Norwegian School of Economics

Bergen, spring 2016

Retail food supply chain restructuring and product waste

An optimisation approach for minimising costs in three- and four-stage retail food supply chains

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Master thesis, MSc in Economics and Business Administration,

Business Analysis and Performance Management

NORWEGIAN SCHOOL OF ECONOMICS

Abstract

In this thesis, mixed-integer linear programming models for optimising product distribution in three- and a four-stage retail food supply chains (SC) are formulated, and use of the models are exemplified in a case study with large amounts of data. The four-stage supply chain model is comprised of production plants, warehouses, cross docking facilities, and retail stores. The three-stage supply chain model excludes the cross docking facilities, but includes a stricter division of shelf life between the supply chain actors. The models minimise total cost by making decisions on production volumes, inventory levels and shipped product volumes. A product quality measure is explicitly integrated in the models as an index on product volumes. In the case study, historical data from a large, Norwegian meat-processing corporation is used to run the models in order to capture differences in costs incurred in the two supply chain structures. Data for four products with varying demand patterns, degree of demand uncertainty and shelf life lengths are run. The results show that lack of information sharing within the supply chain will increase waste for all products, and that shorter shelf life has a greater impact on waste volumes than that of uncertainty in demand.

Preface

Working on this thesis has been a great experience. It has been challenging and, at times, frustrating, and I have learned a lot about data processing, optimising, and supply chain management that I think will be useful in my future working life.

I would like to thank my supervisor Mario Guajardo for great advice throughout the writing process, and for being always available to guide me on the right track.

I would also like to thank everyone at Nortura who have worked to produce all the data that I required for the thesis, and especially Halvor Hjelle and Bjørn Tore Lindseth for showing interest for the thesis right away.

Lastly I would like to thank my family. My sister Marita for inspiring talks, read-throughs and grammar advice. My brother Erik for feedback on the MILP-models, and by mother and father Rigmor and Helge, for financial and moral support throughout my time at NHH.

Bergen, 20 June 2016

Steffen Silden Langelo

Contents

Table of figures

1. Introduction

In a world with an ever-increasing population and a shortage of food, companies have a moral obligation to maximise utilisation of raw materials and make sure the products reach consumers with as little waste of food as possible. Minimising waste is also in the food-producing companies' interest from an economic perspective, as spoiled products mean loss of revenue and reduced profitability of their operations. As the large retail chain corporations' power over the retail supply chain increases (Volden, 2003), food-producing companies may lose access to information of actual consumer demand, and be left with greater uncertainty when planning production and product distribution.

This thesis presents a case of a large, Norwegian meat-processing company that is currently facing this problem. Retail chain corporations have demanded that they be allowed to take over the part of regional distributors, making Nortura's warehouses redundant. This also has an impact on how great a part of the products' shelf life is assigned to Nortura, making production and distribution planning more difficult.

The aim of this thesis is three-fold. First, I formulate a mixed-integer linear programming (MILP) model for optimising product distribution in a four-stage food supply chain consisting of production plants, warehouses, cross docking facilities, and retail stores. The model explicitly considers product quality throughout the supply chain. In this model formulation, the production company controls the warehouses and the inventory levels of the entire supply chain. The wholesalers' role in this model formulation is only cross docking and last-leg distribution.

I then formulate an MILP-model of the same supply chain, excepting the cross docking facilities, where wholesalers control warehouses. In this formulation, information on inventory levels and retail demand is not shared between the food production company and the wholesalers, resulting in both keeping safety stocks in their storage facilities.

Lastly, I exemplify use of the models by running them with historical data from the Nortura case, in an attempt to analyse how the restructuring of the supply chain will impact the total costs, including cost of waste, in the supply chain as a whole.

2. The company

Nortura is a large Norwegian corporation dealing in slaughtering, cutting and refining meat from cattle, sheep, goats, pigs and poultry, as well as collecting, cleaning, sorting and packing eggs. It is a cooperation owned by about 19,000 egg and meat producers from all over the country and employs about 5,550 people. In 2015, Nortura had a turnover of 22.2 billion NOK. Customers include retailers, industry and commercial kitchens (Nortura, 2015). This paper focuses on the meat processing part of the company, poultry excepted, and their retail customers.

Nortura operate 16 slaughterhouses, from which the production plants receive the raw material for processing and packing. The meat processing is carried out at 13 production plants. Each of the production plants is specialised for a unique set of products with little or no overlap in products between plants. The production plant at Rudshøgda, for instance, produces bacon, pre-cut steaks and a variety of meat patties and rissoles, among other products. Other plants specialise in other meat products, such as sausages, cured meat or cold cuts.

Nortura's main retail customer base is comprised of three large retail corporations, some of which have multiple retail chain brands in their portfolio. Together these corporations held over 93% of the Norwegian retail market in 2015 (nielsen.com). As large corporations, they have expanded vertically within the supply chain, taking over the part of wholesalers and distributors (Volden, 2003). This fits well with McLaughlin's (2002, as referenced in Lütke Entrup et al., 2005) findings in the UK. Although they have only taken over the role of the wholesaler, "wholesaler" will henceforth refer to the retail corporations' distribution network, in order to distinguish them from the retail stores. The wholesalers manage the transportation of products from Nortura's warehouses to the wholesalers' warehouses, as well as distribution to the individual retail stores.

2.1 Current downstream supply chain

Nortura operate five regional warehouses, each serving retail customers in their respective regions. Each of these warehouses holds inventory of all products with expected demand at any certain time, and receives products from all Nortura production plants. In addition, each production plant has storage capacity for finished products. Nortura warehouses currently receive orders from each individual retail store and prepare bulk shipments for retail stores served by the same warehouse. In general, the wholesalers pick up shipments at the Nortura warehouses and ship the products to one of their own warehouses. These warehouses act only as cross docking facilities and do not hold inventory of Nortura products. After cross docking, shipments are distributed to the individual retail stores. As a rule, each retailer is served by one cross docking facility, and each cross dock is served by one Nortura warehouse.

Ownership of the product is transferred when the wholesaler picks up the shipment at the Nortura warehouse. As the ownership is transferred to the wholesaler, risk is also transferred, meaning that Nortura need not concern themselves with products surpassing their shelf life after they have left the warehouse.

Figure 1 shows the current downstream supply chain with $1, \dots, p$ production plants, $1, \dots, w$ regional warehouses, $1, \dots, c$ cross docking facilities, and $1, \dots, r_c$ retail stores served by cross docking facility c.

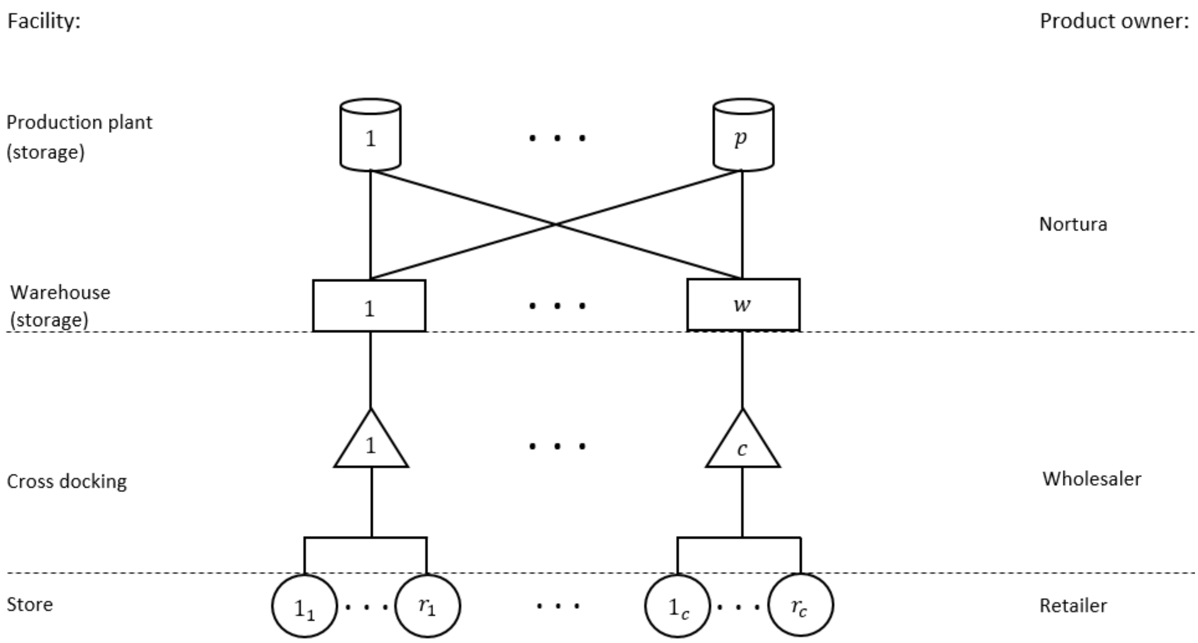

Figure 1: Current supply chain structure.

2.2 Division of shelf life

Nortura's perishable products are all marked with an expiration date, after which the product is no longer saleable to consumers. The producer is responsible for estimating the shelf life of their products (mattilsynet.no). A product's shelf life is divided between the producer, wholesaler and retailer; The Standardization Committee for the Norwegian Retail Industry issues standards for the division of shelf life. Take for example a product with a total shelf life of 30 days. The producer is given 5 days of the shelf life, the wholesaler gets 9 days, and the retailer gets the remaining 16 days (STAND, 2007).

If the producer holds a quantity of a product for longer than their apportioned period, they will usually have to accept a lower price for the product from the wholesaler, though in some instances the product is deemed unsaleable. In Nortura's case, if the product is unsaleable, it may be reintroduced into the production process in order to be heat-treated or used as an ingredient in other products with a longer shelf life. If further processing is not possible and the product is unsaleable, a last resort is donating the product to charity instead of throwing away food that is completely edible.

With the current supply chain structure, Nortura get both the producer's and most of the wholesaler's portion of a product's shelf life. This is because the wholesaler only picks up the products at Nortura's warehouses, cross docks them at one of their own warehouses and ships them to the retail stores, the whole process taking only one to three days. The longer shelf life portion gives Nortura a great deal of flexibility when planning production and distribution, and helps keeping the cost of waste down.

2.3 Restructured downstream supply chain

Recently, the retail corporations have demanded that they be allowed to take over the role that Nortura's warehouses currently hold, so that the retail warehouses start holding inventory of the products. This way, Nortura's warehouses will be shut down, and only the production plants will hold inventory for Nortura. The new supply chain structure will also incur a new division of shelf life between the supply chain actors, relocating the wholesaler's portion of shelf life from Nortura to the retail corporation's distribution network. At the same time, Nortura will no longer receive orders directly from the retail stores, but from the retail warehouses. These warehouses will surely need to operate with a safety stock to cover fluctuations in demand, and thereby increase the total volume of products in transit within the supply chain. In addition, each of Nortura's production plants will have to keep inventory of their set of products, including a safety stock of their own. Nortura fear that the new supply chain structure will result in a large increase in waste costs. Indeed, van der Vorst et al. (2009) identify information transparency and synchronising logistical decisions with consumer demand as two key strategies in order to attain joint supply chain objectives.

Figure 2 displays the restructured supply chain, where Nortura's warehouses have been removed, and the retail corporations' warehouses hold inventory. Each warehouse w is served by all production plants p. Each retailer r is served by only one warehouse.

