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From Tactical to Operational Routes in a Grocery Supply Chain

Quantifying the Impact of Increased
Information Sharing Between a Wholesaler
and a Transport Company

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Maybe this time Sisyphus will reach the top...

Problem Description

The grocery industry is influenced by promotional and seasonal products. These are challenging because they require inventory build-ups and changes in the tactical distribution plans compared to the normal order pattern.

In this thesis, we aim to examine the optimal distribution of grocery products in the light of information sharing between a wholesaler and a third party transport company in the grocery industry. The time the transport company receives information regarding outgoing orders determines when they can start the planning of the respective orders. We strive to analyze how the possibility to deliver parts of customer orders before scheduled delivery time, as a consequence of increased information sharing, affects the transportation performance.

The study will be conducted using an operation research framework. The planning horizon of the study is on an operational and tactical level, using time resolution of both days and more refined time blocks. We want to study the potential effects of increased information sharing, focusing on tactical opportunities that result from the realization of increased information sharing. An extended analysis of the output will then be used to examine if there is an effect, i.e. why/which factors make information sharing beneficial, or why is it there no potential.

Interesting aspects includes deviation between tactical and choice of operational routes, leveling of outgoing order volumes, order types' effect on the results, redistribution of cargo, change in route plans and the assignment of trucks.

Our work will try to achieve a reasonable balance between an easy applicable model and complex enough to give realistic basis for comparison for analysis of the results.

Preface

The content of this Master's thesis is a continuation of our specialization project in the fall semester of 2017, see Celius and Goldsack (2017). This thesis comprises the work performed during our last semester at the Norwegian University of Science and Technology (NTNU). Our degree specialization is in Managerial Economics and Operations Research at the Department of Industrial Economics and Technology Management.

We would like to thank our supervisors for their valuable contributions. Both your genuine interest in this topic and our work was truly motivating. Peter Schütz deserves a special gratitude for excellent guidance and feedback throughout the thesis. Even though your constructive critique was not always easy to deal with, your dry humor and funny comments repeatedly made our day, you are råbra. Furthermore, we like to thank Heidi Dreyer for connecting us with the industry partners and providing alternative viewpoints.

We would also like to give a special thanks to our industry partners who wish to remain anonymous. Without their input data and them taking the time to answer our many questions, the result would not have been the same.

I owe a special thanks to you, Madeleine, and I to you, Ebba. For discussions, your constructive feedback, support and friendship. It has been a pleasure.

We would like to acknowledge family and friends for being there throughout this fantastic and challenging journey at NTNU. And last but not least, a very special thank goes to each of our significant others. Thank you for your unconditional support despite all the highs and lows throughout this thesis process.

Ebba Celius & Madeleine Goldsack

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Abstract

In this thesis, we quantify the value of information sharing between a wholesaler and a transport company in the Norwegian grocery supply chain. Particularly, we investigate whether sharing of information at an earlier time with a transport company has any benefits to the actors, alone and combined. And if it has, how large are the benefits and why do they arise? Further, we study whether adding extra flexibility to the requirements of each actor impacts the potential benefits.

The view on benefits of information sharing in the literature is two-fold. One wing is solely positive, while the other one presents a more skeptical stance claiming benefits are limited due to complexity, cost and risks. Information sharing between actors in a supply chain has been widely investigated. Despite this interest, no or little research considers information sharing with transport providers.

We introduce two mathematical models that reflect the planning situation for the wholesaler and the transporter in an optimization framework. Both models' primal goal is to fulfill retailer demand, but they have different incentives. Furthermore, both models represent set covering problem formulations. The models are generic in order to conduct different analysis with them.

In order to evaluate the impact of information sharing, we distinguish between three different information sharing cases. The difference lies in when each actor receives information and can make decisions accordingly. We only differ between daily information and weekly information. In the case of daily information, decisions made on one day are independent of decisions made on other days. For weekly information, all decisions are made by considering the entire week as a whole. Additionally, we define two types of added flexibility. Shifting allows transporting demand on a different time than scheduled, while time-independent route selection allows choosing routes that may violate transport agreements.

We find with the mathematical models that there are no benefits to the actors from improved information sharing alone. When extra flexibility is added, there are differences from improving information sharing, though the impact is limited. Both shifting and route selection cause a one truck reduction in weekly truck usage. However, only when adding route selection flexibility is the truck reduction a result of increased information sharing. Lastly, allowing both shifting and route selection flexibility is very beneficial for the wholesaler, as a cost reduction of 14.8 % is achieved. For the transport company, however, there is a negative effect as the number of necessary trucks increases up to two, depending on the information sharing case. In conclusion, from our two mathematical models, we find that the increase of information sharing does not give any potential benefits, but it might when adding flexibility and simultaneously aligning the actors' incentives.

Sammendrag

I denne masteroppgaven kvantifiseres verdien av informasjonsdeling mellom en grossist og et transportselskap i den norske dagligvarebransjen. Vi undersøker hvorvidt det at en grossist deler informasjon med et transportselskap tidligere er fordelaktig for aktørene, både hver for seg og samlet. Dersom økt informasjonsdeling har potensielle fordeler hvor store er de og hvorfor oppstår de?

Informasjonsdeling er et tema som har blitt forsket på mye de siste årene, spesielt i verdikjedesammenheng. Holdningen til fordelene ved informasjonsdeling er todelt. Den ene er utelukkende positiv, mens den andre er mer skeptisk og påpeker at potensielle fordeler er begrenset grunnet risiko, kostnader og kompleksitet generelt. På tross av interessen rundt temaet gjelder forskningen lite eller aldri transportører.

Vi presenterer to matematiske modeller som reflekterer planleggingssituasjonen for grossisten og transportøren i en optimeringsramme i form av mengdedekningsproblemer. De to modellene har ulike insentiver, men begges primærmål er å oppfylle butikkenes vareetterspørsel. Modellene er generiske for å kunne gjennomføre mange ulike analyser med dem.

For å evaluere effekten av informasjonsdeling skiller vi mellom tre informasjonsdelingsnivåer. Forskjellen ligger i når hver aktør mottar informasjon som er betingelsen for når planleggingen av transport kan starte. Vi skiller mellom daglig og ukentlig informasjon. Med daglig informasjon blir beslutninger tatt uavhengig av andre dager i uken. Med ukentlig informasjon blir beslutninger tatt ved å vurdere alle dager i uken som en helhet. I tillegg definerer vi to typer ekstra fleksibilitet for å undersøke hvorvidt også andre faktorer påvirker effekten av informasjonsdeling. Flytting tillater transport av varer på en annen tid enn planlagt, mens tidsuavhengig rutevalg gir mulighet til å velge ruter som kan bryte transportkrav.

Resultatene fra de matematiske modellene viser at det ikke er noen forskjeller mellom informasjonsdelingsnivåene når man ikke tillater ekstra fleksibilitet, men også ved ekstra fleksibilitet ser vi at verdien av informasjonsdeling er begrenset. Ved både flytting og rutevalgsfleksibilitet reduseres ukentlig lastebilbruk med en. Imidlertidig er det kun med rutevalgsfleksibilitet at denne reduksjonen kommer som følge av informasjonsdeling. Til slutt kombinerer vi de to overnevnte fleksibilitetene, noe som er fordelaktig for grossisten da de oppnår en kostnadsreduksjon på 14,8 %. Imidlertid forverres transportselskapets forhold da lastebilbruken i dette tilfellet øker med opptil to, avhengig av informasjonsdelingsnivået. Med dette konkluderer vi at økt informasjonsdeling alene ikke gir noen potensielle fordeler, men at det kan være fordelaktig å tillate ekstra fleksibilitet samtidig som insentivene til de ulike aktørene samkjøres.

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Chapter 1

Introduction

Transportation of groceries is one of the main growth drivers in the Norwegian domestic transport work on the road (Hovi and Hansen (2009)). Simultaneously, transportation cost constitutes 33 % of the total operating cost for Norwegian wholesalers in the grocery industry (Johannson (2015); Eyefreight (2015)). Additionally, trends toward more centralized logistics systems in the grocery industry imply longer transport distances and greater need for transportation (Grønland et al. (2014)). Hence, transportation is more important than ever before in the grocery industry. As transportation cost represents one of the biggest cost drivers for the grocery industry, the improvement of transport efficiency could potentially improve the overall performance of the supply chain (Srinivas and Srinivas (2008)).

Transportation of retailer demand in the Norwegian grocery industry follows a repetitive pattern with high variation between transported volume between different days in a week (Celius and Goldsack (2017)). A smooth pattern implies less uncertainty and better resource utilization. Oppositely, high variations pose a challenge to the transportation system. This applies to for instance wholesaler and retailer inventories as well as truck capacities.

Furthermore, some Norwegian retail chains use promotions as their main demand stimulating activity (Kiil (2017)). Promotions can cause a short time increase in sales of the promoted good that can equal many hundred percentages of normal sales (Gedenk et al. (2010)). Additionally, the end-customers' demand can change from day to day with as much as 50 % in the promotion period (Ettouzani et al. (2012)). Consequently, demand for promotional products is very difficult to forecast and manage as it increases fluctuations in the supply chain (O'Donnell et al. (2006)). This might also contribute to the high variations in the repetitive transportation patterns.

From a wholesaler perspective, promotional products differ from non-promotional ones by when their order information is known. Information regarding promotional products are known months in advance, while non-promotional orders are normally known maximum a couple of days in advance (Dreyer et al. (2018)). Different information availability entails different planning possibilities for orders of the product types.

Currently, planning of retailer demand distribution is for every retail chain conducted in two stages by two different functions. The first stage is conducted by the wholesaler function that is responsible for the general and long-term planning. The second planning stage includes the more detailed planning of daily execution distribution, this is conducted by the transporter function. The two functions can either be divisions within the same company or two different companies. For third party transport providers, information regarding retailer orders are received less than 24 hours before departure, independent on when the wholesaler function receives the information (Hagen and Stefansson (2013)). Increased information availability suggest enhanced probability to improve planning and capacity utilization.

Bø et al. (2011) interviewed Norwegian transport companies and their partners. They found that the participants believed that limited information sharing was the biggest obstacle to achieving increased business efficiency. Nevertheless, no or little research regarding information sharing is related to third party logistics providers. In other words, whether increased information sharing actually has potential benefits is not investigated.

In this thesis, we study the effect of increased information sharing. We quantify the potential benefits of increased information sharing between a wholesaler and a transport company. We establish two mathematical models that each reflect the planning situation for distribution of retailer demand by the two different actors. The effect of information sharing is evaluated by modeling *when* each actor receives information. We only distinguish between daily and weekly information to differ between decisions made daily independent of other days or every day in the week combined. We also allow for additional types of flexibility to examine whether the value of information sharing is dependent on other factors. In other words, is there anything to gain from increased information sharing, and if so, how large are the benefits. Just as important is the managerial insight related to *why* the effects are as they are.

It should be noted that we do not consider an implementation of increased information sharing, but we want to asses whether it is worth investing in this type of integration. To limit the scope of the analysis we solely focus on the transportation from a wholesaler to retailers and information only from wholesaler to a transporter.

The thesis is structured as follows: First, an introduction to the Norwegian grocery industry focusing on the relationship between a wholesaler and a transport company is presented in Chapter 2. Chapter 3 elaborates on the related literature for supply chain, information sharing and mathematical models which can be used to formulate and solve the problem. In Chapter 4, verbal presentations of the models are presented, followed by the mathematical model formulations in Chapter 5. Then, in Chapter 6, a description of the data instance and how given data is adapted to the models. The results of the analysis of information sharing are presented and discussed in Chapter 7. Here we also critically review our results and models and indicate possible future research. Lastly, Chapter 8 presents a conclusion to our work.

Chapter 2

Background

The following chapter intends to provide the reader an overview of planning and execution of grocery transportation in Norway. We focus on road-based transportation and the link between a wholesaler and a transport company. First, Section 2.1 gives a general introduction to the Norwegian grocery industry. Second, Section 2.2 elaborates on categorization and ordering processes for different groceries. Lastly, Section 2.3 addresses planning of transportation in the light of information sharing.

2.1 The Norwegian Grocery Industry

In this section, the Norwegian grocery industry is introduced. We provide market shares, an overview over focal actors and their relations. We also highlight the importance of transportation.

2.1.1 The Market Consisting of Wholesalers and Grocery Stores

At the end of 2016, there were in total 3814 grocery stores, i.e. retailers, in Norway, and the Norwegian grocery market had a total net turnover of 169 413 billion NOK (Nielsen (2017)). During the 90s there were structural changes in the Norwegian grocery market which lead to a vertical integration of the supply chain, especially between the wholesaler and retailer (Wifstad et al. (2018)). Consequently, there are no longer any independent merchant wholesalers in the Norwegian grocery market (Authority (2011)). A market share overview is given in Figure 2.1, and the three largest Norwegian actors in the grocery market are namely NorgesGruppen, Coop and Rema 1000.

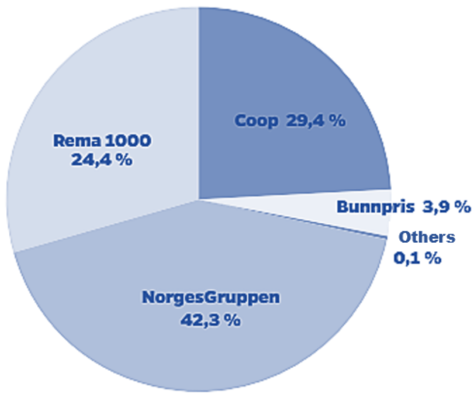


Figure 2.1: Grocery market share overview (Nielsen (2017))

Each of the actors controls a grocery chain and have a subsidiary responsible for the wholesaler functions; Coop has Coop Norge, Rema 1000 has Rema Distribusjon and NorgesGruppen has ASKO (Wifstad et al. (2018)). As for the retailers, NorgesGruppen uses different names for each of the retailer chains, such as Meny and Kiwi, while Coop applies name combinations including Coop, such as Coop Prix and Coop Obs. Rema 1000 keep one name throughout their chain. Bunnpris is an example of an actor that does not have an integration between the retailer and wholesaler level. Instead, they are cooperating with NorgesGruppen to make use of their procurement and distribution services (Solem (2016); Oslo Economics and Oeconomica (2017)). Often, the retail chains connected to a wholesaler are divided into different segments; discounter, convenience store, supermarket and hypermarket. In recent years, the share of discounters has increased and is currently the major segment (Oslo Economics and Oeconomica (2017)). Rema 1000 differs from the other actors by only operating in the discounter segment. Coop is located on the other side of the scale, operating in all the segments. Furthermore, NorgesGruppen have all segments except hypermarkets, while Bunnpris have discounters and supermarkets (Wifstad et al. (2018)). For more information regarding the grocery chains segments, see Wifstad et al. (2018).

The Norwegian retailers are either usually chain owned or franchise shops. Franchising entails that the retailer works as an independent store, but has the right to use the retail chain's business model and brand. Chain owned, on the other hand, entails that the retail chain owns the store, and hires a store manager to deal with the daily operation. While Rema 1000 only have franchise shops, NorgesGruppen, Coop and Bunnpris have a mix of both types of ownership structure (Oslo Economics and Oeconomica (2017); Wifstad et al. (2018)).

2.1.2 The Supply Chain's Actors, Functions and the Importance of Transportation

The grocery industry includes numerous actors. The Norwegian grocery supply chain traditionally consists of four to five different types of actors, namely producers, manufacturers, wholesalers, retailers and consumers (Strandhagen (2008)). Figure 2.2 provides an illustrative overview of the supply chain's actors and their roles. The figure additionally displays the typical flow of goods through the supply chain demonstrated with directional arrows between the actors as explained by Chopra and Meindl (2016) and Strandhagen (2008). The company logos are added for understanding and not to imply that some are more important than others. The blue box indicates the focal actors in this thesis.

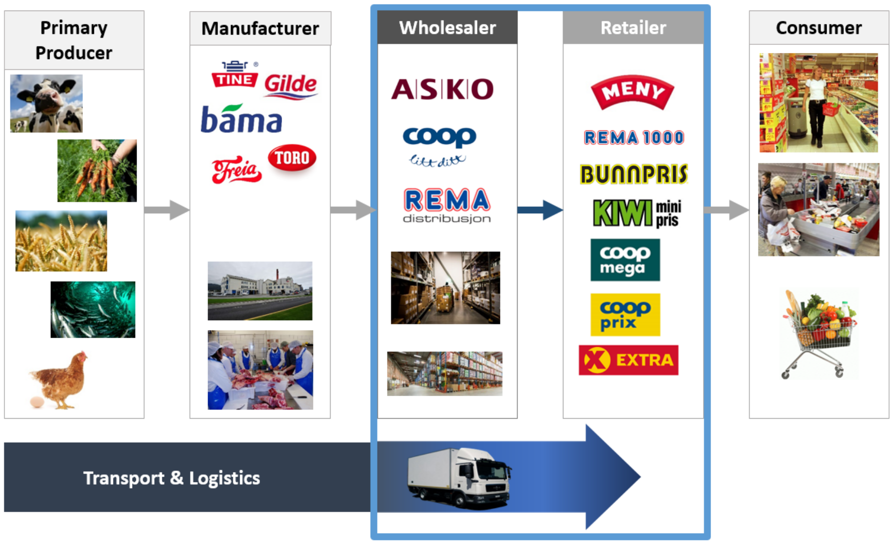


Figure 2.2: Grocery supply chain, standard illustrative overview. Adapted from Strandhagen (2008)

The actors in the grocery supply chain are responsible for performing different functions. The primary producers produce raw materials. The raw materials are transported to the manufacturers that process the raw materials into intermediate and finished products. Wholesalers purchase in bulk from the manufacturers. They act as middlemen as they distribute and sell products to retailers, thereby connecting the retailer's operations with the manufacturers' (Hübner et al. (2013)). If the wholesaler and retailer level are integrated, then the wholesaler also has additional responsible functions, such as deciding product promotion (Dreyer et al. (2018)). The retailers order and buy products through the wholesaler and resell in small quantities to the consumers. Lastly, the consumers buy products from the retailers. The movement of goods from one actor to the next in the supply chain, as indicated by the solid arrows between the actors in the figure, is conducted by transport companies.

It is noticeable that transport and logistics in Figure 2.2 are not represented as an actor, but solely a function or service illustrated as an arrow below the other actors in the supply chain. However, this is typical for supply chain representations. Even in the Norwegian National Transport Plan of 2015 (Marskar et al. (2015)), freight transport is referred to as first of all being a link in production networks. This might be explained by the extensive use of outsourcing of logistics activities to a third party provider over the past years (Jensen et al. (2014); Grønland et al. (2014))

Nevertheless, transportation is of importance especially in terms of cost. For Norwegian wholesalers in the grocery industry transportation cost constitute 33% of the total operating cost (Johannson (2015)). As these actors have expenses of billions of NOK, even a few percentages of cost-saving account for a substantial monetary sum. The cost aspect is also particularly relevant for the Norwegian grocery industry due to an increased centralization trend for all the actors in the supply chain (Grønland et al. (2014)). This entails that the groceries must be transported over longer distances. Consequently, the importance of and need for transportation is higher than ever before.

With a share of 73.37 %, road freight by truck is the dominating mode of transportation in terms of transport performance in Norway (Wethal and Lund (2017)). Furthermore, road freight by truck is the common mode of transportation for all the three Norwegian wholesalers (Coop Norge SA (2017); Rema 1000 (2016); NorgesGruppen (2016)). Some studies show that most of the costs related to logistics are coming from last mile distribution (Gevaers et al. (2011); Goodman (2005); Erengüç et al. (1999))

2.2 Categorizing Groceries Based on Ordering Processes

There are numerous ways to characterize groceries. Our categorization is made with respect to planning transportation where other aspects, such as demand, are incorporated. More specific, we distinguish between *product types* based on their respective *ordering processes.*

2.2.1 Product Types

In addition to implying different ordering differences, product types also reflect the current grocery retailing environment. In particular stable prices, promotions and seasonality. We differentiate between the following three product types:

- *Ordinary Products*
  Ordinary products refer to day-to-day retailer orders. Additionally to having stable prices, the groceries of ordinary products follow more or less the same

demand pattern throughout the year, every year, when adjusted for promotions and disturbances (Hübner (2011)). Ordinary products are ordered using a combination of manual orders and automatic replenishment programs (Thingsaker (2015)) or traditionally, only with manual orders (Yao and Dresner (2008)). Ordinary products are used by retailers to maintain a high service level for their customers, meaning they aim to avoid stock-outs (Hübner (2011)). They are usually ordered a few days in advance (Dreyer et al. (2018)).

- *Promotional Products*
  Promotional products are promoted with commercials, usually at a lower than average price. After the promotion period, the prices are raised (Anderson et al. (2017)). In Europe in 2004, between 12,1% and 25,0% of sales of groceries were made on promotion (Gedenk et al. (2010)). Compared to 2004 numbers, the share is higher today due to intense competition in the retail market causing a considerable increase in the frequency, number and extent of promotions (Ailawadi et al. (2001); McKinnon et al. (2007)). In fact, for some retail chains, promotions are currently the most used demand-stimulating activity (Kiil (2017); Ailawadi et al. (2001)). Promotional products can only be ordered manually, and retailers strive to have promotional products in-house before the start of the promotion period. They are usually ordered months in advance (Dreyer et al. (2018)).

- *Seasonal Products*
  Seasonal products have demand peak the same season(s) or occasion every year (OECD Statistics Directorate (2003)). It can either be related to consumption based on cultural tradition (Watson (2012)) or natural supply availability of raw materials. It is normal to combine expected season peaks with promotions (Bogomolova et al. (2015)). Seasonal products differ from the two other product categories by overlapping with both of them in terms of the ordering process. In other words, seasonal products either have the same ordering process as ordinary or promotional products. Therefore, this product type will not be discussed any further. However, seasonality in demand and ordering in general will.

Product type should not be confused with commodity group. To clarify, commodity groups such as dry and frozen foods compose the product types. Every commodity group can be part of any product type.

2.2.2 Ordering Processes

Different ordering processes for ordinary and promotional products imply that the roles and responsibilities are different for the actors involved. However, the most important difference between the two ordering processes is related to information availability. In particular, at what time actual aggregated retailer orders become known.

Ordering is roughly divided into two processes; manual and automatic. The ordering process reflects which actor is responsible for placing the order. A manual ordering process implies that the retailer must place manually generated orders with the wholesaler by using the retail chains' ordering platforms. However, the wholesaler is responsible for distribution of the groceries that the retailer orders contain. For the automatically generated orders, the wholesaler is responsible. The use of automatic replenishment programs is an attempt to integrate the supply chain, in particular retailers and wholesaler, in order to serve consumer needs faster, better and cheaper (Aastrup et al. (2008)). In this context, Vendor Managed Inventory (VMI) is a broadly used tool in the grocery industry (Kiil (2017)). Orders for ordinary products are generated either manually or both manually and automatically. Orders for promotional products are solely generated manually.

For manually generated orders for ordinary products, each retailer tries to avoid stock-out. This way they ensure high in-store service levels and customer satisfaction. Retailers must adhere to stipulated order deadlines in terms of both day and time of day in order to receive their orders in time. The lead time for ordinary orders differs between less than a day to a couple of days, primarily depending on the location of the retailer with respect to the wholesaler. This entails that also certain order information is defined by these stipulated order deadlines.

Orders of seasonal products can both be generated automatically and manually. Seasonal orders can be generated automatically because the forecasts for the automatic replenishment programs additionally take seasonal variations into account (Thingsaker (2015)). However, seasonal variations will be affected if the seasonal products are part of a promotion, implying that seasonal promotional products cannot be generated automatically.

Promotional planning, for which the wholesaler is responsible, starts up to half a year ahead of the promotion period's start and includes decisions regarding promotional type, assortment and prices (Hübner et al. (2013); Dreyer et al. (2018)). When these decisions are finalized for each retail chain, the retailers can access this information in a portal for promotions and manually place pre-orders (Thingsaker (2015)). The lead time for promotional products is around three months and these aggregated retailer pre-orders are then used to update promotion forecast and confirming product availability with suppliers and adjusting and coordinating retailer pre-orders (Dreyer et al. (2018)). This entails that certain promotional order information is available months in advance of delivery to the retailers. Replenishment of promotional products during the promotion period, however, is uncertain and represents an opportunity for the retailers to fine-tune promotional orders based on actual consumer demand.

Promotions normally cause a short time increase in sales of the promoted good. This increase can be many hundred percentages of normal sales (Gedenk et al. (2010)). The demand can also change from day to day with as much as 50 % in the promotion period (Ettouzani et al. (2012)). Demand for promotional products is very difficult to forecast and manage as it increases fluctuations in the supply chain (O'Donnell et al. (2006)). Furthermore, as promotions continuously vary between different foods and goods in varying times of the year, they require a more thorough planning both in terms of demand and supply, and the coordination between them (Dreyer et al. (2018)). Consequently, promotional products require a chain of active interactions between several supply chain actors.

