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Delivery Frequency Optimization and Transportation Costs Minimization at Etos

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Acknowledgements

This thesis is written as the graduation project for the Master Business Analytics at the Vrije Universiteit Amsterdam. Business Analytics is a multidisciplinary program, aimed at improving business processes by combining insights from mathematics, computer science, and economics. The Master's degree is concluded with a six-month individual internship at a company. During my internship at Etos, I had the opportunity to combine my passion for data and logistics in a challenging project.

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Finally, I must express my very profound gratitude to my parents and to my twin brothers for providing me with unfailing support and continuous encouragement throughout my years of study and through the process of researching and writing this thesis. This dissertation stands as a testament to their unconditional love and encouragement. Thank you.

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Abstract

Currently, no adequate method exists for determining how frequently a retail store in a supply chain should receive deliveries from its distribution center. Existing methods neglect many crucial constraints, such as the necessity to account for maximum store storage capacities and the volume of load carriers.

This thesis addresses the problem by outlining a new method for determining the optimal number of deliveries within a proposed periodic cycle (in weeks) and the vehicle routing problem of these delivery distributions to the stores of Etos to gain control over the outbound transportation costs. For these research topics, a Mixed Integer Programming optimization model is developed that is solved using Gurobi for the replenishment process of the supply chain of Etos. A Capacitated Vehicle Routing Problem with Time Windows, in which vehicles have a predefined capacity and stores must be served after the earliest and before the latest time window bounds, is translated and implemented into an optimization model that determines the optimal delivery schedule minimizing the transportation costs and taking the optimal number of deliveries as input for demand.

It is shown that, with the currently available data, our two sequentially used Mixed Integer (Quadratically Constrained) Programming optimization models (optimization of delivery frequency and Capacitated Vehicle Routing Problem with Time Windows) are able to make accurate predictions on the cumulative total transport cost up to and including week 36 of 2022. A heuristic approach was chosen to produce a working solution within a reasonable time frame. Instead of looking for a perfect solution, heuristic strategies look for a quick solution that falls within an acceptable range of accuracy. Because a heuristic approach emphasizes speed over accuracy, it is often combined with optimization algorithms to improve results.

The evaluation of results shows that, with a periodic cycle of two weeks, we can theoretically reduce the total cumulative transport costs by 38.6% and decrease the cumulative number of deliveries by 47.3%. Nevertheless, these implementations of results and the inclusion of possible PostNL delivery approaches might be an interesting field of study for further research. Recommendations include investigating methods to optimize the intermediate lead time of deliveries; optimize the delivery day and time of the Etos stores; and optimize the workload distribution of the warehouse. These recommendations are related to the feasibility of the actual implementation of the proposed models.

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Chapter 1

Company Description

1.1 Description of Host company: Etos

Etos originates in 1919 as a part of Philips under the name “Philips Coöperatieve Verbruiksvereeniging”. The company was founded due to the decrease in sales related to the price increase. In 1931, Etos become independent of Philips and took the name Etos, which stands for “Eendracht, Toewijding, Overleg en Samenwerking”. Currently, Etos is an entity of Ahold Delhaize. This happened in 1973 when Albert Heijn overtook Etos. In 2000 was the next development, namely the possibility to buy their products online. The store also won the title of “Beste drogisterij” seven times, with the first win in 2008.

Etos, the largest health and wellness platform in the Netherlands, has been customers’ trusted drugstore for over a hundred years. With 550 stores throughout the Netherlands, an online store, around 5,400 employees, of which 2,400 are certified druggists, we work together on the mission of helping the customer feel good every day. As a reliable drugstore and the largest digital health platform in the Netherlands, we are there for our customers with advice, service, and products. Every week we help more than 1 million customers in our stores and on Etos.nl, and on an annual basis, we provide more than 30 million pieces of advice on health, appearance, balance, exercise, and nutrition.

Figure 1.1: *Example of Etos Store | Etos Leidschendam.*

1.2 Department of Supply Chain Tactics

As a Data Analyst & Data Scientist within Supply Chain Tactics, my team and I are part of the Supply Chain of Etos together with the Replenishment Fulfilment and Warehouse Fulfilment departments. The department consists of a diverse group of people in different functions, with the aim of jointly ensuring the best product availability (for our approximately 8 million customers in our approximately 550 stores and in our webshop) at the lowest possible cost!

In our daily work, we spruce up a lot of ideas to realize improvement opportunities. More in detail: my team and I develop smart solutions that make it possible to have our products available to our customers in the best possible way. The Supply Chain Tactical team is responsible for managing, optimizing, and innovating the Supply Chain of Etos, from supplier to the store shelf. This implies the following:

① **Warehouse Replenishment:** Making the best possible order for our suppliers based on data and algorithms.

② **Warehouse Improvement:** The continuous search for improvements in our distribution center processes to enhance the warehouse's performance.

③ **Store Replenishment:** Continuously improving our store orders based on signals from stores and our own analyses.

④ **Store Item Forecasting:** Making the best possible sales forecast for our stores based on data and algorithms.

⑤ **Data & Tooling:** Developments of tooling & dashboards (including Toolbox), automating activities, and developing add-ons on existing IT systems.

An organizational chart of only four layers can describe the organization of Etos. This organizational chart is visible in Figure 1.2. The chart shows that Etos has six main departments, namely: Supply Chain, Retail Operations, Finance, Merchandise, Marketing & E-Commerce, and HR. From the chart, we can observe the department of Supply Chain Tactics is part of the Retail Operations (Supply Chain) and is highlighted in yellow.