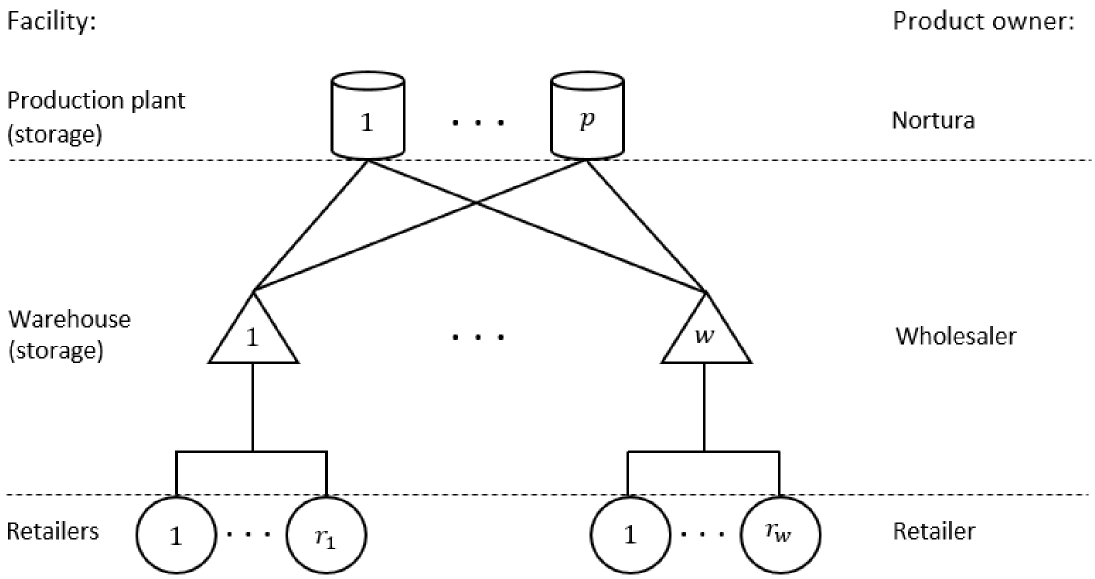

Figure 2: Restructured supply chain.

3. Research question

In light of the situation that Nortura are facing, this paper will attempt to formulate MILP-models to represent both the current and the restructured supply chains described in the previous chapter. I will then exemplify use of the models in a case study by running them with historical data from Nortura. The following research questions are formulated:

1. How can the supply chains be modelled with a discrete measure of product quality?
2. Should the company expect changes in the cost structure of products after the restructuring?
    a. Which costs will change, and by how much?
    b. How will the changes in costs vary between products with different demand uncertainties?
    c. How will the changes in costs vary between products with different shelf life lengths?

4. Literature review

In this section, I take a look at the published literature relevant for the research questions and modelling of the problem in the thesis.

4.1 Optimisation in supply chains with perishable products

Product quality is one of the most important characteristics to consider throughout the food supply chain. Low product quality at the end demand point (retail store) can result in anything from low sales rates because of the product's appearance at one end of the scale, to making the consumer critically ill on the other end (Smith and Sparks, 2004).

The literature on supply chain optimisation in the meat industry is not very extensive. In their study, Gribkovskaia, Gullberg, Hovden and Wallace (2006) optimise the collection and stocking of livestock at abattoirs to reduce transportation costs, while maintaining animal welfare. Another study, by Bixby, Down and Self (2006), takes a look at an integrated system of linear programming-models in Swift & Company, used to dynamically schedule beef processing in real time based on received orders. As the output of different meat cuts varies according to the different ways of cutting a carcass, the system helps reduce inventory of cuts with low demand. Animal welfare and inventory turnover both have an effect on product quality, and are important factors for the quality level and value of the end product (Gribkovskaia et al. 2006, Bixby et al. 2006).

Literature on optimisation of supply chains with perishable products is also not very comprehensive. One study by Lütke Entrup et al. (2005) integrates shelf life in three MILP-models for optimising yoghurt production. Shelf life considerations are integrated by assigning product batches for covering demand at a certain later date. The models do not take distribution of finished products into account, "because it is often performed by retail organizations" (p. 5078).

A more explicit integration of shelf life considerations can be found in Rong et al. (2011). They formulate an MILP-model for optimising distribution in a generic, three-stage food supply chain. The model minimises costs of production, transportation, cooling, storage and waste. By implementing quality levels as an index q on decision variables, they are able to track product batches with different quality levels throughout the supply chain. The index is an integer measure of quality levels, which degrades from one time period to the next, depending on temperature decisions made in the model. Decisions on temperature are made for all stages of the supply chain, including transportation. They also introduce a maximum quality level q_{max}, and a minimum quality level required by retailers, q_{min}. If the quality level of a product batch does not satisfy the quality requirement by any retailer, the batch is discarded, and waste cost is incurred. The model assumes that production batches can vary in terms of quality, meaning that producers can chose which level of quality to produce. In their model, retailer demand start in time period 1. In order for the model to satisfy this demand, the planning interval is expanded by the maximum lead time from a producer to a retailer, ω_{max}, making the planning interval $[1 - \omega_{max}, \dots, H]$, where H is the planning horizon.

4.2 The bullwhip effect

According to Lee et al. (1997), the bullwhip effect (BWE) is the phenomenon where the orders received by a supplier have greater variance than actual sales of the ordered products, and the variance is amplified upstream in the supply chain. In other words, the supplier may receive multiple orders covering the same demand and then experience a fall in ordered quantities, even if demand is fairly linear. When the supplier then orders components or raw products, the effect is transferred to their suppliers, and amplified. This variance makes it challenging to plan procurement, production and inventory, and can incur an increase in a number of costs. Lee et al. (1997) state that when present, the BWE may increase costs of inventory, warehousing, manufacturing and transportation, among others. They identify four causes for the BWE: demand signal processing, rationing game, order batching and price variations.

Demand signal processing can attribute to the BWE even when the actors in the supply chain act completely rational, if they base their forecasts on historical demand from their customers, and not on actual demand from further down the supply chain. Consider an example of a supply chain consisting of consumers, a retailer, a wholesaler and a supplier, each holding a certain inventory of a product. If the retailer experiences an increase in demand from consumers in period t, the forecast for period $t + 1$ will increase. As a consequence, the retailer's safety stock will also increase, and their next order to the wholesaler will include the forecast and the increase in safety stock. Acting only on the orders from the retailer, the wholesaler will also increase their next order with their own forecast and added safety stock. When the supplier receives the order from the wholesaler, the consumer demand has been inflated twice over. Even if consumer demand in period $t + 1$ turns out to be equal to the retailer's forecast, the supply chain is loaded with an excess quantity of the product.

The rationing game is described as a situation where demand for a product is greater than the supply, and actors in the supply chain place orders that are larger than what would be the case if supply were unlimited (Lee et al. 1997). In this situation, the ordered quantities are greater than what the forecast implies. In a supply chain with non-perishable products, the supply chain actor would risk being stuck with a large inventory and the resulting added capital costs. In addition, in a supply chain of perishable products, the actor would risk seeing a portion of the inventory go to waste as the products exceed their shelf life.

Order batching occurs when multiple customers (e.g. assembly plants) place their orders in the same time period. This can be often be seen in plants operating on a monthly planning cycle using MRP systems. These plants tend to place their orders for the next month at the end of the month. When many plants order at the same time, the supplier of these plants are subject to the "hockey stick" phenomenon, where the demand graph increases greatly at the end of the period.

Price variations can create and contribute to the BWE when the price of a product from a distributor varies over time. For instance, if a distributor randomly lowers the price from P_H to P_L, one would expect to see a rise in demand in that period, as customers hoard products, and a drop in demand in the consecutive periods, as the customers consume/sell from their increased inventory (Lee et al. 1997).

4.3 Demand patterns and XYZ-analysis

For Nortura, as for most producers, demand patterns vary between products and over time. Some products have a relatively stable demand all year with low uncertainty/volatility; others have a seasonable demand with moderate uncertainty, and others yet have a seemingly random demand pattern, which results in high uncertainty. These products can be categorised by their demand patterns and level of uncertainty by doing an XYZ-analysis, where X-products have stable demand, Y-products have variable demand (seasonality), and Z-products have random/irregular demand patterns (Dhoka and Choudary, 2013; Scholz-Reiter et al., 2012). A visualisation of the different demand patterns can be seen in Figure 3 below.

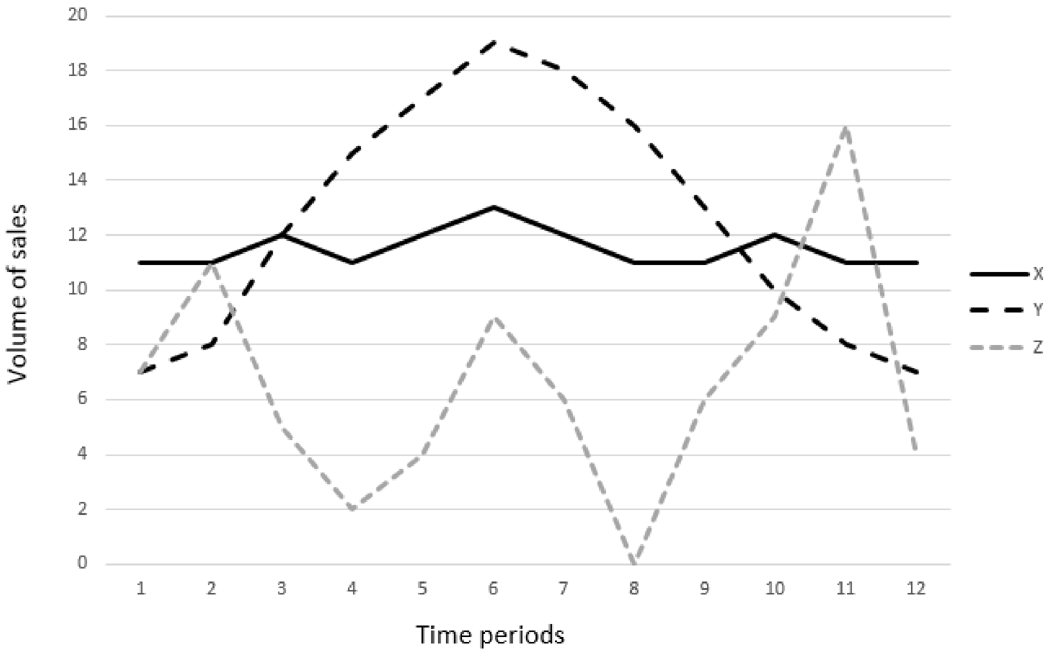

Figure 3: Demand patterns for XYZ-products.

4.4 Food supply chain redesign

Literature on supply chain management (SCM) has, since the 1980s, stressed the importance of collaboration between all actors in the supply chain, in order to better satisfy consumer demand at lower costs (van der Vorst and Beulens, 2002). In light of the aforementioned vertically expanding behaviour of retail corporations, a brief look at key aspects of SC redesign and integration seems in order.

Van der Vorst and Beulens (2002) present a list of key SC redesign strategies for attaining joint SC objectives in a generic SC:

- Redesign the roles and processes in the supply chain
- Reduce customer lead times
- Synchronise all logistical processes to customer demand
- Coordinate and simplify logistical decisions
- Create information transparency in the supply chain
- Jointly define chain objectives and performance indicators

Van der Vorst et al. (2009) further expand on this list by adding the redesign strategy *to change the environmental conditions under which products are transported and stored*, in order to improve on product quality, meaning temperature regulation and modified atmosphere packaging.

5. Methodology

5.1 Research design

To answer the research questions, MILP-models are formulated to represent the current, four-stage supply chain, and the restructured, three-stage supply chain. Both models are then applied in a case study of Nortura's ongoing restructuring of their downstream supply chain, using historical data. The aim of the case study is firstly to exemplify use of the models and secondly, to measure differences in volumes produced, transported and wasted, and the affiliated costs.

5.2 Data collection

The data for this paper can be divided into two categories: qualitative data on the structure of the supply chain and the decision-making processes, and quantitative historical data from 2015. The qualitative data, mainly a description of the company and both the current and the future (restructured) downstream supply chain, was gathered from Nortura mainly per telephone, email and one meeting in person with logistics manager Halvor Hjelle and planning manager for the internal supply chain, Bjørn Tore Lindseth.