To summarize, the information availability is highly different for the different product types from a wholesaler perspective. For ordinary products, the wholesaler has the opportunity to forecast orders the same way as with the automatically generated orders. However, as actual and forecast orders might be different, the order information is not certain before an order is placed. And as stated above, this is normally maximum a couple of day before departure from the wholesaler. The case is different for promotional products. Consequently, as the retailers must place their orders months in advance of the promotion period also this information is available months in advance.

2.3 Planning of Transportation

Planning of transportation is related to distributing goods between different sites for outgoing orders (Hübner et al. (2013)). Planning requires interaction and information sharing between the actors involved. In this section, we aim to explain how the planning of transportation is currently happening, why there is potential for improving it.

2.3.1 From a Tactical Route Plan to Operational Routes

A tactical route plan is developed by the wholesaler and specifies long-term, future routes for a region based on average forecast demand scenarios (Hübner et al. (2013)). Forecast for average demand implies uncertain information. The objective of a tactical route plan is to minimize transportation costs while constructing robust routes and taking constraining delivery requirements into account. The latter represents delivery agreements between wholesaler and retailers, specifying delivery frequency and time. Delivery frequencies for retailers are determined based on their expected order patterns (van Donselaar and Broekmeulen (2013)) and location (Vegdirektoratet (2014)). Consequently, some retailers get deliveries multiple times a day, others a few times a week dependent on size and location of the retailer. The routes are fixed for each day of the week, implying the same route is set up to serve the same retailers, the same day of the week, every week. It also specifies which retailers are to be visited on which route, in what order, on which day and time of day. The route plan is constructed so that an integer number of trucks is assigned to each route and is based on average demand scenarios. On the other hand, the plan cannot take the actual volume of orders and availability of trucks into account, and routes in the tactical route plan are therefore considered uncapacitated.

Operational routes are the day-to-day routes made up from combining the tactical route plan with actual order information. Operational routes are the routes used to distribute retailer orders, executed by the transport company. These routes require and are based on certain information. As the tactical plan is designed for an average demand scenario, they might not be optimal to use for distribution when the orders do not represent an average demand scenario. Deriving operational routes from a tactical plan also involves assigning operational resources such as personnel and trucks for actual delivery jobs (Hübner et al. (2013)).

An illustrative overview of the necessary activities and directed information flows to go from a tactical route plan to operational routes is provided in Figure 2.3. The illustration is based on the written description of Dreyer et al. (2018).

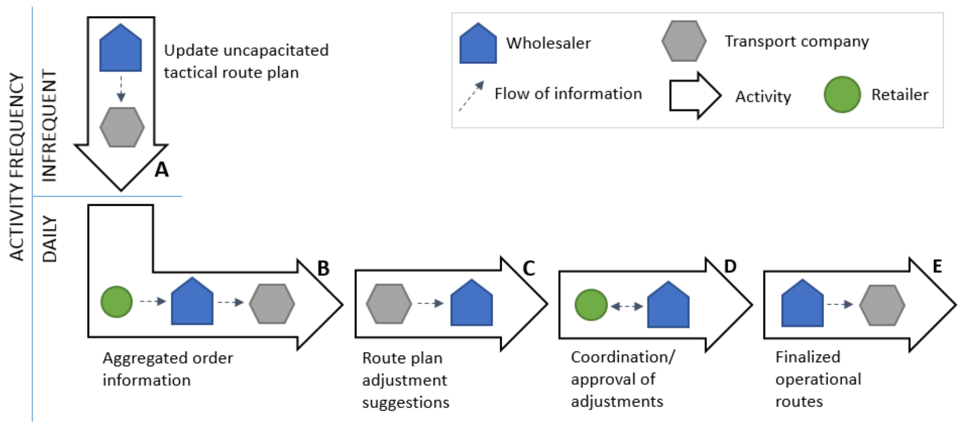


Figure 2.3: Going from a tactical route plan to operational routes with information flows

Figure 2.3 shows how the transition from the tactical route plan over to the development of the operational routes. The tactical route plan is changed if long-term developments in actual or expected order patterns occur or in the case of new retailer delivery agreements. Furthermore, the transport company continuously receives information regarding these changes, see arrow **A**. As indicated above, operational routes are generated based on a tactical plan by taking actual retailer order information into account. In other words, the main difference between the tactical and operational routes is the possibility to plan according to actual retailer order information. The day before departure, the wholesaler aggregates retailer orders for all product types and gives this information to the transport company, see arrow **B**.

At point **B**, the transport company has obtained the tactical route plan that is based on general demand scenarios for the next day and actual retailer information for the same day. The transport company suggests adjustments to the tactical route plan if actual orders and forecasts deviate. These adjustments are also suggested based on truck capacities, see arrow **C**. Adjustments, if necessary, include adjusting the volume delivered to each retailer on each route and suggesting that some goods should be delivered on a different time than scheduled. In this way, improved cost minimization based on truck fleet utilization can be achieved. It should be noted that these adjustments presume the goods in the retailer orders are available at the time of departure from the wholesaler. However, all changes to the tactical plan must be coordinated and approved by both wholesaler and retailers before executed by the transport company, represented by arrow **D** and **E** respectively.

The transport company can start the operational planning of transportation only when they receive information regarding outgoing orders. Regardless of the product type, retailer order information is shared with the transport company the day before departure from the wholesaler. Especially for promotional products, order information is available weeks in advance. Using more information earlier could potentially be beneficial in terms of reducing transportation costs by enhancing the truck fleet utilization. Information sharing within a company might be challenging (Li and Lin (2006)), and if the transportation is outsourced then the transition from tactical to operational is even more challenging due to the information flow cross-organizational.

2.3.2 Weekly Grocery Freight Pattern from Wholesaler to Retailers

Retailer orders in grocery retail have a repetitive pattern (Hübner et al. (2013)), implying also a repetitive delivery pattern. Repetitive delivery patterns increase the stability of planning and workload and consequently minimize operational costs directly dependent on the delivery patterns (Holzapfel et al. (2016)). In other words, this increases predictability and consequently lowers the chance of unexpected costs related to resource allocation.

Figure 2.4 shows a typical pattern of departures from a Norwegian, regional wholesaler for a low, medium and high demand week. The route lengths differ between less than a day to several days, therefore the pattern for deliveries at retailers might look slightly different.

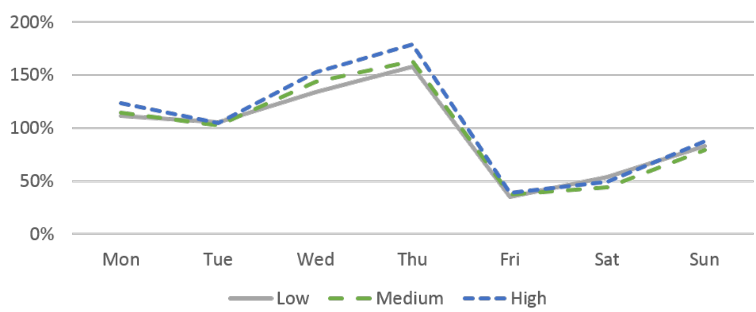


Figure 2.4: Transported retailer demand volume from a Norwegian wholesale for low, medium and high demand weeks. 100 % represents the overall average. From Celius and Goldsack (2017)

The three different demand weeks in Figure 2.4 have a similar weekly freight pattern. The pattern can be explained based on consumer behavior. Consumers do most of the grocery shopping in the weekend, including Friday. The retailers prepare for the weekend rush by filling their inventories, thus receive the cargo on Thursday in order to prepare for the weekend. By receiving the orders before the weekend rush they do not need extra labor to handle both serving consumers and reception of goods. Therefore, the lowest number of departures on Friday can be explained by retailer unwillingness to receive orders in the weekend. The increasing number of departures after Friday is due to the necessity of filling up inventories after the weekend.

Promotional products also contribute to the freight peak on Thursday. Due to inventory restrictions, it is advantageous for the retailer to receive promotional goods as late as possible. However, as stated in Section 2.2.1, the groceries must be in-house before the start of the promotion period. This together with deliveries only on fixed days, making deliveries of promotional products together with weekend volume a natural choice as this is the last possible departure time for the retailer to get their goods in time.

Even though this weekly demand pattern is repetitive, it implicates challenges for the transportation system. As can be seen in Figure 2.4, the number of daily departures differ more than 100 % during the week for every demand week. This implicates a high variation of demand and transported volume. This is challenging for a transport company that has a fixed fleet of trucks. Considering only the extreme cases, they must decide if it is most profitable to have a fleet that can serve all levels of demand or to have a smaller fleet and rent external capacity for peak days. For the freight pattern as displayed in Figure 2.4, the first option implies high fixed costs and a significant number of trucks often not being in use. The second option entails high variable costs related to external capacity, but a fleet where all owned trucks are in use at all times. None of these options are optimal. With a less varying demand pattern, it would be possible to lower overall costs.

2.3.3 Daily Volume Leveling and Information Sharing

Transport companies that operate in markets with significant differences in peak and non-peak demand (periods) often seek to negotiate for a leveling of demand with the wholesaler (Lim et al. (2008)). It should be noted that leveling of transported volume, also called shifting, here implies transportation of (parts of) orders on a different day than scheduled. As explained and illustrated in Section 2.3.2 and Figure 2.4, daily departures differ more than 100% during the week in the distribution of groceries from wholesaler to retailers. Thus, transport companies in this market have an incentive to negotiate for leveling. For instance, it might be favorable to deliver a pallet on a different day than to deliver it with a new truck the same day if the total route capacity is exceeded the current day. However, to implement shifting, certain prerequisites must be in place.

In order to be shifted, a commodity group must possess the quality of storability. Shifting implies that groceries are delivered either earlier or later than scheduled. In the case of an early delivery, the commodity will be at the retailer inventory earlier than planned. In the case of a late delivery, the commodity must be stored at the wholesaler warehouse or in a truck until it is delivered to the retailer. It should be noted that storability also requires storage capacity, i.e. inventories must handle the additional stock. However, regardless of the location of the inventory, the importance is that the grocery does not deteriorate when being stored.

As indicated in Section 2.2.2, ordinary and promotional products are different in terms of certainty and information availability as a consequence of their ordering processes. Information regarding promotional products is known weeks in advance of delivery, as opposed to ordinary products which order information might be known less than a day in advance. Even though forecasts for ordinary products are quite accurate, they are not certain. As promotional products are the only products with certain information availability well in advance of the delivery, promotional products can be delivered earlier than planned. Once again, this requires that retailer inventories can handle the extra volume.

The different product types necessitate different delivery requirements. An important aspect with deliveries of promotional products is that they must be delivered no later than the beginning of the promotion period, see Section 2.2.1. Hence, there exists a possibility for early delivery of promotional products. This requisite does not apply to ordinary products due to uncertainty. As stated in see Section 2.2.1, the orders of ordinary products are used to avoid stock-outs and to maintain a high service level. However, if they are not at the risk of stock-outs immediately after a planned delivery, the retailers should be willing to accept a delivery later than planned given it is within reasonable time.

Table 2.1 provides an overview of shiftable groceries, based on the argumentation in this section. Non-storable products are delivered as ordered. Storable products have the potential to be shifted depending on product type; promotional may be delivered earlier and storable ordinary may be delivered later.

Table 2.1: Shiftable groceries based on product type and storability

	Early Delivery		Late Delivery	
	storable	non-storable	storable	non-storable
ordinary	non-shiftable	non-shiftable	**shiftable**	non-shiftable
promotional	**shiftable**	non-shiftable	non-shiftable	non-shiftable

2.4 Differences in Incentives and Goals Between the Wholesaler and the Transport Company

Incentives for the different actors are crucial in order to understand their conflicting interests in processes and procedures.

The wholesaler's main concern is the cost of transporting pallets, i.e. invoiced cost for the number of transported pallets. The pallets are therefore optimized in the sense that they are assembled in the most compact and cost-efficient way. In most cases, the pallet cost reflects the transported volume, i.e. it is a constant unit cost per pallet (Bø et al. (2011)). The cost increases the longer the distance the pallets are transported.

The wholesaler is further concerned with the utilization of the inventory capacity. As a consequence, the wholesaler would like to level the daily arrival and departure of pallets. On the other hand, the wholesaler has a high interest in satisfying the retailers and their requirements. This includes the inventories restrictions at the retailers. Additionally, it is the wholesaler that plans and is responsible for the marketing of promotions. They have therefore the incentive to level and plan according to both the promotions arriving on time as well as leveling the daily departure of pallets. From Figure 2.4 we see the demand has high variations and is not leveled. This is because most of the demand is generated from POS and is therefore highly dependent on end-customers demand pattern. Consequently, there is a trade-off between utilization of resources and fulfilling the end-customers demand.

The transport company is concerned with the actual cost of transporting the pallets which is not necessarily directly linked to the aggregated transported volume. The transport cost is highly dependent on the number of trucks and of the utilization of them. These costs are more dependent on the number of trucks used and which routes are driven, rather than the number of pallets transported. Use of rented truck is another important cost the the transport company is concerned about. They must make use of rented trucks if their own truck capacity is insufficient. These cost components give the transport company high incentives to utilize their overall truck capacity. Lower transport cost for the transport company can result in lower unit pallet cost for the wholesaler as the invoiced pallet cost reflects the transport company's operating cost.

Chapter 3

Literature Review

This chapter gives a review of relevant literature for analyzing information sharing and transportation in an optimization-related context. The existing research in the field of logistics is usually two-fold: One part is of qualitative research, deriving business strategies. The other part, however, considers more quantitative studies and operational research. In this literature review, both types of studies are considered. Section 3.1 discusses relevant literature for the supply chain as well as the decisions in different planning levels. In Section 3.2, the literature on information sharing within an supply chain, as well as its impact is reviewed. Then Section 3.3 look at what influence promotion have on the supply chain. Lastly, Section 3.4 covers solution methods in general regarding logistics and transportation.

3.1 The Supply Chain

It is well recognized that there is a great potential for cost saving when coordinating the decisions involved in a supply chain (De Matta and Miller (2004); Hall and Potts (2003)). Supply chain management (SCM) includes the design of, planning for and operation of a network of suppliers, production facilities, warehouses, and distribution centers in order to satisfy customer demand (Schütz et al. (2009)). The processes in a supply chain consist of physical and information flows, as well as financial flows. Section 3.1.1 go through the different planning levels in the supply chain, while Section 3.1.2 go through the research on transportation as a part of the supply chain.

3.1.1 Planning Levels

Decisions and planning are important aspects of SCM. In a supply chain the planning can be divided into three different levels; strategic, tactical and operational. Every planning level are distinguished depending on the duration, size and scope of the decisions within (Hübner et al. (2013); Chopra and Meindl (2016); Mula et al. (2010)). The strategic level usually considers time horizons of more then one year, and requires approximate and aggregated data while the operational level involves short-term decisions, often less than an hour or a day, and requires transactional data (Vidal and Goetschalckx (1997)). The tactical level falls in between those two extremes with respect to the duration, and the amount and accuracy of data required.

Strategic	**Tactical**	**Operational**
• Physical network design • Information systems design • Make-or-Buy	• Service network design • Capacity planning • Route planning	• Scheduling & adjustment of the route plan • Arrangement of cargo • Assigning routes to vehicles

Figure 3.1: Planning levels in a supply chain

Figure 3.1 illustrates the main decisions in the different levels regarding transportation planning. For this thesis, the interface between the tactical and operational planning is the most relevant. However, it should be noted that the strategic decisions determine the design and development of the physical network of a business and can be related to the location of facilities, make-or-buy decisions, and choice of which information systems to implement (Crainic and Laporte (1997)). These decisions then form constraints for the tactical and operational planning levels.

The tactical planning level forms a bridge between the strategic and operational planning levels (Schmidt and Wilhelm (2000a)). The tactical decisions are concerned with 'where' and 'how' issues such as deciding primal routes and the size of the truck fleet (Crainic and Laporte (1997); Crainic (2000)), as well as positioning inventories to use in the operational planning level (Schmidt and Wilhelm (2000a)).

The operational planning level, on the other hand, is more interested in 'when' issues (Crainic and Laporte (1997)). During operational decision-making, the implementation and adjustment of schedules are made based on decisions from the tactical and strategic planning levels. This includes crew scheduling, dispatching of vehicles and the allocation of scarce resources, all to assure in-time delivery of final products to customers (Caris et al. (2008)). Operational decisions are done in a highly dynamic environment where the time factor plays an important role, and detailed representations of vehicles, facilities and activities are essential (Crainic (2000)). The operational planning level can significantly affect customer service, so it is an important component in providing a unified logistics system (Schmidt and Wilhelm (2000b)). See the review by Mula et al. (2010) for an overview of mathematical programming models for supply chain production and transport planning branched between the strategic, tactical and operational planning levels.

3.1.2 Transportation as an Integrated Part of the Supply Chain

Most of the work reported in the literature addresses the supply chain from a strategic or tactical point of view to optimally configure and manage the system according to some economic objective (Mula et al. (2010); Beamon (1998); Erengüç et al. (1999); van Hoek et al. (2001); Schmidt and Wilhelm (2000a)). Research to analyze short-term distribution scheduling from an operational perspective has been conducted, although the problem has been dealt with primarily independent and decoupled from a supply chain environment (Chandra and Fisher (1994); Chen and Vairaktarakis (2005); Ertogral et al. (1998)). Furthermore, Aristizabal and Brenninkmeijer (2017) state that lean principles, e.g. leveling of demand, have been applied extensively in manufacturing settings, while the logistics domain remains a relatively unexplored lean frontier.

A lot of research has been done regarding the manufacture/retail relationship, but the physical process of moving the product has largely been ignored (Fernie and Sparks (2014)). The research is also usually done from the wholesaler/retailers perspective and little is explored regarding the transporter's perspective (Bø et al. (2011)). Transportation is considered as a function in the supply chain and normally not as an independent actor. Thus, there exists a gap in literature between the increased amount of logistics service providers and their significance as an actor. Consequently, transportation as an integrated part of the supply chain is not generally considered and there is lack of research coordinating third-party actors in the supply chain (Yingzhao and Jing (2009)). There is a generally accepted theory concerning outsourcing of logistics and transportation being an obvious trend in supply chain management (Langley (2015); Van Hoek (1998); Sahin and Robinson (2002); Yingzhao and Jing (2009)). Without the linking of transportation, a powerful logistics strategy cannot bring its capacity into full play (Srinivas and Srinivas (2008)), since transport is one of the largest components of the cost structure of a business' logistics (Eyefreight (2015)). The reason for lack of research could be that transportation is seen as a necessary evil (Eyefreight (2015)), and an inevitable source of cost and risk (Bonfill et al. (2008)), rather than a potential area for cost savings when integrated with the supply chain.

3.2 Conflicting Viewpoints on Information Sharing

The task of determining what information should be shared when and with whom is a complex task. Chopra and Meindl (2016) state that information improves the utilization of supply chain assets and the coordination of supply chain flows to increase responsiveness and reduce cost. Information is a key driver that can be used to provide higher responsiveness while simultaneously improving efficiency. However, there are two distinct views in the literature considering the value and benefit of information sharing. Namely, whether shared information could lead to improvement to the supply chain or if the potential benefits are highly limited (Kembro and Näslund (2014)).

The first viewpoint indicates that the benefits of information sharing in supply chains, in reality, are limited due to complexity, costs and risks (Kemppainen and Vepsäläinen (2003); Samaddar et al. (2006); Jungbae Roh et al. (2008); Vanpoucke et al. (2009)). Vanpoucke et al. (2009) state that companies often are disappointed by the low benefit-cost ratio of information sharing applications. Lee and Whang (2000) highlight the dilemma in information sharing on how to allocate the claimed benefits of increased information sharing in supply chains. Hall and Saygin (2012) argue that the act of transferring data between activities alone will not improve supply chain performance unless the information is accompanied by more robust requirements for collaboration/-cooperation.

Gustavsson and Jonsson (2008) argue that information in a supply chain must be of the right quality if it is used to make decisions. They find that in the case of insufficient information quality, additional information leads to increased costs in the supply chain, and a mismatch in supply and demand. Dimensions of quality are related to accuracy, timeliness, correctness, and ease of use. Chan and Chan (2009) find that partial information sharing may perform reasonably well compared to full information sharing, indicating there might be a trade-off between the benefit of the information and the relative cost. Lee et al. (2000) conclude that information sharing is most beneficial when lead times are long, demand variation is high and demand correlation over time is high.

The *bullwhip effect* occurs when the variance of orders may be larger than that of sales, and distortion tends to increase as one moves upstream in the supply chain (Lee et al. (1997a)). Bø et al. (2011) find that bullwhip effect additionally affect the transport costs: The further upstream in the supply chain the transportation occurs, the higher the fluctuations in demand and this consequently increases costs. Although the precise causes of the bullwhip effect remain under debate, it is generally agreed that a lack of inter-company communication combined with large time lags between receipt and transmittal of information are at the root of the problem (Metters (1997)).

The second viewpoint is that shared information could potentially lead to benefits. Benefits include creating value via enhanced planning and decision-making processes (Mohr and Spekman (1994); Sahin and Robinson (2002)), as well as improved supply chain coordination, bullwhip effect reduction, and decreased supply chain costs (Anand and Mendelson (1997); Lee et al. (1997a)). Some research also concludes that shared information may lead to improved long-term relationships by sharing information at different organizational levels between members in the supply chain (Sanders and Premus (2005)).

The overall trade-off of information sharing is complexity versus value (Chopra and Meindl (2016)). Good information helps a firm improve both efficiency and responsiveness, but more information is not always better. More information increases complexity and cost of both infrastructure and analysis exponentially while marginal value diminishes. Therefore, a supply chain must evaluate the minimum information required to accomplish the desired objectives. Information utilization has only received limited scientific attention despite its connection and importance for information sharing (Jonsson and Myrelid (2016); Myrelid (2015)). Kembro and Näslund (2014) could not find empirical evidence that benefits of information sharing in supply chains actually exist.

3.3 Promotions' Influence on the Supply Chain

Promotional tools are used to increase sales, build brand value and recognition, strengthen market positioning, and launch new products (Boundless). This section discusses the influence promotions have on the supply chain. Gedenk et al. (2010) conclude that due to development of new technologies the promotions are becoming more flexible, and predict that larger parts of the promotion budgets of retailers and manufacturers will be spent on in-store promotions.

Promotions usually consist of a high-low pricing strategy which results in a peak during the discount week, often followed by a steep drop in demand during the following weeks. The opposite strategy, *Every Day Low Prices* (EDLP), is based on keeping the overall prices lower by smoothing the demand and thereby increase the effectiveness of the supply chain (Chopra and Meindl (2016)). The two pricing strategies lead to very different demand profiles that the supply chain must serve. In spite of their importance within pricing strategies, seasonal sales and promotions have received little attention within the literature (McGoldrick et al. (2000); Kiil (2017); Powers and Closs (1987)).

Seen with purely "supply chain alignment glasses", an EDLP strategy would benefit the chain the most due to lower variability and the fact that high-low pricing leads to desynchronized delivery and purchase (Lee et al. (1997b)), and would further benefit transportation costs. On the other hand, the supply chain includes marketing, customers preference and other factors that lead to strategies involving sales promotions.

(Buzzell and Quelch (1990)) suggests EDLP and identified manufacturer trade promotions as the main difficulty in achieving coordination in the supply chain. On the contrary, Hoch et al. (1994) compare EDLP and high-low pricing in the supermarket grocery industry. They find that gross profit was 35 % greater when employing a high-low versus an EDLP strategy. Papers by Hoch et al. (1994) and Ho et al. (1998) built models that additionally advocate promotions at store-level. Iyer and Ye (2001) find that manufacturer and retailer price variation can play a valuable role in improving logistics system performance in promotional retail environments. Kiil (2017) concludes that the main challenge for managing promotional products is a lack of cross-functional coordination and the use of sporadic and separate processes. This results in separate plans and only passive involvement of suppliers and customers.

Price fluctuations increase the bullwhip effect on orders placed by retailers as manufacturers will not be able to meet the full retailers demand due to inaccurate demand pattern (Kusi-Sarpong (2012)). The lack of demand signaling, i.e. information distortion, leads to multiple forecasts and lack of visibility (Lee et al. (1997b)). According to Kusi-Sarpong (2012) trade promotion can persuade the retailer to order and hold more units than the normal amount. Manufacturers put forward the volume allowances concept to get the retailers to hold enough stock in their warehouses or stores, which end up in stock reallocated from the manufacturers to the retailers as well as the customers. Thus, the order volume has higher variations and uncertainties and thereby affect transportation.

