	1,58%
N	186783	-0,66%	1,06%

[15] *The calculation to receive the change of batch size is calculated: Nbr of items on one pallet / Nbr of items used in the main scenario.*

The improvement of the model's performance in better meeting the target fill rate is further illustrated in *Figure 7.14.* The pattern shows, more or less, an unambiguous result that decreasing batch size to one pallet renders a higher fill rate compared to the main scenario. Additionally, an interesting observation is that the only item that actually deteriorated its achieved fill rate was item 165735, which was the only item that actually increased the batch size compared to the main scenario. Thus, these results indicate that as the batch size drastically decreases, the model improves its performance as the achieved fill rate improves.

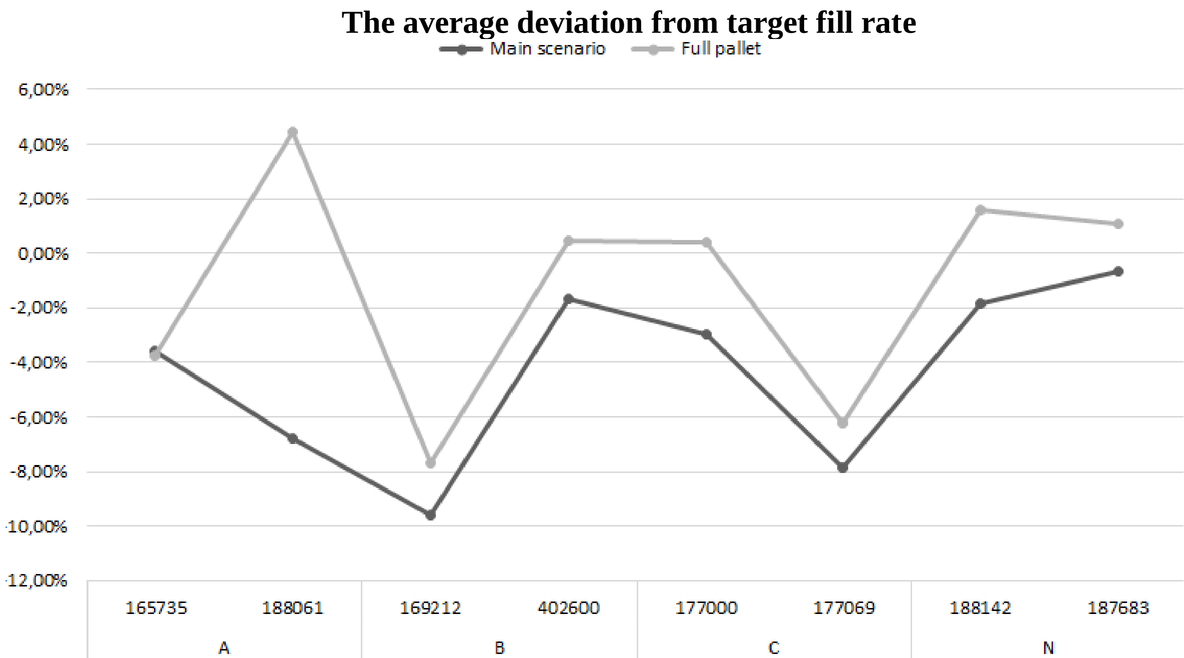

Figure 7.14. The average deviation from the target fill rate, sorted by classification.

When comparing the absolute mean deviation from target fill rate, a small improvement of 1.25% can be seen, see *Table 7.11*. Even though 1,25% is rather low, the values in *Table 7.10* indicates that the model's performance has improved for the majority of the items. Hence, a further analysis regarding the upstream demand and the DCs seemed interesting.

Table 7.11. The absolute mean deviation from the target fill rate.

Main Scenario	One pallet batch size
4,45%	3,2%

7.4.3.2 Expected fill rates at the DCs - *Batch size of one pallet*

Table 7.12 presents the result if only analyzing the deviation for the DCs and one pallet as batch size. 5 of 8 items improved the deviation from target fill rate, where several items improved the fill rate considerably compared to the main scenario.

One interesting observation is that from the perspective that "too large" deviation from target fill rate is undesirable, item 186783 performs worse when decreasing the batch size. However, in terms of achieving high fill rates, item 186783 actually improved the fill rate compared to the main scenario since it resulted in 2,07% above target fill rate instead of 1%. The other two items that worsened their deviation only worsened by 0,06% and 0.23%, which can be seen as neglected. These findings are also clear *Figure 7.15*, which illustrates the pattern of the tabulated values.

Table 7.12. The average deviation from the target fill rate, only including the DCs.

Classification	Art Nbr	Main scenario	One pallet batch size
A	188061	-9,04%	3,41%
A	165735	-4,16%	-4,22%
B	169212	-10,69%	-8,88%
B	402600	1,64%	1,87%
C	177000	-3,37%	-0,91%
C	177069	-9,66%	-8,11%
N	188142	-2,00%	0,59%
N	186783	1,00%	2,07%

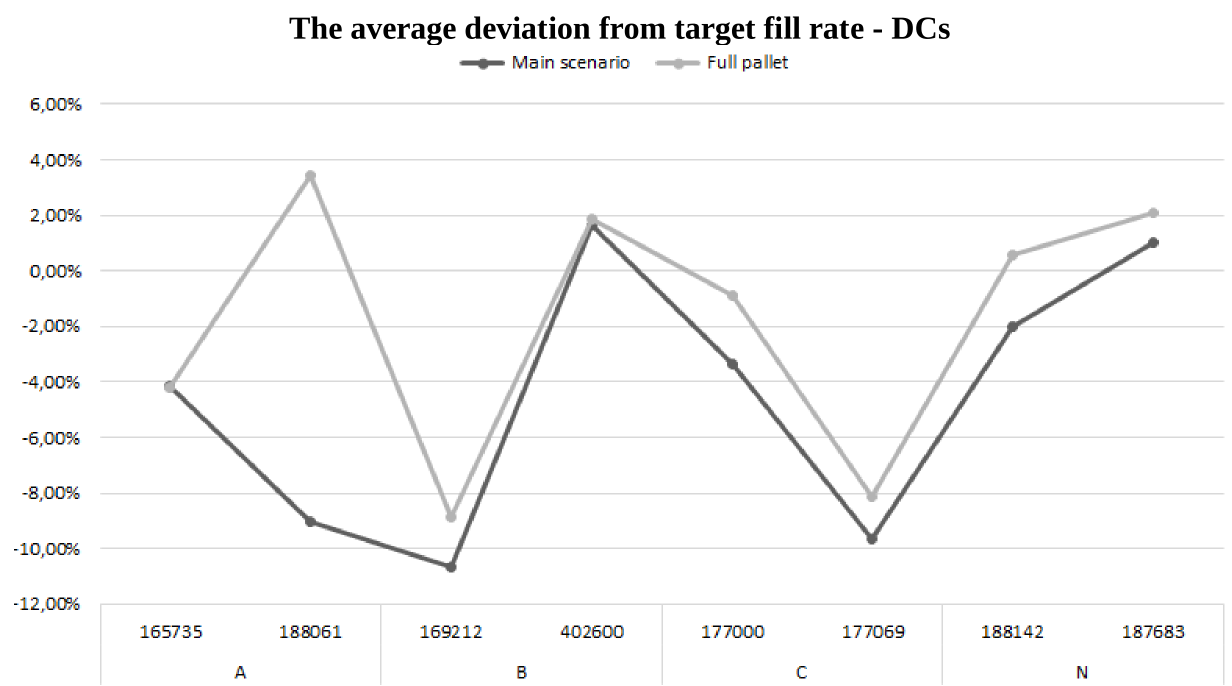

Figure 7.15. The average deviation from the target fill rate only including the DCs.

The absolute mean deviation from target fill rate, only including the DCs, is illustrated in *Table 7.13.* As seen in the table, an improvement of 1.41% was obtained at the DCs when using the batch size of one pallet. The achieved result thus indicates that small batch sizes which correspond to one pallet appear to have a positive impact on achieving target fill rate at the DCs.

Table 7.13. The absolute average deviation from the target fill rate, only DCs.

Main Scenario	One pallet batch size
5,17%	3,76%

7.4.3.3 Expected fill rates for upstream demand - *Batch size of one pallet*

The result regarding upstream demand can be interpreted as both positive and negative. As seen in *Table 7.14,* only 4 of 8 items have green boxes which indicates mixed results. As discussed above, it is of course not desirable that the deviation from target fill rate becomes too high. However, for item 188061, 177000 and 188141 actually goes from a negative value to a positive value. That is, the items go from undershooting the target fill rate to overperforming. In this case, it is important to note that there are advantages and disadvantages with both aspects. On one hand, it is crucial to meet customer requirements which means that higher achieved fill rates are necessary. On the other hand, may too high fill rate increase the inventory levels, which also is not desirable. This is a trade-off the companies themselves must consider in order to find the best solution for them.

Table 7.14. The average deviation from the target fill rate, only including upstream demand.

Classification	Art Nbr	Main scenario	One pallet batch size
A	188061	-2,23%	6,45%
A	165735	-1,94%	-2,30%
B	169212	-6,27%	-4,02%
B	402600	-8,30%	-2,29%
C	177000	-1,69%	4,41%
C	177069	-2,50%	-0,64%
N	188142	-1,39%	4,56%
N	186783	-5,65%	-0,96%

Studying the pattern in *Figure 7.16,* it is clear that the scenario with one pallet batch size increases the achieved fill rate. Except for item 165735, which was the only item that increased its batch size compared to the main scenario, all items performed better in terms of achieving target fill rate.