The quantitative data set was gathered from Nortura's databases by mr. Hjelle and mr. Lindseth. As some of the data files were very large, a user on Nortura's intranet was set up for me so that I could download files directly, rather than receiving them via email. The most relevant data includes historical forecasts, actual demand from warehouses and retailers, volumes transported, shelf life, and volume and cost of waste for multiple products. All quantitative data stems from, and covers, the year 2015.

Safety stock and re-order point

Nortura's warehouses operate with a combined safety stock and re-order point. The formula for calculating the re-order point for a product at a warehouse is: $\left(\frac{\sum_{d=t+1}^{t+10} forecast_d}{10}\right) * x$, where t is the day the formula is used, and $t + 1$ is the next day. In plain text, the safety stock equals the average of the forecast for the next 10 days multiplied with an integer number x. This integer represents the transportation lead time from the production plant to the warehouse, expressed in number of days. An order is issued when inventory dips below this point. For the most part, this means that orders are issued to the Rudshøgda production plant every weekday, assuming there is a forecasted demand, since the transportation lead time from plant to warehouse is only one to two days.

Forecasts

A data set with daily and weekly demand forecasts for nine products was received. The forecasts are made at each warehouse, and the sum of these is one of the inputs used by the production plant as a basis for production planning.

Demand and product flows

The demand data consists of two worksheets: demand data from Nortura's warehouses to the Rudshøgda production plant, including orders and volumes shipped, and a worksheet with demand data from retail stores to the six warehouses. This worksheet includes, among other things, orders, volumes shipped, delivery dates, customer numbers and retail chain membership of the individual retail store. Together, these worksheets consist of over 335 000 MS Excel rows.

Waste

A worksheet with recorded waste was also received, containing volumes, costs and week numbers for occurred waste at the Rudshøgda production plant, and aggregated numbers for the six warehouses. For the case study, average cost of waste per kilogram is calculated for each product. Actual waste of products for Nortura lies between 1 % and 2.5 %. However, waste in the data set for the selected four products is a lot less, and lies between 0 % and 1.5 %, with an average of only 0.42 %. This may come from the fact that three out of the four products have fairly long shelf lives compared to the rest of Nortura's products, and therefore it is easier to plan distribution and avoid waste for these products. On the other hand, there may be discrepancies between actual waste and reported waste. In the analysis I will compare the results from the model mainly with reported waste for each product.

Distance between facilities

In order to calculate lead times and variable transportation costs, the distances between facilities must be known. The number of facilities included in the study is 4,137, one of which is a production plant, 6 are Nortura warehouses, 23 are cross docking facilities, and the remaining 4,107 are retail stores. Even though retail stores are assigned to cross docking facilities of the same retail chain, which limits the number of distances by some degree, more than 35,000 distances have to be measured.

Collecting addresses

The data set does not include addresses for retail stores. Rather, the retail store name is on the form “retail chain” “geographical location,” e.g. “Snarkjøp Stranda” (fictional name). Two approaches were tested to collect the addresses for the stores: an HTML-scraping macro in MS Excel, and using the Google Maps Geocode Application Programming Interface (API).

When typing a store name in the search bar on http://maps.google.com, the address of the store will appear in the search bar after the search has finished. As the address appears, it should be possible to find the address as a string in the resulting website’s source code. In the HTML-scraping approach I attempted to write an Excel macro that opens an Internet Explorer window where it enters an http-address for a Google Maps search, for each store. It would then look up the tag-ID of the string containing the address, and write the address string in a cell in the spreadsheet. Before writing the Excel macro, each store name was split into different cells. The cells were then gathered in a string function, resulting in an http-address for a Google Maps search for each retail store. The problem with this approach is, as it turns out, that the tag-ID for the string containing the address in the website source code changes after each search, making it very difficult to do an HTML-scrape without scraping the whole source code, and process it further.

In the Google Maps Geocode API approach, two scripts were written in the programming language Python, using the free version of the integrated development environment PyCharm. The Google Maps API were not able to transform store names to addresses directly, as store names are already seen as a type of address string.

Therefore, the first script transforms retail store names to latitude – longitude coordinates. This script imports the Google Maps library and creates a client with an API-key manually created on the Google Maps Geocoding API website. The script then reads retail store names from a .CSV file, checks them one by one via the Google Maps Geocoding API, and writes the resulting coordinates in a second .CSV file. Each API-key allows the user to check coordinates or addresses of 2,500 geographical points per day. A free Google account can generate 13 API-keys in total. This total also includes API-keys from other Google Maps APIs, e.g. the Google Maps Distance Matrix API.

The second script does a so-called reverse geocoding, transforming latitude-longitude coordinates to addresses using the same method as above, but with coordinate input instead of store names, and slight modifications in the code.

Measuring distances

In order to measure distances between the facilities, a third Python script were written. This script uses the Google Maps Distance Matrix API to check distances between addresses. As each API-key allows the user to collect distances between 2,500 geographical points each day, a single Google account can measure about 15,000 distances each day when utilising all available API-keys.

Firstly, the script imports the Google Maps library and creates a client, like the two other scripts. The script then reads a manually created .CSV file with a list of all addresses to be checked. The script checks the distance between a constant starting point (e.g. cross docking facility 1) and each address in the .CSV input file. Lastly, the script writes the resulting data in a .CSV output file.

Transportation cost

Variable transportation cost

Transportation from the production plants to Nortura's warehouses is handled by external transport companies. Nortura enter into annual agreements with these companies, paying a fixed fee for transportation of an expected volume of pallets transported on each distance. These fees vary between distances, but the average price per pallet per kilometre is quite similar for all distances. As products differ in density, and thus weight per pallet, a variable transportation cost per kilogram per kilometre is calculated.

Fixed transportation cost

In addition to the variable transportation cost, a fixed cost should also be calculated per shipment in order to capture the cost of shipment frequency. This cost represent the time spent on order handling, preparing the shipment, and loading and offloading the truck. Nortura do not currently calculate fixed transportation costs. However, up until 2005 Nortura (then Gilde) handled their own distribution in cooperation with Prior and Tine, and mr. Hjelle was able to produce a cost calculation from 2005. Every month Statistics Norway, on behalf of the Norwegian Truck Owner Association (Norges Lastebileier-Forbund), issues a cost index for truck transportation in Norway. The cost index measures the change in average costs for a sample of Norwegian trucking companies. The index was first published in 1998, setting the basis value for January 1998 = 100. In 2009, the weights for the index were changed some, and a new basis was set, making January 2009 the new basis value of 100 (ssb.no). The cost index from 2005-2016 is represented in Table 1 below. The increase in cost is calculated with the following formula: $\left(\frac{138.1}{128}\right) * \left(\frac{119.9}{90.1}\right) - 1 = 0.436$, meaning the cost index increased by 43.6%. By multiplying the fixed cost per shipment from the 2005 calculation by 1.436, we get a reasonable estimate of today's fixed transportation costs.

	1998 basis	2009 basis
Jan. 2005	128	
Jan. 2007	138.1	90.1
Jan. 2009		100
Jan. 2016		119.9

Table 1:Truck transport index 2005 – 2016.

Transportation lead time

Transportation lead times were calculated by dividing the distance between facilities by an average speed of 65 km/hour. This average speed was recommended by Nortura. Lead times are measured in whole days, and a truck can operate 13.5 hours per day. With this in mind, an IF-function was written in Excel, that returns an integer number of lead time days.

Inventory holding cost

Timme, S. G. (2003) states that inventory holding cost consists of two parts: *inventory noncapital carrying cost* plus *inventory capital charge*. Under inventory noncapital carrying cost he lists warehousing, obsolescence, pilferage, damage, insurance, taxes, and administration and other. He calculates inventory capital charge as $inventory * capital\ cost$. As the capital cost, he recommends calculating the company's Weighted Average Cost of Capital (WACC), which is the opportunity cost for the company's average risk investment (Timme, 2003).

Nortura do not usually calculate inventory holding cost, and therefore no inventory noncapital carrying costs can be calculated. However, some form of holding cost should be included in the optimisation model. As a compromise, the weighted average capital cost multiplied with the value of the average annual inventory is chosen. This will not accurately represent the actual inventory holding cost, but it will, at least, give the model an incentive for holding inventory at a minimum.

5.3 Mixed-Integer Linear Programming-models

When modelling the two versions of the supply chain, I draw on the model by Rong et al. (2011), which explicitly considers quality degradation in a food supply chain. In contrast to the model by Rong et al., however, my models do not consider decisions on temperature levels in storage or transportation, as these are seen as fixed. The quality level of a product batch is measured in an integer number of remaining shelf life days, which is represented by the index q. As they come out of production, all products have a known number of remaining shelf life days, $qmax$. Similarly, each product has a minimum number of shelf life days required by retail stores, $qmin$.

The first model presented considers a four-stage food supply chain consisting of production plants, warehouses, cross docking facilities, and retailers. The inventory balance constraints measure inventory on day t based on inventory levels, volumes received and volumes shipped on day $t-1$. This way, inventory levels on the first day of the planning interval are not constrained. To mitigate this, and to let the model satisfy demand on day 1, $-qmax$ is added to the interval, not dissimilar to Spitter et al. (2005). The resulting planning interval is $\{-qmax, \ldots, T\}$, where T is the planning horizon.

Although this is chiefly a general model, constraint (10) is included specifically to fit the Nortura case. The constraint ensures that warehouses hold safety stock when there is forecasted demand. As the safety stock is calculated as the average of the next 10 days' forecast, an extra 10 days should be added to the planning horizon T.

The "sufficiently great, positive number", A, constrains the volumes transported between facilities. To ensure that the number is in fact great enough, it should be greater than the maximum demand during a time period equal to $qmax - qmin$. This way, if a batch is both produced and shipped to a warehouse with lead time equal to zero on day t, that batch can be used to satisfy demand from the day of production until the day the product batch is unsaleable.

5.3.1 Current downstream supply chain model formulation

The following assumptions are made:

- All stages of the supply chain comply with the temperature requirements of the products in question.
- Production plants have unlimited production capacity on weekdays.
- All products have an initial remaining shelf life of $qmax$.
- Product volumes produced and/or received can be shipped the same day.
- Each retailer can only be served by one cross docking facility.
- All facilities require the same number of remaining shelf life days, $qmin$.
- Safety stock is held by warehouses. The calculation of safety stock is based on Nortura's current method.

Sets:

P: Production plants.

W: Warehouses.

C: Cross docking facilities.

R: Retail stores.

H: All facilities with storage capacity, $H = P \cup W$.

I: All predecessor facilities, $I = P \cup W \cup C$.

S: All successor facilities, $S = W \cup C \cup R$.

K_i: Predecessor facilities for facility $i \in S$.

L_i: Successor facilities for facility $i \in I$.

Q: Set of shelf life days.

U: Set of weekend days, $U \subset \{1, \ldots, T\}$.

Parameters:

$demand_{i,t}$: Demand volume at retailer $i \in R$ on day $t \in \{1, \dots, T\}$.

$forecast_{i,t}$: Forecasted demand volume at warehouse $i \in W$ on day $t \in \{1, \dots, T\}$.

$lt_{i,j}$: Transportation lead time from facility $i \in I$ to facility $j \in L_i$.

$dcost_{i,j}$: Cost of transporting one kilogram of product from facility $i \in I$ to facility $j \in L_i$.

$qmax$: Maximum shelf life days for the product.

$qmin$: Minimum remaining shelf life days required by retailers.

$pcost$: Direct production cost per kilogram of the product.

$ftcost$: Fixed cost per shipment.

$wcost$: Cost of waste per kilogram of the product.

$ucost$: Unit cost, used to calculate inventory holding cost.

$capcost$: Capital cost in percent.

T: The planning horizon, meaning the last day in the planning period.