To our knowledge, there are no papers researching the effect promotions have on transportation, only the manufacturing process or the supply chain as a whole.

3.4 Quantitative Planning of Transportation

Quantitative models are important as base for plans that aim to minimize the sum of inventory costs, production costs, transportation costs, and costs of capacity extensions (Chopra and Meindl (2016)). Quantitative models are central in the planning of physical distribution and logistics (Laporte (1992)). Extensive research in logistics in supply chain management is done in the fields of production-inventory and inventory replenishment (Kapuscinski and Tayur (1999); Glasserman (1999); Chen (1999); Chopra and Meindl (2016)). Planning of transportation, however, is conducted primarily with transportation routing problems. The *Traveling Salesman Problem* (TSP) and the *Vehicle Routing Problem* (VRP) are the most well-known and applied transportation routing problems. However, as the VRP is a generalization of the TSP only the VRP will be properly explained. Crainic and Laporte (1997) define the VRP as a tactical problem, while the operational problem is described as the response in real time. The VRP is discussed in Section 3.4.1, while set-covering formulations of the VRP are presented in Section 3.4.2.

3.4.1 The VRP

The VRP is an optimization problem that includes a given set of customers with demand and a fleet of vehicles. The problem itself makes the best routes in order to serve the customers with the available number of vehicles. The routes always start and end from a central depot Several versions of the problem can be defined, depending on a number of factors, constraints and objectives. Extensions might include time windows (VRPTW), both pick-up and delivery demand (VRPPD) and that vehicles may be assigned to multiple routes (VRPMT). For more comprehensive overviews of different versions of the VRP, see Caceres-Cruz et al. (2015), Crainic and Laporte (1997), Toth and Vigo (2015) or Laporte (1992).

One of the basic versions of the VRP with multiple vehicles (instead of just one as with the TSP) is the *the Capacitated VRP* (CVRP). In the CVRP, every customer corresponds to a delivery and the demands are deterministic, known in advance, and may not be split. The vehicles are identical and based at a single central depot, and the capacity restrictions for the vehicles are imposed. The objective is to minimize the total cost of serving all the customers.

Below follows a vehicle flow formulation of the asymmetric, i.e. direction dependent, CVRP where the objective is to minimize the cost for traveling on different arcs while visiting customers. The set of customers is denoted $\mathcal{N}$, where the depot is included as node 0. There exist a set of arcs, (i, j) , between the set of customers. A non-negative cost, c_{ij}, is associated with each arc and represents the travel cost spent to travel from node i to node j. The set of vehicles is denoted $\mathcal{V}$, with the index v for each individual truck. The variable x_{ijv} is 1 if arc (i, j) is traversed by vehicle v in the optimal solution. y_{iv} takes value 1 if customer i is served by vehicle v in the optimal solution and takes value 0 otherwise.

$$
\begin{aligned}
\min \quad & \sum_{i\in\mathcal{N}}\sum_{j\in\mathcal{N}}\sum_{k\in\mathcal{V}} c_{ij}x_{ijv} && && (3.1)\\
\text{s.t.} \quad & \sum_{v\in\mathcal{V}} y_{iv} = 1 && i \in \mathcal{N}\backslash\{0\} && (3.2)\\
& \sum_{v\in\mathcal{V}} y_{0v} = K && && (3.3)\\
& \sum_{j\in\mathcal{N}} x_{ijv} = \sum_{j\in\mathcal{N}} x_{jiv} = y_{iv} && i \in \mathcal{N}, v \in \mathcal{V} && (3.4)\\
& \sum_{i\in\mathcal{N}} D_i y_{iv} \le C && v \in \mathcal{V} && (3.5)\\
& \sum_{i\in\mathcal{S}}\sum_{j\in\mathcal{S}} x_{ijv} \le |\mathcal{S}| - 1 && \mathcal{S} \subset \mathcal{N}\backslash\{0\}, |\mathcal{S}| \ge 2, v \in \mathcal{N} && (3.6)\\
& y_{iv} \in \{0, 1\} && i \in \mathcal{N}, v \in \mathcal{V} && (3.7)\\
& x_{ijv} \in \{0, 1\} && i, j \in \mathcal{N}, v \in \mathcal{V} && (3.8)
\end{aligned}
$$

Constraint (3.2) imposes that each customer is visited exactly once, while (3.3) ensures that K vehicles leave the depot. (3.4) makes sure the same vehicle enters and leaves a given customer. Constraint (3.5) is the capacity restriction for each vehicle v which makes this a capacitated problem. Constraint (3.6) is the sub-tour elimination constraint which imposes that for each vehicle v at least 1 arc leaves each vertex set S visited by v and not containing the depot. Since this problem grows exponentially with the size of the problem one usually considers only a limited subset of these constraints and to add the remaining ones only if needed, by using appropriate separation procedures. The last two constraints, (3.7) and (3.8), impose integer requirements on the variables.

3.4.2 The Set-Covering Formulation of the VRP

According to Toth and Vigo (2015), the most common way to solve a VRP is as a vehicle flow formulation that uses a binary variable x to indicate if a vehicle traverses an arc in the optimal solution (e.g. CVRP in the equations (3.1)-(3.8)). Another approach to solving the VRP is the use of *Set-Partitioning* (SP) or a *Set-Covering* (SC) formulation to find the best routes at the lowest cost (Balinski and Quandt (1964); Toth and Vigo (2015); Dayarian et al. (2015); Desrochers et al. (1992); Baldacci et al. (2011); Cacchiani et al. (2014); Rousseau et al. (2002); Campbell and Thomas (2008)).

SP or SC formulations use a possibly exponential number of binary variables, each associated with a different feasible route. More specifically, let $\mathcal{R} = \{1, ..., R\}$ denote the collection of all the feasible routes, with index r. Each route has an associated cost c_r. In addition, let a_{ir} be a binary coefficient that takes value 1 if node i is visited (i.e. covered) by route R_r and takes value 0 otherwise. The binary variable $x_r, r \in \mathcal{R}$, is equal to 1 if and only if route R_r is selected in the optimal solution. The model for an SP is:

$$\min \quad \sum_{r \in \mathcal{R}} c_r x_r \tag{3.9}$$

$$\text{s.t.} \quad \sum_{r \in \mathcal{R}} A_{ir} x_r = 1 \qquad i \in \mathcal{N} \tag{3.10}$$

$$\sum_{r \in \mathcal{R}} x_r = K \tag{3.11}$$

$$x_r \in \{0, 1\} \qquad r \in \mathcal{R} \tag{3.12}$$

Constraint (3.10) imposes that each customer i is covered by exactly one of the selected routes, and (3.11) requires that K routes are selected. The model becomes an SC problem by changing constraint (3.10) to an inequality, meaning a node can be visited by more than exactly one route, see Equation 3.10'.

$$\sum_{r \in \mathcal{R}} A_{ir} x_r \geq 1 \qquad i \in \mathcal{N} \tag{3.10'}$$

One of the main benefits of the SP or SC approach is the flexibility of the very general model. It may easily take into account several constraints as, for example, time windows, since route feasibility is implicitly considered in the definition of set $\mathcal{R}$. The main challenge on the other hand, is generating the feasible routes. There are two main approaches to this, either generate all possible routes a priori or generating them iteratively while solving the SP or SC. The explicit generation of all feasible routes is normally impractical due to the huge number of variables.

A common approach to solve the VRP as an SP or SC problem iteratively is by using column generation (Dayarian et al. (2015)). Equation set (3.9)-(3.12) would then be the master problem, using a partial set of feasible routes that is enriched iteratively by solving a sub-problem. The sub-problem is used to find new routes that offer a better way to visit the customers. Each feasible solution in the sub-problem is represented as a new column in the master problem, where each new column could potentially improve the current optimal solution in the master problem (Desrosiers and Lübbecke (2005)). The sub-problem can include for instance constraints concerning capacity and time windows. See Dayarian et al. (2015) for a thorough literature review of the advancement of column generation and the use of set-covering in the area of VRP.

One of the main drawbacks of solving VRP as a master and a sub-problem with SP or SC is the huge number of variables as well as the necessity of generating all feasible routes (Toth and Vigo (2015)). Exact methods are limited to small problem sizes, and even heuristic methods are intractable in the face of real-world-sized instances (Campbell and Thomas (2008)). Generating a favorable new route is already NP-hard since a new route need to solve multiple TSPs (Laporte and Nobert (1980)). Heuristics for the sub-problem could be avoided if the routes are found a priori, as is the situation when looking at an operational perspective where tactical routes are already solved at an earlier stage.

In this thesis, we establish two mathematical models that reflect the planning situation of a wholesaler and a transport company, i.e. going from tactical route planning to operational execution. We use an SC approach as we are given a set of pregenerated, tactical routes.

Chapter 4

Problem Formulation

We use the planning process going from a tactical route plan to operational routes to study the effect of information sharing between the actors responsible for the respective planning processes. In this case, tactical planning is carried out by a wholesaler and operational planning is concluded by a transport company, respectively. We do this by establishing two deterministic, mathematical models that represent the selection of routes and consequently the necessary number of trucks to serve retailer demand based on the different selection criteria of the two actors.

First, in Section 4.1 we address how information sharing is defined and analyzed. Then, the wholesaler and transporter model are listed in Section 4.2. Thereon, information sharing and models are combined in Section 4.3. Common, general model features are presented in Section 4.4. Lastly, shifting as added flexibility resulting from increased information availability is elaborated in Section 4.5.

It should be noted that tactical planning in this chapter refers to what the supply chain literature would consider as a transition state between tactical and operational planning.

4.1 Information Sharing Cases

The terms information and information sharing hold many of the same aspects, but they are still different. The content of information is conditional on who receives it and when. While information to the wholesaler refers to retailer order information only, information to the transport company includes both retailer order information and tactical routes as decided by the wholesaler. We refer to information sharing as the wholesaler sharing information with the transport company.

The wholesaler cannot share information they do not possess, meaning the transport company cannot receive information before the wholesaler does. As the transport company is dependent on a tactical route plan, they receive information from the wholesaler after tactical route planning is carried out, but sufficient time before next day's departure so that they can conduct the operational planning. However, the wholesaler can choose to await sharing information they possess. Nevertheless, both actors are dependent on information in order to conduct tactical and operational planning.

We distinguish between information availability regarding next day's departures only and for a whole week. In this respect we introduce the *planning horizon*, which is a set of future day(s) information is known for, implying that it is possible to plan according to available information only. We distinguish between daily & weekly information.

In order to evaluate the effect of information sharing, we define different *information sharing cases*. These cases differ by when information is revealed for the two actors. In particular, information sharing cases reflect when information is shared with the transport company, dependent on when information is available for the wholesaler. We define the following information sharing cases: daily-daily, weekly-daily and weekly-weekly. Differences between the output of these cases are used to determine the quantified effect of information sharing.

4.1.1 Daily-Daily

In the daily-daily (DD) information sharing case, both actors plan on a daily basis. We refer to use of information on a daily basis as *daily information*. The wholesaler might receive information earlier than one day in advance but only use daily information to plan next day's transport at the end of the current day. The wholesaler uses the information regarding the next day to generate a tactical route plan for that day, which they share with the transport company. Equivalently, the transport company conducts operational planning regarding next day's departures only. In summary, the wholesaler shares the information they use themselves with the transport company. However, daily information is limited. The DD information sharing case founds a benchmark for an information sharing analysis and is illustrated in Figure 4.3.

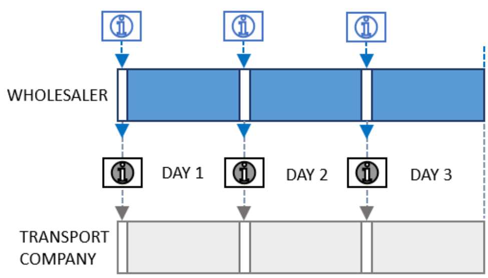


Figure 4.1: Illustrating the actors' planning horizon and information availability for the DD information sharing case

Figure 4.1 illustrates the actor's planning horizon and information availability for the DD information sharing case. Both wholesaler and transport company only use daily information for planning.

4.1.2 Weekly-Daily

In the information sharing case daily-weekly (WD), the information availability of the two actors is asymmetric. The wholesaler has a planning horizon of a week, the transport company of one day. Just before the beginning of the week, the wholesaler has full information regarding all demand for the entire following week. Departures are then planned for. With a week-long planning horizon, the wholesaler is able to make a tactical route plan that takes every day in the week into account. The wholesaler provides information to the transport company on a daily basis, implying a day-long planning horizon for the transport company. Thus, the transport company is provided with daily information, and hence is in the same planning situation as in the DD information case. The WD information sharing case is illustrated in Figure 4.2.

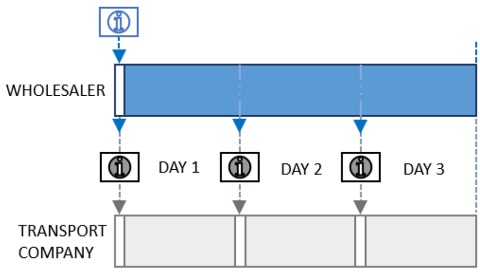


Figure 4.2: Illustrating the actors' planning horizon and information availability for the WD information sharing case

Figure 4.2 illustrates the actor's planning horizon and information availability for the WD information sharing case. The wholesaler has full information for the entire week (here consisting of 3 days), but gives the transport company daily information.

4.1.3 Weekly-Weekly

In the weekly-weekly (WW) information sharing case, both the actors have a week-long planning horizon. The wholesaler is in the same planning situation as in the WD information sharing case. The difference between the WD and WW lays in the information sharing. The wholesaler shares all information with the transport company in the beginning of the week instead of daily information blocks. Consequently, also the transport company is able to plan the daily operational routes based on a weekly perspective. The WW information sharing case is illustrated in Figure 4.3.

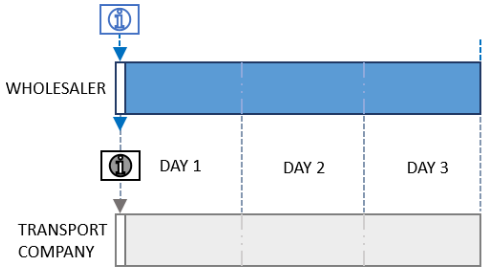


Figure 4.3: Illustrating the actors' planning horizon and information availability for the WW information sharing case

Figure 4.3 illustrates the actors' planning horizon and information availability for the WW information sharing case. The wholesaler receives full information for the entire week (here consisting of 3 days), and shares all this information with the transport company, also at the beginning of the week.

4.2 The Planning Levels

A wholesaler and a transport company are facing the problem of determining the optimal set of routes in order to satisfy the retailers' demand. The set of retailers, the time the retailers should be served and their respective orders vary from day to day. Routes are chosen based on fulfilling retailers' order requirements and cost minimization. As tactical and operational planning reflect different viewpoints for planning decisions, the mathematical formulations differ slightly.

4.2.1 Tactical Route Plan

Planning concerning the tactical route plan is done with *the wholesaler model*. The wholesaler model represents the planning viewpoint of a wholesaler, focusing on general planning. To fulfill retailer orders and requirements is the wholesaler's primal task.

The wholesaler chooses routes and allocates pallets, i.e. retailer orders, to the chosen routes. Fulfilling retailer orders also entails ensuring retailer inventory levels are not exceeded. The wholesaler has two cost incentives that drive the choices related to fulfilling retailer orders, i.e. transportation cost. Firstly, pallet cost is a fixed cost connected to transporting a pallet on a given route. Secondly, the wholesaler aims to have an even freight pattern during the week, i.e. that the transported number of pallets is similar every day in the week. We call this *daily leveling* as it refers to leveling of aggregated demand between days in the week. The purpose of daily leveling is to increase predictability and resource utilization. The more the aggregated daily demand deviate from a set target demand, the higher is the associated penalty cost. The wholesaler aims to minimize all its costs.

The input to the wholesaler model is the retailer orders and a set of tactical routes. Furthermore, tactical routes are a given set of routes. They are formed based on average demand forecasts. As the routes do not take actual truck capacities or demand into account, they are uncapacitated. Each day, only a subset of the tactical routes is available. Each subset contains different routes. Implying, that routes are fixed to days so for example, that only "Monday"-routes can be chosen on a Monday. This also means that certain retailers can only be visited on certain days. Additionally, retailers' delivery requirements are embedded in the tactical routes. Hence, by restricting which routes can be chosen which day of the week, only tactical routes that fulfill delivery requirements are available.

The tactical output consists of pallets on routes. In other words, a set of routes and demand on each route in the set.

4.2.2 Operational Routes

Operational route planning is done with *the transporter model*. The transporter model represents the planning viewpoint of the transport company, focusing on detailed planning. The transport company's responsibility is to utilize their fleet of trucks while fulfilling retailer transport requirements. This is done by the combination of placing retailers' orders on trucks and trucks on available routes. They aim to do this while minimizing their costs, i.e. fixed costs related to having a truck and variable costs for deploying a truck on a route.

The input to the transporter model is operational demand and a set of operational routes. The operational input is defined similarly as the tactical input but differs slightly. Both operational demand and set of routes are dependent on the wholesaler model. In general terms, the operational planning is a more detailed planning based on the tactical planning. For routes, each daily subset of operational routes is dependent on the chosen tactical routes the same day. Operational route selection also takes truck capacities into account.

The operational output consists of which demand is transported by which truck on which route.

4.3 Coordination of Planning and Information

In this section, we aim to combine the two modeling components by describing the transition from the wholesaler model to the transporter model and how this is dependent on the applicable information sharing case.

4.3.1 Model Interaction

The wholesaler is responsible for general planning, while the transport company takes care of the detailed planning based on the wholesaler's plans. Figure 4.4 illustrates the interaction between the wholesaler model and the transporter model.

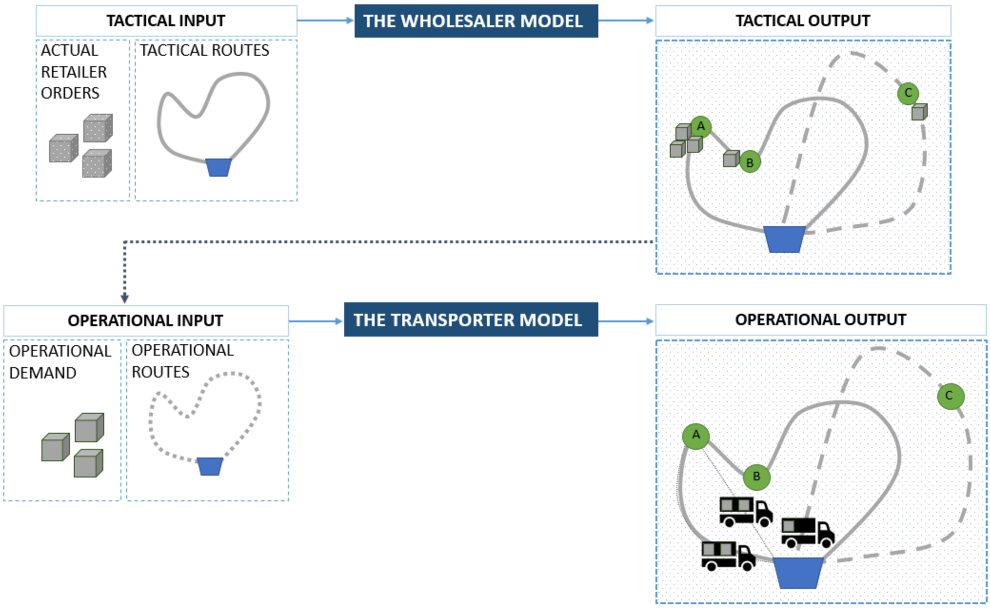


Figure 4.4: Coordination between the wholesaler and transporter model. The green circles represent retailers, while the blue trapezoid represents the wholesaler

Figure 4.4 illustrates that the tactical planning conducted in the wholesaler model is decisive for operational planning conducted in the transporter model. In the wholesaler model, which demand is to be delivered to which retailer on which tactical route is decided. In the transporter model, which demand is to be delivered to which retailer on which operational route using which truck is decided. Input in the transporter model is based on the output from the wholesaler model. Below follows an overview of the transition from input in the wholesaler model to output in the transporter model.

- **Demand**
  - Wholesaler
    Input: actual retailer orders
    Output: demand on route
  - Operational
    Input: retailer demand with wholesaler adjustments (if possible)
    Output: demand on truck on route

- **Routes**
  - Tactical
    Input: given set of routes, only a subset of routes is available each day
    Output: the chosen tactical routes in the wholesaler model
  - Operational
    Input: tactical route output and supplementary routes
    Output: the chosen operational routes in the transporter model

4.3.2 Administration of Information Availability

The same type of information availability, i.e. daily or weekly information, is handled the same way in the wholesaler model as in the transporter model.

In the case of daily information new information is provided each day only regarding next day's transport. Daily information is handled by iteratively solving the model, i.e. the model is solved once for every day in the week. Each iteration is conducted independently of other iterations. This implies that planning decisions made one day will not affect decisions made other days, neither forth nor back in time.

For each iteration, the model will choose the (combination of) routes best fitted to serve the retailers with demand that day. Furthermore, as routes are chosen based on cost minimization routes are chosen to the lowest cost as seen from that day only. The solutions for a week with daily information is the aggregated daily solutions. As decisions for one day are independent of decisions other days, we assume that neither solutions for different iterations can be combined. Daily information is handled in the wholesaler model only in the DD information sharing case. In the transporter model, it is handled both in the DD and the WD information sharing case.

In the case of weekly information, full information is available for and used by the actor regarding every day in the entire week. Weekly information is handled by solving the model once for all available information. As all information is known regarding demand and transport requirements for the planning horizon, routes can be chosen accordingly. This means that a solution for weekly information will consider routes for all time periods combined. Weekly information is handled in the wholesaler model in both the WD and the WW information sharing case. In the transporter model, it is handled only in the WW information sharing case.

Combining information availability with the model interaction between the wholesaler model and the transporter model, we get the following administration of information availability for the different information sharing cases:

- DD: The wholesaler model is solved iteratively for daily information. Then, the transporter model is solved iteratively for daily information using the daily information

- WD: The wholesaler model is solved once for weekly information. Then, the transporter model is solved iteratively for daily information using the daily information
- WW: First the wholesaler model is solved once for weekly information, then the transporter model is solved once for weekly information

4.4 Model Components

The descriptions in Section 4.4.1 and 4.4.3 apply for both the wholesaler model and the transporter model. Section 4.4.2 only considers aspects in the transporter model.

4.4.1 Retailer Demand & Pallet Categories

The retailers are in general different in terms of demand, inventory levels and timely length from the wholesaler. As fulfilling retailer demand is the main goal in both the wholesaler model and the transporter model, retailer demand is what drives the two models. Demand information is specified in terms of departure time (not delivery time). Hence, we operate with *fixed departure*. Demand on a given day is specified as the number of pallets of a *pallet category*. The term pallet category defines the property of the groceries placed on a pallet. We distinguish between storable promotional (SP), storable ordinary (SO) and non-storable (NS). If a pallet category is "storable" it means it can be delivered at a different time than scheduled. Promotional implies the groceries can be transported earlier than scheduled, while ordinary implies it can be transported later than scheduled. See the applied pallet category overview in Table 4.1.

	Storable	Non-Storable
Ordinary	SO	NS
Promotional	SP	NS

Table 4.1: Overview of pallet categories

We assume the NS pallets are placed in the store of the retailer at once, while the storable pallets are temporarily placed on the retailer's inventory. The size of the inventory for storable pallets is specified for each retailer.

4.4.2 Fleet of Trucks

On a daily basis, the transporter model deploys trucks on routes in order to serve a subset of retailers. We assume more than one truck can be used to serve one retailer the same day. The trucks the transporter model uses are homogeneous. This implies that all trucks can visit all retailers, be deployed on every route, and have the same capacity. We assume all pallet categories can be carried simultaneously in the same truck. Furthermore, the transporter model has the opportunity to choose from two sets of trucks consisting of either external or own trucks. They are distinguishing by assigning a higher fixed cost for use of external trucks.

4.4.3 Time Resolution & Routes

We distinguish between three different time resolutions; week, day and time period. A week consists of 7 days and a day is divided into 4 time periods. End of horizon implies we only consider what happens in the models for one week at a time.

All routes start and end at the wholesaler. A route is defined by the subset of retailers it contains and its departure time and return time. For routes, time is specified in terms of time periods. Travel times together with a fine time resolution enables possibilities for multiple departures and route combinations within the same day.

Further, departures from the wholesaler can only happen at the beginning of a time period. In other words, the beginning of each time period represents a time slot for departures from the wholesaler. This implies that departures cannot happen other times than these specific times.