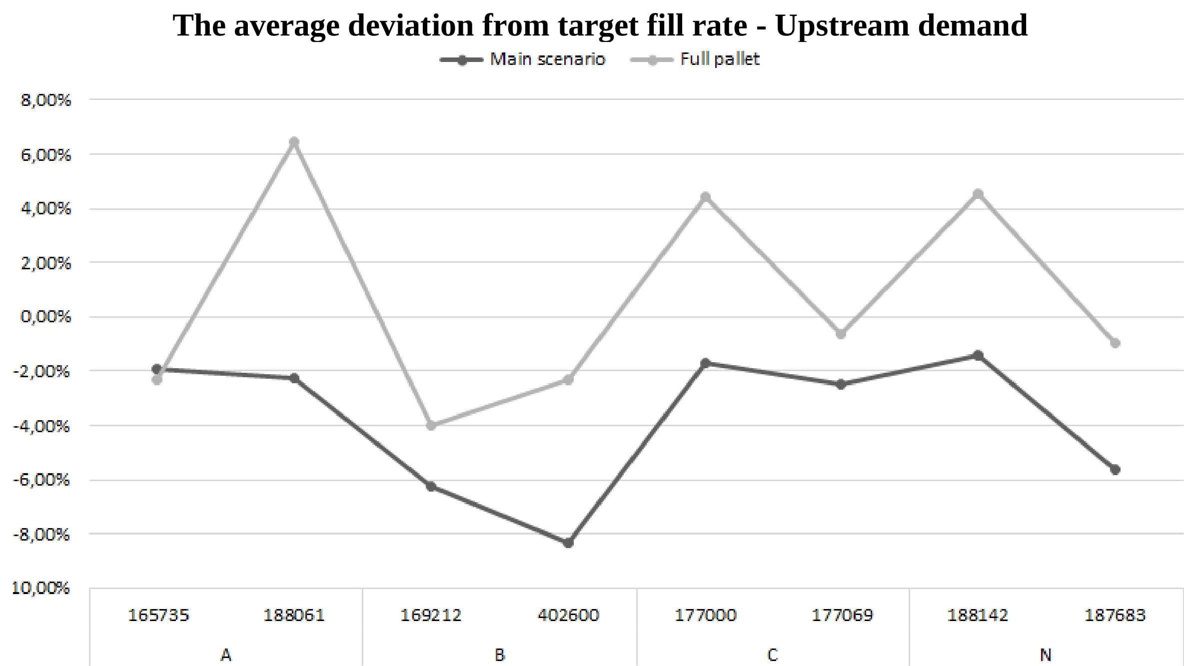

Figure 7.16. The average deviation from the target fill rate only includes the upstream demand.

The absolute mean deviation from target fill rate was improved by 0.55% compared to the main scenario, see *Table 7.15*. This demonstrates that even though some items increase the deviation from target fill rate, the overall result is an improvement. It thus means that the result indicates an improvement in terms of achieving target fill rate not only at the DCs, but also for upstream demand.

Table 7.15. The absolute mean deviation from the target fill rate.

Main Scenario	One pallet batch size
3,75%	3,20%

7.4.3.4 Expected stock on hand - *Batch size of one pallet*

Based on the above presented result of higher achieved fill rates, it was not entirely unexpected that the total stock level had increased. As shown in *Table 7.16*, an increase of approximately 1400 units was obtained.

Table 7.16. The total expected stock on hand.

Classification	Art Nbr	Main scenario	One pallet batch size
A	188061	3275	3290
A	165735	1235	1244
B	169212	3523	3999
B	402600	1851	2286
C	177000	649	867
C	177069	681	764
N	188142	314	398
N	186783	442	505
Total		**11971**	**13352**

Analyzing each item's total stock on hand in the whole system, see *Figure 7.17*, the result shows that the stock level is slightly higher for each item or relatively similar to the levels in the main scenario. So far, the obtained result indicates that better fill rate also resulted in a certain increase of stock levels.

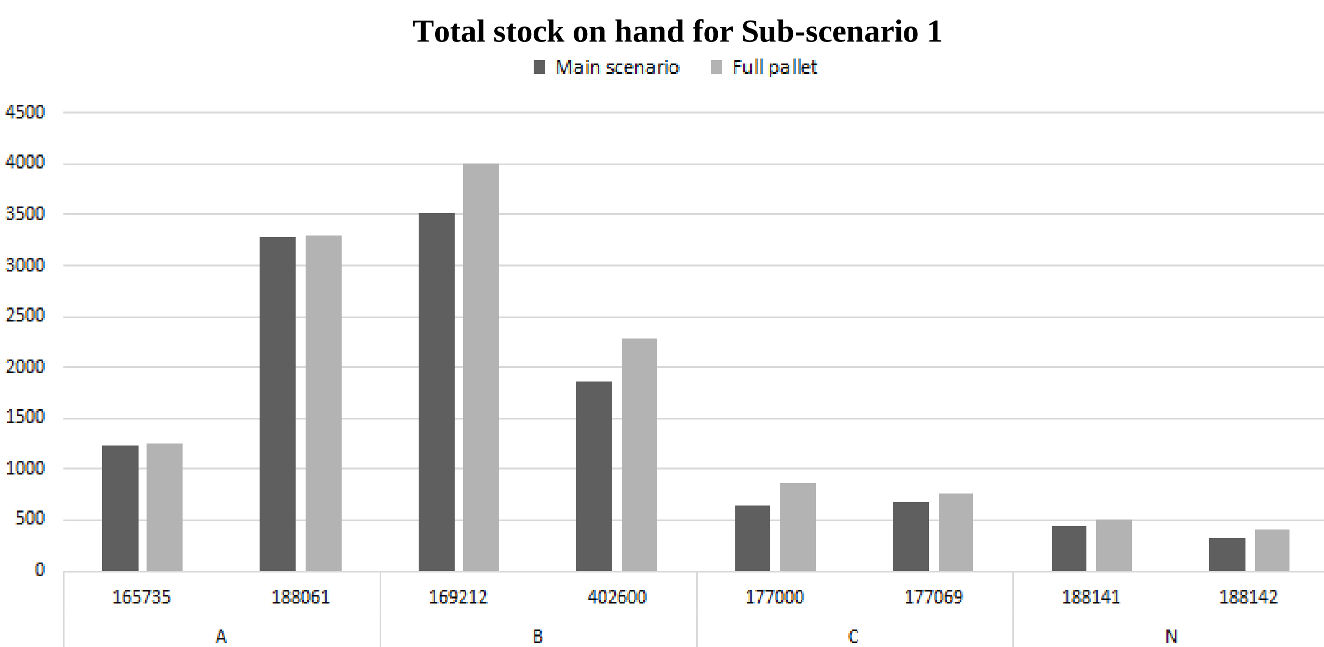

Figure 7.17. The total stock on hand compared to the stock level at the main scenario.

7.4.2.1 Expected stock on hand at the DCs - *Batch size of one pallet*

Only analyzing the obtained stock levels at the DCs, decreasing batch size resulted in a slight increase of 153 items. This can be seen in *Table 7.17*. It seems to show that one pallet batch size can contribute to increasing the fill rate at the DCs but at a cost of rather small increase of stock levels. This is also seen in *Figure 7.18*, where it is clear that the majority of items either obtained the same stock level as before or a slight increase.

Table 7.17. The average stock on hand in the DCs.

Classification	Art Nbr	Main scenario	One pallet batch size
A	188061	673	792
A	165735	215	215
B	169212	1028	1074
B	402600	64	64
C	177000	88	92
C	177069	145	137
N	188142	75	67
N	186783	46	47
Total		**2333**	**2486**

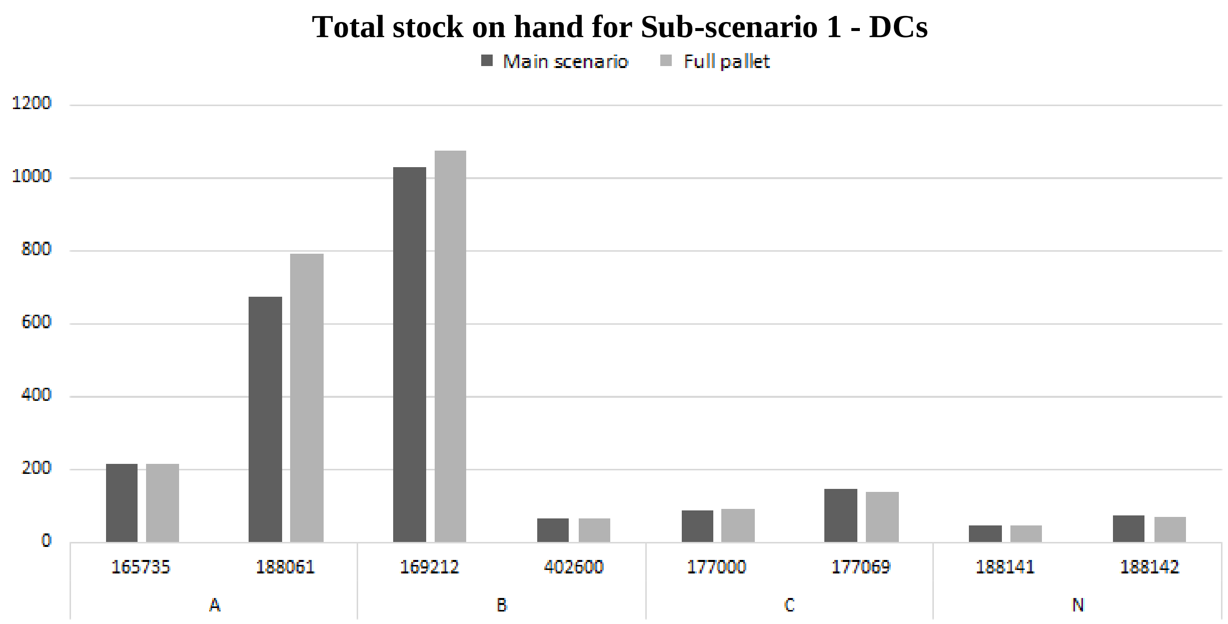

Figure 7.18. The total stock on hand only including the DC.

7.4.3.5 Expected stock on hand at the CWH - *Batch size of one pallet*

The increase of total stock in the system seems to mainly be a result of a large increase of stock at the CWH. The values presented in *Table 7.18* shows that the stock level at the CWH increased with 1228 items.

Table 7.18. The average stock on hand for the CWH.

Classification	Art Nbr	Main scenario	One pallet batch size
A	188061	2602	2498
A	165735	1020	1029
B	169212	2495	2925
B	402600	1787	2221
C	177000	561	775
C	177069	536	627
N	188142	240	331
N	186783	396	458
Total		**9638**	**10866**

The increase of stock at the CWH can be explained by the use of the naïve method to estimate the induced backorder costs as earlier explained,

Studying *Figure 7.19*, the majority of the items increased their stock level, which all together resulted in a relatively large increase of stock. This means that even if the fill rate has improved, the result shows that the total stock levels at the CWH will also increase to some extent. It can also be established that the total increase of stock in the system mainly takes place at the CWH and not the DCs.