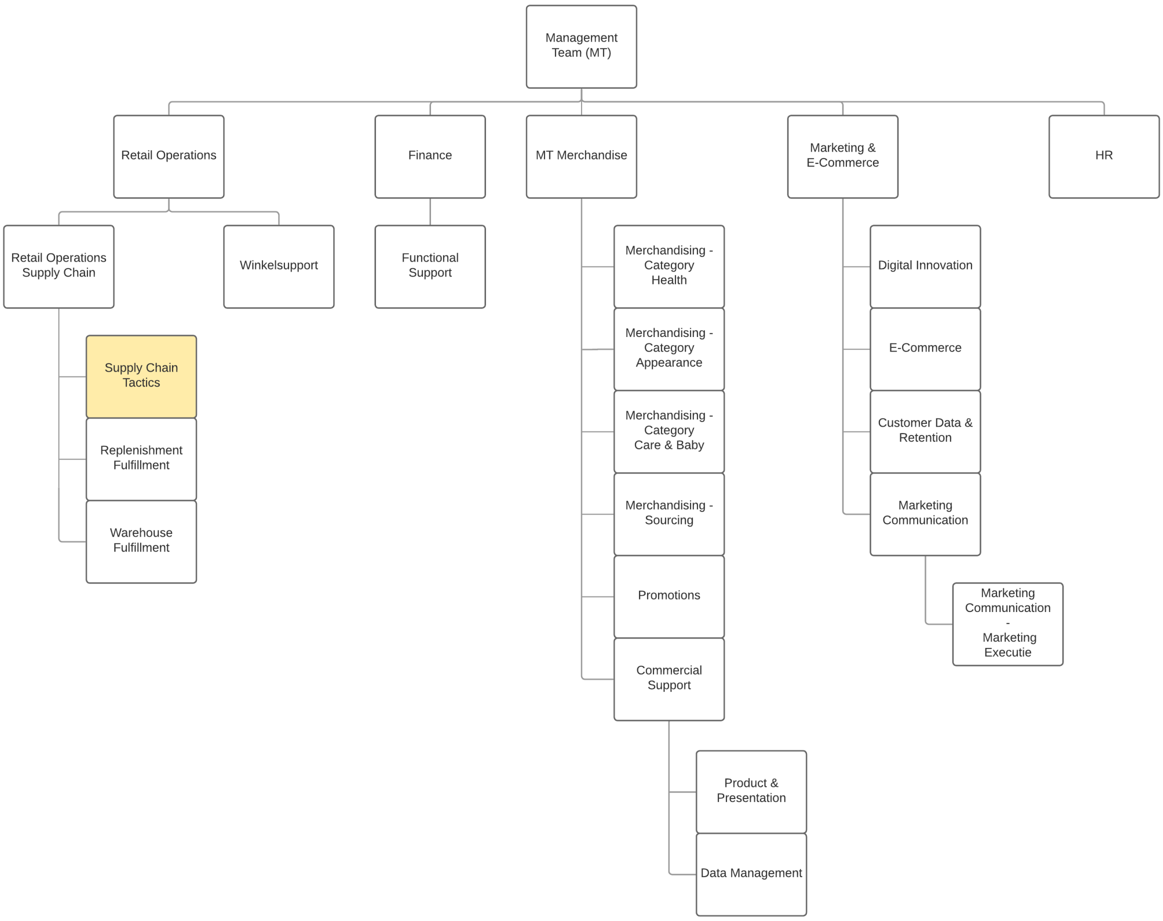


Figure 1.2: *Organizational Chart of Etos.*

Figure 1.3: *Distribution Center of Etos in Beverwijk.*

Chapter 2

Introduction of Problem

2.1 Introduction of Subject

The topic of Supply Chain Management is very wide and involves many factors. Supply Chain Management has been defined, by Cornell Engineering University [1] as the "design, planning, execution, control, and monitoring of supply chain activities with the objective of creating net value, building a competitive infrastructure, leveraging worldwide logistics, synchronizing supply with demand and measuring performance globally."

It includes the movement and storage of raw materials, work-in-process inventory, and finished goods from point of origin to point of consumption. Interconnected or interlinked networks, channels and node businesses are involved in the provision of products and services required by end customers in a supply chain. Warehouse management, routing problems, goods receipt, and order creation are only some aspects that belong to this argument. Another important feature of Supply Chain Management is the determination of the delivery frequencies in distribution management. In fact, they are often used, and determining them is therefore an important decision in the design and operation of distribution networks.

Retailers serve consumers by providing a variety of products to them. Thereby, they have to be able to sell any product at the demand of the consumer. However, this is not always feasible, as items compete with each other for scarce shelf space and backroom storage. Typically, a retailer has pre-determined the amount of shelf space allocated to each item and for each store. Furthermore, the retailer sets the frequency of deliveries to each store. The availability of the item depends on whether the order is large enough to protect the store from stock out between the order arrival and the arrival of the next order.

Nowadays different modeling approaches exist to decide on delivery frequencies. The goal of this thesis is therefore to describe the problem statement in the context of Etos, outline which factors play a role, and present an overview of different quantitative operations management approaches that can provide decision support for Etos.