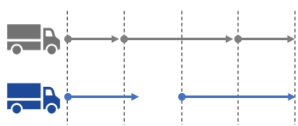


Figure 4.5: Illustrating departure times and route combinations

In Figure 4.5, transportation is conducted in four time periods, indicated by the vertical lines. The arrows represent route lengths, and the color of the arrow distinguish two different possible route combinations. The gray truck completes three routes, consisting of an integer number of time periods. The blue truck, on the other hand, only completes two routes over a little more than three time periods. If a route length exceeds the duration of one time period, it cannot be used for freight before the consecutive departure time even though it is not in use most of the time period. This is illustrated in Figure 4.5. Furthermore, at a certain time, only a subset of trucks are available for new assignments, depending on previous assignments and route length of those assignments.

4.5 Added Flexibility

We distinguish between two different types of added flexibility. In Section 4.5.1 added flexibility related to transporting retailer demand on a different time than scheduled is elaborates. Route selection as added flexibility is explained in Section 4.5.2.

4.5.1 Shifting

Shifting refers to the departure of (parts of) retailer orders on a different time than originally scheduled. This type of added flexibility is possible only in the case of weekly information. Early shifting can only be conducted by the wholesaler model and only applies to the pallet category SP. Late shifting can only be carried out by the transporter model and only applies to SO pallets. As we have an end of horizon time frame, orders can only be shifted within the week (not outside of it).

The maximum number of pallets within a pallet category that potentially can be shifted is specified by a given ratio, hereby called *shifting ratio*. The ratio is defined per retailer as a given amount of retailer demand for the given, shiftable pallet category. The shifting ratio for SP pallets, specified in the wholesaler model, might be different from the shifting ratio for SO pallets, specified in the transporter model. Similarly, the possible number of time periods an order can be shifted is also specified and might be different for SO and SP pallets.

Shifting has different implications for each of the information sharing cases. The more available information implies greater possibilities for shifting. The following applies to each of the information sharing cases:

- DD: No shifting is possible for either model as the planning horizon is limited to a day. In this case, wholesaler and operational demand are identical.
- WD: The models have asymmetric information. The wholesaler that has a weekly planning horizon and can exercise early shifting of SP pallets. Shifting is not possible in the transporter model. As only the wholesaler model has the opportunity to shift orders, the wholesaler demand input and operational demand input might be different.
- WW: Both models have weekly information. The wholesaler model has the possibility of early shifting of SP pallets. The transporter model can perform late shifting of SO pallets. When both models can shift, wholesaler demand input, operational demand input and operational demand output might not be the same.

Figure 4.6 summarizes the bullet list above by illustrating which pallet category that potentially can be shifted by which model and information sharing case.

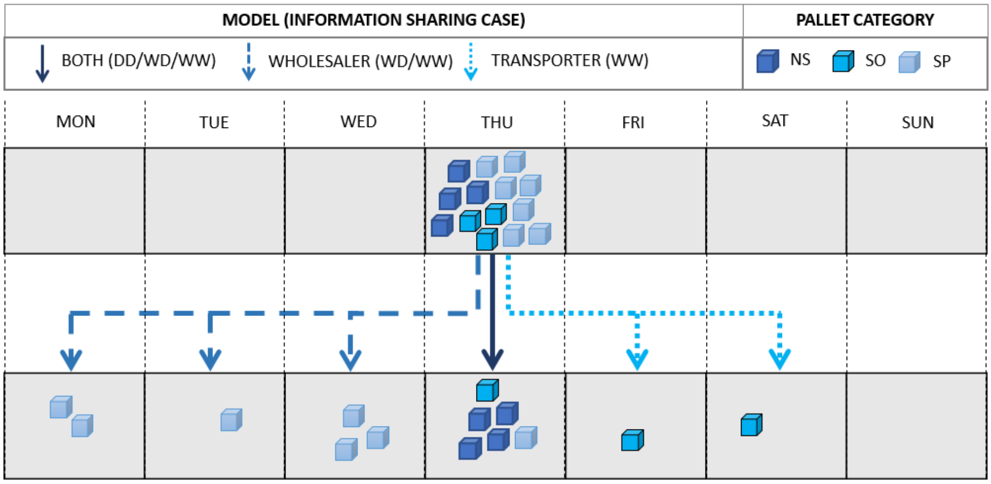


Figure 4.6: Illustrating possibility for early shifting for the wholesaler & late shifting for the transporter model for the different information sharing cases

One model can shift forth in time and the other one can shift back in time, but the models can shift one pallet category each. This implies that the transporter model cannot shift the same demand back as the wholesaler has shifted forth in time. However, the transporter model can potentially conduct late shifting of demand that accounts for the same number of pallets to the same retailer as the wholesaler modeled scheduled for early shifting.

4.5.2 Route Selection

We define route selection flexibility as *time-independent* route selection, meaning there are no time restrictions related to when routes can be chosen. This implies that any route in the set of routes can be chosen any day of the week.

This route selection flexibility can apply to both the wholesaler and the transporter model. Both at the same time or just one at a time. However, the available set of routes is dependent on the model. Meaning that the tactical routes are available for the wholesaler model, while the operational routes are available for the transporter model.

Chapter 5

Mathematical Models

In this chapter we propose mathematical formulations for the wholesaler model and the transporter model. As stated in the previous chapter, the models are used as tools to study the effect of information sharing between the two actors. Hence, the formulations are formulated focusing on applicability in order to conduct analysis so that the same models can be used for different model run instances. This is possible as information sharing cases are primarily distinguished by different input data. All the mathematical notations are declared in Section 5.1. Thereafter, the wholesaler and transporter model are presented in Section 5.2 and 5.3, respectively. Coherent model formulations can be found in Appendix A and B.

5.1 Notation

The wholesaler and transporter model have many similar components. All notations are provided below. The checklist to the right indicates which model applies which notation. "W" and "T" imply the wholesaler model and transporter model, respectively.

Indices		W	T
i :	Retailer	☒	☒
r :	Route	☒	☒
v :	Truck	☐	☒
t :	Time period for *actual* departure	☒	☒
ρ :	Time period for *scheduled* departure	☒	☒
d :	Day in the planning horizon	☒	☐
p :	Breakpoint	☒	☐

Sets

$\mathcal{N}$:	Set of retailers	⊠	⊠
$\mathcal{R}$:	Set of routes	⊠	⊠
$\mathcal{V}$:	Set of trucks	☐	⊠
$\mathcal{T}^P$:	Set of time periods in the planning horizon	⊠	⊠
$\mathcal{T}^W$:	Set of days in the planning horizon	⊠	☐
$\mathcal{T}_d^D$:	Set of time periods in day d, $\mathcal{T}_d^D \subseteq \mathcal{T}^P$	⊠	☐
$\mathcal{P}$:	Set of breakpoints	⊠	☐

Parameters

α :	Shifting ratio	⊠	⊠
β_p :	Allowed number of pallets for breakpoint p	⊠	☐
A_{ir} :	Takes the value 1 if retailer i is on route r, 0 otherwise	⊠	⊠
B_{rt} :	Takes the value 1 if route r can be chosen in time period t, 0 otherwise	⊠	⊠
C_r^P :	Cost of transporting one pallet on route r	⊠	☐
C_p^L :	Penalty for deviating from daily target demand in breakpoint p	⊠	☐
C_r^R :	Route cost for route r	☐	⊠
C^{Own} :	Truck cost for using an owned truck	☐	⊠
C^{Rent} :	Truck cost for using a rented truck	☐	⊠
$\overline{D}$:	Daily target demand	⊠	☐
D_{it}^{NS} :	Retailer i's demand of NS pallets scheduled for time period t	⊠	⊠
D_{it}^{SP} :	Retailer i's demand of SP pallets scheduled for time period t	⊠	⊠
D_{it}^{SO} :	Retailer i's demand of SO pallets scheduled for time period t	⊠	⊠
I_i :	Retailer i's inventory size	⊠	☐
I_i^0 :	Retailer i's inventory in the beginning of the week	⊠	☐
K_r :	Number of consecutive time periods a truck is unavailable if assigned to route r	☐	⊠
m :	Number of owned trucks	☐	⊠
Q^V :	Truck capacity	☐	⊠
E :	Maximum number of time periods a SP pallet can shifted forth in time	⊠	☐
L :	Maximum number of time periods a SO pallet can be postponed	☐	⊠

Variables

y_{irt}^{NS} :	NS pallets for retailer i on route r leaving in time period t	☒	☒
y_{irt}^{SP} :	SP pallets for retailer i on route r leaving in time period t	☒	☒
y_{irt}^{SO} :	SO pallets for retailer i on route r leaving in time period t	☒	☒
$w_{i\rho t}$:	Number of pallets for retailer i scheduled for time period ρ and leaving in time period t	☒	☒
σ_{dp}^{+} :	Pallets above target demand on day d for breakpoint p	☒	☐
σ_{dp}^{-} :	Pallets below target demand on day d for breakpoint p	☒	☐
γ_{it} :	Storable pallets in inventory at retailer i in time period t	☒	☐
x_{rtv} :	A binary variable with value 1 if truck v leave in time period t on route r	☐	☒
δ_v :	A binary variable that takes value 1 when truck v is used in the planning horizon	☐	☒

5.2 The Wholesaler Model

The wholesaler model reflects the wholesaler's planning perspective. It is based on the sets, indices, parameters and variables presented in Section 5.1. Below follows an explanation of the objective function and all constraints.

5.2.1 The Objective Function

The objective function, Equation (5.1), essentially reflects different cost incentives for the wholesaler. The two terms express volume leveling and minimization of transportation cost, respectively. The value of the different cost parameters relative to each other implicates the incentives' importance. The wholesaler model's objective function is as follows:

$$\min \quad P^W = \sum_{d\in\mathcal{T}^W}\sum_{p\in\mathcal{P}} C_p^L(\sigma_{dp}^{+} + \sigma_{dp}^{-}) + \sum_{i\in\mathcal{N}}\sum_{r\in\mathcal{R}}\sum_{t\in\mathcal{T}^P} C_r^P(y_{irt}^{NS} + y_{irt}^{SO} + y_{irt}^{SP}) \tag{5.1}$$

The first term of the objective function represents the daily demand leveling. An even number of transported pallets each day in the week entails even use of capacity, both inventories and number of trucks. The cost of deviating is set to C_p^L, where the cost increases piecewise linearly with breakpoint p with increased deviation from the target demand. The sum over the breakpoints of the decision variables σ_{dp}^{+} and σ_{dp}^{-} are on day d the number of pallets higher and lower than the target demand.

The second term reflects the cost related to transporting a pallet on a route. C_r^P is the unit cost of transporting a pallet on route r. The longer the route, the higher the unit cost. Further, the decision variable for the different pallet categories, y_{irt}, indicates the number of transported pallets from the wholesaler, specified by retailer i, route r and time period t. As demand for a retailer is specified for retailer and time, the wholesaler model will choose to serve retailers on routes with the lowest accompanying pallet cost.

5.2.2 The Constraints

The wholesaler model must for each retailer satisfy the different pallet categories of demand. Below follows all the constraints regarding retailer demand.

$$\sum_{r \in \mathcal{R} | A_{ir}=1} y_{irt}^{NS} = D_{it}^{NS} \qquad i \in \mathcal{N}, \qquad t \in \mathcal{T}^P \tag{5.2}$$

$$\sum_{r \in \mathcal{R} | A_{ir}=1} y_{irt}^{SO} = D_{it}^{SO} \qquad i \in \mathcal{N}, \qquad t \in \mathcal{T}^P \tag{5.3}$$

$$\sum_{t=\rho-E}^{\rho} w_{i\rho t} = D_{i\rho}^{SP} \qquad i \in \mathcal{N}, \qquad \rho \in \mathcal{T}^P \qquad |t > 0 \tag{5.4}$$

$$\sum_{r \in \mathcal{R} | A_{ir}=1} y_{irt}^{SP} - \sum_{\rho=t}^{t+E} w_{i\rho t} = 0 \qquad i \in \mathcal{N}, \qquad t \in \mathcal{T}^P \qquad |\rho \leq |\mathcal{T}^P| \tag{5.5}$$

$$w_{i\rho\rho} \geq (1-\alpha) D_{i\rho}^{SP} \qquad i \in \mathcal{N}, \qquad \rho \in \mathcal{T}^P \tag{5.6}$$

$$w_{i\rho t} \geq 0 \ \ \& \text{ integer} \qquad i \in \mathcal{N}, \qquad \rho \in \mathcal{T}^P, \qquad t \in \mathcal{T}^P \tag{5.7}$$

Constraint (5.2) and (5.3) reflect demand that must depart the same time period as scheduled. They represent the non-shiftable demand, which in the wholesaler model is the NS and SO pallets. The demand is listed as the number of pallets for retailer i with departure time t. A retailer can only be served on routes that include them. Therefore, we add $A_{ir} = 1$ to only sum over the subset of routes that visit the specific customer. A_{ir} represents possible combinations of retailers and routes. Since both NS and SO pallet are non-shiftable in the wholesaler model, they could be merged to one constraint. However, they are distinguished because they are treated as different input in the transporter model.

In the wholesaler model, SP pallets have the potential to be shifted. Shifting represents added flexibility in the sense that the time period for scheduled and actual departure might differ. The extra flexibility entails additional constraints for this pallet category. SP pallets can be delivered up to E number of periods earlier than scheduled. $w_{i\rho t}$ reflects the number of SP pallets for retailer i with scheduled departure at time period ρ and actual departure at time period t. Constraint (5.4) ensures that demand of SP pallets is transported to the retailer in time. For each retailer i this constraint sums the SP pallets that depart between the allowed number of early time periods and on time ρ. This must equal the retailer's total demand ordered to time ρ. Furthermore, constraint (5.5) ensures that the SP pallets transported to retailer i with actual departure at time t, i.e. y_{irt}^{SP}, corresponds to the sum of SP pallets that can depart that period restricted by scheduled delivery time and E, i.e. $w_{i\rho t}$. Constraint (5.6) ensures that the shifted demand does not exceed what is allowed specified by the shifting ratio. Lastly, constraint (5.7) ensures that the decision variable $w_{i\rho t}$ is non-negative and only can take integer values.

Due to the nature of the model, and that the routes only contain a set of retailers, there is a lot of zero elements and infeasible solutions. The next constraints remove some of these solutions.

$$\sum_{t\in\mathcal{T}^P}(y_{irt}^{NS}+y_{irt}^{SO}+y_{irt}^{SP})\leq M_1A_{ir} \qquad i\in\mathcal{N}, \qquad r\in\mathcal{R} \tag{5.8}$$

$$\sum_{i\in\mathcal{N}}(y_{irt}^{NS}+y_{irt}^{SO}+y_{irt}^{SP})\leq M_2B_{rt} \qquad r\in\mathcal{R}, \qquad t\in\mathcal{T}^P \tag{5.9}$$

$$y_{irt}^{NS},y_{irt}^{SO},y_{irt}^{SP}\geq 0 \ \text{ \& integer} \qquad i\in\mathcal{N}, \qquad r\in\mathcal{R}, \qquad t\in\mathcal{T}^P \tag{5.10}$$

Constraint (5.8) prevents decision variable y_{irt} for all pallet categories to take infeasible values as conveyed by A_{ir}, i.e. one can only serve retailers that exist on a route. Correspondingly, constraint (5.9) restricts all y_{irt} on a route to only choose allowed departure time. The parameter B_{rt} states whether a route r can be used in time period t. The big Ms are set sufficiently high, meaning M_1 equals the highest total demand out of all the retailers, while M_2 equals the highest demand out of all the time periods. Both constraints force all y_{irt}s to zero if A_{ir} or B_{rt} is zero for the given combination of (i, r, t). Furthermore, constraint (5.10) ensures the decision variables y_{irt} for all pallet categories are non-negative and only can take integer values.

Retailer inventory balance and restrictions are formulated in constraint (5.11)-(5.14).

$$\sum_{r\in\mathcal{R}|A_{ir}=1}(y_{irt}^{SO}+y_{irt}^{SP})-\gamma_{it}+\gamma_{i(t-1)}\leq D_{i(t-1)}^{SO}+D_{i(t-1)}^{SP} \quad i\in\mathcal{N}, \quad t\in\mathcal{T}^P \tag{5.11}$$

$$\gamma_{it}\leq I_i \qquad i\in\mathcal{N}, \quad t\in\mathcal{T}^P \tag{5.12}$$

$$\gamma_{i0}=I_i^0 \qquad i\in\mathcal{N} \tag{5.13}$$

$$\gamma_{it}\geq 0 \qquad i\in\mathcal{N}, \quad t\in\mathcal{T}^P \tag{5.14}$$

The retailer inventory only concerns storable pallets, i.e. SO and SP pallets. The NS pallets are assumed to be placed in the store at once. Constraint (5.11) controls the inventory balance from one time period to the next. The number of pallets placed in inventory for a given time period and retailer, i.e. γ_{it}, must equal the previous time period's inventory level, $\gamma_{i(t-1)}$, plus the actual number of storable pallets, $y^{SO}_{irt} + y^{SP}_{irt}$ and subtracting the number of storable pallets ordered from last time period, $D^{SO}_{it-1} + D^{SP}_{it-1}$. Further, constraint (5.12) ensures that the inventory at any time period cannot exceed the retailer's inventory size, I_i. The initialization of the retailer inventory for every retailer at the beginning of the planning horizon, I^0_i, is established in constraint (5.13). The storable demand ordered before the beginning of the week, $D^{SO}_{i0} + D^{SP}_{i0}$, are known demand from the end of the previous planning horizon. Constraint (5.14) ensures that the decision variable γ_{it} only can take non-negative values.

Constraints (5.15)-(5.17) handle the wholesaler's daily demand leveling incentive.

$$\sum_{i\in\mathcal{N}}\sum_{r\in\mathcal{R}}\sum_{t\in\mathcal{T}^D_d}(y^{NS}_{irt} + y^{SO}_{irt} + y^{SP}_{irt}) + \sum_{p\in\mathcal{P}}(\sigma^-_{dp} - \sigma^+_{dp}) = \overline{D} \qquad d \in \mathcal{T}^W \tag{5.15}$$

$$\sigma^+_{dp} + \sigma^-_{dp} \leq \beta_p \qquad d \in \mathcal{T}^W, \quad p \in \mathcal{P} \tag{5.16}$$

$$\sigma^+_{dp}, \sigma^-_{dp} \geq 0 \qquad d \in \mathcal{T}^W, \quad p \in \mathcal{P} \tag{5.17}$$

$\overline{D}$ is the daily target demand. In constraint (5.15) the deviation from the target demand is calculated. Constraint (5.16) ensures that the number of pallets deviation within a breakpoint p cannot exceed a parameter β_p. Constraint (5.17) makes sure σ^+_d and σ^-_d are non-negative and continuous.

5.3 The Transporter Model

The transporter model reflects the transport company's planning perspective. It is based on the sets, indices, parameters and variables presented in Section 5.1. We indicate which parameters that are unique for the transporter model by adding $\widehat{\ }$ to the notation. Below follows an explanation of the objective function and all the constraints.

5.3.1 The Objective Function

As in the wholesaler model, the objective function in the transporter model, Equation (5.18) reflects different cost incentives for the transport company. The value of the different cost parameters relative to each other implicates incentive importance. The main objective is based on both minimizing number of routes and the number of trucks, and the transporter model's objective function is set to:

$$\min \quad P^T = \sum_{r \in \widehat{\mathcal{R}}} \sum_{t \in \mathcal{T}^P} \sum_{v \in \mathcal{V}} C_r^R x_{rtv} + (\sum_{v=1}^{m} C^{\text{Own}} \delta_v + \sum_{v=m+1}^{|\mathcal{V}|} C^{\text{Rent}} \delta_v) \tag{5.18}$$

The first term of the objective function is related to the operational cost of each route, C_r^R. This reflects the time it takes to complete the route, i.e. the longer the route, the higher the cost. Further, x_{rtv} is a binary decision variable set to 1 if a truck v is assigned to route r with departure in time period t, and 0 otherwise. $\widehat{\mathcal{R}}$ represents the set of routes that is generated as a consequence of the wholesaler model output.

The second term minimizes the necessary number of trucks in the planning horizon, represented by δ_v. To keep track of the number of trucks in use, as well as *if* a truck is used at any time, the binary variable δ_v is 1 if a truck is used at any time and 0 otherwise. This could be seen as a fixed cost, C^{Own}, for using an own truck and C^{Rent} for using a rental truck. The two terms do not operate independently of each other, but rather find if there is a trade-off between the number of routes and number of trucks necessary.

5.3.2 The Constraints

An important difference between the wholesaler and transporter model is related to truck and consequently truck capacities. In particular, the limitation on the number of pallets that can be transported on routes due to the capacity of the trucks.

$$Q^V \sum_{v \in \mathcal{V}} x_{rtv} - \sum_{i \in \mathcal{N} | \hat{A}_{ir}=1} (y_{irt}^{NS} + y_{irt}^{SO} + y_{irt}^{SP}) \geq 0 \qquad r \in \widehat{\mathcal{R}}, \qquad t \in \mathcal{T}^P \tag{5.19}$$

Constraint (5.19) makes sure enough trucks are assigned to a route in order to serve all the retailers located on a route. Route capacity is the truck capacity Q^V times the number of the trucks assigned to a route, indicated with the decision variable x_{rtv}. Then, for a given route r in a given time period t, the transported number of pallets cannot exceed that route's capacity. The pallets served are only summed up for retailers that exist on each route, denoted with $\hat{A}_{ir}$. The parameter $\hat{A}_{ir}$ changes dependent on the set of routes it is subject to.

Further, constraints (5.20)-(5.23) control the restrictions for the decision variable x_{rtv} related to the assignment of trucks. x_{rtv} indicates which truck is assigned to which route in which time period.

$$\sum_{r \in \widehat{\mathcal{R}}} \sum_{t'=t}^{t+K_r} x_{rt'v} \leq 1 \qquad t \in \mathcal{T}^P, \qquad v \in \mathcal{V} \tag{5.20}$$

$$\sum_{r \in \widehat{\mathcal{R}}} \sum_{t'=t}^{t+K_r} \sum_{v \in \mathcal{V}} x_{rt'v} \leq |\mathcal{V}| \qquad t \in \mathcal{T}^P \qquad |(t+K_r) \leq |\mathcal{T}^P| \tag{5.21}$$

$$\sum_{v \in \mathcal{V}} x_{rtv} \leq |\mathcal{V}| \hat{B}_{rt} \qquad r \in \widehat{\mathcal{R}}, \qquad t \in \mathcal{T}^P \tag{5.22}$$

$$x_{rtv} \in \{0,1\} \qquad r \in \widehat{\mathcal{R}}, \qquad t \in \mathcal{T}^P, \qquad v \in \mathcal{V} \tag{5.23}$$

Firstly, a truck v can only be in use once in each time period t, represented by constraint (5.20). This implies that if a truck is in use at time t it cannot be assigned to a new route that same time period. The number of time periods a truck is unavailable is defined by the route length, K_r. Secondly, constraint (5.21) prevents the use of more trucks than what the fleet of trucks allows. Thirdly, constraint (5.22) removes infeasible solutions of x_{rtv}. x_{rtv} is forced to zero if a route r cannot depart at time period t, defined by $\hat{B}_{rt}$. Constraint (5.23) restricts the decision variable x_{rtv} to take a binary value.

In addition to the descriptions above, in particular constraint (5.20) and (5.21) are also used to keep track of when trucks are in use. However, these are not sufficient, and constraints (5.24)-(5.26) are added.

$$\sum_{r \in \widehat{\mathcal{R}}} \sum_{t \in \mathcal{T}^P} x_{rtv} \leq M_1 \delta_v \qquad v \in \mathcal{V} \tag{5.24}$$

$$\delta_{v+1} - \delta_v \leq 0 \qquad v \in \mathcal{V} \tag{5.25}$$

$$\delta_v \in \{0,1\} \qquad v \in \mathcal{V} \tag{5.26}$$

These constraints make use of the decision variable δ_v, which indicates if truck v is used in the planning horizon. Constraint (5.24) is a big M constraint and requires δ_v to be strictly positive if truck v is in use at least once during the planning horizon. M_1 is set sufficiently large. Furthermore, constraint (5.25) is a symmetry breaking constraint, ensuring that the trucks with the lowest index are used first. Constraint (5.26) ensures δ_v to take a binary value.