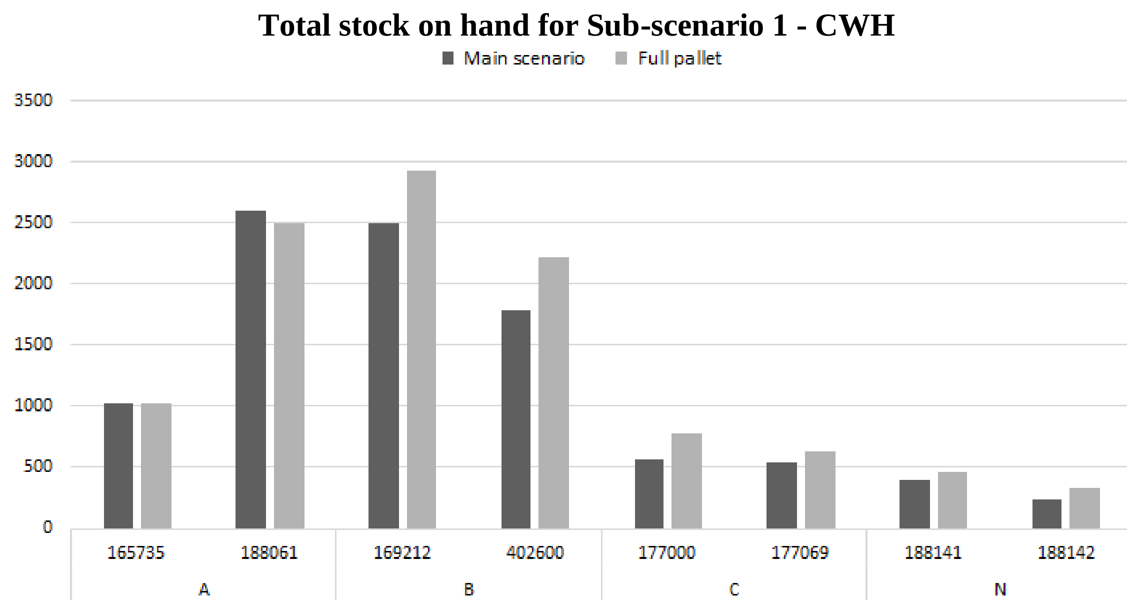

Figure 7.19. The total stock on hand only, including the CWH.

7.4.4 Summary of sub-scenario 1

To conclude, when half the batch size and a quarter batch size was simulated, the result seemed mixed. The hypothesis was that these changes were too diminutive in order to affect the result. This since the quantities between supplier and CWH is considerably large compared to the internal batch sizes at Duni. However, when instead using one pallet as the batch size, the simulations resulted in that both DCs and upstream demand improved their fill rate.

The result also indicates that a decrease of batch size improves the model's ability of calculating the reorder points due to improved performance of achieving the target fill rates. Although this is at the price of increased inventory levels. The improved performance of the model is somehow expected due to the relative difference of the batch sizes between supplier to CWH and CWH to DCs decreased. Excessive differences between these may affect the model's performance negatively, which also seems to be the case in this study. Additionally, from an inventory management perspective it is only reasonable that it is simpler to optimize a system which does not use such extremely large order quantities.

The improved performance of reduced batch sizes was expected. This since no other costs are taken into account. The smaller the batch size is, the better from an inventory control perspective where excessive stock caused by batching can be avoided.

What do the main findings from sub-scenario 1 indicate for Duni? The result implies that the model's performance is improved by a decrease of batch sizes. This means that if Duni were to implement coordinated control with the use of a similar model used in this thesis in the future, the company should investigate if the order size from the suppliers to the CWH could be decreased.

With that said, the analysis regarding the reduction of batch sizes does not include any guidelines of which batch size is most suitable for Duni's current supply chain. The analysis regarding the most optimal order quantity for each item should include further costs for all relevant nodes in their supply chain.

7.5 Sub-scenario 2

Characteristics of *sub-scenario 2:*

- Divergent structure
- *Changes in lead time* between CWH and DCs due to new central warehouse location.
- *Changes in lead time* between supplier and CWH due to new central warehouse location.
- The same order quantity as Duni has today between supplier and CWH.
- Average values the internal shipment quantity between CWH and DCs.

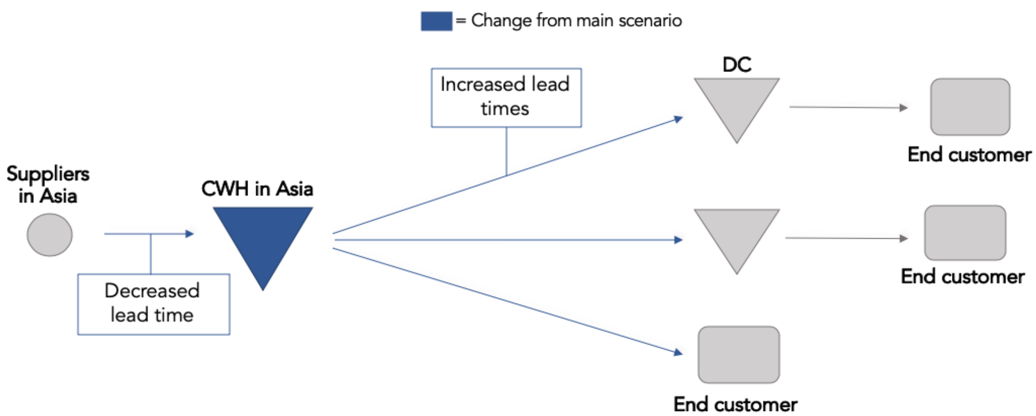

Figure 7.20. Reminder of sub-scenario 2 presented in chapter 3.

7.5.1 Expected fill rates - *Changed lead times*

The expected fill rate for *sub-scenario 2* is presented in *Table 7.19*, together with the values from the main scenario. As seen in the table, a general observation is that even if the lead times changes the majority of the test items still seems to undershoot the target fill rate.

Comparing the result from the main scenario with the result with changed lead times, the numbers show once again mixed results. As seen in the table, the green boxes indicate an improvement compared to the main scenario, while a red box indicates a worsening. Overall, 5 of the 8 test items improved the fill rate when lead times were changed, even though it only was a relatively small improvement for some items.

Table 7.19. The average deviation from the target fill rate.

Classification	Art Nbr	Main scenario	Change of lead time
A	165735	-2,94%	-3,58%
B	169211	-3,80%	-3,43%
B	169212	-9,58%	-7,13%
C	177000	-2,66%	-0,38%
C	177069	-7,77%	-4,95%
N	188142	0,16%	-0,62%
N	188141	-1,73%	-1,16%
N	187683	-1,34%	-6,49%

By plotting the values in *Figure 7.21* and only analyzing the pattern it seems that changed lead times indicates an overall improvement compared to the main scenario. However, just as in *sub-scenario 1* the results are quite varied which again makes it difficult to state a distinct result. Furthermore, it is also important to keep in mind that the result indicates the model's ability to perform, rather than which result that is best for Duni.

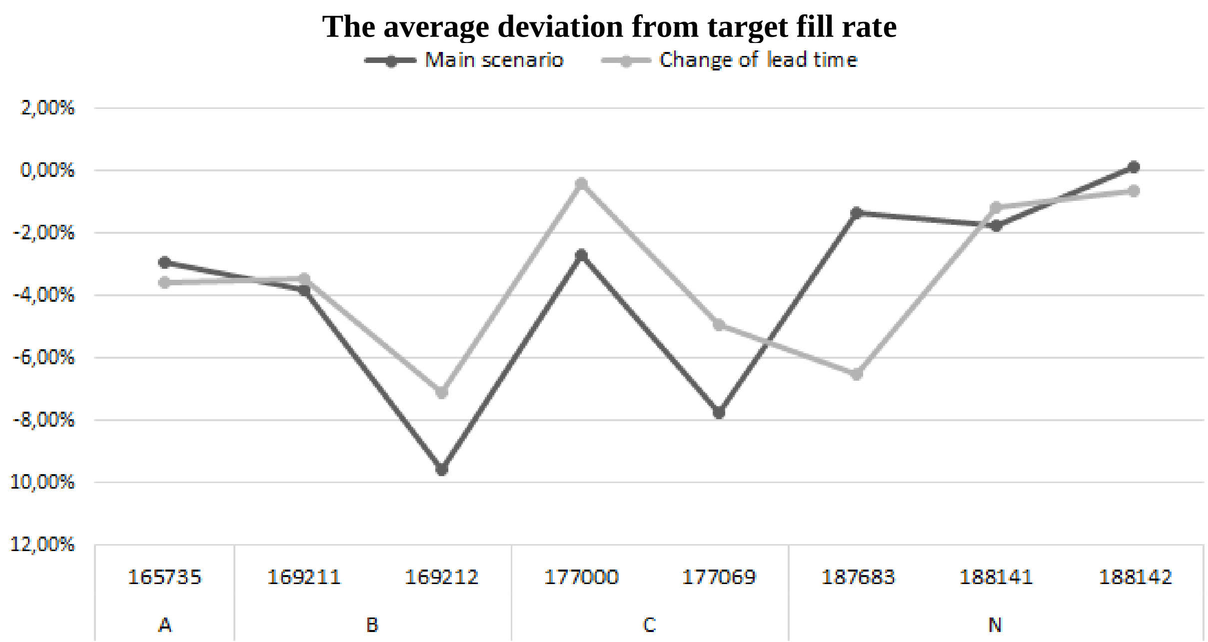

Figure 7.21. The average deviation from the target fill rate, sorted by classification.

If instead analyzing the absolute mean deviation for the 8 selected items for sub-scenario 2, the values in *Table 7.20* was obtained. Compared to the main scenario, changing the lead times seems to improve the target fill rate slightly yet with only 0,28 %. It can hence be argued that no significant improvement can be demonstrated for the entire system when decreasing lead times between suppliers and CWH and increasing the lead times between CWH and DCs.

Table 7.20. The absolute mean deviation from the target fill rate.

Main Scenario	Change of lead time
3,75%	3,47%

7.5.1.1 Expected fill rates at the DCs - *Changed lead times*

Only studying the DCs, the expected fill rates for *Sub-scenario 2* is summarized in *Table 7.21*. It can be seen there is an improvement in achieved fill rates for 6 of 8 items, where the improvement of achieved fill rates can be further confirmed in *Figure 7.22*. Changed lead times thus seem to indicate a positive impact at the DCs in terms of better achieved fill rates.

Table 7.21. The average deviation from the target fill rate, only including the DCs.