A: A sufficiently great, positive number.

Decision variables:

$produced_{i,q,t}$: Volume produced with remaining shelf life $q \in Q$ at production plant $i \in P$ on day $t \in \{-qmax, \dots, T\}$.

$trans_{i,j,q,t}$: Volume transported with remaining shelf life $q \in Q$ from facility $i \in I$ to facility $j \in L_i$ on day $t \in \{-qmax, \dots, T\}$.

$inv_{i,q,t}$: Inventory with remaining shelf life $q \in Q$ on the start of day $t \in \{-qmax, \dots, T\}$ at facility $i \in H$.

$waste_{i,t}$: Volume gone to waste at facility $i \in H$ on day $t \in \{-qmax, \dots, T\}$.

$\alpha_{i,j,t}$: Binary variable. 1 if products are sent from facility $i \in I$ to facility $j \in L_i$ on day $t \in \{-qmax, \dots, T\}$, 0 otherwise.

$\beta_{i,j}$: Binary variable. 1 if cross docking facility $i \in C$ serves to retailer $j \in L_i$, 0 otherwise.

Objective function:

$$
\begin{aligned}
\min \quad & \sum_{i\in P}\sum_{q\in Q}\sum_{t\in\{-qmax,\dots,T\}} pcost * produced_{i,q,t} \\
& + \sum_{i\in I}\sum_{j\in L_i}\sum_{t\in\{-qmax,\dots,T\}} ftcost * \alpha_{i,j,t} \\
& + \sum_{i\in I}\sum_{j\in L_i}\sum_{q\in Q}\sum_{t\in\{-qmax,\dots,T\}} dcost_{i,j,} * trans_{i,j,q,t} \\
& + \sum_{i\in H}\sum_{t\in\{-qmax,\dots,T\}} wcost * waste_{i,t} \\
& + \sum_{i\in H}\sum_{q\in Q}\sum_{t\in\{-qmax,\dots,T\}} \frac{(ucost * inv_{i,q,t})}{365} * capcost
\end{aligned} \tag{1}
$$

s.t.

$$waste_{i,t} = inv_{i,q,t} \qquad \forall i \in H,\ \forall q \in \{Q | q = qmin - 1\},\ \forall t \in \{-qmax, \dots, T\} \tag{2}$$

$$inv_{i,q-1,t} = inv_{i,q,t-1} + produced_{i,q,t-1} - \sum_{j\in\{L_i | qmin + lt_{j,i} \le q \le qmax\}} trans_{i,j,q,t-1} \qquad \forall i \in P,\ \forall q \in \{Q | qmin \le q \le qmax\},\ \forall t \in \{-qmax + 1, \dots, T\} \tag{3}$$

$$inv_{i,q-1,t} = inv_{i,q,t-1} + \sum_{j\in\{K_i | qmin \le q \le qmax - lt_{j,i} |\ t > -qmax + lt_{j,i}\}} trans_{j,i,q+lt_{j,i},t-lt_{j,i}-1} - \sum_{j\in\{L_i | qmin + lt_{i,j} \le q \le qmax\}} trans_{i,j,q,t-1} \qquad \forall i \in W,\ \forall q \in \{Q | qmin \le q \le qmax\},\ \forall t \in \{-qmax + 1, \dots, T\} \tag{4}$$

$\sum_{j \in \{L_i | qmin + lt_{i,j} \le q\}} trans_{i,j,q,t} = \sum_{j \in \{K_i | q \le qmax - lt_{j,i} | t \ge -qmax + lt_{j,i}\}} trans_{j,i,q+lt_{j,i},t-lt_{j,i}} \quad \forall i \in C,$
$\forall q \in Q, \ \forall t \in \{-qmax, \dots, T\}$ (5)

$demand_{i,t} = \sum_{j \in K_i} \sum_{q \in \{Q | qmin \le q \le qmax - lt_{j,i}\}} trans_{j,i,q+lt_{j,i},t-lt_{j,i}} \qquad \forall i \in R, \ \forall t \in$
$\{1, \dots, T\}$ (6)

$inv_{i,q,t} = 0 \quad \forall i \in H, \ \forall q \in \{Q | q = qmax\}, \ \forall t \in \{-qmax, \dots, T\}$ (7)

$produced_{i,q,t} = 0 \quad \forall i \in P, \forall q \in Q, \ \forall t \in U$ (8)

$produced_{i,q,t} = 0 \quad \forall i \in P, \ \forall q \in \{Q | q <> qmax\}, \ \forall t \in \{-qmax, \dots, T\}$ (9)

$\sum_{qmin \le q \le qmax} inv_{i,q,t} \ge lt_{j,i} \left(\frac{\sum_{d=t+1}^{t+10} forecast_{i,d}}{10} \right) \ \forall i \in W, \ \forall j \in K_i, \ t \in \{1, \dots, T-10\}$ (10)

$\sum_{q \in \{Q | q \ge qmin + lt_{i,j}\}} trans_{i,j,q,t} \le \alpha_{i,j,t} * A \quad \forall i \in I, \ \forall j \in L_i, \ \forall t \in \{-qmax, \dots, T\}$ (11)

$\sum_{q \in Q} trans_{i,j,q,t} \le \beta_{i,j} * demand_{i,t+lt_{i,j}} \quad \forall i \in C, \ \forall j \in L_i, \ \forall t \in \{-qmax, \dots, T\}$ (12)

$\sum_{j \in K_i} \beta_{j,i} = 1 \qquad \forall i \in R$ (13)

$produced_{i,q,t} \ge 0 \quad \forall i \in P, \ \forall q \in Q, \ \forall t \in \{-qmax, \dots, T\}$ (14)

$trans_{i,j,q,t} \ge 0 \qquad \forall i \in I, \ \forall j \in L_i, \ \forall q \in Q, \ \forall t \in \{-qmax, \dots, T\}$ (15)

$inv_{i,q,t} \ge 0 \qquad \forall i \in H, \ \forall q \in Q, \ t \in \{-qmax, \dots, T\}$ (16)

$waste_{i,t} \ge 0 \qquad \forall i \in H, \ \forall t \in \{-qmax, \dots, T\}$ (17)

$\alpha_{i,j,t} \in \{0,1\} \qquad \forall i \in I, \ \forall j \in L_i, \ \forall t \in \{-qmax, \dots, T\}$ (18)

$\beta_{i,j} \in \{0,1\} \qquad \forall i \in C, \ \forall j \in L_i$ (19)

The model's objective function (1) minimises the costs of production, transportation, inventory capital cost, and wasted products. Both fixed and variable transportation costs are calculated. Constraint (2) measures the volume of wasted products, more specifically the volume of products that have a remaining shelf life of one day less than $qmin$. Constraints (3) and (4) measure the inventory at production plants and warehouses respectively. They also ensure that all products shipped will have minimum $qmin$ of remaining shelf life when reaching their destination. Constraint (5) ensures that product volumes received from warehouses are shipped to retailers on the same day. It also ensures that products will have minimum $qmin$ of remaining shelf life when reaching the retailer. Constraint (6) forces the model to satisfy all demand at retailers. Constraint (7) completes constraints (3) and (4), letting there be no inventory with remaining shelf life equal to $qmax$. This is necessary because produced volumes are measured on the day after production at the earliest. Constraints (8) and (9) make sure no production is planned on weekends, and that all products have an initial remaining shelf life equal to $qmax$ respectively. Constraint (10) is, as mentioned earlier, specific to the Nortura case and the way they calculate safety stock. Constraint (11) causes the binary variable $\alpha_{i,j,t}$ to be equal to 1 if products are shipped from facility i to facility j on day t, and equal to 0 otherwise. Constraints (12) and (13) make sure the binary variable $\beta_{i,j}$ is equal to 1 if shipments are made from cross docking facility i to retailer j, and that only one cross docking facility can serve each retailer, respectively. Constraints (14) through (19) are non-negativity and binary constraints.

5.3.2 Restructured downstream supply chain model formulation

In the following model, the cross docking facilities have been removed, production plants and warehouses different $qmin_i$, which is the minimum remaining shelf life required by the next stage in the SC, and both production plants and warehouses keep a safety stock.

The following assumptions are made:

- All stages of the supply chain comply with the temperature requirements of the products in question.
- Production plants have unlimited production capacity on weekdays.
- All products have an initial remaining shelf life of $qmax$.
- Product volumes produced and/or received can be shipped the same day.
- Each retailer can only be served by one warehouse.
- Retailers and warehouses require a different number of remaining shelf life days.
- Safety stock is held by both warehouses and production plants. The calculation of safety stock is based on Nortura's current method.

Sets:

P: Production plants.

W: Warehouses (former cross docking facilities).

R: Retail stores.

I: Both predecessor facilities and facilities with storage capacity, $I = P \cup W$.

S: Successor facilities, $S = W \cup R$.

K_i: Predecessor facilities for facility $i \in S$.

L_i: Successor facilities for facility $i \in I$.

Q: Shelf life days.

U: Weekend days, $U \subset \{1, \dots, T\}$.

Parameters:

$demand_{i,t}$: Demand volume at retailer $i \in R$ on day $t \in \{1, \dots, T\}$.

$forecast_{i,t}$: Forecasted demand volume at warehouse $i \in I$ on day $t \in \{1, \dots, T\}$.

$lt_{i,j}$: Transportation lead time from facility $i \in I$ to facility $j \in L_i$.

$dcost_{i,j}$: Cost of transporting one kilogram of product from facility $i \in I$ to facility $j \in L_i$.

$qmax$: Maximum shelf life days for the product.

$qmin_i$: Minimum remaining shelf life days required by the next stage in the supply chain, for facility $i \in I$.

$pcost$: Direct production cost per kilogram of the product.

$ftcost$: Fixed cost per shipment.

$wcost$: Cost of waste per kilogram of the product.

$ucost$: Unit cost, used to calculate inventory holding cost.

$capcost$: Capital cost rate.

T: The planning horizon, meaning the last day in the planning period.

A: A sufficiently great, positive number.

Decision variables:

$produced_{i,q,t}$: Volume produced with remaining shelf life $q \in Q$ at production plant $i \in P$ on day $t \in \{-qmax, \dots, T\}$.

$trans_{i,j,q,t}$: Volume transported with remaining shelf life $q \in Q$ from facility $i \in I$ to facility $j \in L_i$ on day $t \in \{-qmax, \dots, T\}$.

$inv_{i,q,t}$: Inventory with remaining shelf life $q \in Q$ on the start of day $t \in \{-qmax, \dots, T\}$ at facility $i \in I$.

$waste_{i,t}$: Volume gone to waste at facility $i \in I$ on day $t \in \{-qmax, \dots, T\}$.

$\alpha_{i,j,t}$: Binary variable. 1 if products are sent from facility $i \in I$ to facility $j \in L_i$ on day $t \in \{-qmax, \dots, T\}$, 0 otherwise.

$\beta_{i,j}$: Binary variable. 1 if warehouse $i \in W$ serves retailer $j \in L_i$, 0 otherwise.