2.2 Problem Statement

Many companies are trying to reduce inventory carrying costs at each stage in the supply chain. For the retail stores of Etos, this generally includes reducing the amount of merchandise on the shelves and in the backroom, an area that is not on the sales floor and is used for storing excess products. Companies that have successfully implemented programs reducing store inventory have realized large savings in carrying costs. In doing so, however, retailers have often had to increase the frequency of deliveries from their distribution centers in order to keep products on the shelves, resulting in increased transportation costs. Particularly with the uncertainty in fuel prices, there is rising interest in taking a closer look at the trade-off between carrying and product handling costs and transportation costs, and in trying to determine the optimal delivery frequency and outbound scheduling planning that will result in the lowest overall costs.

The rising cost of transportation is of particular concern to the retail grocery industry, which moves large volumes of low-margin goods. For that reason, this problem is of high relevance to Etos. The stores of Etos stores are severely constrained in the number of deliveries they require each week because of factors such as limited shelf space, little or no backroom storage, large demand uncertainty, and an increasing number of Stock Keeping Units (SKUs) being sold at each store.

Constraints such as limited vehicle capacity and the necessity of a fixed delivery (routing) schedule further complicate the issue. These tight constraints and necessities make reducing the delivery frequency to these stores quite difficult. Some research has been done in this area, but existing models do not incorporate the constraints of both limited physical space at the store and the necessity for deliveries to fall on fixed days of the week.

This paper addresses this problem by providing a method for analyzing the delivery frequency from the main distribution center to a retail store. For this thesis, we worked with retailer Etos to develop a method for determining the delivery frequency for each individual store based on a set of characteristics including shelf space, transportation costs, inventory costs, and product handling costs. The proposed methodology also includes the addition of post-delivery goods via PostNL and an application of the vehicle routing problem for planning an outbound schedule to give Etos insights into the (cumulative) total cost of transportation.

2.3 Research Question

The outbound logistics planning of the delivery frequency and route scheduling from the DC to the stores of Etos is considered to be an integrated replenishment fulfillment and distribution planning problem. The aim of this research of outbound logistics planning is to increase the operational efficiency of the outbound logistics operation and reduce the accommodated transportation costs in the supply chain of Etos. Based on the problem definition and the goal, the following research question had been defined:

Can Etos improve its supply chain responsiveness as well as its cost of transportation through optimal transport flow, and delivery frequency control and vehicle routing using mathematical optimization techniques?

If these individual predictions can be made accurately, they can be used to compute an estimate of the number of deliveries for a periodic cycle. In combination with the vehicle routing problem, Etos will get an indication of the (cumulative) total transport cost in advance so so that they can discuss savings measures accordingly.

In addition, Etos can also review its current process. Determining the importance of outbound logistics planning will give them insight into which factors might influence and contribute to supply chain responsiveness and transport efficiency. This results in the following sub-question:

① Identify the current order-and-delivery schedule and the workload and capacity limitations at the distribution center and stores.

② What are the vehicle and store capacity limitations of the retail stores operating under the current order-and-delivery schedule?

③ What methodology and heuristic approach benefits both the model performance and the result when trying to minimize the optimization objective?

④ What factors might influence and contribute to supply chain responsiveness, cost of transportation, and number of routes of Etos?

⑤ What parameter settings result in optimally integrated outbound logistics planning for the supply chain of Etos?

2.4 Research Approach

In general, mathematical optimization projects have a fixed structure. This structure is also applied in this research, and an overview is shown in Figure 2.1. The first step is to understand the problem. This consists of understanding the business needs, defining appropriate research questions and researching related literature to the topic. They will be discussed in Section 2.3 and in Chapter 3, respectively.

Secondly, we look at the processes as they are in use in the current situation. The processes of most relevant topics within the supply chain of Etos and related to my problem statement are described in Chapter 4.

The third step is the collection of data that is used for the mathematical model. How the data is collected, cleaned, and prepared as described in Chapter 5. Once the data is prepared, it can be used as input for the optimization models.

Chapter 6 outlines and explains the methodology of two optimization models used to answer the research questions. Section 6.2 outlines the methodology of the optimal delivery frequency. Section 6.3 outlines the methodology of the Capacitated Vehicle Routing Problem with Time Windows (CVRPTW). In Section 6.1, we discuss the coherence of both optimization models and how it uses the collected data as well as intermediate outcomes as input values for optimization.

Next, we discuss the results of the implementation of both methodologies to make predictions and determine the outcome of the (cumulative) total transport cost in Chapter 7. In this chapter, we also discuss the performance of the models, the experimental setups, and related evaluations that benefit the outcome.

Finally, we draw a conclusion and make recommendations based on the results en evaluations in Chapter 7.9. We end this thesis with a discussion of the capabilities and limitations of relevant modeling approaches and other possible subjects for future research discussed in Chapter 7.9.