Classification	Art Nbr	Main scenario	Change of lead time
A	165735	-3,59%	-3,34%
B	169211	-4,06%	-3,06%
B	169212	-10,69%	-6,47%
C	177000	-2,81%	-1,18%
C	177069	-9,12%	-5,06%
N	188142	-0,53%	-1,40%
N	188141	-1,99%	-1,60%
N	187683	0,81%	-1,60%

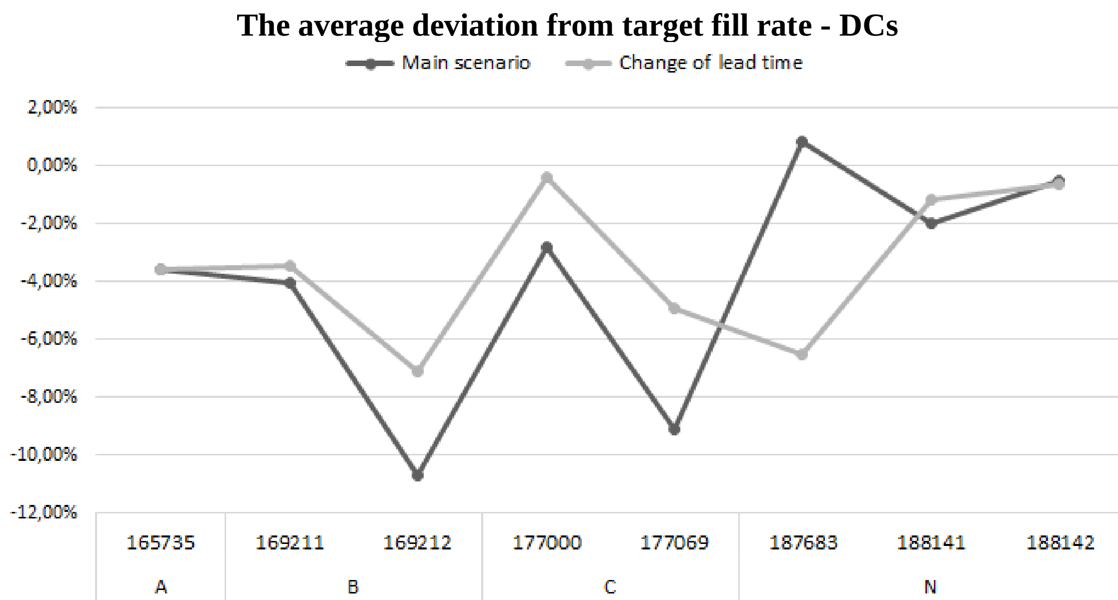

Figure 7.22. The average deviation from the target fill only including the DCs.

The absolute mean average deviation from the target fill rates confirms an improvement of the achieved fill rate by 1,16% when the lead times are changed, see *Table 7.22*. However, although several of the items resulted in an improvement, the overall total improvement with "only" 1,16% can be argued to be relatively low compared to what investment that may be needed to change the location of the CWH.

Table 7.22. The absolute mean deviation from the target fill rate, only including the DCs.

Main Scenario	Change of lead time
4,20%	3,04%

7.5.1.2 Expected fill rates at the upstream demand - *Changed lead times*

For the upstream demand however, there is an inferior performance as the lead times are changed. 9 of 10 items performed worse in terms of achieving fill rate if one compares the main scenario with the sub-scenario 2, which is seen in *Table 7.23.*

Table 7.23. The average deviation from the target fill rate.

Classification	Art Nbr	Main scenario	Change of lead time
A	165735	-1,00%	-4,53%
B	169211	-3,02%	-4,88%
B	169212	-6,27%	-9,77%
C	177000	-2,22%	2,85%
C	177069	-3,71%	-4,52%
N	188142	2,20%	2,50%
N	188141	-0,94%	0,57%
N	187683	-5,65%	-19,32%

The tabulated values are plotted in *Figure 7.23,* where the difference between the two cases can further be confirmed. Decreasing the lead times between suppliers and CWH and increasing the lead time between CWH and DCs does not seem to result in benefits at the CWH for Duni, but rather a distinct worsening.

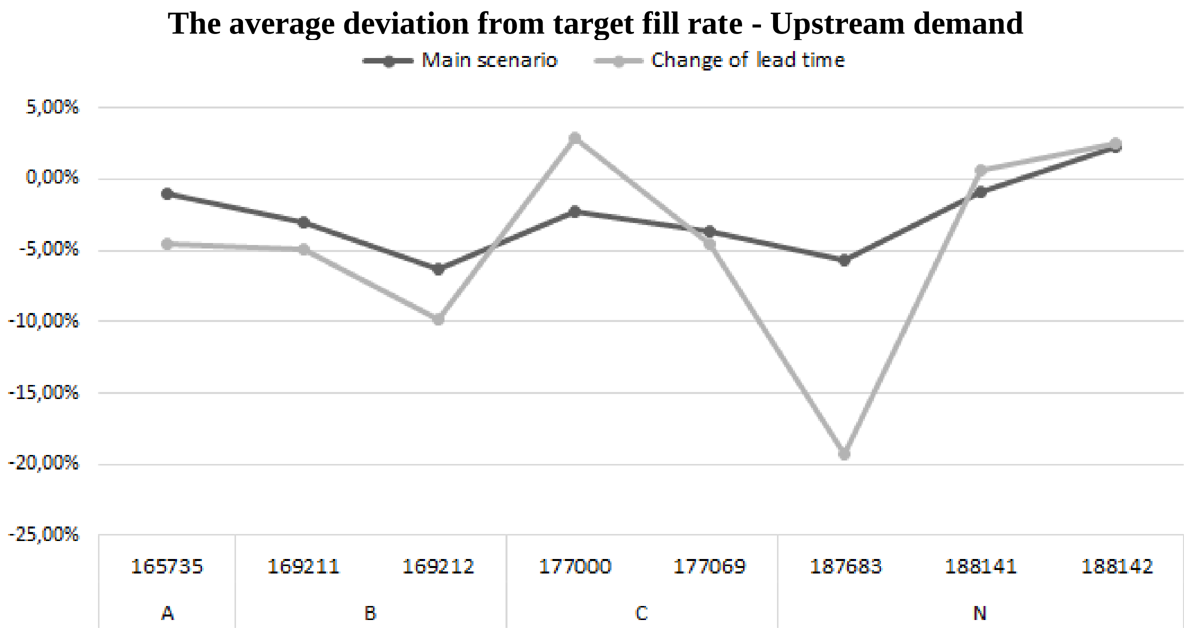

Figure 7.23. The average deviation from the target fill, sorted by classification.

The *absolute mean deviation* also confirms the inferior performance of the model in sub-scenario 2, see *Table 7.24.* When changing the lead times, the absolute mean deviation from the target fill rate increased with 2,99%.

Table 7.24. The absolute mean deviation from the target fill rate.

Main Scenario	Change of lead time
3,13%	6,12%

7.5.2 Expected stock on hand - *Changed lead times*

The total expected stock on hand for sub-scenario 2 is presented in *Table 7.25*. Comparing the main scenario with Sub-scenario 2, the total stock on hand has increased slightly when the lead times are changed. More precisely, with 434 units increase for sub-scenario 2.

Table 7.25. The total stock on hand.

Classification	Art Nbr	Main scenario	Change of lead time
A	165735	1288	1000
B	169211	842	467
B	169212	3029	4307
C	177000	620	657
C	177069	664	676
N	188142	442	186
N	188141	285	318
N	187683	363	354
Total		**7531**	**7965**

In *Figure 7.24*, the tabulated values are plotted. While most items actually either decrease the total stock or perform relatively similarly to the main scenario, item 169212 increases its stock level significantly. Without regard to this item, changes lead times thus seems to generate lower inventory levels compared to the main scenario. However, due to the large increase of stock for item 169212 the reduction of total stock levels disappears.

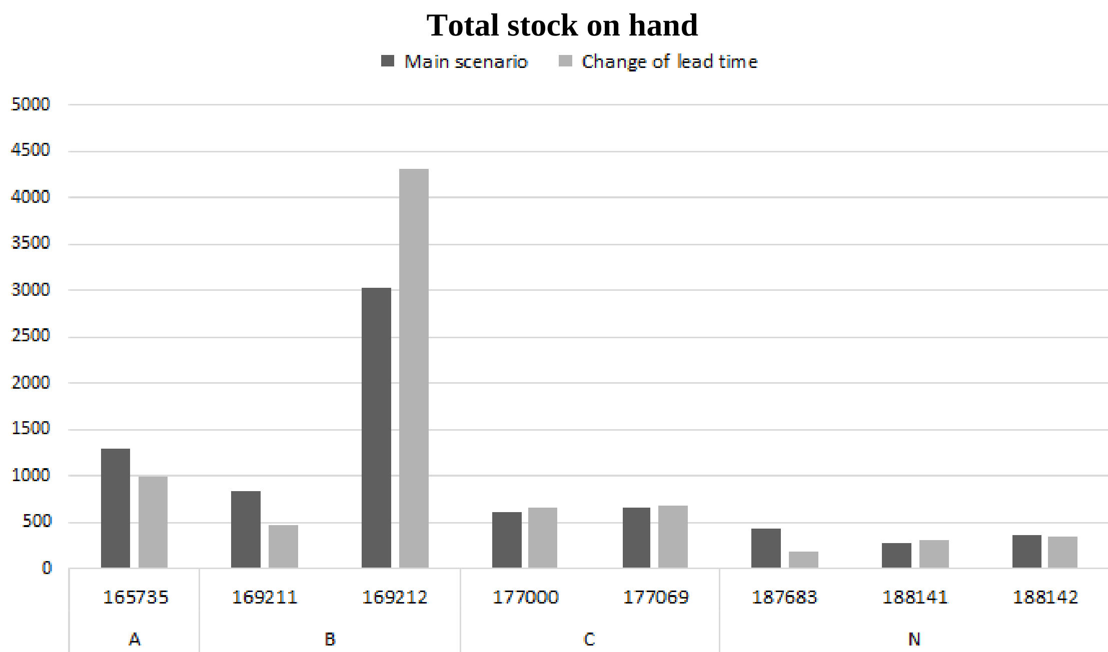

Figure 7.24. The total expected stock on hand.

7.5.2.1 Expected stock on hand at the DC - *Changed lead times*

As the lead time decreases to the CWH and increases to the DCs, an interesting finding is that the stock is reallocated in the system. Based on the values in *Table 7.26*, it appears that stock is pushed downstream towards the DCs and thus closer to the end customers. The total stock level at the DCs is increased by 4536 units when the lead time changes.

Table 7.26. The total stock on hand only including the DCs.

Classification	Art Nbr	Main scenario	Change of lead time
A	165735	217	722
B	169211	3	367
B	169212	534	3279
C	177000	88	343
C	177069	134	493
N	188142	46	82
N	188141	64	184
N	187683	76	226
Total		**1160**	**5696**

Regardless of which item is analyzed, all items have increased their stock levels at the DCs which is seen in *Figure 7.25*. The result hence indicates that when lead times increase between the DCs and end customers, coordinated inventory control suggests that more stock should be allocated at the DCs. This is also in accordance with presented theory since higher inventory levels at the DCs helps to ensure on-time-deliveries despite increased distance.