When it comes to fulfilling retailer demand, the demand restrictions in the transporter model are similar to the ones in the wholesaler model.

$$\sum_{r\in\widehat{\mathcal{R}}|\hat{A}_{ir}=1} y_{irt}^{NS} = \widehat{D}_{it}^{NS} \qquad i\in\mathcal{N}, \qquad t\in\mathcal{T}^P \tag{5.27}$$

$$\sum_{r\in\widehat{\mathcal{R}}|\hat{A}_{ir}=1} y_{irt}^{SP} = \widehat{D}_{it}^{SP} \qquad i\in\mathcal{N}, \qquad t\in\mathcal{T}^P \tag{5.28}$$

$$\sum_{t=\rho}^{\rho+L} w_{i\rho t} = \hat{D}_{i\rho}^{SO} \qquad i\in\mathcal{N}, \qquad \rho\in\mathcal{T}^P \qquad |t\leq|\mathcal{T}^P| \tag{5.29}$$

$$\sum_{r\in\widehat{\mathcal{R}}|\hat{A}_{ir}=1} y_{irt}^{SO} - \sum_{\rho=t-L}^{t} w_{i\rho t} = 0 \qquad i\in\mathcal{N}, \qquad t\in\mathcal{T}^P \qquad |\rho\geq 0 \tag{5.30}$$

$$w_{i\rho\rho}\geq(1-\hat{\alpha})\hat{D}_{i\rho}^{SO} \qquad i\in\mathcal{N}, \qquad \rho\in\mathcal{T}^P \tag{5.31}$$

$$w_{i\rho t}\geq 0 \ \text{ \& integer} \qquad i\in\mathcal{N}, \qquad \rho\in\mathcal{T}^P, \qquad t\in\mathcal{T}^P \tag{5.32}$$

The demand for the transporter model is created from the output from the wholesaler model. The demand with actual departure in time period t in the wholesaler model is demand with scheduled demand in time period t in the transporter model, i.e. $y_{irt}^{Wholesaler} \rightarrow \hat{D}_{it}$. Constraint (5.27) is the same as constraint (5.2) in the wholesaler model, ensuring all NS pallets must depart when scheduled. In the transporter model, the SP pallets must depart when scheduled. This is ensured with constraint (5.28).

Constraints (5.29)-(5.32) keep track of the shifting of SO pallets. Constraint (5.29) ensures that a retailer's full order of SO pallets is transported within the specified shifting time. SO pallets scheduled for time period ρ cannot depart later than $\rho+L$. Furthermore, constraint (5.30) ensures that the SO pallets that depart in time period t, y_{irt}^{SO}, is the same as the sum of shifted SO pallets that can be transported in that time period. As in the wholesaler model, constraint (5.31) controls the number of SO pallets that can be shifted depending on the shifting ratio $\hat{\alpha}$. Constraint (5.32) restricts the decision variable $w_{i\rho t}$ to be a non-negative integer.

As in the wholesaler model, the transporter model also has a lot of zero elements and infeasible solution that are known in advance. The next constraints remove some of these solutions.

$$\sum_{t\in\mathcal{T}^P}(y_{irt}^{NS}+y_{irt}^{SO}+y_{irt}^{SP})\leq M_2{\cdot}\hat{A}_{ir} \qquad i\in\mathcal{N}, \qquad r\in\widehat{\mathcal{R}}, \tag{5.33}$$

$$\sum_{i\in\mathcal{N}}(y_{irt}^{NS}+y_{irt}^{SO}+y_{irt}^{SP})\leq M_2{\cdot}\hat{B}_{rt} \qquad r\in\widehat{\mathcal{R}}, \qquad t\in\mathcal{T}^P \tag{5.34}$$

$$y_{irt}^{NS}, y_{irt}^{SO}, y_{irt}^{SP}\geq 0 \ \text{ \& integer} \qquad i\in\mathcal{N}, \qquad r\in\widehat{\mathcal{R}}, \qquad t\in\mathcal{T}^P \tag{5.35}$$

Constraints (5.33) - (5.35) are the same as constraints (5.8) - (5.10) in the wholesaler model. Constraints (5.33) and (5.34) remove infeasible solutions y_{irt}, while constraint (5.35) restricts the decision variable y_{irt} to take an integer and non-negative value.

Chapter 6

Data Instance and Preprocessing

In this chapter we introduce the data the model input is based on. In particular, we will explain the parameter values in Table 6.1. This implies explaining how the received data is modified and why. Explanations focus on application in the mathematical models. The received data is provided by a Norwegian wholesaler and includes route plans and retailer demand information for both delivered and ordered goods. In addition, we have received general information from the wholesaler.

Firstly, the geographical locations the data is based on are presented in Section 6.1. Then, in Section 6.2 the route data and modifications are explained. Retailer demand is introduced in Section 6.3. How the data is adapted to time periods is presented in Section 6.4. Lastly, cost related choices are explained in Section 6.5.

6.1 The Transport Area

Figure 6.1 geographically represents the retailers that the transport company is responsible for as well as location of the wholesaler. The wholesaler location also indicates the warehouse where all cargo is shipped from. However, the warehouse will only be referred to as the wholesaler in order to prevent any confusion. We can see that the transport company covers the area from mid-Norway (gray dots) to the upper part of Nordland county (blue dots). The data received regards the northmost retailers from the wholesaler. This area is hereby referred to as *the transport area* (blue circle). The transport area includes 39 retailers.

Table 6.1: The applied model parameters

Parameter	*Notation*	*Value* [Min, Max]
Number of tactical routes	$\lvert\mathcal{R}\rvert$	23
Number of operational routes	$\lvert\hat{\mathcal{R}}\rvert$	222
Number of retailers	$\lvert\mathcal{N}\rvert$	39
Number of time periods	$\lvert\mathcal{T}\rvert$	28
Number of available trucks	$\lvert\mathcal{V}\rvert$	15
Number of own trucks	m	8
Truck capacity [# pallets]	Q^V	60
Inventory capacity	I_i	[1, 19]
Target demand	$\overline{D}$	125
Share of shiftable SP-pallets	α	0.9
Share of shiftable SO-pallets	$\hat{\alpha}$	0.2
Time periods early shifting	E	28
Time periods late shifting	L	11
Travel time [#periods]	K_r	[4, 11]
Cost of pallet on route	C_r^P	[0.74, 1.27]
Cost of demand leveling	C^L	[1,4]
Cost of truck on route	C_r^R	[246, 637]
Cost of using own truck	C^{Own}	1000
Cost of using rented truck	C^{Rent}	2000

The transport area contains relatively few retailers compared to mid-Norway, but the geographical distances and travel time from the wholesaler are long. The long distances entail high transportation cost per retailer. 10 trucks with truck capacity of 60 pallets are assigned to the transport area at all times. We use a truck capacity of 60 pallets in the model. Furthermore, we want to ensure that the models has enough available trucks to find feasible solutions at all times, hence we set the fleet of trucks to 15 trucks. Furthermore, when distinguishing between own and rental trucks we set number of own trucks to 8. This way we assume the probability of seeing some effects when applying rental trucks is bigger.

6.2 Tactical Routes

The tactical routes are the set of available routes in the wholesaler model. In this section the route data and how it is modified is described. The routes in the tactical route plan for the transport area consist of:

Figure 6.1: Location of the transport area and the wholesaler

- Day & time of departure from wholesaler
- Retailers on route
- Day & time of delivery to retailers

The routes in the tactical route plan are driven at the same time every week. Meaning the route plan has Monday routes, Tuesday routes, and so on. A route is considered as unique if there is no other route that has the identical route components as listed above. Every route in the provided data is unique. In total there are 24 routes, and the number of daily routes differ between one and five. An overview over the number of daily routes are shown in Figure 6.2.

As all retailers must be served at the given time and routes are fixed to days the freedom to choose what to transport on which route is dependent on whether routes are overlapping. *Overlapping routes* are routes that have the same departure time the same day and include at least one common retailer. The received data includes two occasions with overlapping routes. There is only one occasion with overlapping routes on Saturday where one route is overlapping two other routes. For all the other days in the week, the scheduled routes must be driven in order to serve the retailers.

6.2.1 Creating Travel Times

The original tactical route data is incomplete in the way that it does not specify the time it takes to complete a route, i.e. the *travel time*.

The data includes departure time from the depot and delivery time to the last retailer on the route, but it lacks information regarding when a truck that has been deployed on a route can be deployed on a new route. Therefore, we must generate the additional time components on every route. This is done by using a 3-step procedure. Firstly, we estimate and add the time it takes to serve a retailer. This is on average 30 minutes. Secondly, we add the driving time from the last retailer on the route and to the wholesaler. This is done by finding the driving distance from the retailer to the wholesaler and then estimate return time using a truck speed of 60 km/h. And thirdly, the time from a truck returns to the wholesaler and until it can be deployed on a new route is estimated to be 1.5 hours. When we add total return time, the travel times for the tactical routes are as illustrated in Figure 6.3.

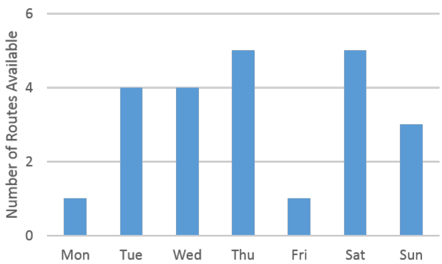


Figure 6.2: Number of daily available tactical routes

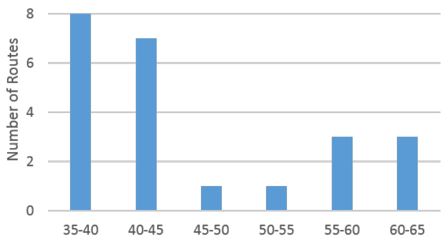


Figure 6.3: Travel time [integer hours] for the tactical routes

We see that most of the routes' travel times are between 35-45 hours. This means trucks assigned to these routes will be unavailable for one and a half and up to two days. The longest travel time is 65 hours. The routes with the longest travel times are all driven during the weekend. The routes that depart Saturday and Sunday arrive at the retailers on Monday and Tuesday.

6.2.2 Route Modifications

Due to the content of the received route data, we need to make additional modifications in order to use it as input in the mathematical models.

- *Manipulation of cross-docking*
  The route data includes two types of cross-docking that we need to handle. The first cross-docking is related to retailer demand that originates from a central depot before it arrives at the wholesaler. All routes that are connected to this

type of cross-docking have start time given as departure time from the central depot. We adjust the start time to being departure time from the wholesaler. The second cross-docking is through a terminal between the wholesaler and some retailers on some routes. In the models, we treat the terminal as a retailer. Hence, at all times all retailer demand that goes through the terminal will in the model be adjusted to demand to the "retailer-dummy". Therefore, all retailers that are served through the terminal are removed from the route and replaced with the "retailer-dummy". In total, 12 retailers are connected to the terminal.

- *Removing the exception route*
  One of the 24 tactical routes is driven by a special truck that can only transport frozen groceries. We remove this route from the set of tactical routes because the models use homogeneous trucks and frozen groceries are not considered as a separate pallet category. This means that there are 23 available tactical routes.

- *From hours to time periods*
  We operate with time periods and not hours in the mathematical model. Hence, route departure times and return times are given in terms of time periods. Travel times are rounded up to an integer number of time periods.

6.2.3 Supplementary Routes

Operational routes consist of the set of tactical routes in addition to *supplementary routes*. The supplementary routes are sub-routes of the tactical routes and serve a subset of retailers for a given tactical route. For instance, if a tactical route can serve two retailers, there will be two supplementary routes serving one retailer each.

In addition to following the same route modifications as the tactical routes (see Section 6.2.1 and 6.2.2), the supplementary routes are generated with some extra assumptions and considerations:

- *Neighbouring retailers*
  Supplementary routes can only consist of retailers that are served in a consecutive order on the corresponding tactical route. Therefore, a tactical route with n retailers will have supplementary routes with 1 to $n - 1$ retailers, given that the retailer are consecutive.

- *Time to first retailer on route*
  Due to the distance from the wholesaler to the transport area, driving regulations imply that the time it takes to complete a route is much longer than the distance would suggest. These considerations are incorporated in the tactical routes, but need to be included in the supplementary routes unless the first retailer in the tactical and supplementary route is the same. For all calculations regarding time length we use a speed of 60 km/h. The additional time length for a tactical route due to driving regulations is assumed to be the difference between scheduled and

calculated time for reaching the first retailer on that route. The time length to reach the first retailer on a route is thereby the calculated driving time in addition to the difference between scheduled and calculated time from the corresponding tactical route.

- *Fixed departure time*
  Departure time from the wholesaler for the supplementary routes remains the same as their corresponding tactical route independent on which retailers are visited on the supplementary route. This is because the mathematical models apply fixed departure. In reality, a supplementary route that only visits the last retailer(s) on a tactical route would depart later but come back at the same time as the tactical route. This is a simplification that entails that we can no longer ensure retailer delivery requirements are being fulfilled.

- *Excluding routes without reduced travel time*
  In terms of time periods, the total travel time of many of the supplementary routes and the corresponding tactical route are the same. Only the supplementary routes with reduced travel time is included in the set of operational routes. This entails that 21 tactical routes have supplementary routes.

Combining all the components from the list above results in 199 supplementary routes. It should be noted that the longest tactical route that includes 15 retailers accounts for over one-third of all the supplementary routes.

6.2.4 Restricting Route Selection

We need to restrict which routes can be chosen to serve which retailers at which time. Two different matrices are generated to fulfill these requirements. The matrix A_{ir} defines which retailers can be visited by which routes.

As for the matrix that restricts route selection with respect to time, B_{rt}, we propose two different variants in order to distinguish between different variants of route selection freedom. Firstly, we create a strict B_{rt} that fully corresponds to the given data in the tactical route plan. In this matrix, the routes are only allowed to depart during the given period. Secondly, we create a mild B_{rt} which opens up the possibility of choosing a route on a different day that specified by the tactical route plan as long as the route depart at the same time every day. This matrix will give an unrealistic degree of freedom compared to the real world due to restrictions and delivery requirement, but on the other hand, provides insight to the effect increased of being able to choose among a larger selection of routes in each period.

The two matrices are created the same way for the two models, but they are different as the set of tactical and operational routes are different.

6.3 Demand

The received demand data and the handling of this data are described in this section. The demand is extracted from a four week period between New Year and Easter in 2018. Furthermore, demand data includes actual retailer orders for that period in addition to planned transportation of the actual orders.

6.3.1 Aggregating to Pallet Categories

Retailer demand is in the data distinguished depending on the following components:

- Commodity group: dry, fresh, frozen or fruit and vegetables
- Location before transport: cross-docking or wholesaler
- Ordering process: 11 different ones. Distinguished by combinations of ordering platforms, whether the order is pre-ordered, whether the order is generated manually or automatically and whether the order is ordinary or promotional

We aggregate this data into the pallet categories NS, SO and SP based on wholesaler opinions in order to make realistic aggregations/decisions. Firstly, only groceries of commodity group "dry" are considered as storable. They account for 56.8 % of the total demand volume. Secondly, six ordering processes are regarded as promotional. Demand that is "dry" and promotional compose the SP pallets. The non-promotional and "dry" demand complete the SO pallets. All demand that is not "dry" goes under the pallet category NS. An overview of the aggregated shares of the three different pallet categories in the four week period is illustrated in Figure 6.4. How SP and SO pallets are distributed among retailers and tactical routes is illustrated in Figure 6.5 and 6.6, respectively. For a more detailed overview of daily volume of pallet categories transported on the tactical routes in the four week period, see Appendix C.

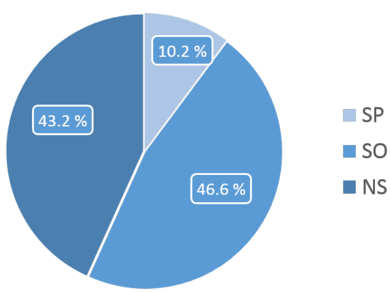


Figure 6.4: Average share of pallet categories in the 4 week demand data

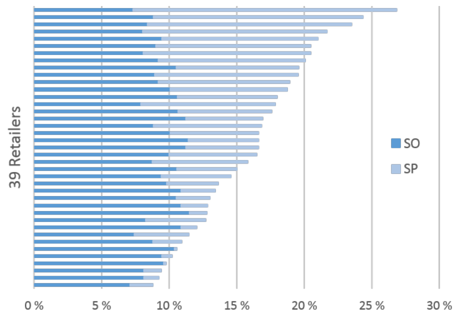


Figure 6.5: Share of SP and SO pallets per retailer

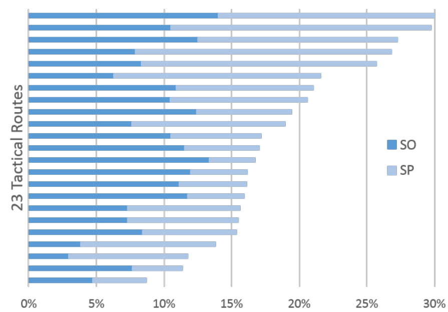


Figure 6.6: Share of SP and SO pallets per tactical route

From the figures, it is clear that the amount of SP pallets vary with roughly 20 percentage points for both routes and retailers in the four week period. The SO pallets vary less between the routes and retailers. How the pallet category share is divided among the different retailers and routes is likely to have an impact on the possibility of shifting. Retailers with a low share of shiftable orders are less likely to be affected by added flexibility than retailers with higher shares. Correspondingly will compositions of pallet categories on routes have a higher probability to be altered for routes with a high share of shiftable orders than the ones with a low share.

Daily distribution of pallets with respect to pallet category is illustrated in 6.7. There is a repetitive pattern between the weeks. For all weeks Friday is the day with the lowest number of transported pallets, while Saturday is the day with the highest. Similarly are Monday and Wednesday the days with second lowest and highest transported number of pallets, respectively.

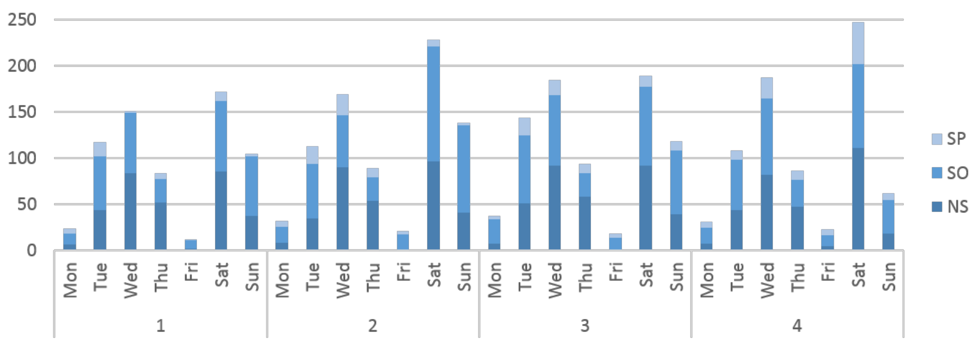


Figure 6.7: Daily retailer demand departing from the wholesaler over the 4 weeks indicating share of pallet categories

Despite the weekly patter, we see variations in the retailer orders with respect to the share of pallet categories and number of pallets. This applies to days in the same week and from one week to another. Week 1 has the lowest total demand and the lowest share of SP pallets. The total demand is the highest for week 2, but week 4 has the highest share of SP pallets. Week 3 falls somewhere between week 2 and 4. Hence, we will mainly base our analysis on retailer demand from week 3 as this is considered as representative for all the provided demand data.

Only actual retailer orders contain promotional information. As part of the problem formulation concerns promotional goods, we want information regarding promotional products to be as accurate as possible. Hence, we only consider this demand data, i.e. not the corresponding transport demand.

6.3.2 Determining Demand Related Parameters

- *Target demand*
  The average daily transported demand over the four week period is roughly 150 pallets. However, we choose a target demand of 125 pallets. This way we penalize the peaks more than the lows.

- *Retailer inventory*
  Retailer inventory is based on their actual order history and is defined as the number of pallets a retailer can put storable pallets (SP and SO pallet) in storage. We assume the retailer inventory can handle additional 10% of the maximum number of storable pallets in the four week period. The retailer inventory is rounded up to an integer number of pallet.

- *Shifting of SP pallets*
  The wholesaler states that 90 % of the SP pallets may be shifted to another time as long as they arrive before or on the ordered time. Hence, we choose the shifting ratio of SP pallets in the wholesaler model as 0.9 and number of days an order can be shifted is 7. Due to the end of horizon time frame, shifting can only happen within the given week, this also applies to shifting of SO pallets.

- *Shifting of SO pallets*
  We assume the number of pallets the transport company can shift back in time is roughly the same as the wholesaler can shift forth in time. This gives a shifting ratio for SO pallets in the transporter model of 0.2 ($0.2 * 46.6\% \approx 0.9 * 10.2\%$). Furthermore, we assume the retailers want the SO pallets as soon as possible. Hence, we allow departures of SO pallets to be postponed maximum 2 days.

6.3.3 Modification of Demand

In order to use the actual retailer orders as demand input in the mathematical models we need to do certain adjustments.

- *Fixed departure time*
  In the mathematical models, we only use fixed departure. Hence, we adjust re-

tailer orders to correspond to departure time instead of delivery time. A retailer's departure time for a given order corresponds to the nearest existing departure time for routes that include this retailer in the tactical route plan.

- *From low to high demand*
  The data received is for a low demand period. However, the wholesaler and transport company both state that the high demand periods are the ones that are challenging for the transport system. We assume similar implications for our model results. Celius and Goldsack (2017) find that the difference between high and low demand season for a Norwegian Wholesaler is around 10 %. Therefore, we adjust the demand upward 10 % to achieve an approximation of a high demand season.

- *From volume to an integer number of pallets*
  Originally, the retailer demand is given in volume $[m^3]$. The wholesaler states that the conversion from volume to pallets deviate around 1 depending on the grocery on the pallet. However, we use a more conservative conversion of 1 pallet = 0.9 m^3 as we round up to an integer number of pallets after the conversion. In particular, each pallet category (NS,SP,SO) of every retailer order is rounded up to an integer number of pallets. As demand is given in an integer number of pallets, the models will only place and shift integer number of pallets. Hence, integer requirements will be fulfilled without imposing integer variable requirements.

All these modifications together with the share of pallet categories per retailer affect the potential number of pallets that can be shifted. As the shifting ratio is defined per retailer order the minimum number of pallets of a pallet category the order must contain in order to be shifted is as follows:

$$\text{SP: } w_{i\rho t} \cdot 0.9 \geq 1 \implies w_{i\rho t} \geq \left\lceil \frac{1}{0.9} \right\rceil = 2$$

$$\text{SO: } w_{i\rho t} \cdot 0.2 \geq 1 \implies w_{i\rho t} \geq \left\lceil \frac{1}{0.2} \right\rceil = 5$$

Many retailer orders contain less than these minimum limits. Therefore, it is not possible to reach the theoretical shifting potential of 0.9 for SP or 0.2 for SO. An overview of the actual shifting potentials together with the total number of pallets for each pallet category is found in Table 6.2.

Table 6.2: Total and actual number of shiftable pallets per pallet category for week 3

	Number of pallets		
	NS	SO	SP
Total	464	489	128
Actual shiftable	0	66	69

6.4 Time Periods

A time period is the smallest time resolution in both the models. There are 4 time periods in a day and consequently 28 time periods during the 7 days week. This implies that each time period is 6 hours long.

We choose the division of the time periods to reflect the route data, both departure times and return times. Primarily, for each day we study time slots with multiple departures, defining this as the beginning of a time period. Figure 6.8 illustrates the four periods within twenty-four hours.

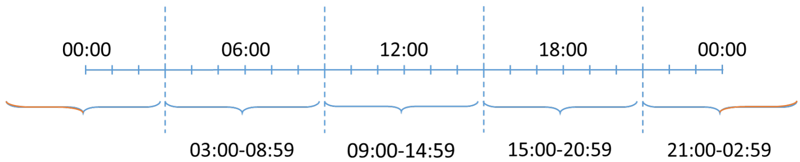


Figure 6.8: Time horizon each day converting periods into hours

As can be seen in Figure 6.8, the last time period in a day includes some hours of the consecutive day. This is a consequence of focusing on corresponding multiple departure times with the beginning of a time period. However, as we operate with fixed departure and departures only occur between 5 AM and 6 PM this will not impact the results. Figure 6.9 shows the 28 time periods in a week.

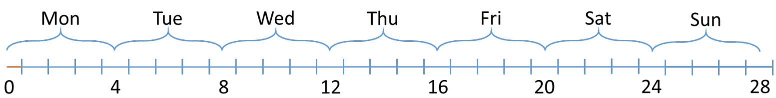


Figure 6.9: Total time horizon converting days into periods

This fine time resolution with time periods allows route combinations within the same day. Meaning it allows a more realistic representation of trucks' availability and use. The disadvantage, however, is a higher computational time.

6.5 Cost

- *Route & pallet cost*
  The route cost reflects the time length of the respective route. This gives route costs varying between 246 and 637. We assume all operating costs related to deploying a truck on a route is included in the route cost. Pallet cost is a fixed cost for using a given route to transport one pallet. This cost is calculated as route cost divided by 500, which gives a pallet cost around 1.