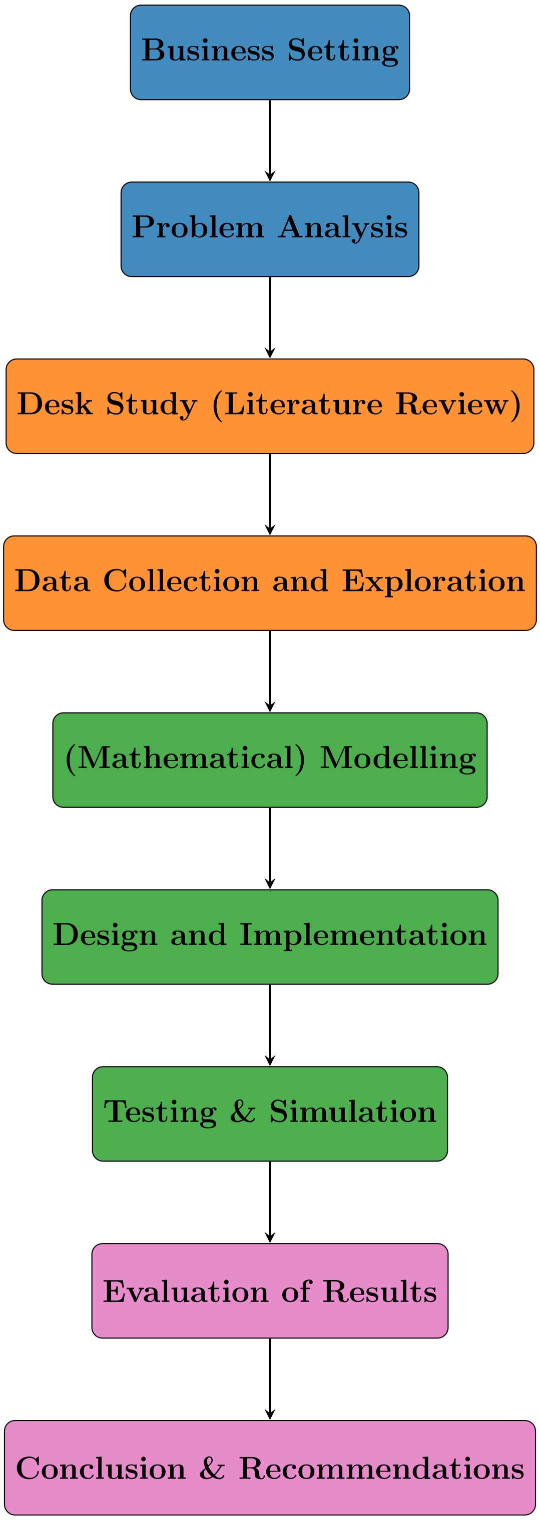


Figure 2.1: *The Research Structure Adopted in This Thesis and Which is Typical in A Mathematical Optimization Project.*

Chapter 3

Literature Review

The problem addressed in this study refers to the area of scheduling and routing. The literature on scheduling theory is very extensive. Therefore, this literature review is restricted to publications directly addressing the scheduling and routing of retail stores. All upcoming subsections describe relevant information that applies to both my problem statement and the current challenge within the supply chain of Etos.

3.1 Out-of-Stock Rate

Corsten and Gruen (2005) [2] provides an overview of the problem to increase on-shelf availability. They report on their own empirical findings at retailers and review other studies between 1996 and 2003. The average out-of-stock (OOS) rates were found in those studies about 7 to 10 percent. The rates are different depending on the product category, e.g. fresh food categories (perishables) tend to have higher rates. However, the figures are subject to the measurement methods applied. Corsten and Gruen also review different methods that define and measure OOS. Aastrup and Kotzab (2010) [3] review two research streams dealing with OOS. The first is about consumer responses to OOS, the second is about the root causes of OOS: They propose to seek the optimal level of OOS in terms of cost and gains instead of striving for a minimal OOS rate. Trautrims et al. (2009) [4] contribute to this gap. They explore the relation and trade-off between on-shelf availability and profitability of a retailer.

3.2 Economic Order Quantity

The Economic Order Quantity (EOQ) takes into account all costs which are impacted by the order size, namely inventory holding costs, ordering costs, purchase costs (including volume discounts), and stock-out costs. Transportation costs are generally included in the ordering costs if there is a fixed charge per delivery. If all or part of the transportation cost is based on the number of items ordered, the variable portion of the cost is generally added to the purchase price. Even though the EOQ is appropriate in many applications for finding the optimal order size, and therefore the order frequency, it does have its limitations (Silver et al. (1998) [5]). The limitation of the EOQ model that becomes particularly apparent when trying to apply it to a retail grocery store is non-financial considerations, such as delivery time windows and labor availability. The EOQ model also becomes difficult to use when looking at the several thousand SKUs that are shipped on a single truck, each with a different demand pattern.

3.3 Replenishment Schedule

Balintfy (1964) [6] has done work in determining the replenishment schedule by looking at it in terms of a Joint Replenishment Problem (JRP). The JRP refers to a situation where several different products can be ordered together for one fixed cost for the entire order (usually referred to as a major setup cost) and an additional charge per product (minor setup cost). In the case of transporting inventory from a warehouse to a retail store, the transportation cost would be the major setup cost, and there would be little or no minor setup cost. This is the case because the delivery cost remains the same (to the point when the truck is filled) regardless of the size of the delivery, with the possible exception of small incremental order-picking costs, depending on how the orders are picked.

Under Balintfy's method, each product is assigned a can-order and a must-order level. When one product drops below its must-order level, all products below its can-order level are ordered. Enough of each product is ordered to raise its level to an order-up-to-level. For grocery retailers, this is not a logical replenishment method because with several thousands of SKUs and in many cases very limited shelf space, the can-order and must-order numbers will be very close to the same. This method also does not lend itself to a fixed delivery schedule, nor does it incorporate truck capacity constraints.