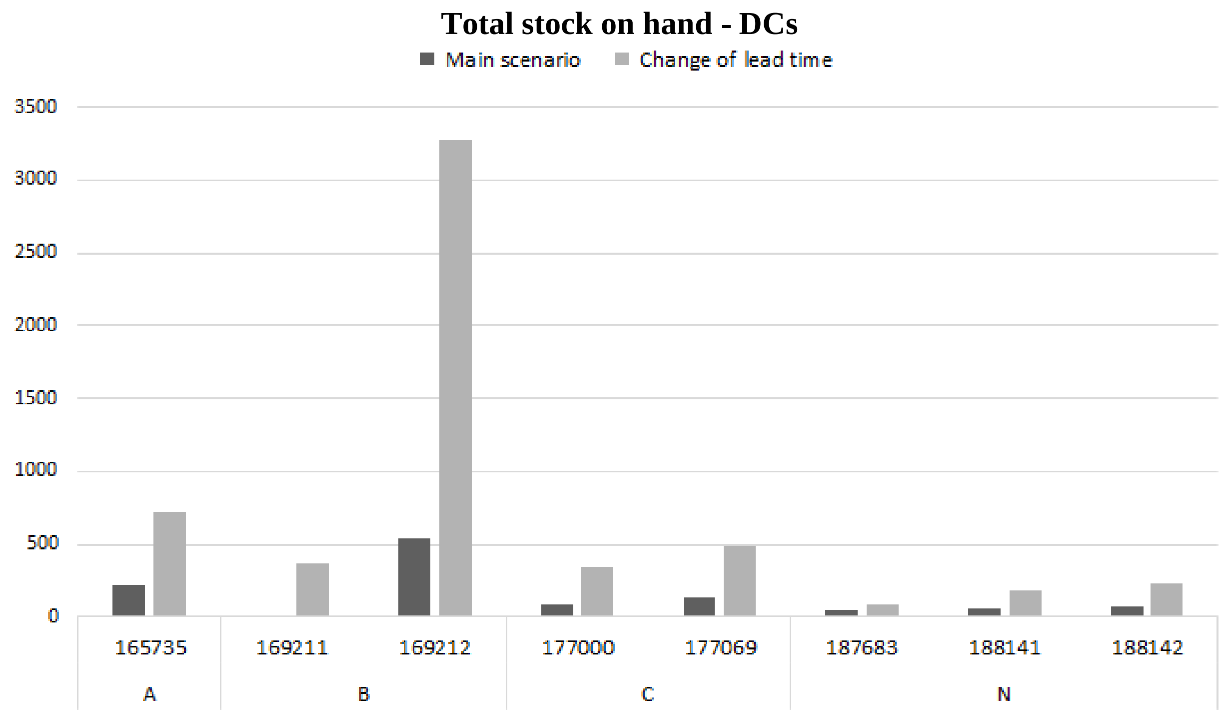

Figure 7.25. The total expected stock on hand only including the DCs.

7.5.2.2 Expected stock on hand at the CWH - *Changed lead times*

Aligned with the presented theory and previous findings regarding the increased stock levels at the DCs, the stock level decreased drastically at the CWH as the lead times were changed according to sub-scenario 2. This is illustrated in *Table 7.27*, where a total decrease of 4102 units in the CWH is seen.

Table 7.27. The total stock on hand only including the CWH.

Classification	Art Nbr	Main scenario	Change of lead time
A	165735	1071	278
B	169211	839	100
B	169212	2495	1028
C	177000	532	314
C	177069	530	183
N	188142	396	104
N	188141	221	134

N	187683	287	129
Total		**6371**	**2269**

The tabulated values are illustrated in *Figure 7.26* below. The result shows that all items decrease their stock levels at the CWH, which was expected based on the findings regarding stock levels at DCs. When decreasing the lead times between the suppliers and CWH, coordinated inventory control thus suggests that the inventory levels can be reduced significantly at the CWH.

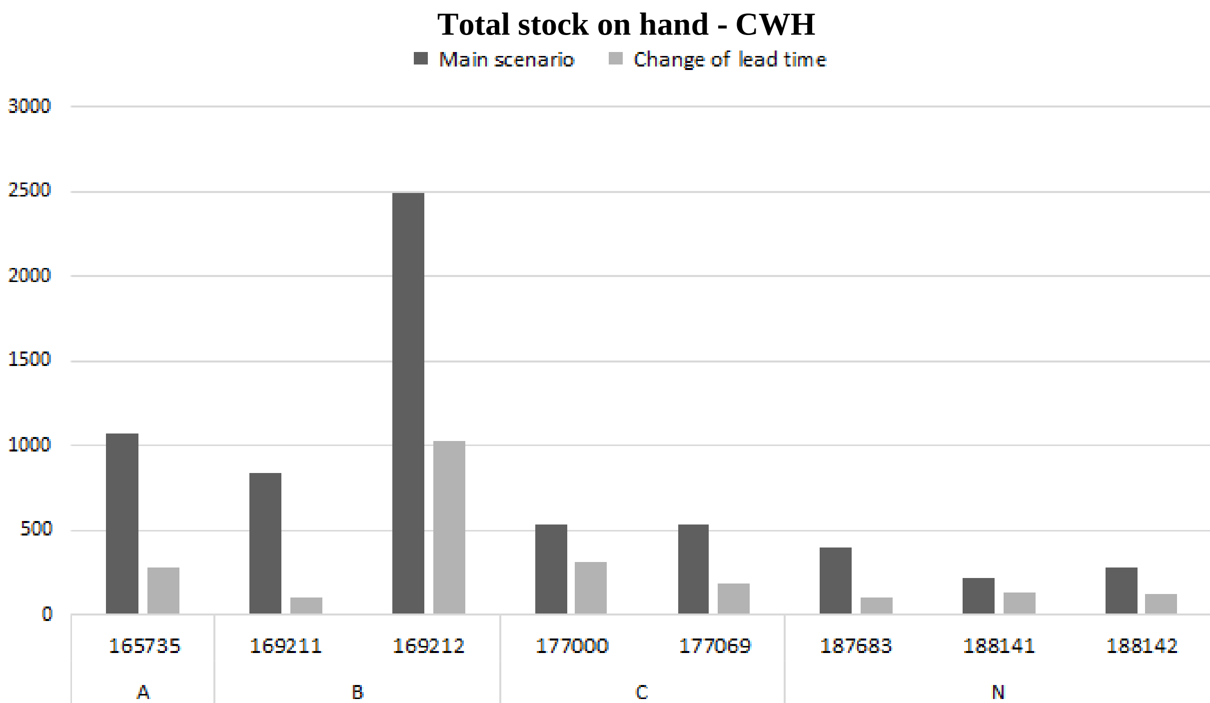

Figure 7.26. The total expected stock on hand only including the CWH.

7.5.3 Summary of sub-scenario 2

To conclude, the presented result of sub-scenario 2 shows that if a CWH is located closer to the suppliers, the stock will be reallocated. More specifically, the overall fill rate and total stock level would roughly stay the same for the whole system, but the stock would be pushed downstream towards the DCs. This result was unambiguous regardless of type of item.

Adjusted lead times neither lower the total inventory levels nor reduce the deviation from target fill rate for the whole system. However, it provides opportunities for Duni to understand how stock should be allocated if the company decides to open a new CWH in Asia. The obtained result also corresponds to what can be expected according to theory. As the CWH moves to Asia and the lead time to DCs increase, the so-called pooling effect at the CWH decrease. Pooling means in essence, that the sum of a number of independent stochastic variables has a lower variance than if each individual variance is summarized separately. Hence, if the CWH quickly can supply the DCs with stock, the stock levels at the DCs can be reduced. Consequently, stock is held centrally in the system. If shortage at the DCs occurs, the CWH provides the DC with new stock. As the lead times between CWH and DCs are short, the central inventory acts as a buffer against the DCs. The uncertainty during the lead time for all DCs can be seen as “pooled” at the CWH as not all DCs will get shortage at the same time.

If the CWH instead is located further away, it will be more challenging for the CWH to easily supply the DCs with new stock if shortage occurs. Thus, each DCs must hedge against uncertainty during longer lead times and the pooling effect at the CWH is reduced. Theoretically, more inventory is expected at the DCs when the CWH moves to Asia. Assuming all other cost are equal, a new CWH location will hence result in reallocation of resources in the supply chain.

It is also interesting to consider how the upstream demand is affected of a new location of the CWH. If the new CWH location is far away from the end customer, there is a probability that the customers will order from the DCs closest to them instead. A consequence of the new structure may thus be that the upstream demand is reduced. Furthermore, if changing the location of the CWH it should be noted there is a high demand of the current upstream demand in the area around Germany and it may be wise to keep that location but change it to DC instead. As a consequence, the upstream demand would decrease from the CWH located in China and the system would become more like a traditional multi-echelon inventory system with lower share of stock in the CWH and higher levels in the DCs. To confirm this a more thorough investigation should be performed, where more aspects need to be included.

CHAPTER 8

DISCUSSION, CONCLUSIONS AND RECOMMENDATIONS

This chapter summarizes and discusses the main findings from a broader perspective. A recommendation to Duni is presented and also general further steps that the company should consider. Lastly, some assumptions made are discussed and suggestions for further research.

8.1 Discussion and Conclusion

Based on the main findings from the presented result, the research questions and purpose of this thesis can now be answered. The most appropriate inventory method to determine reorder points for Duni seems to be coordinated inventory control. This since that method best fulfilled the objective to meet end customer service requirements with as little inventory as possible. However, the benefits with reducing inventory levels and hence tied up capital could not be explicitly determined due to the fact that none of the chosen models actually meet target fill rate for all items. Apart from that, the coordinated inventory control method performed better compared to uncoordinated inventory control. Furthermore, the benefits and drawbacks of the both control methods were discussed in *section 7.3.*

The final purpose was to perform a sensitivity analysis of the future scenarios, which was performed by analyzing the result from sub-scenario 1 and sub-scenario 2. A consolidation point may provide benefits if Duni succeeds in efficiently reducing the quantities between supplier and CWH as the model rendered better fill rate for all nodes in the supply chain. However, this was at the price of an increase in total inventory levels of approximately 12%. On the other hand, the majority of Duni's products are low value products and the largest cost is rather the transport cost and not the holding cost. Furthermore, as Duni today is struggling with immature suppliers who only want to produce against a fixed PO, reduced purchase sizes, meaning MOQ, may reduce the risk of constantly producing and purchasing too much. Once again, it should be emphasized that the results obtained from sub-scenario 1 assumes that Duni applies coordinated control with the BM-C model.