Objective function:

$$\min \quad \sum_{i\in P}\sum_{q\in Q}\sum_{t\in\{-qmax,\dots,T\}} pcost * produced_{i,q,t}$$

$$+\sum_{i\in I}\sum_{j\in L_i}\sum_{t\in\{-qmax,\dots,T\}} ftcost * \alpha_{i,j,t}$$

$$+\sum_{i\in I}\sum_{j\in L_i}\sum_{q\in Q}\sum_{t\in\{-qmax,\dots,T\}} dcost_{i,j,} * trans_{i,j,q,t}$$

$$+\sum_{i\in I}\sum_{t\in\{-qmax,\dots,T\}} wcost * waste_{i,t}$$

$$+\sum_{i\in I}\sum_{q\in Q}\sum_{t\in\{-qmax,\dots,T\}} \frac{(ucost*inv_{i,q,t})}{365} * capcost \qquad (20)$$

s.t.

$$waste_{i,t} = inv_{i,q,t} \qquad \forall i\in I,\ \forall q\in\{Q|q=qmin_i-1\},\ \forall t\in\{-qmax,\dots,T\} \quad (21)$$

$$inv_{i,q-1,t} = inv_{i,q,t-1} + produced_{i,q,t-1} - \sum_{j\in\{L_i|qmin_i+lt_{j,i}\le q\le qmax\}} trans_{i,j,q,t-1} \qquad \forall i\in P,\ \forall q\in\{Q|qmin_i\le q\le qmax\},\ \forall t\in\{-qmax+1,\dots,T\} \quad (22)$$

$$inv_{i,q-1,t} = inv_{i,q,t-1} + \sum_{j\in\{K_i|qmin_j\le q\le qmax-lt_{j,i}|\ t>-qmax+lt_{j,i}\}} trans_{j,i,q+lt_{j,i},t-lt_{j,i}-1} - \sum_{j\in\{L_i|qmin_i+lt_{i,j}\le q\le qmax\}} trans_{i,j,q,t-1} \qquad \forall i\in W,\ \forall q\in\{Q|qmin_i\le q\le qmax\},\ \forall t\in\{-qmax+1,\dots,T\} \quad (23)$$

$$demand_{i,t} = \sum_{j\in K_i}\sum_{q\in\{Q|qmin_i\le q\le qmax-lt_{j,i}\}} trans_{j,i,q+lt_{j,i},t-lt_{j,i}} \qquad \forall i\in R,\ \forall t\in\{1,\dots,T\} \quad (24)$$

$$inv_{i,q,t} = 0 \quad \forall i\in I,\ \forall q\in\{Q|q=qmax\},\ \forall t\in\{-qmax,\dots,T\} \quad (25)$$

$$produced_{i,q,t} = 0 \quad \forall i\in P, \forall q\in Q,\ \forall t\in U \quad (26)$$

$$produced_{i,q,t} = 0 \quad \forall i\in P,\ \forall q\in\{Q|q<>qmax\},\ \forall t\in\{-qmax,\dots,T\} \quad (27)$$

$$\sum_{qmin_i\le q\le qmax} inv_{i,q,t} \ge \left(\frac{\sum_{d=t+1}^{t+10} forecast_{i,t}}{10}\right) \qquad \forall i\in P,\ \forall t\in\{1,\dots,T-10\} \quad (28)$$

$$\sum_{qmin_i\le q\le qmax} inv_{i,q,t} \ge lt_{j,i}\left(\frac{\sum_{d=t+1}^{t+10} forecast_{i,d}}{10}\right) \quad \forall i\in W,\ \forall j\in K_i,\ t\in\{1,\dots,T-10\} \quad (29)$$

$$\sum_{q\in\{Q|q\geq qmin+lt_{i,j}\}} trans_{i,j,q,t} \leq \alpha_{i,j,t} * A \quad \forall i \in I,\ \forall j \in L_i,\ \forall t \in \{-qmax, \dots, T\} \tag{30}$$

$$\sum_{q\in Q} trans_{i,j,q,t} \leq \beta_{i,j} * demand_{i,t+lt_{i,j}} \quad \forall i \in C,\ \forall j \in L_i,\ \forall t \in \{-qmax, \dots, T\} \tag{31}$$

$$\sum_{j\in K_i} \beta_{j,i} = 1 \quad \forall i \in R \tag{32}$$

$$produced_{i,q,t} \geq 0 \quad \forall i \in P,\ \forall q \in Q,\ \forall t \in \{-qmax, \dots, T\} \tag{33}$$

$$trans_{i,j,q,t} \geq 0 \quad \forall i \in I,\ \forall j \in L_i,\ \forall q \in Q,\ \forall t \in \{-qmax, \dots, T\} \tag{34}$$

$$inv_{i,q,t} \geq 0 \quad \forall i \in H,\ \forall q \in Q,\ t \in \{-qmax, \dots, T\} \tag{35}$$

$$waste_{i,t} \geq 0 \quad \forall i \in H,\ \forall t \in \{-qmax, \dots, T\} \tag{36}$$

$$\alpha_{i,j,t} \in \{0,1\} \quad \forall i \in I,\ \forall j \in L_i,\ \forall t \in \{-qmax, \dots, T\} \tag{37}$$

$$\beta_{i,j} \in \{0,1\} \quad \forall i \in C,\ \forall j \in L_i \tag{38}$$

The objective function (20) is the same as for the first model. Constraints (21) through (27) are the same as for the first model, except for the $qmin$ parameter, which has been changed to $qmin_i$ in order to capture the different minimum shelf life requirements of wholesaler warehouses and retailers. Constraint (28) is new, making sure production plants keep a safety stock. In contrast to (29), which ensures warehouse safety stocks and is multiplied by the lead time from plant to warehouse, the safety stock in (28) is not multiplied, making plants hold only one average day's forecast as safety stock. Constraints (29) through (38) have not been changed from the previous model.

6. Case study

To exemplify use of the models, historical data from Nortura is implemented in the models. In the following sections, I present the scope of the case study, the historical data collected and data processing methods performed.

6.1 Scope of the case study

Due to the restricted scale of this paper, the case study is limited to one production plant and four products, but includes all Nortura warehouses and retail customers. The geographical distribution of the production plant and warehouses is presented in Figure 4 below. All 23 cross docking facilities and 4,107 retail stores are included in the case study. Both cross docking facilities and retailers have distributions similar to that of the warehouses, with concentrations around cities, and a higher density in the southern part of the country versus the northern part. They are not plotted on a map due to the sheer number of facilities, which would cover the map completely.

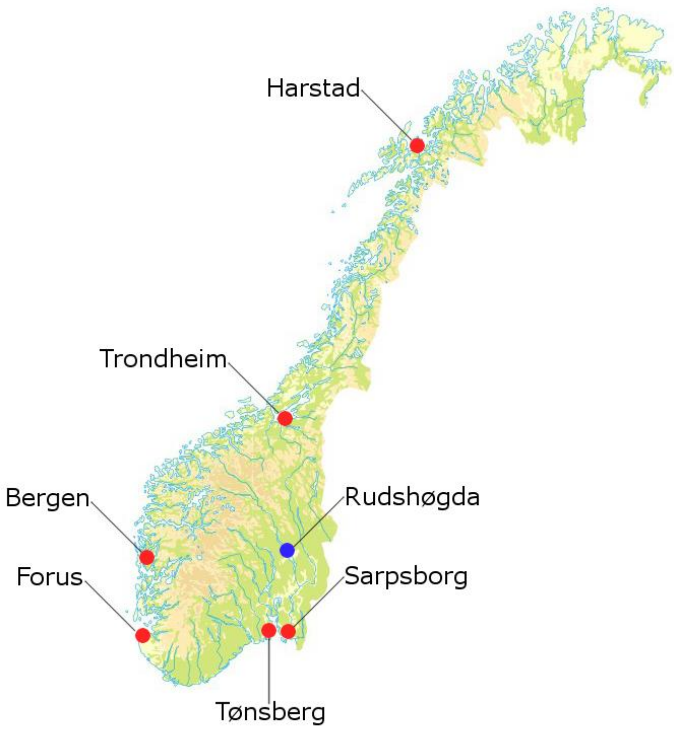

Figure 4: Geographical distribution of the production plant (blue) and warehouses (red) in the case study.

Three products A, B, C and D are chosen for the case study. Product A has a high demand with low uncertainty all year, product B has seasonal demand with low uncertainty, and product C has a seasonal demand with high uncertainty. Product D has low demand and medium uncertainty, and has a very high unit cost, and therefore also a high waste cost. The reason for choosing these products is to highlight the effect of different SC strategy decisions on products with differences in demand patterns, uncertainty in demand, and shelf life lengths.

The shelf life distribution is shown in Table 2, and average weekly demand for the whole year is shown in Figure 5.

Product	Producer	Wholesaler	Retailer	Total shelf life
A	10	10	22	42
B	7	9	20	36
C	3	6	11	20
D	8	10	22	40

Table 2: Shelf life distribution of products A, B, C and D.

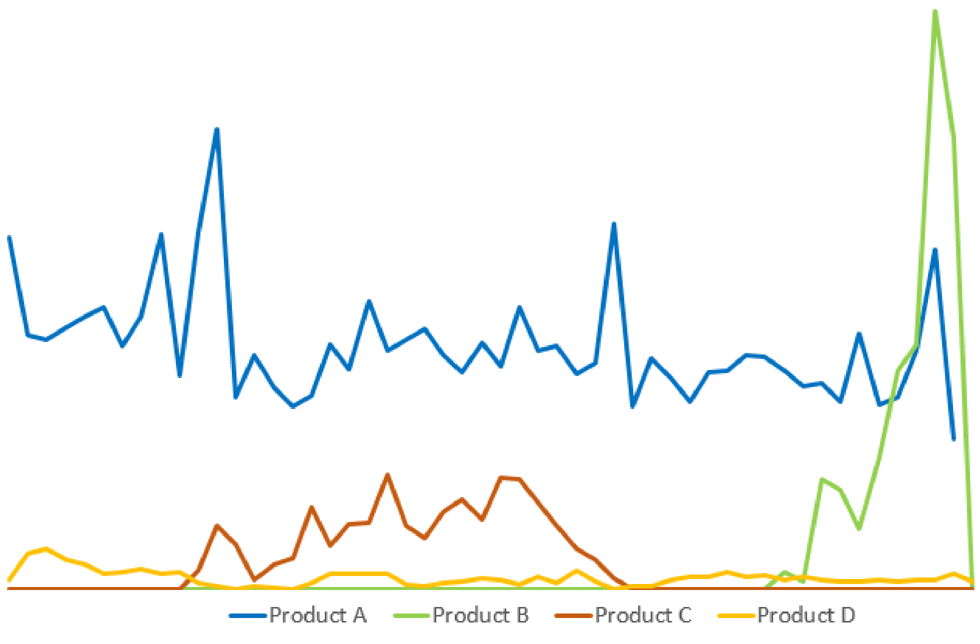

Figure 5: Average weekly demand for the four products.

6.2 Running the models

The models were coded in A Mathematical Programming Language (AMPL), and run using the IBM ILOG CPLEX solver. The first run was done using the data set for product A. The product was chosen because it has the most extensive data set, with the highest number of both customers and demand days. This way, if the run was successful, running the data sets for the other products should be successful as well. The models are run with a planning interval of $\{-qmax, \ldots, 375\}$ in order to capture differences between historical data supplied by the company, and data produced by the model. 10 days are added at the end of the interval in order for the safety stock constraints (10), (28) and (29) to calculate safety stock for the last of the 365 days of the year.

The run was firstly done using a laptop with a 2.5 GHz CPU and 8 GB RAM, with an additional 50 GB allocated virtual memory. The run was terminated by the software after 10-15 minutes due to insufficient memory. The model was then run in a computer cluster. After approximately 12 hours, the model still was not solved, having a mixed-integer optimality gap of 2.74 %. This gap is the difference between the best integer solution found, and the optimal value of linear programming relaxation (Fourer, Gay and Kerninghan, 2003). The goal is to have no gap, i.e. 0 %.

To allow for multiple runs to be executed simultaneously, two Amazon Web Services (AWS) Elastic Compute Cloud (EC2) instances were created. An EC2 instance is a virtual computer which is hosted by a server centre. Virtual CPU (vCPU), memory, storage, and network capacity is allocated to the instance according to the specifications of the instance type. The instances are rented on an hourly basis, and can be started and stopped as needed. A stopped instance does not incur any costs. The instance types created was one r3.xlarge instance and one r3.8xlarge instance rented from a server centre in Ireland. The R3 instance types are memory optimised instances with varying levels of allocated capacity and price. The allocated CPU, memory and storage capacities, and the price of the rented instances can be found in Table 3 below. The total cost of renting instances for the thesis amounted to $182.83.