- *Truck cost*
  Truck cost represents the one-time fixed cost of using a truck. The incentive of limiting the number of trucks should be of more importance than choosing cheaper routes. Hence, we set the truck cost to use an own truck to 1000. Similarly, we assume the transport company tries to avoid using rental trucks because it is more expensive, hence rental truck usage cost is set to 2000.

- Leveling cost
  The leveling cost is the penalty related to deviating from the daily target demand. We want the importance of the penalty to increase with the number of deviating pallets. The cost structure is then piece-wise linear and has the values as given in Figure 6.10.

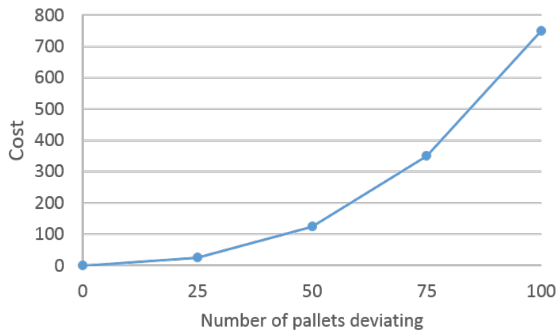


Figure 6.10: Breakpoints for the leveling cost of pallets

Chapter 7

Computational Study

In this chapter, the results from the computational study are presented. The implementation of the models is described in Section 7.1, also including technical information and instance overview. The effect of information sharing is first analyzed in Section 7.2 with the base instance. In Section 7.3 and 7.4 information sharing is studied when including shifting and time-independent route selection as added flexibility, respectively. The combination of the two types of flexibility is studied in Section 7.5. Lastly, an overall result comparison is presented in Section 7.6.

7.1 Implementation

The computational procedure is done with MATLAB®version R2015a - 8.5.0.197613, 64-bit and commercial optimization software Xpress IVE version 1.24.06 64 bit, with Xpress Mosel version 3.8.0 and FICO®Xpress Optimizer version 27.01.02. All instances have been performed on a computer with a 3.60 GHz Intel®Core i7-4790S processor and 16.0 GB RAM running Microsoft®Windows 7 Enterprise operating system.

7.1.1 Iterative Procedures

The three different information sharing cases have different iteration methods. In order to implement these iterations, we use MATLAB®. The program creates and stores sets, parameters and input data as well as the output data of the optimization. Within the programming script in MATLAB®, the optimization procedures in Xpress are called and then MATLAB®store the data. See Figure 7.1 for an illustration of the iterations done in the three different information sharing cases. The light blue processes are run by MATLAB®and the dark blue are run by Xpress.

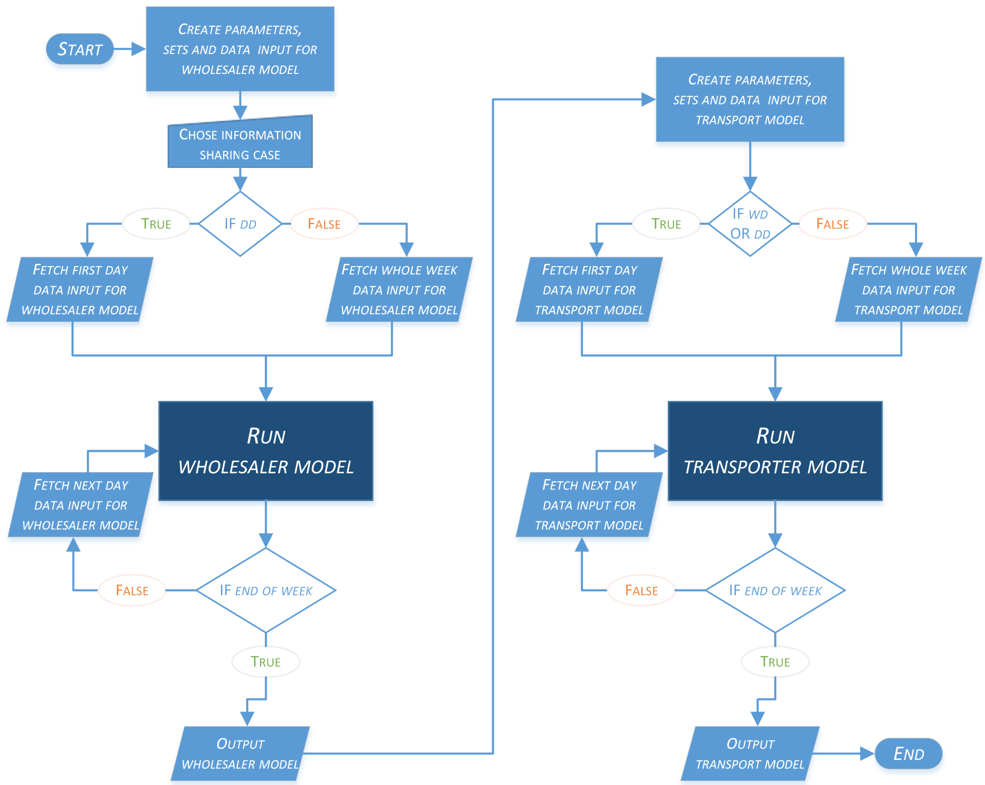


Figure 7.1: Flowchart for implementation in Matlab (light blue) and Xpress (dark blue)

7.1.2 Performance Indicators

In order to evaluate information sharing for the different instances, we consider various performance indicators.

Performance indicators for both models:

- *Cost*
  Cost changes indicate changes in fulfillment of incentives. For the wholesaler model this entails leveling incentive and pallet cost minimization. For the transporter model, it indicates the necessary number of trucks and route choices
- *Number of shifted pallets*
  For the instances including shifting, the number of shifted pallets indicates the exploitation of the shifting potential

Additional performance indicators for the transporter model:

- *Necessary number of trucks*
  This is the main performance indicator
- *Filling rate*
  Average filling rate reflects both truck utilization and number of departures

It should be noted that the cost in the wholesaler model and the transporter model should not be compared with each other to assess whether one is better off than the other. The cost in each model is used as a tool to compare information sharing cases and to determine whether added flexibility is beneficial or disadvantageous. Cost in the transporter model will not be in focus, since the model has other indicators of higher importance. The average filling rate originates from the number of departures and the demand. Therefore, comparing filling rates or comparing the number of departures have the same meaning when the total demand for the planning horizon is the same. Other model results, such as chosen routes, pallets on routes and pallets on trucks are important as they explain the performance indicators. However, we choose not to include all results as performance indicators as the different results are connected to each other.

7.1.3 Instances

Our models are generic in order to perform different analysis on the impact of information sharing. We study different instances which are distinguished by the added flexibility in the model(s). In each instance, all the three information sharing cases are included. Figure 7.2 provides an overview over the instances considered in this chapter. It should be noted that for all instances the fleet of trucks only consists of owned trucks. Rented trucks are included in what-if analysis.

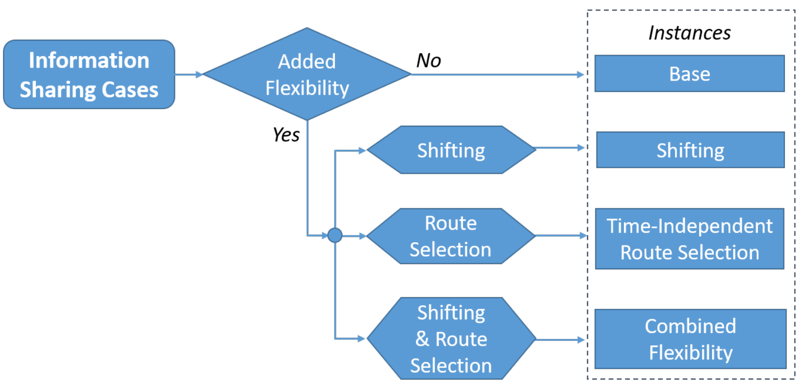


Figure 7.2: Instance overview

7.1.4 Technical Information

We conduct tests to check how software settings and sets and parameters affect the computational time and gap. The most important findings are as follows:

- *Depth first cutting strategy*:
  By applying this cutting strategy in the branch and bound procedure in Xpress the computational time is reduced and feasible solutions are found more quickly. This is a more aggressive cutting strategy, generating a greater number of cuts, and results in fewer nodes being branched due to pruning.
- *The number of trucks*:
  If the number of available trucks equals the number of necessary trucks in the model, the computational time in the transporter model is higher than if the number of available trucks is slightly bigger. However, if the available number of trucks is much higher than necessary, the computational time also increases due to the enlargement in the number of variables. Therefore, we choose to keep a fleet of 15 trucks. This can be explained as the model look primarily for feasible solutions with a limited number of available trucks. While the procedure goes easier if there is some slack.

By implementing these components, the remaining number of variables and constraint after Xpress' presolve procedure can be seen in Table 7.1. It is clear that the transporter model is more complex and larger computational problem than the wholesaler. This is first and foremost due to the binary variables in the transporter model. Additionally, the wholesaler model can choose between 23 routes, which are non-overlapping with one exception. The transporter model, on the other hand, can choose from the same 23 routes as the wholesaler model, in addition to 199 supplementary routes. The latter includes many overlapping routes. The different instances increase the size of the problems relative to the base instance and combined is the largest. This is due to having the most flexibility and thereby more combinations to go through.

Table 7.1: Number of variables and constraints for the different instances

Instance	Wholesaler Model		Transporter Model	
	Variables	Constraints	Variables	Constraints
Base	56	35	4410	494
Shifting	109	48	4574	501
Time-Independent Routes	56	35	6004	604
Combined	152	53	8572	849

The computational time for each of the information sharing cases in the base instance is seen in Table 7.2. This is the aggregated total time for all iterations and for the situations of daily iterations see Appendix D. The wholesaler model is solved to optimality within seconds due to the low degree of freedom. The selection of routes is limited due to routes being fixed to time periods and no overlapping (with one exception). Therefore, the wholesaler model has no other choice but to place the demand on the relative few available routes in the set of tactical routes. At the same time, since there are no capacity restrictions on the routes, the model finds for each retailer, the route with the lowest pallet cost. The computational time in DD is longer than in WD for the wholesaler model. The problem is solved to optimality relatively fast and the computational time includes the necessary time to generate the problem. Hence, since DD is computed from seven days, while WD is computed in one iteration for the whole week.

Table 7.2: Aggregated computational time [s] to reach optimality in the base instance for every information sharing case

	DD		WD		WW	
	Wholesaler	Transporter	Wholesaler	Transporter	Wholesaler	Transporter
Time	1.301	13.710	0.297	14.014	0.228	7204.54

The transporter model needs 7204.54 seconds to reach a gap of 0 % and conclude optimality for the WW in the base instance. This is higher than for the wholesaler because the number of variables and constraints are much higher for the transporter model. A longer planning horizon is the main reason for the relatively high computational time. However, the optimal solution was found after 4.4 seconds. By looking at the process of reaching optimality, the transporter model finds the optimal solution relatively fast, but the gap does not reduce and did not change in 48 hours. Gap performance was improved by using a depth first algorithm due to achieving a better lower bound, rather than searching for a better solution. This is because the nature of the problem implies multiple optima and the lower bound is the best indication if it is optimal or not. See Appendix E for the gap development.

The trend of the different information sharing cases is seen in the other instances as well. For the other instances, we see the same trend with an increase in the computational time with weekly information. It is the transporter model's computational time in the WW information sharing case that is predominant compared to the rest. For all instances, we accept a gap of 0.01 %, since the problem at this point is probably closing the gap, rather than finding the optimal solution.

7.2 The Base Instance

In this section, we study the effect of information sharing with no added flexibility. We aim to find out whether increased information sharing is beneficial without allowing any type of extra flexibility, meaning each retailer must be served in accordance with actual demand and at the scheduled time. This is what we refer to as *the base instance*. The base instance has a more detailed description of the analysis than the other instances. This gives an insight into the extent of the data and the algorithm, but only the performance parameters are discussed in the other instances.

Table 7.3 shows the performance parameters for the base instance. All the three information sharing cases show that the maximum number of necessary trucks is 12 and the total number of departures is 28. By only looking at the performance indicators, the three information sharing cases are identical and show no cost benefits of increased information sharing.

Table 7.3: Performance parameters for the time-independent route selection

Instance	Wholesaler Cost [Base=100 %]	Number of Necessary Trucks	Number of Departures	Filling Rate
DD	100 %	12	28	64.4 %
WD	100 %	12	28	64.4 %
WW	100 %	12	28	64.4 %

7.2.1 Trucks in Use, Departures and Returns

Figure 7.3 shows the daily number of necessary trucks. Here the number of departures and returns are the aggregated number of all the four time periods in the day. This means that if a truck returns one day, it does not necessarily entail that the same truck can be deployed on a new route the same day. This depends on which time period the truck returns and the next departure time (if any) the same day.

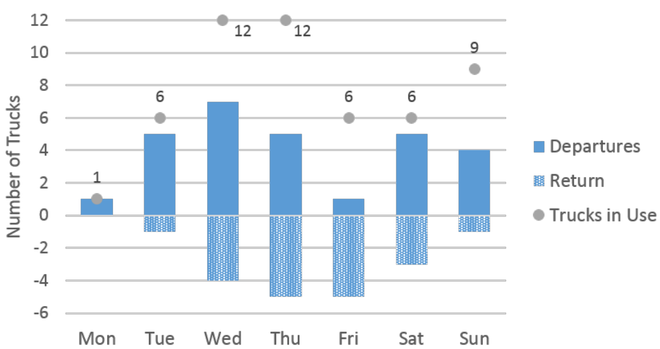


Figure 7.3: Number of trucks that leave and return within the day, as well as the maximum number of trucks in use each day

The number of trucks in use represents the number of trucks assigned to routes and used during the day. From the figure, we see that this varies through the whole week. Wednesday has high demand compared to the rest of the week and therefore have the highest number of necessary trucks. Due to the highest truck usage on Wednesday, also Thursday has equally high truck usage. We can see on Thursday that there are more than twice as many trucks in use than there are departures. This is caused by the long travel times combines with daily demand. The number of daily departures reflects the number of trucks needed for that day as all the routes use at least 4 time periods to return and therefore could not be used within the same day.

7.2.2 Route Selection

The routes chosen by each model are identical for all the information sharing cases in the base instance. However, the tactical and the operational routes are not the same. Table 7.4 provides an overview over routes chosen in the base instance for both the wholesaler model and the transporter model during each day of the week. "S" refers to supplementary route, ^{WW} indicates when information sharing case WW differs from DD and WD. * implies that number of pallets exceed truck capacity on a route.

From Table 7.4 we can see that all the 23 routes in the set of tactical routes are chosen in the wholesaler model. Hence, the wholesaler model must choose every route in order to satisfy transport requirements as there is no flexibility related to choosing routes. Furthermore, since the wholesaler model chooses all the tactical routes, then all the operational routes are available for the transporter model. This includes the tactical routes and their supplementary routes. This entails that the transporter model has some more flexibility related to route selection as the available number of routes increase from 23 in the wholesaler model to 222 in the transporter model.

If the number of pallets placed on a tactical route in the wholesaler model is less than the truck capacity of 60 pallets and there are no overlapping operational routes, the operational route chosen in the transporter model equals the tactical route chosen in the wholesaler model. This is reasonable as every retailer that can be served on a tactical route has demand the same time period that route can be chosen. Furthermore, the cost of one tactical route is always cheaper than two corresponding supplementary routes. The only exception is for route 17 and this is due to overlap of some retailers with route 20. Route 20 or any supplementary routes are not chosen by the transporter model. This is because route 20 is the only one with overlap to the other routes available on the same day. Route 17 receives additional pallets and apply a cheaper supplementary route to cover all the demand at retailer 20. In other words, when there are no overlapping routes, supplementary routes will only be chosen if the demand for a route exceeds the capacity of one truck.

If the number of pallets on a tactical route exceeds the truck capacity of 60 (marked with * and bold in Table 7.4), the corresponding operational routes either consist of two supplementary routes or one tactical and one supplementary route. Which alternative the transporter model chooses depends on the cost of the supplementary route relative to the tactical route as well as which retailers are included in which supplementary route and the retailers' demand. The route cost is identical for chosen supplementary routes where WW is different from the two other information sharing cases. Hence, the solutions suggest multiple optima. Differences are caused by algorithmic differences between the iterative and non-iterative model run procedures.

Table 7.4: Pallets on routes for the base instance

Departure Day	Wholesaler Model		Transporter Model	
	Route	Nr of Pallets	Route	Nr of Pallets
Mon	1	53	1	53
Tue	2	46	2	46
	3	51	3	51
	4	36	4	36
	5	**65***	S5.1	21
			S5.2	44
Wed	6	**63***	6	57, 60^{WW}
			S6.1	6, 3^{WW}
	7	57	7	57
	8	**68***	S8.1	36
			S8.2	32
	9	**61***	9	56
			S9.1	5
Thu	10	25	10	25
	11	15	11	15
	12	47	12	47
	13	30	13	30
	14	19	14	19
Fri	15	25	15	25
Sat	16	**65***	S16.1	36, 39^{WW}
	17	34	17	60, 58^{WW}
			S17.1	60, 59^{WW}
	18	46	18	46
	19	56	19	56
	20	57	-	-
Sun	21	55	21	55
	22	44	22	44
	23	**64***	S23.1	30
			S23.2	34

7.2.3 Filling Rates

For all the information sharing cases in the base instance, the average daily filling rate is 64.4 %. Furthermore, the common, minimum and maximum filling rates are listed as 8.33 % and 100 %, respectively. The number of pallets on each operational route in Table 7.4 also indicates the filling rate on each truck when assigned to a given route. We see that DD and WD have identical filling rates, while WW deviates on a few routes.

WW differs from DD and WD in two time periods. In both cases, the wholesaler model chooses to deliver more pallets on a shorter route than a long one which can serve the same retailers since the travel time is decisive to cost. However, pallet cost is only a cost component in the wholesaler model, which for the three information sharing cases give the same results.

As there is no such thing as pallet cost in the transporter model, the assembling of truck compartments will be indifferent to an optimal solution in this model. And as the iteration process in the transporter model differs in the WW this, the results are two different multiple optima. Therefore, the differences between WW and the two other information cases are rooted in how daily and weekly information in the transporter model affects the algorithm.

7.2.4 What-If Analysis

In this section we see how the change of either demand scenario or the cost of trucks affect the model.

Demand Week

The analysis above is conducted for demand week three. There are four demand weeks available for input. By running the base instance on them we could not find any indication that there are any differences between the information sharing cases. The number of departures, returns and trucks in use for the four different weeks could be found in Appendix F.

Rented Trucks

Here we test two situations where the number of own trucks are 8. There were no differences with rented trucks compared to the base instance. The increase in cost is solely connected to the additional truck cost related to rent of trucks. The routes chosen are identical to the base instance for all the information sharing cases. Hence, base with rented trucks require the same number of trucks in order to fulfill demand. The placement of pallets and filling rates are similar as in the base case, but there are some differences. And again, as filling rates are not represented as a cost incentive in the transporter model. Hence, different filling rates reflect multiple optima. This imply that truck cost is indifferent to the selection of routes and necessary number of trucks. This was also the case when we tested for the other demand scenarios.

7.2.5 Evaluating the Base Instance

The different information sharing cases in the base instance provide the same results. Any differences are caused by multiple optima combined and algorithmic differences between the iterative procedure for the respective information sharing case. These findings suggest that only sharing information in itself is not sufficient to reduce the costs or be beneficial for neither actor.

Many factors might impact the results. Firstly, the truck use and route selection might be affected by previous and future weeks. Nevertheless, the necessary number of trucks during the week is not likely affected. This is because Wednesday is the day that defines the maximum number of trucks in the week due to peak demand and routes for Saturday and Sunday all return no later than Tuesday. Additionally, the findings in this section suggest that if the results would be affected by input from other weeks, then all information sharing cases would be affected the same way.

Second, the transport area entails long travel times and a relatively few number of retailers and tactical routes. Generating and including more overlapping tactical routes could possibly change the outcome of information sharing as it provides more freedom and room for making changes. For that reason, a transport area located closer to the wholesaler could possibly show a higher effect of information sharing as this would suggest a higher possibility of combination of routes and consequently trucks on routes. The same argument applies to why the use of rented trucks does not show any effects on route choices. The retailers must be chosen no matter what and so the routes must be driven, independently on the cost of the truck. In the case of shorter travel times and a higher route selection, then renting may show different results. However, we assume the result here is also highly dependent on the cost structure of rental trucks with respect to route cost and own trucks.

Our models have used a cost structure that favors the reduction of the necessary total number of trucks. However, whether the transport company prefers to use as few trucks or routes as possible differ between situations and company preferences. The transport company may want to have an additional truck in order to handle demand and supply uncertainties. Additionally, if the unused trucks can be assigned to other jobs then it is more important to reduce the number of departures than minimizing the size of the fleet of trucks.

As the results from the base instance indicate that information sharing alone cannot affect cost reduction, we will further see if added flexibility has an impact in the effect of information sharing.

7.3 Shifting

In this section, we study the effect of information sharing when shifting is applied. By this we mean that the wholesaler may shift pallets to an earlier time in the WD and WW information sharing case, and the transporter model may shift to a later time in WW. For thorough explanations regarding route selection, use of trucks, etc., the reader is referred to the previous section. As shifting only is possible in WD and WW, DD is not affected and will therefore be the same as in the base instance.

The shifting done by the wholesaler and transporter model are described in Section 7.3.1 and Section 7.3.2, respectively. Section 7.3.3 describes the interactions the models have in the different information sharing cases and what consequences these have for the transporter model. Lastly, a what-if analysis is conducted in Section 7.3.4.

7.3.1 The Wholesaler Model

In the wholesaler model, SP pallets can have early shifting up to 7 days in both the WD and the WW information sharing case. Since the input and parameters are the same for the wholesaler model in the WD and WW case, results are identical for both the information sharing cases. To specify, in this subsection the WD case is presented and shifting refers to early shifting of SP pallets only and shifting is only added to the wholesaler model. The finding additionally apply to the wholesaler model in the WW case. The wholesaler model achieves a 7.7 % cost reduction when allowing shifting. All the 23 tactical routes are chosen. The cost reduction is caused by *how* pallets are placed on each tactical route, as well as achieving a higher degree of leveling.

Figure 7.4 shows the daily, scheduled number of pallets for the different pallet categories (gray) and the aggregated change due to shifting (blue). Due to leveling cost incentives, the model chooses to shift pallets from a day with high demand to a day with low demand. The dashed line represents the target demand and all days with demand that exceed this value have the incentive to shift pallets to a different day. There is, however, one exception on Thursday. This is the day which originally deviates the least from the target value. The piece-wise linear leveling cost function leads to the increment of pallets on Thursday. Therefore, the model gets a lower total cost by adding additional deviation pallets on Thursday than keeping them on Saturday and Sunday.

In total 52 pallets were shifted, meaning the model shifted 75 % of the pallets that could be shifted (see Table 6.2). A reason for not shifting more is that an order can only be shifted if there exists a route on a day earlier in the week that contains the given retailer. The day that is the most affected by the shifting is Monday that increase demand with 60.4 %. As Monday has scheduled demand lower than leveling target, the pallets are shifted to this day if possible. Monday may receive shifted pallets from all the other days given that the retailers have demand on Monday. Only 4 retailers are served on Monday, but all these experience shifting this day. The shifting to Monday

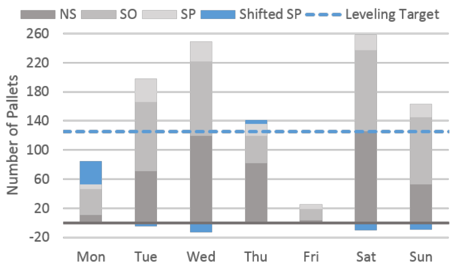


Figure 7.4: Number of scheduled pallets (gray) and aggregated change of pallets due to shifting (blue)

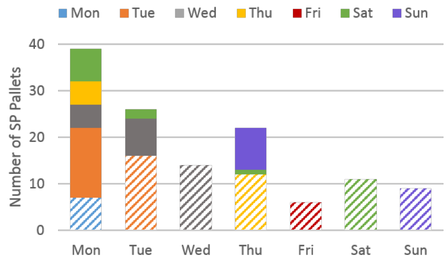


Figure 7.5: Shifted (solid bars) and non-shifted SP-pallets(striped bars) in WD and WW with early shifting

is also restricted by the inventory constraint and this prevents an even higher number of shifting.