3.4 Delivery Frequencies

Cachon (2001) [7] considers a method for determining delivery frequencies that dispatches a truck once the total order size reaches a given threshold. For this method, a continuous review of shelf inventory is needed, and Cachon is able to show that this method performs better than comparable methods which use periodic review. He assigns a dollar value to shelf space but assumes that shelf space is unlimited and determines the optimal allocation for each product.

Again, grocery retailers are often severely constrained by shelf space limitations and generally do not have total freedom to reallocate shelf space. With a product mix that is continually changing, reallocating shelf space based on optimal numbers for thousands of stock keeping units (SKUs) is not practical. Also, dispatching a truck after it reaches a given threshold means that the delivery schedule will not be fixed, which makes it very difficult for grocery stores to schedule their stocking labor.

3.5 The Retail Supply Chain

In the literature, there have been several studies that focused on integrative retail logistics in fast-moving consumer goods (FMCG) supply chains. The retail system of the supply consists of three different subsystems: the distribution center, transportation, and the store, which account for the three largest shares of the operational costs (Kuhn and Sternbeck (2013) [8]). Together, these subsystems define the retail supply chain.

The three different subsystems of the retail supply chain are interrelated, and each subsystem has its own planning and working mechanism. However, each subsystem is dependent on the requirements of the other subsystems, which causes interdependent internal operations planning problems on a tactical level (Kuhn and Sternbeck (2013) [8]). The research of Kuhn and Sternbeck discovered five components of tactical supply chain planning considerably affecting more than one subsystem in the retail supply chain: the order packaging unit, store delivery pattern, store replenishment lead time, store delivery arrival times, and arrival time window, and roll-cage sequencing and loading carriers. Store delivery patterns, and the store delivery arrival times and arrival time window determine the store replenishment lead time. Altogether, these aspects and their interdependencies have the most substantial impact on scheduling and routing.

3.6 Periodic Routing Problems

Gaur and Fisher (2004) [9] studied a periodic inventory routing problem at a supermarket chain in the Netherlands instead of supply chains with vendor-managed inventory with the supplier owning the distribution network. The focus of the research is on transportation and inventory costs, but it disregards the effects on the operations at the DC and the in-store operations costs (Holzapfel, Hübner, Kuhn and Sternbeck (2016) [10]).

Furthermore, Ronen and Goodhart (2008) [11] studied the application of the periodic vehicle routing problem (PVRP) in a retail supply chain. They applied a cost-based approach with several objectives, including transportation costs, DC handling costs, and DC capacities (minimal and maximal capacity utilization). The DC activities and transportation activities are integrated into the approach of Ronen and Goodhart (2008) [11], but in-store operations costs are neglected in the model approach.

3.7 Store Delivery Patterns

Tactical store delivery has already been studied using periodic routing problems. However, these approaches ignored the effect of the design on in-store operations and the corresponding costs. Store delivery patterns integrate the operations at the distribution center, transportation, and stores on a tactical level. Sternbeck and Kuhn (2014) [12] studied the topic of tactical store order delivery patterns in grocery retailing to better integrate and coordinate upstream operations and in-store operations. The research lacks stochastic effects and the delivery patterns used in the model, to determine store-specific delivery patterns, were obtained from a predefined set of store delivery patterns, limiting the solution space of the problem, and this affected the resulting value of the objective function.

The topic of repetitive store delivery patterns has been studied by Holzapfel et al. (2016) [10], in which warehousing, transportation, and in-store operation have been scheduled jointly. They proposed a novel model to minimize total costs in all associated subsystems of a retail distribution chain. A solution approach was developed for clustering stores and selecting delivery patterns that reflect practical requirements. Applying repetitive delivery patterns resulted in considerable benefits when managing DC capacities, transportation routes, and scheduling the workforce for shelf-filling. Although this model seems promising, it only takes the minimum and maximum production capacity per day of the distribution center into account. Furthermore, the model does not take the effect of stochasticity into account and disregards the buffer capacity of the DC in the supply chain.

3.8 Vehicle Routing Problem

This section discusses some relevant literature in the area of scheduling and routing using applications of the vehicle routing problem. A general mathematical formulation of the implementation will be described and discussed in Chapter 6. This section is limited to aspects that are applicable to extend the concepts of a vehicle routing problem and which are relevant to the research conducted in this thesis.

3.8.1 General Definition

The vehicle routing problem (VRP) is a combinatorial optimization that involves finding an optimal design of routes traveled by a fleet of vehicles to serve a set of customers. In the traditional VRP, we try to detect routes for a homogeneous fleet of vehicles to satisfy the customers' demands. Every customer node is visited once by just one vehicle which begins and completes its travel at the central station, and some side constraints must be satisfied.

3.8.2 Vehicles Constraints

The Vehicle Routing Problem (VRP) can be modeled with non-identical vehicles. The typical variability that disturbs the homogeneity is the capacity of the vehicles, but there can be other factors such as different travel times, different costs, or time windows for the vehicles. In the non-identical (or multiple vehicle types) VRP, the vehicles can vary or there may exist categories of vehicles where an upper limit on the capacity of vehicles in each category is given in most cases.

3.8.3 Time Constraints

If we add a time window constraint for each store, one obtains the Vehicle Routing Problem with Time Windows (VRPTW). Time constraints ensure that a vehicle visits a store within a certain time frame. This time window includes the earliest and latest arrival time information. The vehicle may arrive before the time window 'opens', but the store cannot be serviced until the time window opens. It is not allowed to arrive after the time window is closed.