Instance	vCPU cores	RAM	Storage (SSD)	Price per hour
r3.xlarge	4	30.5	1x80 GB	$3.204
r3.8xlarge	32	244	2x320 GB	$0.544

Table 3: AWS EC2 instance type capacities and price (aws.amazon.com).

6.2.1 Relaxation

The thesis is restricted in time to one semester, and the research method requires the model formulations to be run multiple times. Therefore, some form of relaxation has to be made in order to get to more reasonable solve times for the model. Two relaxation approaches are considered: aggregation of retailer demand, and excluding binary variables.

Retailer demand aggregation

The original data set have more than 4,100 retail customers, each with 365 days of demand, resulting in over 1.4 million demand values. Retailers are spread all over the country, with concentrations in the more populated areas. With the original model formulation, shipments from cross docking facilities/warehouses to retailers are done individually, not considering vehicle routing. This is a weakness in the model as, in reality, distribution trucks from cross docking facilities will visit multiple retailers in the same area. With aggregation of demand by geographical area, the model will be easier to solve, and may even result in a more realistic solution in that shipments are made to multiple retailers by the same truck.

Norway is divided into areas with four-digit zip codes. The digits refer to specific geographical areas, with an increasing level of accuracy. The first two digits may, for example refer to one part of a county, while de last two digits refer to different towns or neighbourhoods within that area. As we can see from Figure 6 below, zip code areas are smaller in the southern part of the country where population density is higher, and larger in the northern part of the country, where population is more scattered. By aggregating daily demand on the zip codes' first two digits, I reduce the number of customers from 4,100 to 101, and demand values from more than 1.4 million to a little less than 37,000.

When aggregating demand this way, one has to calculate values of the $dcost_{i,j}$ and $lt_{i,j}$ parameters for the demand areas. First, I calculated new distances from the cross docking facilities to the demand areas. For each cross docking facility and demand area, this was done by counting the number of demand days (i.e. shipments) per retailer, and multiplying this number by the distance from the cross dock in question. The resulting values were then summed up, and divided by the total number of shipments. This way, I get an average distance travelled per shipment. This average distance was then used to calculate new $dcost_{i,j}$ and $lt_{i,j}$ parameters.

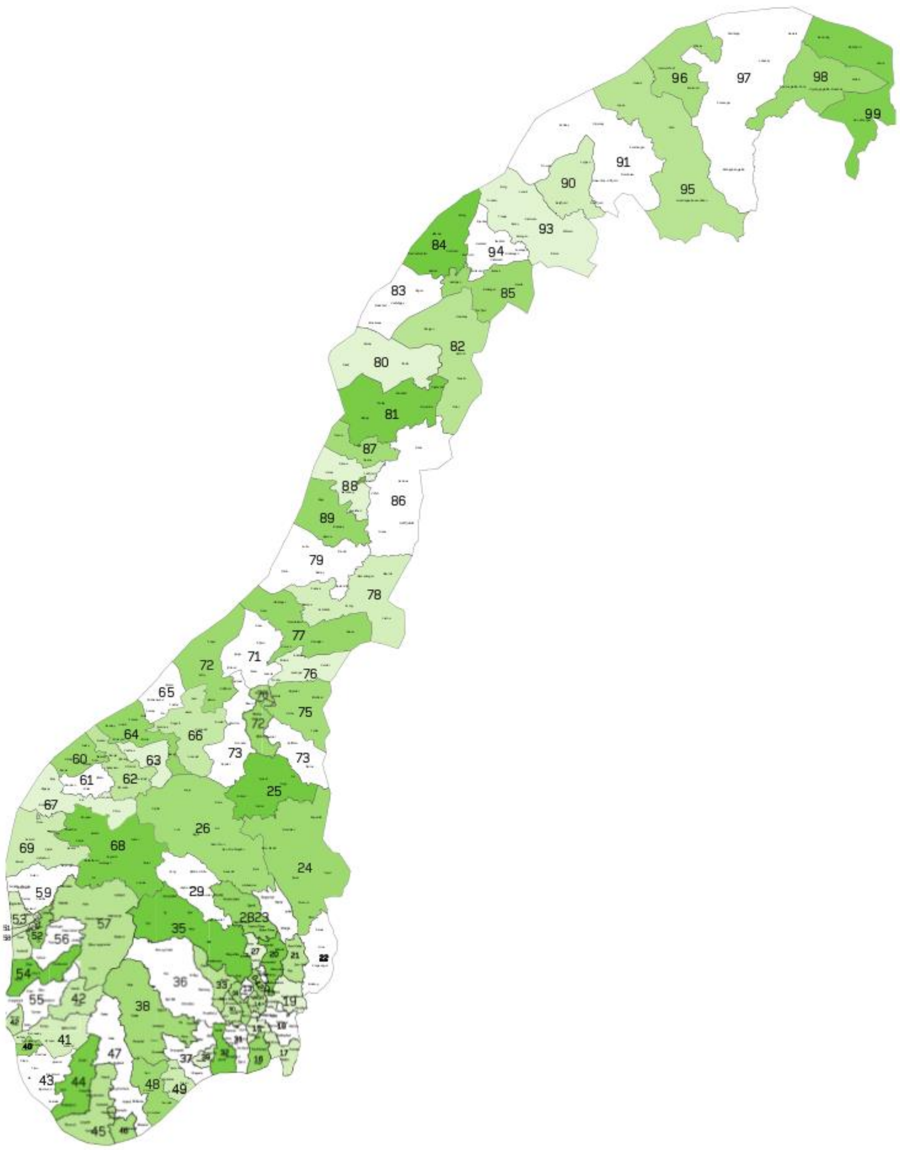

Figure 6: Zip code areas (bring.no).

Excluding binary variables

After additional test runs, it is clear that the binary variable $\alpha_{i,j,t}$ makes the model hard to solve, much more so than the variable $\beta_{i,j}$. This is probably due to the sheer number of $\alpha_{i,j,t}$ variables. By excluding the $\alpha_{i,j,t}$ variable from the model, solver times are drastically reduced, and solutions with a 0 % gap are found. The downside to removing the variable is that the model will not be able to consider fixed transportation costs, as the variable is included in the objective function. This is a weakness in the analysis. However, in respect to the Nortura case, it may not be a major drawback. Nortura already have a very high frequency of shipments, transporting products from production plants to warehouses on an almost daily basis. The time and frequency of these shipments are in fact the only ones that can be chosen by the solver. The demand constraints (6) and (24) enforces shipments between cross docking facilities/warehouses and retailers to be made to satisfy all demand on all days, meaning that these shipments cannot vary as long as the same demand data set is used. As a result, the second summation in the objective functions (1) and (20) are removed from the AMPL model formulations. Also, the constraints (11), (18), (30) and (37) are removed, as these include the $\alpha_{i,j,t}$ variable.

7. Analysis

In this section, I will present the data resulting from the model runs. The models were run with data for all four products. As a consequence of the large data sets, the runs for products A and D were made on the EC2 r3.8xlarge instance. The data sets for products B and C are much smaller, and were run on the r3.xlarge instance to save costs.

7.1 Current supply chain model

The solve times for the current supply chain model varied greatly between the products, with the shortest solve times being those of products B and C at 1 minute each. The longest solve time was that of product A, which was 50 minutes. Optimal solutions were found for all products.

	Solve time (min)
Product A	50
Product B	1
Product C	1
Product D	25

Table 4: Solve times for the current SC model.

The dominating cost type is production cost, which accounts for an average 98.3 % of the objective function value. The next costs are, in descending order: variable transportation cost (1.5%), waste cost (0.2%), and inventory holding cost (0.05%). Although fixed transportation costs were omitted from the model, one can still calculate it by counting the number of shipments and multiplying them by the $ftcost$ parameter. The average fixed transportation cost is 16.2% of the objective function value. The span is large, however, with a minimum value of 4.7 % and a maximum value of 26 %. Figure 7 below shows the cost structure for all the products.

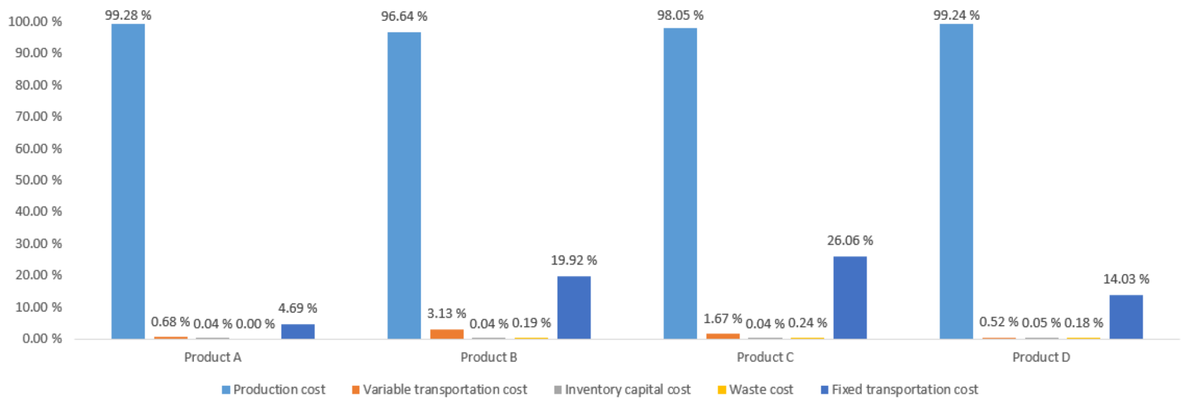

Figure 7: Cost structure comparison, current SC.

The waste volume was reduced for products A, B and C in the optimal solution. There was no waste reported for product D, but compared with the 1.5 % reference, the model waste was very low. Waste volumes, in percent of the total production volumes, are shown in Figure 8.

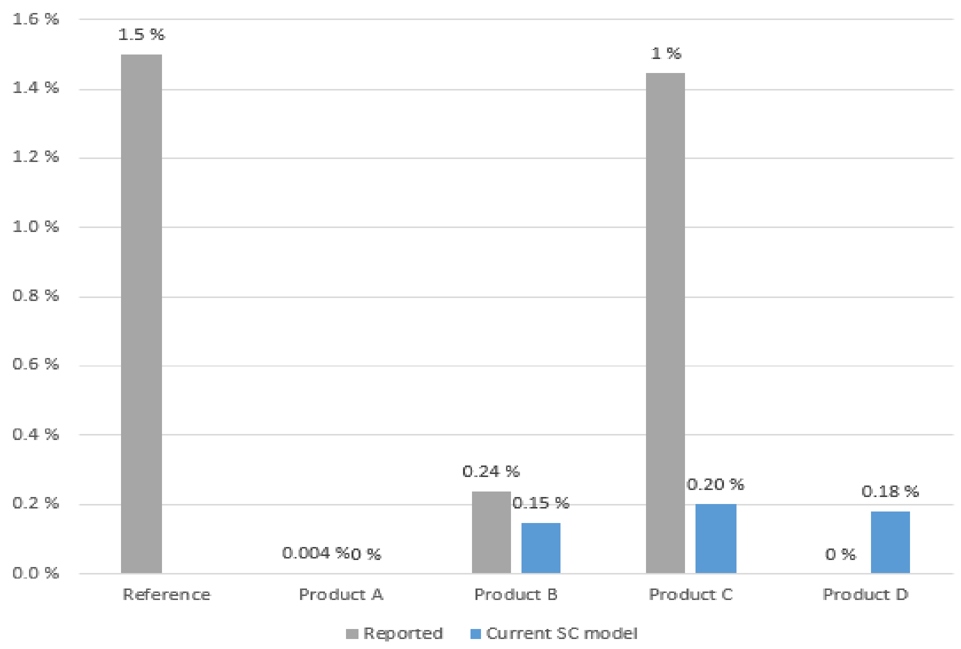

Figure 8: Percentage waste volumes comparison, current SC structure model.