Figure 7.5 illustrates the distribution of SP pallets over the week, indicating which days a pallet is shifted to and from. The striped bars indicate SP pallets that are not shifted and the color represent the day of the week. The solid bars are the shifted pallets and the color indicate which day they are shifted from. Thursday and Tuesday both shift to another day, but additionally receives pallets from another day. This has to do with the arrangement of retailers on different days. The SP pallets shifted to Thursday are weekend orders with retailer demand on Thursday and no other day with lower scheduled demand. On Wednesday the demand decrease with 5.2 % and is the largest reduction of the days. Nothing is shifted to Friday because the retailers served on Friday do not have demand of SP pallets other days of the week exceeding one pallet, and therefore have no potential pallets to shift.

The effect of shifting is influenced by how the pallet category share is divided among the different retailers and routes. Retailers with a low share of shiftable orders are less likely to be affected by shifting than retailers with high shares. Correspondingly, a route with a high share of shiftable orders has a higher probability to be altered for than the ones with a low share. Additionally, the shifting of pallets on a route directly affect the truck filling to trucks assigned on that route.

7.3.2 The Transporter Model

In the transporter model, SO pallets can have late shifting up to 2 days. Shifting in the transporter model is only available in the WW information sharing case and done after the shifting of the wholesaler model. In the transporter model 23 pallets are shifted, i.e. 35 % of possible shiftable SO pallets. The transporter model has the incentive to shift pallets only if this will affect selection of routes and thereby route costs and use of trucks. The transporter model shifts less than the wholesaler model. This is due to the different incentives and that the number of pallets deviating from the leveling target in the wholesaler model is higher than the number of pallets exceeding truck capacity in the transporter model.

Figure 7.6 shows the daily, scheduled number of pallets for the different pallet categories (gray), aggregated change due to early shifting in the wholesaler model (blue) and late shifting in the transporter model (orange). The transporter model chooses to shift opposite of the wholesaler model on Monday, Wednesday and Sunday. Contrary, on Tuesday, Thursday and Saturday the shifting is in the same direction. This implies that the cost incentives in the two models are contradicting some days while amplifying other days. This is mostly dependent on the truck utility for a given day. All the days, exception for Friday and Sunday, shift and postpone SO pallets. See Appendix G to see which days shift to/from each other for the transporter model.

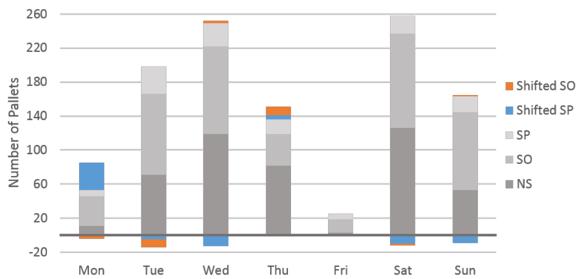


Figure 7.6: Number of scheduled pallets (gray) and aggregated change of pallets due to early shifting (blue) and late shifting (orange)

7.3.3 Evaluating the Differences in Information Sharing Cases

The performance parameters for the shifting instance can be seen in Table 7.5. We see that the wholesaler benefit from the shifting by 7.7 % decrease in cost and that the shifting leads to one less truck necessary. The filling rate and number of departures, on the other hand, does not change.

Table 7.5: Performance parameters for the shifting instance

Instance	Wholesaler Cost [DD=100 %]	Number of Necessary Trucks	Number of Departures	Filling Rate
DD	100 %	12	28	64.4 %
WD	92.3 %	11	28	64.4 %
WW	92.3 %	11	28	64.4 %

Figure 7.7 illustrates the daily number of necessary trucks with and without shifting. Due to the leveling in the wholesaler model, the transporter model must assign one additional truck on Monday in WD and WW compared to DD. The additional

truck usage on Monday also necessitates an additional truck on Tuesday. However, the wholesaler leveling of demand reduce the number of pallets on Wednesday enough to save one truck in the transporter model. As Wednesday is the day which demand is decisive for the necessary number of trucks in the week means that the overall truck need is reduced from 12 to 11 trucks. This implies that even though the wholesaler model does not consider truck usage or capacity, the leveling incentive has a direct impact on the weekly truck need. This also means that the transporter model gains from the leveling incentive in the wholesaler model. The results of the models imply that with shifting, the average number of necessary trucks decrease, but not the number of departures.

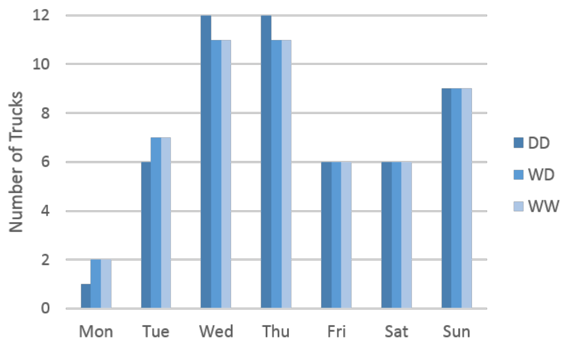


Figure 7.7: Comparing daily number of necessary trucks with and without shifting

Going from WD to WW information sharing case, the change in routes chosen and pallets placed could be explained by three factors. Firstly, the added flexibility together might modify the algorithm to choose a different composition of pallets than in the WD case due to the multiple optima. Secondly, shifting enables the transporter model to choose different, i.e. cheaper, combinations of routes compared to without shifting. This is the situation on Saturday, where two pallets are shifted to Sunday in order to use a better supplementary route. Thirdly, shifting enables to save departures from the wholesaler and thereby the necessary number of trucks. However, the results did not show this, but this is probably due to the end of horizon time frame. To specify, there are 2 supplementary routes on Sunday pallets that correspond to one tactical route in the wholesaler model, which trucks together carry 61 pallets. By shifting one pallet to a later day, i.e. next week, it would be possible to only use one truck instead of two on Sunday. However, we do not allow shifting between different weeks. Therefore, without an end of horizon time frame, there is a high probability that the pallet would be shifted and the WW case would have saved one more departure compared to the WD case.

In the demand scenario of week 3, there are no differences between the information sharing cases WD and WW. Daily truck use and the number of departures are the same. This implies that benefits from information sharing with added flexibility is not caused by information sharing between the two models, but is limited to the added flexibility of early shifting in the wholesaler model. In other words, it is the fact that the wholesaler makes use of the available information earlier, not that when it shares this information with the transport company that is decisive.

7.3.4 What-If Analysis

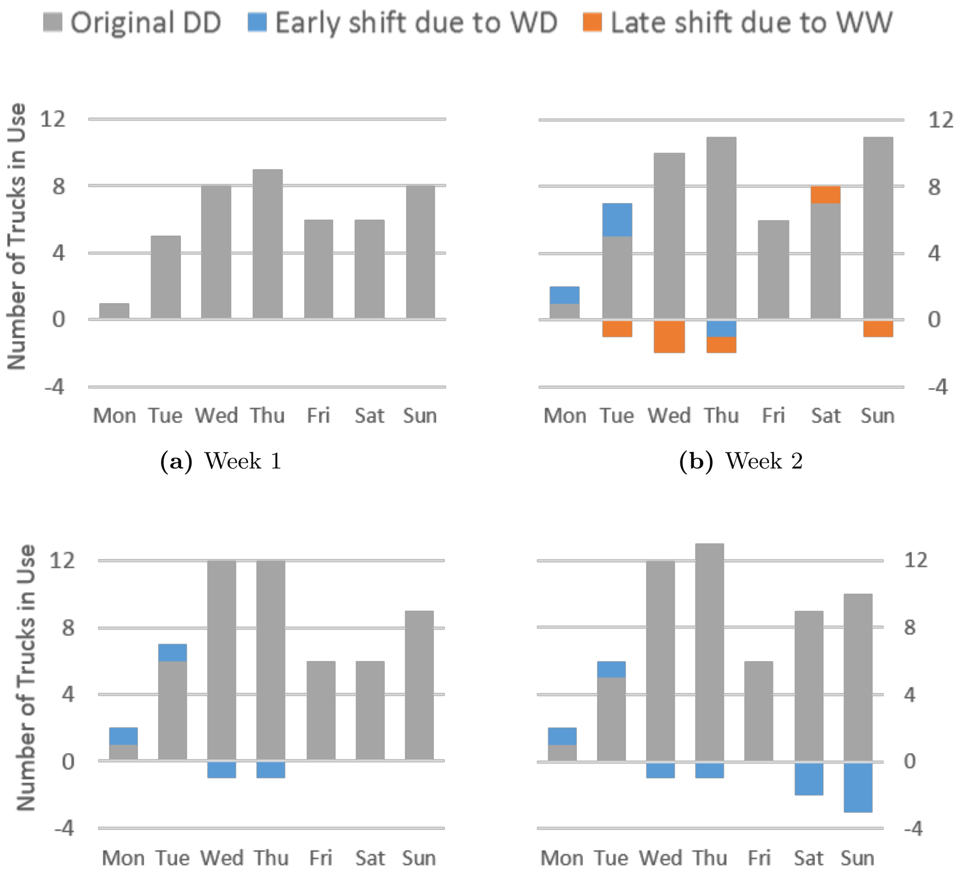
Choice of parameters and sets for the models may be crucial for the results. Therefore, we want to validate the results for the information sharing cases with added flexibility. We look at the effect of changes in three different parameters: demand input, shifting ratio and the number of shifting periods. The renting of trucks does not affect the transporter model and the results are the same in terms of routes and number of trucks and the total cost change due to the extra cost of renting. Therefore, we do not analyze this further.

Demand Week

In Section 7.3.2 we found that improved results when allowing shifting originated from the wholesaler's ability to plan demand distribution. Improvements were not made due to transport company's ability plan better due to increased information sharing. However, we want to check the 3 other weeks from the input data to see if information sharing and late shifting has a decisive impact when the daily demand is different. Figure 7.8 provides an overview of daily truck usage for all the 4 demand weeks for DD and aggregated changes from early shifting in WD (blue) and late shifting in WW (orange).

There are no changes in truck usage between the information sharing cases in week 1 (Figure 7.8a). This implies that for this week, early shifting nor late shifting have any impact in terms of the number of necessary trucks. It should be noted that week 1 is the week with the lowest total demand. Week 2 (Figure 7.8b) is the week with the highest weekly truck usage reduction, but also the only week where late shifting in the transporter model contributes to changes. Due to wholesaler leveling, the transporter model needs additional trucks on Monday and Tuesday in the WD case. However, when late shifting is allowed in WW, the transporter model is able to reduce the truck usage. Additionally, the model changes a tactical route into two supplementary routes on Saturday in order to return in time to reduce the number of trucks on Sunday. This way, the late shifting in WW reduces the maximum necessary number of trucks in the truck fleet. Week 4 (Figure 7.8d) has the greatest changes due to the leveling in the WD case.

From this, we can conclude that the potential of information sharing is highly dependent on the daily variations from each week. When we see such substantial differences between 4 consecutive weeks, we assume the differences are even higher within a year.



(a) Week 1 **(b)** Week 2

(c) Week 3 **(d)** Week 4

Figure 7.8: The number of necessary trucks for each of the four demand weeks when shifting is allowed

Increasing the Shifting Ratio

The shifting of SP pallets is first and foremost influenced by the share of promotional products. The applied data contain a lower share of SP pallets compared to other months of the year. A higher share of SP pallets implies a higher potential for shifting for the wholesaler model, which again influences the transporter model. In this section we analyze what happens to the transporter model when we allow for a higher ratio of the SO pallets to be shifted. This is primarily because the effects of late shifting proved to be insignificant with respect to truck usage. The shifting ratio directly affects the number of pallets that potentially can be shifted and consequently, the number of shifted pallets.

Figure 7.9 shows the number of necessary trucks for three different shifting ratios. We can see that in general, a shifting ratio of 100% has a bigger impact on daily truck usage than a shifting ratio of 30 %. However, the weekly, necessary number of trucks are the same for the two higher shifting ratios. Compared to a shifting ratio of 20%, the increased shifting ratio result in needing one truck less. This might imply that the effect of increasing the shifting ratio is positive but diminishing.

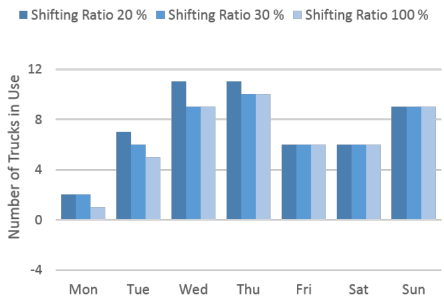


Figure 7.9: Daily truck usage for WW with different shifting ratios

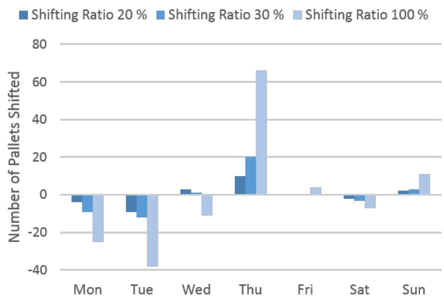


Figure 7.10: Daily late shifting of SO pallets for WW with different shifting ratios

Figure 7.10 shows the daily shifted number of SO pallets with different shifting ratios. The higher the ratio, the more pallets are shifted. Monday and Tuesday are the days where the highest number of pallets are shifted from, while Thursday is the day the most pallets are shifted to. Nevertheless, the number of shifted pallets are significantly higher for a 100% shifting ratio. This leads to one departure saved on Monday (see Figure 7.9).

Currently, the wholesaler allows the transport company to shift a limited number of pallets. However, our model suggests that alternating the shifting ratio does change the impact of late shifting and can be beneficial as it might reduce the number of necessary trucks.

Increasing the Number of Days SO can be Shifted

The transporter model has the possibility to postpone and shift SO pallets up until two days. In this section, we study what happens if they could postpone a delivery with 7 days, i.e. the same number of periods the wholesaler model is allowed to shift earlier in time. Figure 7.11 and 7.12 compare the daily truck usage and number of shifted SO pallets, respectively.

We see that the necessary number of trucks is reduced by one truck when allowing 7 day postponed shifting instead of just 2. More days to shift onto indicates greater shifting potential. More pallets are shifted to the second half of the week. This saves the use of one truck since Wednesday is the decisive part for maximal truck usage during the week.

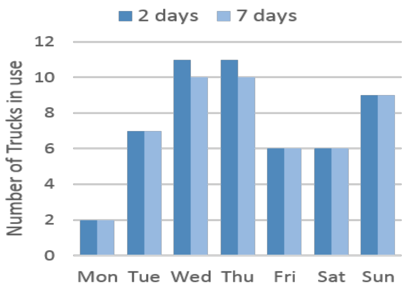


Figure 7.11: Daily truck usage for WW

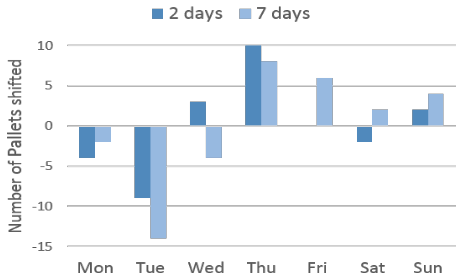


Figure 7.12: Daily late shifted number of SO pallets for WW

7.4 Time-Independent Route Selection

In this section, we study the effect of information sharing when allowing a more flexible route selection. We keep the set of tactical and operational routes but remove the restriction regarding which routes can be chosen which day. In other words, we look at time-independent route selection for both models.This is an alternative to making more routes, and consequently giving the models more freedom. It should be noted that by this relaxation of the models will no longer ensure retailer delivery requirements. Section 7.4.1 and Section 7.4.2 go through the effect the time-independent routes have on the wholesaler and transporter model, respectively before and evaluation of the differences in the information cases in Section 7.4.3. Lastly in Section 7.4.4, a what-if analysis, where the operational routes are unconditional of the tactical routes is conducted.

7.4.1 The Wholesaler Model

Time-independent route selection in the wholesaler model implies that the wholesaler model for each time period can choose from all the 23 tactical routes. All the information sharing cases show identical results with a time-independent route selection. This is because retailer demand is fixed to time periods, and the wholesaler model must select routes for the same pallets regardless of when information is available.

The wholesaler model uses 12 time-independent routes with 47 departures altogether during the week. As demand is fixed, the only cost incentive is pallet cost minimization. This means that the model will place pallets on routes that give the cheapest pallet costs, implying cheap routes. This result in the model choosing the least expensive routes, i.e. the cheapest to serve each retailer, instead of routes that serve more retailers. By comparing with the base instance, we see that instead of choosing one route that serves every retailer with demand on Monday, the wholesaler model chooses three different routes to serve the same retailers.

7.4.2 The Transporter Model

The results in the transporter model are dependent on the route selection in the wholesaler model as the route selection is conditional time-independent. E.g. on Monday the transporter model for DD and WD can only choose between the three tactical routes chosen by the wholesaler and the supplementary routes for these three tactical routes. For WW the transporter model can choose among all the tactical routes chosen by the wholesaler and the supplementary routes every day.

Daily information, i.e. DD and WD, in the transporter model gives identical results as the output from the wholesaler model are identical for all the information sharing cases. However, WW separates from DD and WD. Figure 7.13 illustrates the daily truck usage for the information sharing cases with time-independent route selection and the base instance.

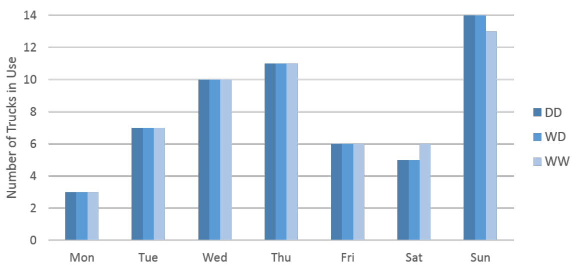


Figure 7.13: Daily truck usage for DD/WD and WW with time-independent route selection compared to the base instance

We see in Figure 7.13 that the transporter model must assign three trucks on Monday instead of one as the retailers can no longer be served with one but three routes as a consequence of the route selection in the wholesaler model. This is the case for 3 of the days. This causes an increased number of necessary trucks during the week compared to the basic instance since the same routes are no longer available. This is because the selection of tactical route in the weekend is poor in terms of truck utilization since the wholesaler place pallets on the cheapest available route for the retailer. This causes Sunday to be the new, decisive day of necessary number trucks during the week instead of Wednesday for the other instances.

7.4.3 Evaluating the Differences in Information Sharing Cases

The performance parameters for the time-independent routes instance can be seen in Table 7.6. The wholesaler model has the same amount of flexibility for all the cases and does thereby not change. The transporter model saves one necessary truck going from WD to WW.

Table 7.6: Performance parameters for the time-independent route selection

Instance	Wholesaler Cost [DD=100 %]	Number of Necessary Trucks	Number of Departures	Filling Rate
DD	100 %	14	35	51.5 %
WD	100 %	14	35	51.5 %
WW	100 %	13	36	50.1 %

The reason for the reduction is that the transporter model chose two shorter supplementary routes on Saturday in the WW compared to the DD and WD. By distributing pallets on one route into two instead, the traveling time was reduced enough to have the trucks return to the departure on Sunday. Thereby the use of an additional truck was avoided and the number of necessary trucks was decreased.

The chosen routes with reduced the traveling time were also available in the DD case. This means that it was not the higher selection of routes in the WW case that manifested the change, but rather the opportunity to plan to return for the next day departures. The number of departure increase and consequently, the filling rate becomes worse, but the model ends up saving compared to the DD case due to saving the maximum number of trucks necessary.

There is a trade-off between the number of departures and the number of necessary trucks. Due to the transporter model cost structure, the number of necessary trucks is favorized.

7.4.4 What-If Analysis

In this section of what-if analysis of the time-independent route selection is conducted. Similar to the other instances, the renting of trucks did not change the result.

The Transporter Model With Unconditional Route Selection

Here we include an additional flexibility to the transporter model where the model disregards the route selection output from the wholesaler model. In other words, the route selection in the transporter model is unconditional and the operational set of routes include the all the tactical and the supplementary routes. From now on the unconditional routes refer to time-independent operational routes that a independent of the tactical routes.

Unconditional route selection results in identical output for the three information sharing cases. This is because all the routes can be chosen at all times. Table 7.7 shows the performance parameters.

Table 7.7: Performance parameters for the unconditional route selection

Instance	Wholesaler Cost [DD=100 %]	Number of Necessary Trucks	Number of Departures	Filling Rate
Unconditional Routes	100 %	9	24	75.3 %

Unconditional route selection leads to additional opportunities for the arrangement of pallets on routes and trucks. The transporter model chooses more shorter routes with unconditional route selection. Shorter routes imply that trucks are available earlier, and hence that less number of trucks are necessary to serve the same demand. With unconditional route selection, only 9 trucks are needed compared to 13 trucks in the WW for the time-independent routes instance. The number of departures decreases by 33.3 %. This implies that the more options of routes, the higher the average filling rate, the better the arrangement of routes and the fewer number of trucks and departures are necessary. In other words, the transporter model benefits from added flexibility in terms of route selection, rather than receiving more information earlier.

7.5 Combined Flexibility

In this section, we increase the level of added flexibility. Section 7.5.1 combines the flexibility of route selection and shifting. Section 7.5.2 conducts a what-if analysis for the combined instance.

7.5.1 Shifting & Time-Independent Route Selection

Here we combine time-independent route selection with the opportunity of shifting, i.e. the combined flexibility instance. Here both the routes and demand from the wholesaler model change and consequently change the input for the transporter model. Table 7.8 shows the performance parameters for the combined instances.

Table 7.8: Performance parameters for the combined flexibility

Instance	Wholesaler Cost [DD=100 %]	Number of Necessary Trucks	Number of Departures	Filling Rate
DD	100 %	14	35	51.5 %
WD	85.2 %	16	42	42.9 %
WW	85.2 %	15	40	45.1 %

From the table, we see that the wholesaler cost have decreased 14.8 % from DD to WD/WW. This is the highest reduction of cost out of all the instances. On the other hand, both the number of necessary trucks and number of departures have increased as well. From the combined DD to the WD the number of necessary tuck have increased by two and departures have increased by 20 %. This implies that the improved information and flexibility in the wholesaler model actually worsen the result of the transporter model. When this information is shared in the WW and the transporter model has combined flexibility the result improve, but is still worse than the DD. This is because the wholesaler model only places pallets on the cheapest route no matter which day and thereby does not take the average demand pattern into account.

Figure 7.14 illustrates the causes for the increased number of departures. The number of trucks in use seems to be more leveled over the days in the WD and WW compared to the DD except for the increase at the end of the week. This may imply that the wholesaler model's leveling does level the trucks in use as well, but at the expense of more departures. Figure 7.15 shows the shifting by both models for the WW. The demand on Friday increases with 76 % after the wholesaler model shift and consequently, the departures increase from one departure on Friday in DD to five departures in the WD and WW. The increase in the necessary number of trucks comes from the increased number of departures on Friday which again increase the number of trucks in use on Saturday.

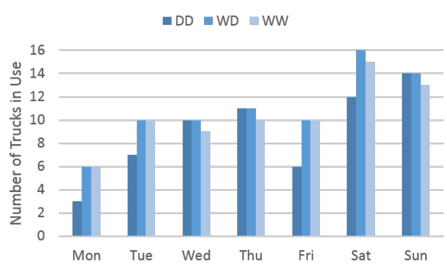


Figure 7.14: Daily truck usage for the combined flexibility

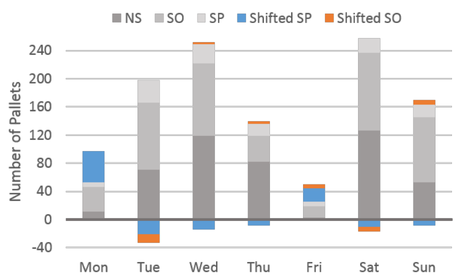


Figure 7.15: Shifting of pallets in the combined instance

These findings imply that added information and added flexibility may actually worsen the results for the transporter model in both regards to number of departure and number of necessary trucks. This shows that the incentives between the models are not aligned, and the leveling in the wholesaler model is at the expense of truck use in the transporter model.

7.5.2 What-If Analysis

We do two what-if analysis for the combined instance; one testing the restrictions of routes and one where the transporter model is the only one allowed to shift.

Unconditional Routes

Here the combined flexibility instance is tested with the added flexibility of unconditional operational routes in the transporter model. Table 7.9 shows the performance parameters. The results for the transporter model improve significantly, decreasing the number of departures with 25 % and the necessary number of trucks with 33 % compared to the WW case of the combined instance. Hence, the additional opportunities of route selection disregarding the wholesaler model improve the transporter model cost largely.

Table 7.9: Performance parameters for the combined instance with unconditional operational routes

	Wholesaler Cost [DD=100 %]	Number of Necessary Trucks	Number of Departures	Filling Rate
Unconditional Combined	85.2 %	10	30	60.3 %

It should additionally be noted that the number of necessary trucks increases by one in the combined instance with unconditional routes, than with only unconditional routes and no shifting (see Table 7.7). On the other hand, the combined instance with unconditional routes lowers the number of necessary trucks compared to with shifting. From this, we conclude the shifting in the wholesaler model worsen the result of the transporter model in the combined instance.