The main finding in *sub-scenario 2* was how the stock was reallocated when lead time changed. The total stock was slightly increased for the whole system which was expected due to reduced pooling effect. Based on this result, no clear incentive for Duni to move their CWH closer to the suppliers could be identified. However, there is one aspect that has not been discussed before. Duni intends to grow globally with their environmentally friendly, outsource products. With more customers and larger distribution in, among others, the US and Australia, the incentives for another location may be clearer. This is something that should be investigated further.

8.2 Recommendation - The next steps at Duni

In order to apply the theoretical findings and multi-echelon inventory control in practice, some further recommendations to Duni are suggested. Regardless of which supply chain structure Duni chooses to proceed with, the result shows that coordinated control should be applied. However, it is necessary to understand that in order to apply coordinated inventory control efficiently in practice, some preconditions should be fulfilled. These conditions are partly adapted from Axsäter (2015, p.295-300), but also based on what the researchers have identified as necessary at Duni.

- *Inventory records* - As stated by Axsäter (2015), one basic precondition in order to use an inventory control method is to make sure that all required data is available. If the data is not correct or contains any errors, the obtained result will not be accurate. During the data collection phase of this thesis, it was realized that there are some inadequate areas in Dunis data system regarding both inventory levels and order quantities. Hence, assumptions have been made to compensate for the areas where data either were missing or incomplete. With this said, Duni should improve the procedures for collecting and updating their inventory records. This means that there should be continuously updated data regarding stock on hand, stock on order, different costs, lead times and backorders that can be applied as input in the multi-echelon inventory control models (Axsäter, 2015).

- *Suitable service levels (IDP)* - One aspect that may be interesting to consider is how Duni has determined the level of target fill rate (IDP) for each classification. As mentioned, A-items have a target fill rate of 96% and thereafter the target fill rate decreases by 2% for each category B to N. Based on interviews with representatives at Duni, these levels are more or less determined without any major reflection. The higher target fill rate, the higher safety stock is needed. It could therefore be of interest for Duni to consider if the target fill rate can be lowered for any classification and consequently lower the safety stock needed.

- *Analyze the needs of customers* - Duni is a company that prioritizes customer flexibility and thus allows almost all different sizes of customer orders. In many cases, the average order size for one item is low, but with some few extreme deviations. As previously mentioned, this means that the coefficient of variation for each item becomes remarkably high, which from an inventory control perspective is not desirable. In addition to the fact that the multi-echelon model performs worse, it also becomes more difficult to control the supply chain from an inventory control perspective.

8.3 Discussion of some simplifications

In the following section, some simplifications made throughout the thesis will be discussed.

- *Assuming constant lead time between supplier and CWH* - The coordinated model tries to take the average delay into consideration between CWH and DCs, while the uncoordinated model only uses the transportation time as lead time. However, in the chosen coordinated model, the lead time is assumed to be constant between the suppliers and CWH. This is obviously an simplification of reality. According to Axsäter (2015), this assumption affects the calculation of lead times by possibly misjudging the level of safety stock that is needed. By not taking factors that may cause dalys into consideration there is a risk that the safety stock will be lower than what is actually needed.

- *Assuming average internal fixed order quantities q_i* **-** An assumption that affects the result is the assumption of fixed order quantities between the CWH and DCs. In reality, Duni's DCs can place orders with various order sizes, which was not taken into consideration in this thesis.

If the demand varies greatly, there is a risk that the values of the fixed quantities differ quite a lot from the values used in practice.

- *Assuming a consolidation and new location of CWH can be simulated by only adjusting batch quantities or lead times* **-** In this thesis, the consolidation point and relocation of the CWH was constructed based on a very simplified assumption. Although the purpose was to give an indication rather than exact results, it should be noted that there are more aspects that affect the result in reality. For instance, from a cost perspective there is a set-up cost or possibly additional cost for education of staff. Furthermore, a consolidation point needs to have some kind of policy, such as a policy based on time or quantity. The time policy refers to that the consolidated shipment is sent at a specific time while the quantity policy refers to that the shipment is sent when it reaches a specific predetermined quantity or volume. Depending on which policy the company chooses, different results may be obtained.

- *Selection of items with a non-probability sample* - As the company wanted to be involved in the selection of test items, there is a risk that the selection of product does not represent the entire product range. It might have been better to use a probability sample when determining the selection of test items.

- *Only simulation 20 items in the main scenario and 8 items in the sub scenarios* - There is no unambiguous answer of how many items that must be simulated in order to consider the sample size large enough to represent the reality. However, a larger sample size would render more reliable and valid results. This since it can be argued that more items would have been needed to ensure that the result applied for all products. With that said, however, it is important to once again remind the reader that the different scenarios in this thesis have been fictitious, where Duni themselves have not fully decided the future product portfolio in their supply chain for outsourced production. The first step for the company is simply to obtain an indication of which strategic direction they should take, which the selection of 20 items and 8 items could fulfil. Furthermore, as the simulations took much longer than expected, there was no time to include more items.

8.4 Further research

As mentioned earlier, both the analytical model and the simulation model have been used in previous research and master thesis projects. This meant that both the choice of mathematical models and the results generated can be seen as validated. However, what distinguishes this master thesis from previous studies is the high coefficient of variation of the demand data that was analyzed. One conclusion drawn for this project is that the approximation with adjusted normal distribution or compound Poisson may not be suitable to apply in practice. It would hence be interesting to investigate if there exist other distributions, for instance gamma distribution, that would be more suitable to apply when the demand has such high coefficient of variation as seen in this thesis project. Furthermore, this master thesis mainly evaluated the naïve method as this method at a first, concise comparison seemed to generate the best results. However, the BM-C which is known to overestimate the need for CWH stock, may not be the best model for Duni to use in a practical application. It is therefore be interesting to further examine if other models that is based on other assumptions might represent a better approximation of Dunis system.

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Appendix

Appendix A - Conducted interviews

Date	Role	Time length	Comment
2020-04-23	Wiktor Hjelm - Controller	1 h	Focus on supply chain project
2020-04-27	Sofia winter - Sourcing manager	45 minutes	Focus on strategic sourcing
2020-04-27	Matthias Stuckmann - Supply chain director	45 minutes	Focus on forecasting and inventory planning
2020-04-30	Per Lundström - Supply chain planner meal service Elena Rydberg - Project manager	1 h	Focus on supply chain planning

Appendix B - Selected test items

The main scenario

Classification	Art number	Art description	Supplier	Batch size	Lead time (days)	Target fill rate
A	188061	LID SALAD BOWL RPET 800/900/1000/1200 ML	deSter	5250	35	96%
A	165735	CANDLES LED 70X40 WARM WHITE	Mega Power Lightning	120	90	96%
A	151527	CANDLES GLASS 65X65 S&S REF. CREAM	Korona	161	14	96%
A	351316	CANDLES ANTIQUE 245X22 WHITE	KCB	80	14	96%
A	351318	CANDLES ANTIQUE 245X22 CREAM	Gala	80	14	96%
B	169212	BOWLS BAGASSE BROWN 900 ml	Qiaowang Pulp Products Ltd.	1050	90	94%
B	778092	DENT.STICK WOOD 3x3000 UNPRINTED	Jordan	50	21	94%
B	170634	CUP PAP/PLA 24CL THANK YOU	President	125	97	94%
B	402600	CUPS PLASTIC 21cl WHITE	Flo Europe	1188	14	94%
B	169211	BOWLS BAGASSE BROWN 600 ml	Qiaowang Pulp Products Ltd.	350	90	94%
C	177000	BOWLS BAGASSE BROWN 800 ML	Qiaowang Pulp Products Ltd.	550	90	92%
C	184243	BOWL 1COMP SMALL PPWH 204X150X64	Miko Pac Poland	9	21	92%
C	184245	LID 1COMP LARGE PP-RED 260X197X15	Miko Pac Poland	12	21	92%
C	177069	LID RPET TR ROUND CRYSTAL DELI	Hang Fung	304	70	92%
C	177004	LID BOWL BAGASSE BR 800/900/1000/1200ML	Qiaowang Pulp Products Ltd.	550	90	92%
N	188142	OCTABAGASSE BAGASSE BROWN 1000ML	Sanxing	250	84	88%
N	188141	OCTABAGASSE BAGASSE BROWN 650ML	Sanxing	333	84	88%
N	187683	CUTL.PACK CPLA WH 3/1 150/150 PETIT ECO	Bifrost	200	77	88%
N	188140	OCTABAGASSE BAGASSE BROWN 400ML	Sanxing	333	84	88%
N	187680	FORKS PETIT ECO CPLA WHITE 15CM	Bifrost	250	77	88%

Sub-scenario 1

Classification	Art number	Art description	Supplier	Batch size main scenario	½ Batch size	¼ Batch size
A	151527	CANDLES GLASS 65X65 S&S REF. CREAM	Korona	161	81	40 40
A	351318	CANDLES ANTIQUE 245X22 CREAM	Gala	80	40	20
B	778092	DENT.STICK WOOD 3x3000 UNPRINTED	Jordan	50	25	13
B	402600	CUPS PLASTIC 21cl WHITE	Flo Europe	1188	594	297
C	177000	BOWLS BAGASSE BROWN 800 ML	Qiaowang Pulp Products Ltd.	550	275	138
C	177069	LID RPET TR ROUND CRYSTAL DELI	Hang Fung	304	152	76
C	177004	LID BOWL BAGASSE BR 800/900/1000/1200ML	Qiaowang Pulp Products Ltd.	550	275	138
N	188142	OCTABAGASSE BAGASSE BROWN 1000ML	Sanxing	250	125	63
N	187680	FORKS PETIT ECO CPLA WHITE 15CM	Bifrost	250	125	63

Sub-scenario 2

Classification	Art number	Art description	Supplier	Batch size	Lead time from supplier	Internal lead time[16]
A	165735	CANDLES LED 70X40 WARM WHITE	Mega Power Lightning	120	3	90
B	169212	BOWLS BAGASSE BROWN 900 ml	Qiaowang Pulp Products Ltd.	1050	3	90
B	169211	BOWLS BAGASSE BROWN 600 ml	Qiaowang Pulp Products Ltd.	350	3	90
C	177000	BOWLS BAGASSE BROWN 800 ML	Qiaowang Pulp Products Ltd.	550	3	90
C	177069	LID RPET TR ROUND CRYSTAL DELI	Hang Fung	304	3	70
N	188142	OCTABAGASSE BAGASSE BROWN 1000ML	Sanxing	250	3	84
N	188141	OCTABAGASSE BAGASSE BROWN 650ML	Sanxing	333	3	84
N	187683	CUTL.PACK CPLA WH 3/1 150/150 PETIT ECO	Bifrost	200	3	77