7.2 Restructured supply chain model

Although the models themselves are fairly similar, and the restructured supply chain one stage shorter than the current supply chain, solve times increased greatly when running the restructured SC model. This is probably due to the double safety stocks in both production plants and warehouses. The shortest solve time is 23 minutes for product B, and the longest solve time is again that of product A, which is 652 minutes.

	Solve time (min)
Product A	652
Product B	23
Product C	42
Product D	87

Table 5: Solve times for the restructured SC model.

Production costs were almost exactly the same in the restructured SC model as in the first model, owing to the fact that the same demand data was used, and there was therefore very little change in the production volume. Variable transportation cost was decreased by between 11 % and 17 % for products A, B and C, but increased 5.6 % for product D. Inventory holding cost increased for all products, with increase rates between 28 % and 67 %. Waste cost varied between the products, but most products had increased waste in the restructured SC. Fixed transportation costs were reduced for all products, from -2.8 % to -39 %. This is probably a result of larger shipments, as there is a greater volume of products throughout the supply chain. Product A still had around 0 % waste, while products B, C and D had increased waste costs of 49 %, 7,800 % and 366 %, respectively. In order to visualise the changes in costs, waste costs have been let out of Figure 9, owing to the fact that it would completely dominate the other cost measures. For product C, which is the product with both the highest uncertainty and the shortest shelf life, the waste cost in this run accounts for 13.9 % of the objective function value (Figure 10).

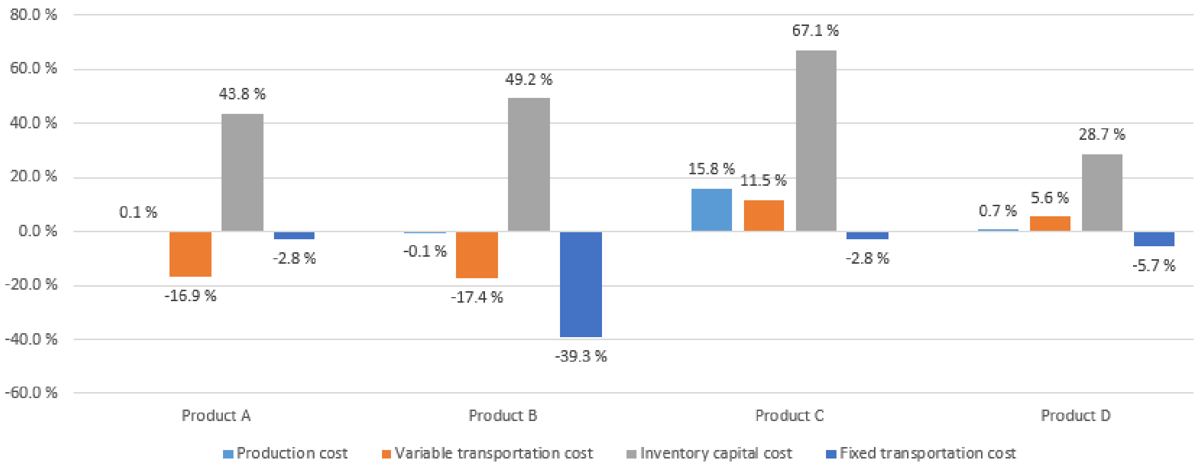

Figure 9: Changes in costs.

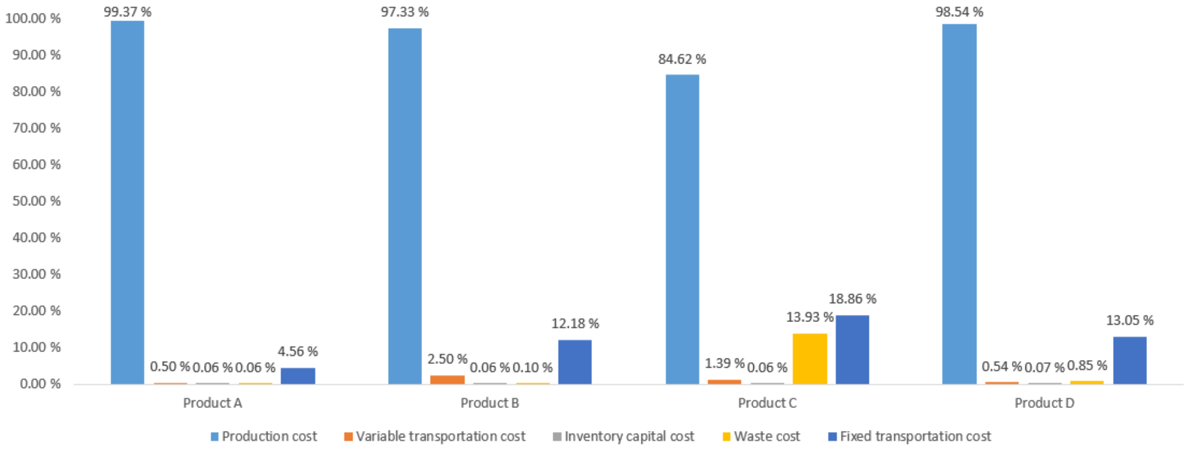

Figure 10: Cost structure comparison, restructured SC.

The great increase in waste cost for product C is, of course, a result of a large increase in waste volume. Waste volume for product C is indeed greater than both that of the current SC model and the reported actual waste for all products. However, for products A, B and D, waste is still under 1 % of the produced volume. For product C, 13.8 % is wasted. In order to visualise the data, product C have been placed in a diagram by itself in Figure 12, less it completely dominates the other products in Figure 11.

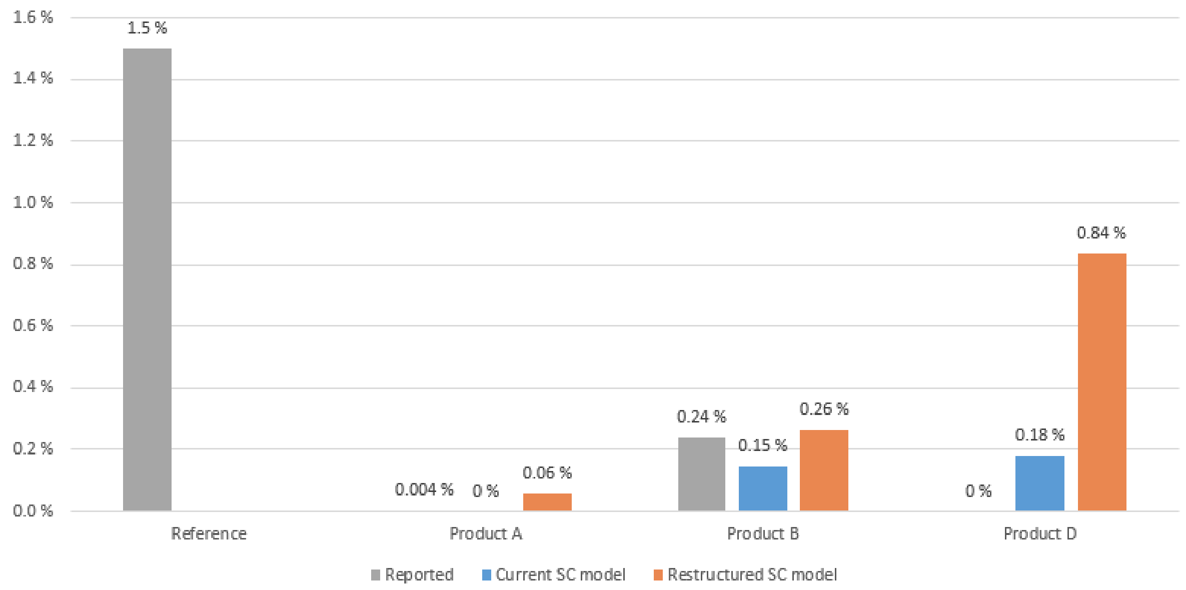

Figure 11: Percentage waste volumes comparison for products A, B and D.

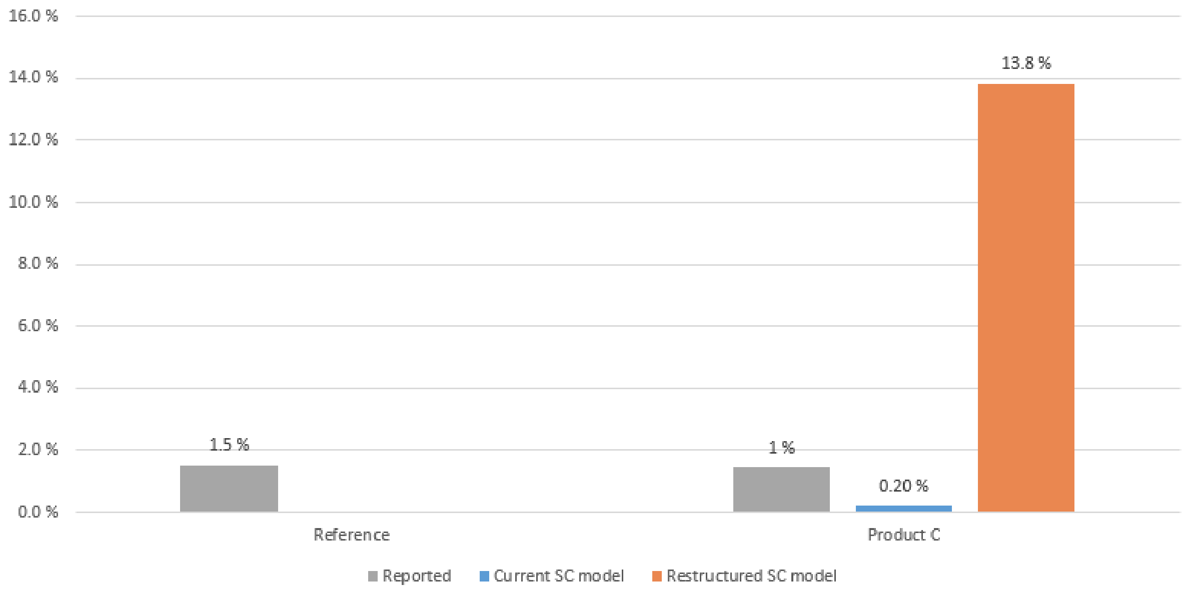

Figure 12: Percentage waste volumes comparison for product C.

In order to check if the large waste volume for products C is a result of the greater uncertainty of demand compared to the other products, or if the shorter shelf life has more of an impact, two hybrid products are defined and run with both models. Hybrid 1 have the demand and forecast data for product B, but have the short shelf life of product C. Hybrid 2 have the demand and forecast data for product C, but the long shelf life of product B. In other words, Hybrid 1 has low uncertainty and short shelf life, and hybrid 2 has high uncertainty and long shelf life. Products B and C are used to compare the resulting waste. As can be seen in Figure 13, it is clear that the products with short shelf life have very high waste percentages, while the products with longer shelf lives have very little waste. The level of uncertainty seems to have little impact on the resulting waste.