Shifting Exclusively for the Transporter Model

Here we look at the combined flexibility of unconditional route selection and shifting, but the wholesaler model is not allowed to shift. In other words, the transporter model has unconditional time-independent route selection with shifting while the wholesaler has only time-independent route selection as a flexibility. Performance indicators are seen in Table 7.10.

Table 7.10: Performance indicators where shifting is exclusively for the transporter model

	Wholesaler Cost [DD=100 %]	Number of Necessary Trucks	Number of Departures	Filling Rate
Exclusive	100 %	9	24	75.3 %

The performance indicators above are identical with the situation of unconditional operational routes in Table 7.7. The chosen routes, however, are not identical. Compared to solely the unconditional routes, the combined flexibility better the objective value in the transporter model by 0.2 %. This is because the added shifting allows the transporter model to chose combinations of routes that are less expensive. This, as well as the identical performance parameters indicate that the transporter model has no synergy effects with added flexibility. Additionally we conclude that the improved results of the combined instance compared to the base instance comes from the extended route selection rather than the shifting.

The objective value in the wholesaler model worsen in this what-if analyses compared to the model performances in the original combined instance. In fact, we do not find any instances where both models perform the best. Either the wholesaler model leveling worsen the transporter model's conditions or the wholesaler model is denied a flexibility and therefore worsen the result. This shows the need of aligning incentives.

7.6 Overall Results Comparison & Discussion

Here we compare the presented instances; base, shifting, time-independent routes and combined. Table 7.11 shows the overall performance of four instances. All the instances in the table are here shown for the WW information sharing case to compare the effect of full information.

Table 7.11: Performance parameters for four different instances with the WW case

Instance	Wholesaler Cost [Base=100 %]	Number of Necessary Trucks	Number of Departures	Filling Rate
Base	100 %	12	28	64.6 %
Shifting	92.8 %	11	27	67.0 %
Time-Independent Route Selection	92.3 %	13	36	50.1 %
Combined	79.1 %	15	40	45.1 %

The wholesaler cost is almost the same when either shifting or time-independent routes are added flexibility, but the combined effect performs the best. We can see from the results that the combined effect is higher than adding the two effects separately ($92.8\% \cdot 92.3\% > 79.1\%$). This could point to some synergy effects in the wholesaler model when combining the different types of flexibility.

The number of departures as well as necessary trucks differs in all the instances. The shifting is the one instance that preform best regarding the lowest number of necessary trucks as well as number of departures. On the other hand, from the what if analysis in Section 7.4.4 showed that with unconditional route selection the necessary number of trucks where 9. The difference between unconditional route selection and time-independent route selection is mainly the number of available routes. From this we can conclude that a bigger selection of routes gives the transporter model better performance than with shifting. The combined effect worsen the results of the transporter model. From Table 7.11 we see that the combined instance actually result in the highest number of departures and thereby the lowest filling rate.

The combined instance have the lowest number of trucks in use on Wednesday and Thursday which is the days with the highest usage of trucks for the other instances. Hence, the leveling from the wholesaler model could give the transporter model a better result in regard of reducing the number of trucks in use on the days of the largest demand. The downside of the combined instance is the increase of departures. This is because the wholesaler model will shift in order to level the pallets without taking the truck capacities into account, and the combined instances amplify this effect. This means the leveling in the wholesaler model might level the use of trucks, but at the expense of adding additional departures, which worsen the filling rate. Hence, increasing flexibility is not necessary beneficial if the incentives of the models are not aligned.

Table 7.12 shows each of the instances improvement with the increased information sharing. The base instance had no improvement. Both of the flexibility of route selections and shifting showed improvement of information sharing by one truck. The combined instance however, showed a worsening of the number of necessary trucks. From this we conclude that information sharing between a wholesaler model and a transporter model have potential benefits, but if the incentives differ too much from each other, then flexibility combinations may actually amplify a negative effect for the transporter model.

Table 7.12: Improvement from DD to WW in the reviewed instances

Instance	Improvement of Necessary Trucks
Base	*0*
Shifting	*Decrease by 1*
Time-Independent Routes	*Decrease by 1*
Combined	*Increase by 1*

Our findings throughout this chapter suggest that only the possibility of added flexibility show some benefits of increased information sharing. In this section we provide managerial insight and real life applications. We additionally critically review our results and models.

Our results depend highly on the characteristics of the grocery industry. First, in the grocery industry lead times are short. Information sharing is most beneficial when lead times are long, demand variation is high and demand correlation over time is high (Lee et al. (2000)). Even though the demand meet the criteria, all the decisions for the transport company are on an operational level and the lead times for them are less than 24 hours. The grocery industry the focus on high responsiveness and high customer service level. This gives incentives to short lead times and consequently

cause less benefits of information sharing. Therefore, applying the same models on a different industry might show different effects of increased information sharing.
The computational time greatly increases from the DD to the WW information sharing case due to the increased complexity. This could also be the reason why planning happen in shorter time intervals in reality. Hence, the benefits of increased information sharing would be difficult or even impossible to implement. This argument is also supported by the fact that it is impossible to have full information for a week, together with the real life challenges related to information sharing between actors in the supply chain. Firstly, information sharing is usually used in different ways by different actors, and thereby not structured correctly or lack crucial information for the part that receives the information. Secondly, information almost always comes with noise when shared. Therefore, to actually achieve benefits of information sharing in reality one would have to implement a system to communicate the information efficiently.

Our results suggest that leveling initiated by the wholesaler improved resource utilization in both models. Increased information sharing proved to be less important. In other words, better planning of promotional products by the wholesaler lowers the need for both (increased) information sharing and planning by the transport company. Therefore, if the wholesaler could implement a new planning procedure for promotional demand and level the demand better with shifting, then the transport company may either decrease the number of trucks assigned to this transport area.

A classical supply chain strategy says that demand leveling will lead to more effective resources utilization. Nevertheless, the benefits of leveling must be weighed against the decreased service level to retailers and consequently consumers. Remember that the current demand pattern illustrates the consumers' buying behaviour. Additionally, as the grocery retail market is highly competitive market, stock-outs are not desired. Promotional products have the advantage of not causing stock outs. Instead, they are used as inventory build-ups before the promotion start. Therefore, these products can be used to level demand without compromising the service level of retailers nor consumers. Therefore, also the transport company should be allowed to shift promotional products as long as they are delivered before the promotion period.

We found that added flexibility for some instances made at least one of the models worse off compared to the base instance. This implies that some sort of feedback loop could have been included to improve the decision making. Therefore, a feedback loop, alternatively a solution triggered feedback, could potentially serve to enhance the cooperation and the alignment of each actor's incentives both in the models and in real life. Not only should feedback loops apply on a short term basis where the wholesaler approves shifting suggestions by the transport company, but also on a long term basis. The wholesaler's planning of promotional products starts months in advance of its distribution. Hence, by coordinating with the transport company the risk of exceeding truck capacities, and consequently needing extra trucks, could be reduced. By establishing a feedback loop, the entire supply chain may benefit, and this may duel the well-known problem of functions working in "silos" where the function optimizes their own incentives and thereby end up with a sub-optimized solution for the supply chain (Fernie and Sparks (2014)).

Chapter 8

Concluding Remarks

In this thesis, we investigated the effect of information sharing between a wholesaler and a transport company. We proposed two mathematical models, each representing the respective actor's requirements and incentives. Information sharing was evaluated by comparing three different information sharing cases, that were distinguished based on whether each model received information daily or weekly. We additionally tested the effect of information sharing when adding different types of flexibility. It should be noted that our conclusions reflect the applied input data on our models, hence other models and other input data might yield other results.

Our results showed that increased information sharing was only beneficial when adding flexibility. Added flexibility reduced the costs in the wholesaler model by up to 14.8 % and made it possible to use one truck less during the week. However, we also found that the added flexibility could be disadvantageous for the transporter company, and thereby the supply chain as a whole. The increased information sharing and added flexibility are therefore only beneficial if the wholesaler and transport company align their incentives. Hence, the transition from a tactical route plan to the operational execution of routes is critical in the implementation of this alignment. Leveling of demand by shifting could potentially lead to cost reduction as long as truck capacities are considered. Using promotional products to level the demand and decrease the pressure on the transportation system on high demand days could reduce the necessary number of trucks and still fulfill retailer requirements.

For future research, a more extensive model incorporating the way the wholesaler replenishes demand while considering truck capacities could be used. The effect of information sharing should additionally be studied for different demand scenarios widespread over the year, possibly also including as a stochastic factor, to incorporate the influence of varying demand. A model with rolling horizon time frame could additionally be used to better demonstrate the transition between weeks, and also expands the possibility of shifting. Lastly, other industries have different demand patterns and storability of products and could show other results.

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Appendix A: The Wholesaler Model

$$\min \qquad P^W = \sum_{d\in\mathcal{T}^W}\sum_{p\in\mathcal{P}} C_p^L(\sigma_{dp}^+ + \sigma_{dp}^-) + \sum_{i\in\mathcal{N}}\sum_{r\in\mathcal{R}}\sum_{t\in\mathcal{T}^P} C_r^P(y_{irt}^{NS} + y_{irt}^{SO} + y_{irt}^{SP})$$

$$\begin{array}{lll}
\sum_{r\in\mathcal{R}|A_{ir}=1} y_{irt}^{NS} = D_{it}^{NS} & i\in\mathcal{N}, & t\in\mathcal{T}^P \\
\sum_{r\in\mathcal{R}|A_{ir}=1} y_{irt}^{SO} = D_{it}^{SO} & i\in\mathcal{N}, & t\in\mathcal{T}^P \\
\sum_{t=\rho-E}^{\rho} w_{i\rho t} = D_{i\rho}^{SP} & i\in\mathcal{N}, & \rho\in\mathcal{T}^P \quad |t>0 \\
\sum_{r\in\mathcal{R}|A_{ir}=1} y_{irt}^{SP} - \sum_{\rho=t}^{t+E} w_{i\rho t} = 0 & i\in\mathcal{N}, & t\in\mathcal{T}^P \quad |\rho\leq|\mathcal{T}^P| \\
w_{i\rho\rho}\geq(1-\alpha)D_{i\rho}^{SP} & i\in\mathcal{N}, & \rho\in\mathcal{T}^P \\
\sum_{t\in\mathcal{T}^P}(y_{irt}^{NS} + y_{irt}^{SO} + y_{irt}^{SP}) \leq M_1 A_{ir} & i\in\mathcal{N}, & r\in\mathcal{R} \\
\sum_{i\in\mathcal{N}}(y_{irt}^{NS} + y_{irt}^{SO} + y_{irt}^{SP}) \leq M_2 B_{rt} & r\in\mathcal{R}, & t\in\mathcal{T}^P \\
\sum_{r\in\mathcal{R}|A_{ir}=1}(y_{irt}^{SO} + y_{irt}^{SP}) - \gamma_{it} + \gamma_{i(t-1)} = D_{it-1}^{SO} + D_{it-1}^{SP} & i\in\mathcal{N}, & t\in\mathcal{T}^P \\
\gamma_{it}\leq I_i & i\in\mathcal{N}, & t\in\mathcal{T}^P \\
\gamma_{i0} = I_i^0 & i\in\mathcal{N} & \\
\sum_{i\in\mathcal{N}}\sum_{r\in\mathcal{R}}\sum_{t\in\mathcal{T}_d^D}(y_{irt}^{NS} + y_{irt}^{SO} + y_{irt}^{SP}) + \sum_{p\in\mathcal{P}}(\sigma_{dp}^- - \sigma_{dp}^+) = \overline{D} & & d\in\mathcal{T}^W \\
\sigma_{dp}^+ + \sigma_{dp}^- \leq \beta_p & d\in\mathcal{T}^W, & p\in\mathcal{P} \\
\sigma_{dp}^+, \sigma_{dp}^- \geq 0 & d\in\mathcal{T}^W, & p\in\mathcal{P} \\
w_{i\rho t}\geq 0 \ \text{\& integer} & i\in\mathcal{N}, & \rho\in\mathcal{T}^P, \quad t\in\mathcal{T}^P \\
y_{irt}^{NS}, y_{irt}^{SO}, y_{irt}^{SP} \geq 0 \ \text{\& integer} & i\in\mathcal{N}, & r\in\mathcal{R}, \quad t\in\mathcal{T}^P \\
\gamma_{it}\geq 0 & i\in\mathcal{N}, & t\in\mathcal{T}^P
\end{array}$$

Appendix B:
The Transporter Model

$$\min \quad P^T = \sum_{r\in\widehat{\mathcal{R}}}\sum_{t\in\mathcal{T}^P}\sum_{v\in\mathcal{V}} C_r^R x_{rtv} + \Big(\sum_{v=1}^{m} C^{\text{Own}}\delta_v + \sum_{v=m+1}^{|\mathcal{V}|} C^{\text{Rent}}\delta_v\Big)$$

$$Q^V \sum_{v\in\mathcal{V}} x_{rtv} - \sum_{i\in\mathcal{N}|\hat{A}_{ir}=1} (\hat{y}_{irt}^{NS} + \hat{y}_{irt}^{SO} + \hat{y}_{irt}^{SP}) \geq 0 \qquad r\in\widehat{\mathcal{R}}, \quad t\in\mathcal{T}^P$$

$$\sum_{r\in\widehat{\mathcal{R}}}\sum_{t'=t}^{t+K_r} x_{rt'v} \leq 1 \qquad t\in\mathcal{T}^P, \quad v\in\mathcal{V}$$

$$\sum_{r\in\widehat{\mathcal{R}}}\sum_{t'=t}^{t+K_r}\sum_{v\in\mathcal{V}} x_{rt'v} \leq |\mathcal{V}| \qquad t\in\mathcal{T}^P \quad |(t+K_r)\leq|\mathcal{T}^P|$$

$$\sum_{v\in\mathcal{V}} x_{rtv} \leq |\mathcal{V}|\hat{B}_{rt} \qquad r\in\widehat{\mathcal{R}}, \quad t\in\mathcal{T}^P$$

$$M_1\delta_v - \sum_{r\in\widehat{\mathcal{R}}}\sum_{t\in\mathcal{T}^P} x_{rtv} \geq 0 \qquad v\in\mathcal{V}$$

$$\delta_{v+1} - \delta_v \leq 0 \qquad v\in\mathcal{V}$$

$$\sum_{r\in\widehat{\mathcal{R}}|\hat{A}_{ir}=1} \hat{y}_{irt}^{NS} = \widehat{D}_{it}^{NS} \qquad i\in\mathcal{N}, \quad t\in\mathcal{T}^P$$

$$\sum_{r\in\widehat{\mathcal{R}}|\hat{A}_{ir}=1} \hat{y}_{irt}^{SP} = \widehat{D}_{it}^{SP} \qquad i\in\mathcal{N}, \quad t\in\mathcal{T}^P$$

$$\sum_{t=\rho}^{\rho+L} \hat{w}_{i\rho t} = \hat{D}_{i\rho}^{SO} \qquad i\in\mathcal{N}, \quad \rho\in\mathcal{T}^P \qquad |t\leq|\mathcal{T}^P|$$

$$\sum_{r\in\widehat{\mathcal{R}}|\hat{A}_{ir}=1} \hat{y}_{irt}^{SO} = \sum_{\rho=t-L}^{t} \hat{w}_{i\rho t} \qquad i\in\mathcal{N}, \quad t\in\mathcal{T}^P \qquad |\rho\geq 0$$

$$\hat{w}_{i\rho\rho} = (1-\hat{\alpha})\hat{D}_{i\rho}^{SO} \qquad i\in\mathcal{N}, \quad \rho\in\mathcal{T}^P$$

$$\sum_{t\in\mathcal{T}^P} (y_{irt}^{NS} + y_{irt}^{SO} + y_{irt}^{SP}) \leq M_2\cdot\hat{A}_{ir} \qquad i\in\mathcal{N}, \quad r\in\widehat{\mathcal{R}},$$

$$\sum_{i\in\mathcal{N}} (y_{irt}^{NS} + y_{irt}^{SO} + y_{irt}^{SP}) \leq M_2\cdot\hat{B}_{rt} \qquad r\in\widehat{\mathcal{R}}, \quad t\in\mathcal{T}^P$$

$$
\begin{array}{llll}
\hat{y}_{irt}^{NS}, \hat{y}_{irt}^{SO}, \hat{y}_{irt}^{SP} \geq 0 \ \text{\& integer} & i \in \mathcal{N}, & r \in \widehat{\mathcal{R}}, & t \in \mathcal{T}^P \\
\hat{w}_{i\rho t} \geq 0 \ \text{\& integer} & i \in \mathcal{N}, & \rho \in \mathcal{T}^P, & t \in \mathcal{T}^P \\
x_{rtv} \in \{0,1\} & r \in \widehat{\mathcal{R}}, & t \in \mathcal{T}^P, & v \in \mathcal{V} \\
\delta_v \in \{0,1\} & v \in \mathcal{V} & &
\end{array}
$$

Appendix C: Distribution of Pallets on Routes and Days

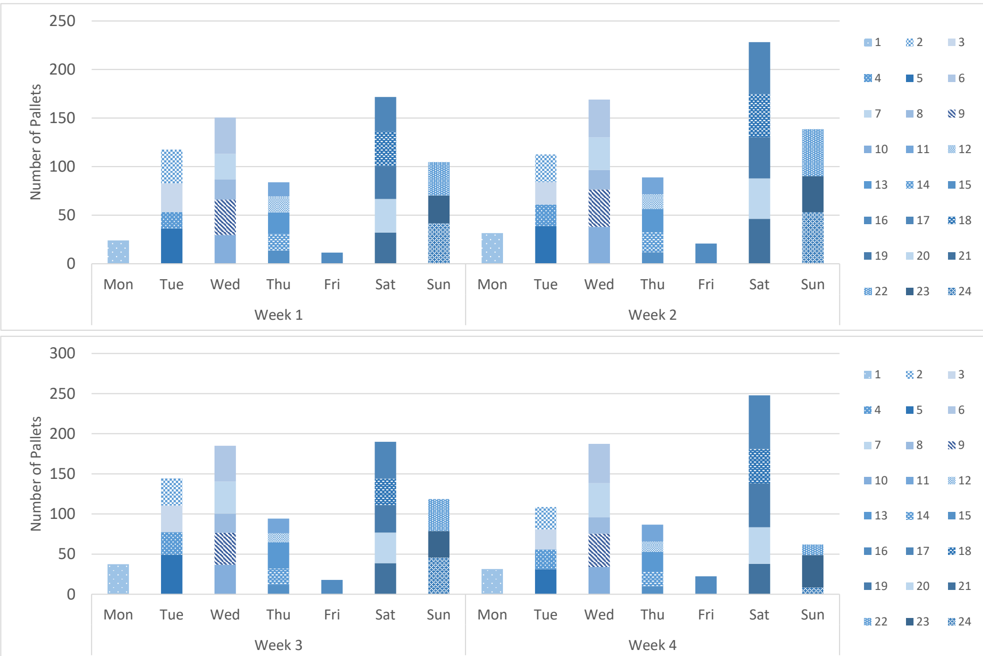


Figure A.1: Distribution of pallets on routes and days

Appendix D: Computational Time for the Base Instance

Table A.1: Aggregated computational time [s] to reach optimality in the base instance for every information sharing case

	DD		WD		WW	
	Wholesaler	Transporter	Wholesaler	Transporter	Wholesaler	Transporter
Mon	0.318	1.510		1.439		
Tue	0.164	1.879		2.030		
Wed	0.163	2.600		2.637		
Thu	0.164	1.448		1.539		
Fri	0.162	1.197		1.304		
Sat	0.165	3.353		3.315		
Sun	0.165	1.723		1.752		
Total	1.301	13.710	0.297	14.014	0.228	7204.54

Appendix E: Development of Gap in the Base Instance

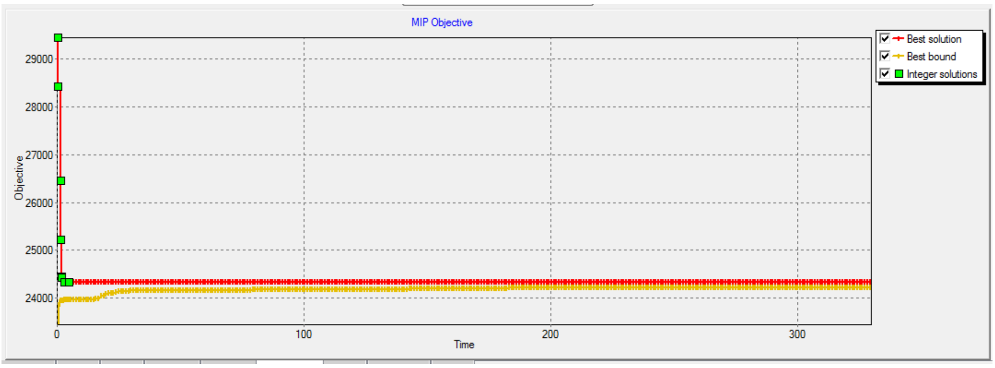
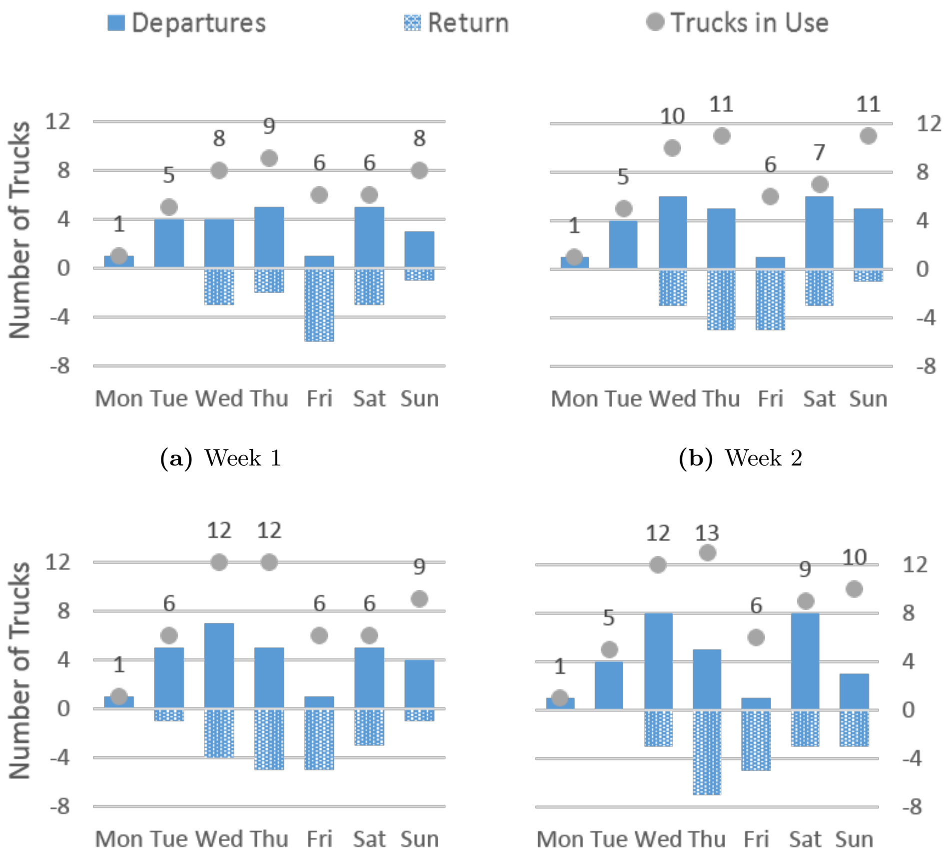


Figure A.2: Development of gap in the base instance

Optimal solution is found within 10 seconds, but not verified before a total computational time of 7204.54 seconds. Figure shows a excerpt portraying the development of the total gap development.

Appendix F: The Base Instance for all Four Weeks



(a) Week 1 **(b)** Week 2

(c) Week 3 **(d)** Week 4

Figure A.3: The number of departures, returns and trucks in use for each of the four demand weeks when there is no added flexibility. These are identical for all the information sharing cases.

Appendix G: Shifting in the Transporter Model

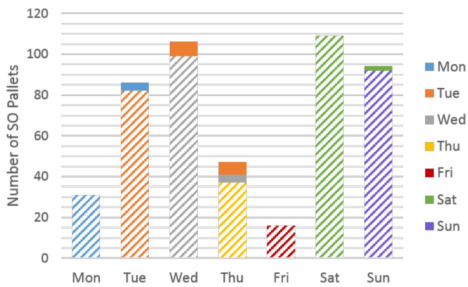


Figure A.4: Late shifting of SO pallets in the transporter model