3.8.4 Objective Functions

The objective function may also differ in VRPs. Below are some types of these objective functions. It should be noted that a combination of these can also be used: the minimum number of vehicles; minimum total distance; the minimum total travel time; the maximum number of stores served with a given number of vehicles; the minimum total waiting time of the vehicles; the minimum variability in the travel times of the vehicles; the efficient loading of the vehicles and minimum variability in the total distance traveled by the vehicles.

3.8.5 Capacitated Vehicle Routing Problem with Time Windows

The Capacitated Vehicle Routing Problem with Time Windows (CVRPTW) is a well-known NP-hard problem, which is an extension of normal VRP, encountered very frequently in making decisions about the distribution of goods and services (Tan et al., 2000) [13]. The CVRPTW can be stated as follows: given a central warehouse, a fleet of vehicles with associated capacity, and a set of stores with known demands (e.g., some quantity of goods to be delivered), find a set of closed routes, originating and ending at the warehouse, that service all stores at minimum cost. Moreover, each route must satisfy capacity and time window constraints (Potvin et al., 1995) [14]. In CVRPTW, a set of decision variables is added to the model to specify the times that services begin and end.

Allowable vehicle capacity and delivery times of the stores add complexity to the VRP because of the time feasibility check for each store. In the VRPs with capacity and time constraints, the service of a store, involving pick up or delivery of goods or services, can start and must end within the time window defined by the earliest and the latest times, respectively, when the store permits the start of service. Furthermore, the number of goods cannot exceed the associated vehicle capacity of the store and the vehicle itself.

3.8.6 Mathematical and Computational Complexity

Being one of the most important problems in Operations Research literature, the Vehicle Routing Problem (VRP) is one of the most difficult problems to solve. The problem is quite close to the Traveling Salesman Problem (TSP). TSP is a well-known NP-Hard problem, where only one vehicle or person visits all the stores. As a Multiple Traveling Salesman Problem (mTSP), the VRP, even for small fleet sizes and a moderate number of transportation requests, is more complicated than Traveling Salesman Problem (TSP). Adding time windows to the VRP results in a more complicated problem than VRP without time windows. Furthermore, Savelsbergh (1985) [15] has shown that even finding a feasible solution to the Vehicle Routing Problem with Time Windows (VRPTW) when the number of vehicles is fixed is itself an NP-Complete problem. Therefore, the development of approximation algorithms or heuristics for this problem is of primary interest to many researchers.

Chapter 4

Existing Operations

This section will not cover all operations of the supply chain of Etos but will instead focus only on the operations relevant to the subject of this thesis. Since no two stores operate in exactly the same manner, this section will focus on general operations which pertain to the majority of the stores. To begin with, Section 4.1 will describe an overview of the current supply chain of Etos. Section 4.2 will elaborate on the replenishment process of Etos and on how the stores place orders from the distribution center (DC). Section 4.3 will explain the operations within the distribution center and how the orders are picked at the DC and how the goods are delivered to the store. At last, Section 4.4 will discuss the process of the outbound distribution of goods to the stores of Etos.

4.1 Supply Chain Overview

Etos is a drugstore retailer with approximately 550 retail stores throughout the Netherlands. The stores are located in metropolitan areas, such as Amsterdam, Rotterdam, and The Hague, as well as many rural areas. The stores vary greatly in physical size and sales volume and therefore have a wide range of delivery schedules. The 550 stores are supplied with articles from one distribution center (DC) and five cross-dock facilities, all of which are owned and operated by external operators. The products moving from the warehousing facilities to the stores are in their entirety transported by external carriers.

4.2 Replenishment Process

Store Replenishment is the process within the Supply Chain organization that deals with the deliveries from the DC to the stores. Store Replenishment aims for optimal product availability in the store. This means sufficiently stocked shelves and as few leftovers as possible. In short, a stock that is tailored to customer needs.

The replenishment process is handled by an internally constructed forecasting algorithm in conjunction with a Retail Operations Solutions (ROS) system, which calculates how much of each product is actually needed at the store and places the order with the DC and a Retail Merchandising System (RMS), which places the order with the supplier of the item. It is worth mentioning that all of our private stores have migrated to an automated replenishment and ordering process and this section will focus on the operations of the stores which have automated this process, but the basic ideas apply to the other stores as well.

In addition to the aforementioned store replenishment functionality, ROS also supports all goods processes in the store. ROS is therefore used both locally by the stores and centrally by the employees of Supply Chain Tactics and Store Support. Stores use it for all their goods processes, such as ordering, inventory management, receiving, and returning. Store Support uses it for scheduling counts, among other things. Supply Chain Tactics and Replenishment Fulfillment use it to perform and maintain store replenishment.

The internally constructed forecasting algorithm gathers Point-of-Sale (POS) data and uses historical data to forecast the sales for each stock keeping unit (SKU) individually on a weekly basis. The forecasting package makes adjustments to the forecast based on day-of-the-week and seasonality factors, price reductions, and whether or not a particular SKU is placed in the two-weekly advertisement.

Once the forecasting software has generated the forecast, the ROS system takes this forecast and calculates how much of each product should be delivered to the store. To make these calculations, the ROS system must also know the current amount of product on the shelf (this information is also supplied by forecasting software), the shelf space allotment, the reorder point, and the case size for each SKU. The RMS (Retail Merchandise System) and SAM (Store Assortment Manager) applications are the main sources of information for this information. Based on the above information, the ROS system calculates the number of products expected to be left on the shelf at the time the next delivery arrives.