[16] *Lead time from CWH to DCs*

Appendix C - Demand distributions based on STATFIT

STATFIT - DEMAND DISTRIBUTIONS OF ORDER QUANTITIES					
	Item number	**Distribution BRA**	**Distribution NRK**	**Distribution PZN**	**Distribution FIN**
A	188061	Negative Binomial (1, $7.94e^{-003}$)	Empirical	Empirical	-
A	165735	Empirical	Empirical	Empirical	Empirical
A	151527	Negative Binomial (1, $7.05e^{-003}$)	Empirical	Empirical	Empirical
A	351316	Negative Binomial (1, $7.17e^{-003}$)	Empirical	Empirical	Empirical
A	351318	Negative Binomial (1, $6.02e^{-003}$)	Empirical	Empirical	-
B	169212	Negative Binomial (1, $6.02e^{-003}$)	Empirical	Empirical	Empirical
B	778092	Negative Binomial (1, $0.925e^{-003}$)	Empirical	Empirical	Empirical
B	170634	Negative Binomial (1, $3.21e^{-002}$)	Empirical	Empirical	Empirical
B	402600	Empirical	Empirical	Empirical	-
B	169211	Negative Binomial (1, $2.97e^{-002}$)	Empirical	Empirical	Empirical
C	177000	Empirical	Empirical	Empirical	Empirical
C	184243	Negative Binomial (3, $2.26e^{-002}$)	-	-	-
C	184245	Negative Binomial ($3.23e^{-002}$)	-	-	-
C	177069	Negative Binomial (3, $2.97e^{-002}$)	Empirical	Empirical	Empirical

C	177004	Empirical	Empirical	Empirical	Negative Binomial (3, 0.844)
N	188142	Negative Binomial (1, 0.126)	Empirical	Empirical	Negative Binomial (1, 0.888)
N	188141	Empirical	Empirical	Empirical	Empirical
N	187683	Empirical	Empirical	Empirical	Empirical
N	188140	Negative Binomial (1, 0.12)	Empirical	Empirical	Empirical
N	187680	Empirical	Empirical	Empirical	Empirical

Appendix D - Results

Reorder points

	Single-echelon				Multi-echelon				
Art number	**CWH**	**DC1**	**DC2**	**DC3**	**CWH**	**VD[17]**	**DC1**	**DC2**	**DC3**
188061	342048	582	38	-	9648	484	905	84	-[18]
165735	433171	4	91	17	5512	153	7	178	37
151527	49661	23	456	26	4293	277	38	692	53
351316	35967	19	61	67	3202	140	33	115	167
351318	37843	23	21	-	3478	51	40	36	-
169212	1491373	46	904	32	22390	498	79	1511	76
778092	14534	-1	13	-	922	0	-1	50	-
170634	4612	55	31	31	546	51	73	58	65
402600	46169	4	14	-	4081	0	16	28	-
169211	401693	3	54	9	4903	137	7	88	23
177000	272024	1	36	7	3147	99	3	66	20
184243	59371	-	-	-	2495	688	-	-	-
184245	67167	-	-	-	3701	0	-	-	-
177069	272299	43	72	6	4090	98	64	104	14
177004	161480	1	22	2	1793	64	2	44	9
188142	102117	5	20	0	1248	45	11	52	6
188141	116574	8	11	1	1364	49	19	31	7
187683	97719	4	-5	-	1480	27	16	0	-
188140	69600	-1	5	1	801	34	6	17	37
187680	60778	6	-2	2	804	39	17	18	23

[17] *VD= virtual DC*
[18] *- = No DC (Only 2 DCs exists for that specific item)*

Average deviation from target fill rates - Main scenario

	Single-echelon				Multi-echelon				
Art number	**CWH**	**DC1**	**DC2**	**DC3**	**CWH[19]**	**VD**	**DC1**	**DC2**	**DC3**
188061	4.00%	-16.34%	-15.74%	-	86.64%	-2.23%	-14.51%	-3.57%	-
165735	4.00%	-5.75%	-14.38%	-19.48%	90.80%	-1.00%	-1.08%	-5.07%	-4.61%
151527	4.00%	-10.75%	-15.99%	-20.67%	85.11%	-3.86%	-1.96%	-4.27%	-4.40%
351316	4.00%	-9.97%	-17.23%	-17.39%	46.29%	-9.64%	-9.27%	-2.29%	-6.55%
351318	4.00%	-	-15.65%	-17.83%	84.43%	-10.54%	-	-3.95%	-4.91%
169212	6.00%	-11.51%	-19.57%	-17.47%	68.84%	-6.27%	-9.11%	-15.62%	-7.33%
778092	6.00%	1.27%	-52.03%	-	94.91%	2.78%	3.50%	2.59%	-
170634	6.00%	-16.01%	-12.66%	-43.50%	81,78%	-3.88%	-5.86%	-2.76%	-25.00%
402600	6.00%	-	0.05%	-15.57%	85.75%	-8.30%	-	4.79%	-1.51%
169211	6.00%	-7.54%	-17.61%	-18.08%	86.25%	-2.08%	-7.27%	-2.84%	-7.75%
177000	8.00%	-6.08%	-13.35%	-19.92%	84.20%	-1.69%	-0.84%	-6.06%	-3.20%
184243	8.00%	0.00%	0.00%	0.00%	89.17%	6.13%	0.00%	0.00%	0.00%
184245	8.00%	0.00%	0.00%	0.00%	97.80%	5.81%	0.00%	0.00%	0.00%
177069	8.00%	-15.81%	-17.44%	-23.98%	80.05%	-2.50%	-8.37%	-6.84%	-13.77%
177004	8.00%	-2.46%	-15.35%	-29.20%	84.70%	-0.86%	-1.62%	-5.02%	-1.72%
188142	12.00%	-7.28%	-14.78%	-19.86%	78.44%	-1.39%	-3.11%	-5.14%	2.26%
188141	12.00%	-13.24%	-15.85%	-21.54%	77.12%	-0.94%	-3.56%	-3.81%	1.39%
187683	12.00%	-15.57%	-6.17%	-	80.64%	-5.65%	0.24%	1.38%	-
188140	12.00%	-18.86%	-20.35%	-61.33%	79.33%	-2.20%	-2.73%	-3.45%	9.18%
187680	12.00%	-10.05%	-17.78%	-40.81%	80.34%	-0.23%	-0.52%	1.46%	3.76%

[19] *In this column the achieved fill rate is tabulated. The CWH for the multi echelon has no target fill rate and hence no deviation.*

Average deviation from target fill rates - Sub-scenario 1

	Main scenario				½ batch size				¼ batch size			
Art number	VD	DC1	DC2	DC3	VD	DC1	DC2	DC3	VD	DC1	DC2	DC3
151527	-3.86%	-1.96%	-4.27%	-4.40%	-3.73%	-2.64%	-3.71%	-4.34%	-4.23%	-2.41%	-3.49%	-4.01%
351318	-10.54%	-3.95%	-4.91%	-	4.00%	-2.41%	-5.12%	-	4.00%	-2.86%	-4.36%	-
778092	2.78%	3.50%	2.59%	-	-5.88%	1.62%	3.36%	-	-7.39%	1.18%	3.39%	-
402600	-8.30%	4.79%	-1.51%	-	-8.58%	4.79%	-1.77%	-	-8.71%	4.61%	-1.87%	-
177000	-1.69%	-0.84%	-6.06%	-3.20%	-2.22%	-1.01%	-6.12%	-3.33%	-1.95%	-0.51%	-5.57%	-3.13%
177069	-2.50%	-8.37%	-6.84%	-13.77%	-3.71%	-8.49%	-10.91%	-7.97%	-4.46%	-9.06%	-11.76%	-8.43%
188142	-1.39%	-3.11%	-5.14%	2.26%	2.20%	-0.64%	-3.62%	2.68%	-2.06%	-3.15%	-5.62%	2.73%
187680	-0.23%	-0.52%	1.46%	3.76%	0.07%	-0.01%	1.47%	4.03%	0.01%	0.06%	1.37%	3.98%

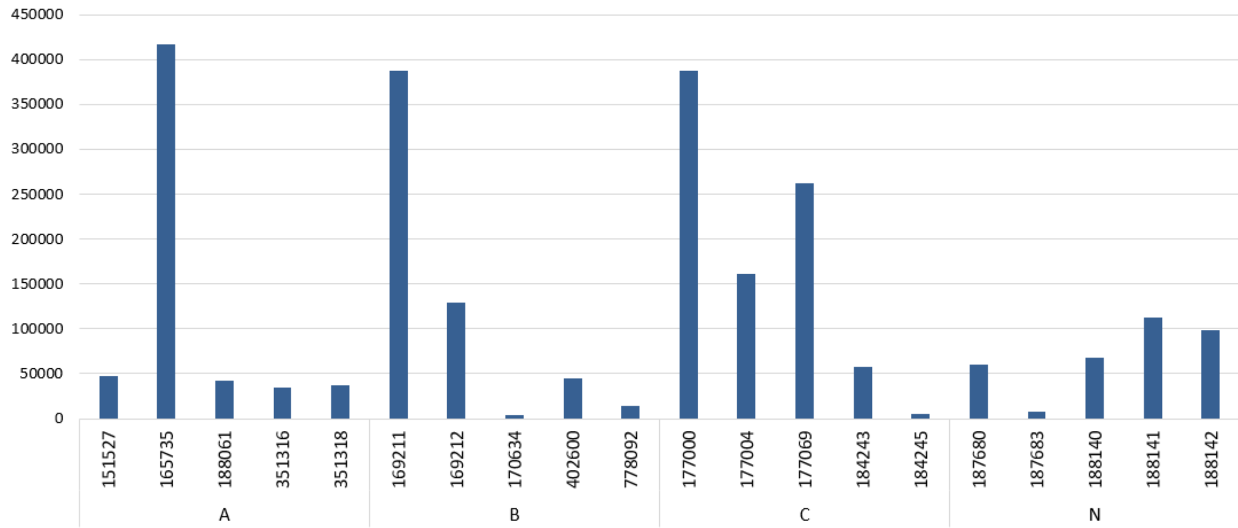
Average deviation from target fill rates - Sub-scenario 1