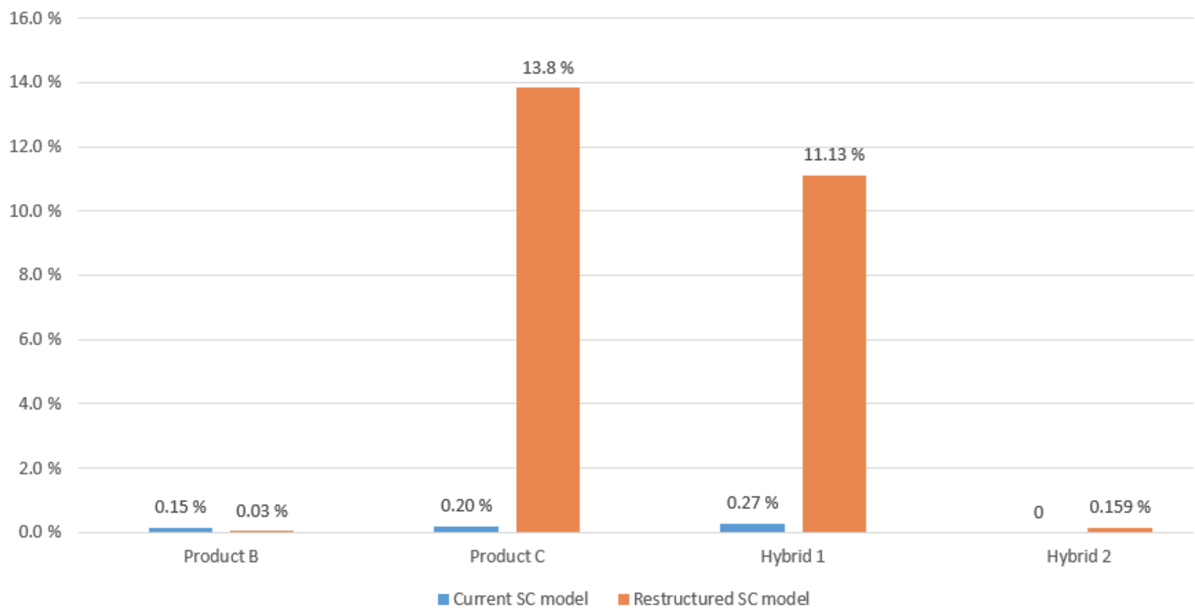

Figure 13: Percentage waste volumes of products B and C, and hybrid products 1 and 2.

8. Conclusion

This paper has presented mixed-integer linear programming models for food product distribution with a discrete measure of product quality in three- and four-stage supply chains. Use of the models has been exemplified in a case study of Nortura's ongoing supply chain restructuring with historical data from 2015. The case study shows how the models can be relaxed to run with very large amounts of data within a reasonable time. Analysis of the results from the case study show that a company that finds itself in a situation similar to Nortura's, should expect increased inventory holding costs and waste costs for all products. Increase in waste costs will be much greater for products with shorter shelf life and high uncertainty in demand, although shelf life lengths have a far greater impact on the resulting waste than that of demand uncertainty.

The main contribution of this thesis lies in the implementation of large, real life data sets in MILP-models that consider product quality explicitly, and in finding ways to relax the model formulations in order to run the models. The presented models could be useful tools to help food supply chain actors analyse and exemplify the consequences of supply chain restructuring.

Further research could attempt to refine the presented model formulations. Information sharing settings could also be implemented in the models to test different scenarios of supply chain integration.

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Appendix

1. AMPL model formulation of the current supply chain.

```
set P;                                  #production plants
set W;                                  #warehouses
set C;                                  #cross docking warehouses
set R;                                  #retailers
set H := P union W;                     #facilities that holds inventory
set I := P union W union C;             #all predecessor nodes
set S := W union C union R;             #all successor nodes
set K{S};                               #predecessor nodes for node s
set L{I};                               #successor nodes for node i
param T := 375;                         #end of the planning horizon
set Q;                                  #shelf life days
set U within 1..T;                      #weekend days



param demand{R,1..T} default 0;    #demand at retailer k on day t
param forecast{W,1..T} default 0;  #forecast for warehouse i on day t
param lt{i in I,L[i]};             #transportation time from facility h to
facility y
param dcost{i in I,L[i]};          #cost of transporting one kg from
facility H to facility G
param qmax;                        #maximum shelf life
param qmin;                        #minimum shelf life required by
retailers
param pcost;                       #cost of producing one kg
param ftcost;                      #fixed transportation cost
param wcost;                       #cost of one kg wasted
param ucost;                       #unit cost, used for measuring inventory
costs
param capcost;                     #inventory capital cost (interest)
param A := #confidential#;



var produced{P,Q,-qmax..T}>=0;               #volume produced at plant i
of product n on day t

var trans{i in I,L[i],Q,-qmax..T}>=0;        #volume sent from facility i
to facility j with shelf-life s on day t
```

```
var inv{H,Q,-qmax..T}>=0;                      #volume with shelf life s in
inventory at facility g at the start of day t

var waste{H,-qmax..T}>=0;                      #volume wasted at facility g
on day t

var beta{i in C,L[i]} binary;                  #binary   variable,   1   if
retrailer j is served by cross docking facility i.



minimize total_cost:
      sum{i in P,q in Q,t in -qmax..T}pcost*produced[i,q,t] +
      sum{i in I,j in L[i],q in Q,t in -qmax..T}(dcost[i,j]*trans[i,j,q,t])+
      sum{i in H,t in -qmax..T}wcost*waste[i,t] +
      sum{i in H,q in Q,t in -qmax..T}((ucost*inv[i,q,t])/365)*capcost;



subject to

waste_cons{i in H,q in Q,t in -qmax..T+10:q=qmin-1}:
      waste[i,t] = inv[i,q,t];

inventory_plants{i in P,q in Q,t in -qmax+1..T:qmin<=q<=qmax}:
      inv[i,q-1,t]   =   inv[i,q,t-1]   +   produced[i,q,t-1]   -   sum{j   in
L[i]:qmin+lt[i,j]<=q<=qmax}trans[i,j,q,t-1];

inventory_warehouses{i in W,q in Q,t in -qmax+1..T:qmin<=q<=qmax}:
      inv[i,q-1,t] = inv[i,q,t-1] + sum{j in K[i]:qmin<=q<=qmax-lt[j,i] and
t>-qmax+lt[j,i]}trans[j,i,q+lt[j,i],t-lt[j,i]-1]      -      sum{j      in
L[i]:qmin+lt[i,j]<=q<=qmax}trans[i,j,q,t-1];

cross docking_balance{i in C,q in Q,t in -qmax..T}:
      sum{j in L[i]:q>=qmin+lt[i,j]}trans[i,j,q,t] = sum{j in K[i]:q<=qmax-
lt[j,i] and t>=-qmax+lt[j,i]}trans[j,i,q+lt[j,i],t-lt[j,i]];

demand_satisfaction{i in R,t in 1..T}:
      demand[i,t]    =    sum{j    in    K[i],q    in    Q:qmin<=q<=qmax-
lt[j,i]}trans[j,i,q+lt[j,i],t-lt[j,i]];

no_inv_qmax{i in H,q in Q,t in -qmax..T:q=qmax}:
      inv[i,q,t] = 0;

no_production_on_weekends{i in P,q in Q,t in U:qmin<=q<=qmax}:
      produced[i,q,t] = 0;
```

```
produce_qmax_only{i in P,q in Q,t in -qmax..T:q<>qmax}:
      produced[i,q,t] = 0;



safety_stock_warehouses{i in W,j in K[i],t in 1..T-10}:
      sum{q in Q:qmin<=q<=qmax}inv[i,q,t] >= ((sum{d in 1..T:t+1<=d<=t+10}forecast[i,d])/10)*lt[j,i];


beta_cons1{i in C,j in L[i],t in -qmax..T:t<=T-lt[i,j]}:
      sum{q in Q}trans[i,j,q,t] <= beta[i,j]*demand[j,t+lt[i,j]];

beta_cons2{i in R}:
      sum{j in K[i]}beta[j,i] = 1;
```

2. AMPL model formulation of the restructured supply chain

```
set P;                              #production plants
set W;                              #warehouses
set R;                              #retailers
set I := P union W;                 #all predecessor and storage facilities
set S := W union R;                 #all successor nodes
set K{S};                           #predecessor facilities for facility s
set L{I};                           #successor facilities for facility i
set Q;                              #shelf life days
param T := 375;                     #end of the planning horizon
set U within 1..T;                  #weekend days


param demand{R,1..T} default 0;     #demand at retailer k on day t
param forecast{I,1..T} default 0;   #forecast for warehouse i on day t
param lt{i in I,L[i]};              #transportation time from facility h to facility y
param dcost{i in I,L[i]};           #cost of transporting one kg from facility H to facility G
param qmax;                         #maximum shelf life
param qmin{I};                      #minimum remaining shelf life required by the next SC stage
param pcost;                        #cost of producing one kg
param ftcost;                       #fixed transportation cost
param wcost;                        #cost of one kg wasted
```

```
param ucost;                    #unit cost, used for measuring inventory
costs
param capcost;                  #inventory capital cost (interest) param
A := #confidential#;



var produced{P,Q,-qmax..T}>=0;              #volume produced at plant i
of product n on day t

var trans{i in I,L[i],Q,-qmax..T}>=0;       #volume sent from facility i
to facility j with shelf-life s on day t

var inv{I,Q,-qmax..T}>=0;                   #volume with shelf life s in
inventory at facility g at the start of day t

var waste{I,-qmax..T}>=0;                   #volume wasted at facility g
on day t

var beta{i in W,L[i]} binary;


minimize total_cost:
      sum{i in P,q in Q,t in -qmax..T}pcost*produced[i,q,t] +
      sum{i in I,j in L[i],q in Q,t in -qmax..T}(dcost[i,j]*trans[i,j,q,t])
      +
      sum{i in I,t in -qmax..T}wcost*waste[i,t] +
      sum{i in I,q in Q,t in -qmax..T}((ucost*inv[i,q,t])/365)*capcost;


subject to

waste_cons{i in I,q in Q,t in -qmax..T_q=qmin-1}:
      waste[i,t] = inv[i,q,t];

inventory_plants{i in P,q in Q,t in -qmax+1..T:qmin[i]<=q<=qmax}:
      inv[i,q-1,t]  =  inv[i,q,t-1]  +  produced[i,q,t-1]  -  sum{j  in
L[i]:qmin[i]+lt[i,j]<=q<=qmax}trans[i,j,q,t-1];

inventory_warehouses{i in W,q in Q,t in -qmax+1..T:qmin[i]<=q<=qmax}:
      inv[i,q-1,t] = inv[i,q,t-1] + sum{j in K[i]:qmin[j]<=q<=qmax-lt[j,i]
and   t>-qmax+lt[j,i]}trans[j,i,q+lt[j,i],t-lt[j,i]-1]   -   sum{j   in
L[i]:qmin[i]+lt[i,j]<=q<=qmax}trans[i,j,q,t-1];

demand_satisfaction{i in R,t in 1..T}:
      demand[i,t]   =   sum{j   in   K[i],q   in   Q:qmin[j]<=q<=qmax-
lt[j,i]}trans[j,i,q+lt[j,i],t-lt[j,i]];
```

```
no_inv_qmax{i in I,q in Q,t in -qmax..T:q=qmax}:
      inv[i,q,t] = 0;

no_production_on_weekends{i in P,q in Q,t in U:qmin[i]<=q<=qmax}:
      produced[i,q,t] = 0;

produce_qmax_only{i in P,q in Q,t in -qmax..T:q<>qmax}:
      produced[i,q,t] = 0;

safety_stock_plants{i in P,t in 1..T-10}:
      sum{q    in    Q:qmin[i]<=q<=qmax}inv[i,q,t]    >=    ((sum{d    in
1..T:t+1<=d<=t+10}forecast[i,d])/10);

safety_stock_warehouses{i in W,j in K[i],t in -qmax..T:1<=t<=T-10}:
      sum{q    in    Q:qmin[i]<=q<=qmax}inv[i,q,t]    >=    ((sum{d    in
1..T:t+1<=d<=t+10}forecast[i,d])/10)*lt[j,i];

beta_cons1{i in W,j in L[i],t in -qmax..T:t<=T-lt[I,j]}:
      sum{q in Q}trans[i,j,q,t] <= beta[i,j]*demand[j,t+lt[i,j]];

beta_cons2{i in R}:
      sum{j in K[i]}beta[j,i] = 1;
```