If the amount projected to be left on the shelf is less than the reorder point, enough product is ordered in increments of cases to restock the shelf. (Replenishment Fulfilment does have the ability to manually change the amount ordered as they deem necessary.) Any product that will not fit on the shelf must be placed in the backroom. Because reducing the number of deliveries per week means that the size of each delivery is increased, fewer deliveries means that there is a greater likelihood that additional products will need to be stored in the back room. This becomes the major trade-off when determining the optimal delivery schedule.

Figure 4.1 has been compiled to visualize the replenishment process as above. Figure 4.2 shows that this process is repeated for a large number of unique articles.

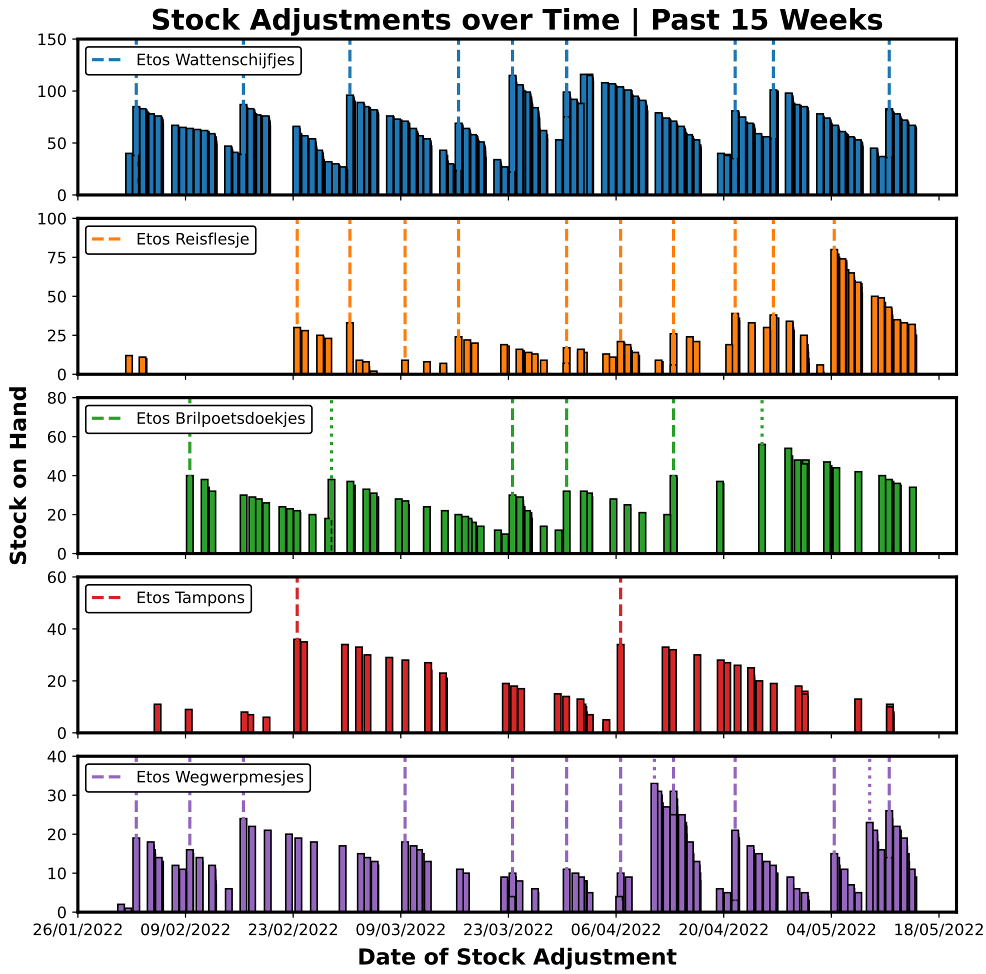


Figure 4.1: *Stock Adjustments of Etos Articles over Time in 15 Weeks.*

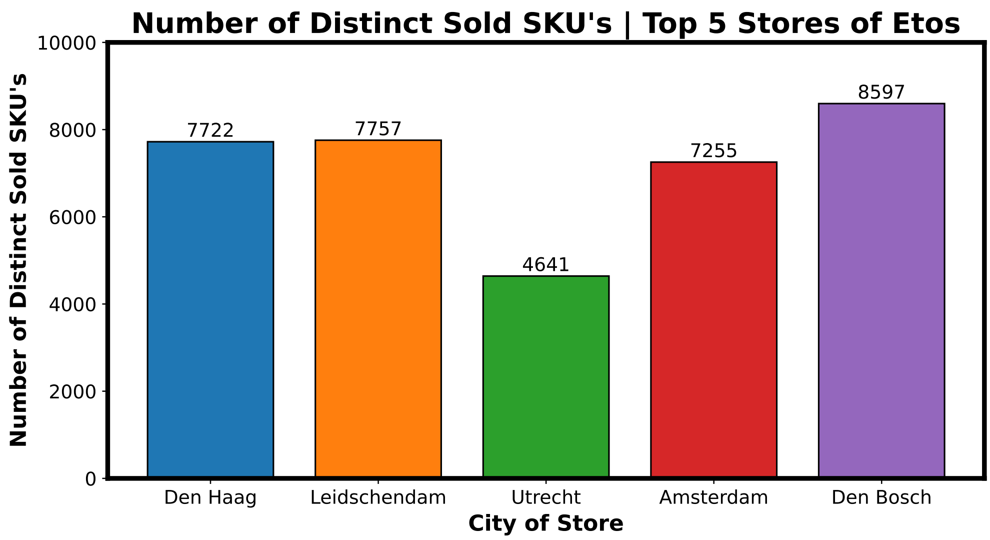


Figure 4.2: *Number of Distinct Sold SKU's of Top 5 Stores of Etos in Past 10 Weeks.*