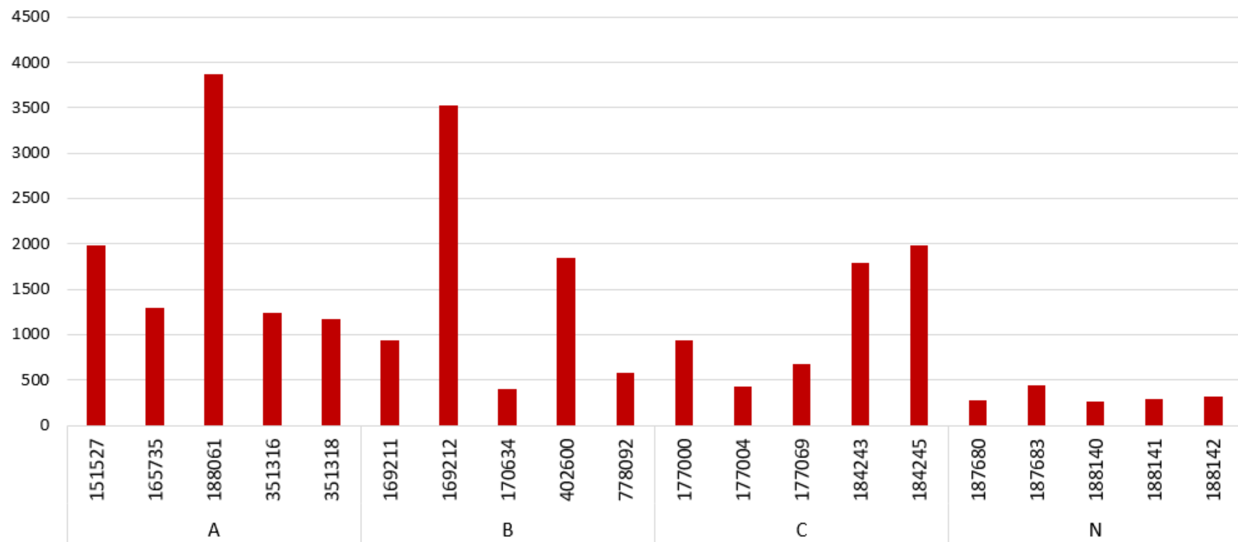
	Main scenario				Batch size of one pallet			
Art number	VD	DC1	DC2	DC3	VD	DC1	DC2	DC3
188061	-2.23%	-14.51%	-3.57%	-	6.45%	1.64%	5.19%	-
165735	-1.94%	-1.44%	-5.68%	-5.36%	-2.30%	-1.58%	-5.97%	-5.12%
169212	-6.27%	-9.11%	-15.62%	-7.33%	-4.02%	-7.54%	-12.42%	-6.69%
402600	-8.30%	4.79%	-1.51%	-	-2.29%	4.76%	-1.02%	-
177000	-1.69%	-0.84%	-6.06%	-3.20%	4.41%	0.97%	-2.48%	-1.23%
177069	-2.50%	-8.37%	-6.84%	-13.77%	-0.64%	-6.69%	-9.84%	-7.80%
188142	-1.39%	-3.11%	-5.14%	2.26%	4.56%	1.26%	-2.33%	2.84%
187683	-5.65%	0.24%	1.38%	-	-0.96%	1.79%	2.34%	-

Average deviation from target fill rates - Sub-scenario 2

	Single-echelon				Multi-echelon			
Art number	CWH	DC1	DC2	DC3	CWH	DC1	DC2	DC3
165735	-1.00%	-1.08%	-5.07%	-4.61%	-4.53%	-1.47%	-4.80%	-3.50%
169211	-3.02%	-2.08%	-7.27%	-2.84%	-4.88%	-2.85%	-5.42%	-0.55%
169212	-6.27%	-9.11%	-15.62%	-7.33%	-9.77%	-4.18%	-11.77%	-2.78%
177000	-2.22%	1.01%	-6.12%	-3.33%	2.85%	-1.52%	-0.61%	-2.23%
177069	-3.71%	-8.49%	-10.91%	-7.97%	-4.52%	-7.51%	-4.17%	-3.60%
188142	2.20%	-0.64%	-3.62%	2.68%	2.50%	-4.58%	-0.57%	0.17%
188141	-0.94%	-3.56%	-3.81%	1.39%	0.57%	-1.84%	-3.56%	0.17%
187683	-5.65%	0.24%	1.38%	-	-19.32%	0.00%	-0.15%	-

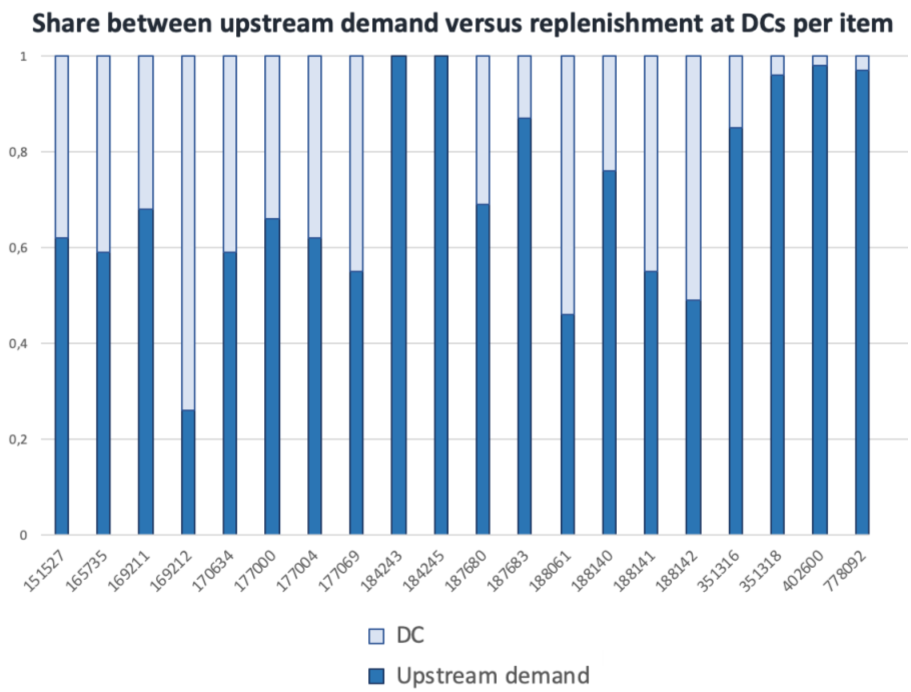
Appendix E - Detailed stock on hand - *Single-echelon vs Multi-echelon*





Appendix F - Share of between upstream demand and DCs

SHARE BETWEEN UPSTREAM DEAMD			
Classificatio	Item numbe	Upstream deman	DC
A	188061	46%	54%
A	165735	59%	41%
A	151527	62%	38%
A	351316	85%	15%
A	351318	96%	4%
B	169212	26%	74%
B	778092	97%	3%
B	170634	59%	41%
B	402600	98%	2%
B	169211	68%	32%
C	177000	66%	34%
C	184243	100%	0%
C	184245	100%	0%
C	177069	55%	45%
C	177004	62%	38%
N	188142	49%	51%
N	188141	55%	45%
N	187683	87%	13%
N	188140	76%	24%
N	187680	69%	31%
Above 40% directly to customer: 19 of 20 items			



Appendix G - Coefficient of variation

At the CWH

Coefficinet of variation				
Classification	ART NO	Mean	St div	Coefficient of variation
A	188061	9473	1240	162
A	165735	4713	544	63
A	151527	3245	658	133
A	351316	2338	500	107
A	351318	2482	539	117
B	169212	20916	2131	217
B	778092	629	191	58
B	170634	464	109	25
B	402600	2924	997	340
B	169211	4386	480	53
C	177000	2978	320	34
C	184243	2719	353	46
C	184245	3062	446	65
C	177069	3834	344	31
C	177004	1769	188	20
N	188142	1194	183	28
N	188141	1371	144	15
N	187683	1229	306	76
N	188140	818	98	12
N	187680	773	136	24

At the DCs

COEFFICIANT OF VARIATION					
Classification	Item number	Upstream dema	DC 1	DC 2	DC 3
A	188061	133,52	Not existing	191,64	38,88
A	165735	71,11	1,98	55,86	18,99
A	151527	117	7,89	169,81	27,99
A	351316	116,01	12,31	43,16	66,62
A	351318	121,39	Not existing	12,99	17,65
B	169212	146,76	18,05	258,18	36,96
B	778092	Not existing	0,1	58,73	33,19
B	170634	24,84	8,29	22,29	81,5
B	402600	345,56	Not existing	17,37	14,79
B	169211	69,98	1,79	17,82	12,49
C	177000	40,62	1,14	24,7	12,28
C	184243	45,77	Not existing	Not existing	Not existing
C	184245	64,9	Not existing	Not existing	Not existing
C	177069	32,86	9,67	39,19	9,56
C	177004	23,72	0,34	14,77	6,32
N	188142	30,55	1,86	33,34	5,31
N	188141	1246,85	309,16	651,75	48,9
N	187683	84,3	8,93	6,39	36,45
N	188140	12,8	1,23	9,92	8,99
N	187680	24,32	6,31	49,26	20,85

* Not existing refers to no flow to the DC for that specific item

Appendix G – General identified challenges at Duni

This thesis project has focused on the field of inventory control, where the research question concentrated on when and how much to order. During this project the authors have identified other challenges for example during interviews, which was outside the scope of this thesis. The improvement potential areas were:

- **Forecasting** (especially on new articles). During the interviews many of the employed expressed that the forecast was not particularly accurate. Dunis is currently using their forecast to replenish their products which can be one of the factors that they are experiencing an inefficient inventory control.

- **Important parameters can be changed by anyone → lock them.** Many parameters can easily be changed in SAP at Duni, by anyone. Some parameters should not be able to change by everyone, but only by a few authorized persons. Otherwise it is a high risk of changes for items and suppliers which might impair the supply chain and delivery performance.

- **Challenging structure of the supply chain.** Many of the employees are experiencing the current supply chain structure challenging and tangled which prevents an efficient way of working.

- **No service requirement on the suppliers.** Duni has a service requirement against their customers, but Duni has no service requirement on their suppliers. If a delay occurs from their supplier, Duni are thereby forced to be able to deliver, even though the root cause occurred earlier in the supply chain out of the companies reach. This is of course something that cost the company a lot in terms of money and relationships with customers and suppliers. An advice to the company would be to negotiate with the suppliers and include service requirements in their contracts.

- **High costs associated with the logistics, in particular transportation costs**. During the interviews some employees have expressed that there are high costs associated with the logistics, especially the transportation of products. This is however something that the author of this thesis cannot confirm since it is not within the area of which has been investigated. An advice is however to look further into this area to be able to cut costs, especially in the times of current situation with Covid-19 where cost savings are vital for all companies.