4.3 Distribution Center Operations

The distribution center (DC) of Etos is somewhat centrally located and averages about 75 kilometers from each private Etos store. The DC warehouses all of our 15716 distinct, active articles and serves as the central storage place for all items as well as the main location for all items that need to be brought to the stores and/or our hubs.

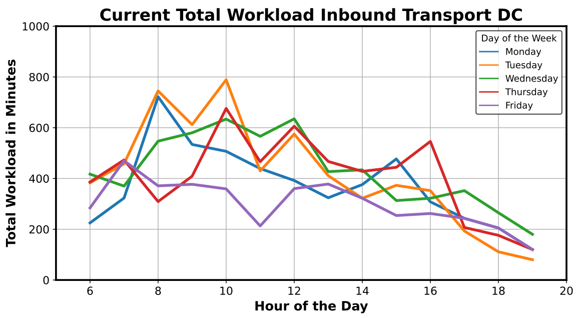
The DC operations that are particularly relevant to the store deliveries are those that are associated with picking an order (combining individual cases of different products onto a container that will be delivered to an individual store) and loading it onto a truck. Orders are received by 16:00 two (working) days before they need to be delivered and are picked up on the (working) day before the delivery date which depends on the scheduled delivery time for each store.

The order picking is directed by a computer system around the arm of the pickers, which receives the order information from the Warehouse Management System (WMS) and reads it off to the picker on an item-by-item basis. The system tells the picker which article and corresponding quantity needs to be picked and in which location he/she can find the article.

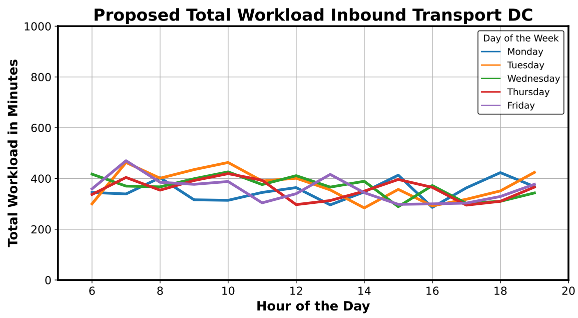
The computer then tells the picker the quantity of that particular article to load onto the trolley. The picker scans the location code to ensure that he/she is at the correct location and loads the quantity of the article onto his/her trolley and tells the system that he has finished by reciting to the system the item quantity. The system then tells him/her the information for the next article. This process is repeated until the route of the order is completed.

The full trolleys are then loaded and/or combined onto an empty container and the picker gets an empty trolley and repeats this process until the entire order for the store is picked and put on containers. Deliveries are picked and dispatched throughout the day from approximately 6:00 to 18:00, although the first orders to be delivered each day are generally picked up the afternoon before as mentioned earlier.

Inbound shipments of products are received and put away throughout the day. The workload involved (in minutes) of incoming goods at the distribution center is illustrated in Figure 4.3a. From a previously executed project, it was investigated whether we could optimize this schedule and distribute the workload more evenly over the week and within the working days. This resulted in a new proposed distribution illustrated in Figure 4.3b.



(a) *Current Total Workload of Inbound Transport in Distribution Center.*



(b) *Proposed Total Workload of Inbound Transport in Distribution Center.*

Figure 4.3: *Improvement of Workload Distribution of Distribution Center of Etos.*

4.4 Outbound Schedules and Transportation

At the time of writing, Etos determines the number of deliveries per week from the DC to a store based on its average weekly sales volume. There is, however, some room for the stores to negotiate on the number of deliveries per week and on which days of the week the deliveries will be made. Stores generally prefer to receive deliveries as frequently as possible (up to daily), mainly for stock level and capacity-related reasons.

The amount of required safety stock is of particular concern for stores with limited shelf space because a greater amount of safety stock means that more products will need to be stored in the back room, which leads to additional handling of the product. On the other hand, when stores have products that stock out for any reason, more frequent deliveries mean that the stores have to wait for a shorter time period until the next delivery arrives, which decreases the amount of time the store is dealing without a particular product.

Furthermore, some stores do not have the physical capacity to store enough products, on the shelves or in the backroom, to allow them to skip an additional delivery day. When this is the case, the delivery frequencies of these stores cannot be altered.

Currently, all Etos stores are supplied several times a week, varying from once a week to 4 times a week. As mentioned earlier, the delivery frequency depends on the average weekly sales volume and the physical store storage capacity. The distribution of the number of times a store receives a delivery is shown in Figure 4.4. From the illustration, we can observe that 432 stores (≈82%) of our WWM stores are supplied with new stock once a week, 88 stores (≈17%) receive a new shipment twice a week and 7 stores (≈1%) receive a new shipment three times a week. There is a single store which gets his goods delivered 4 times a week.

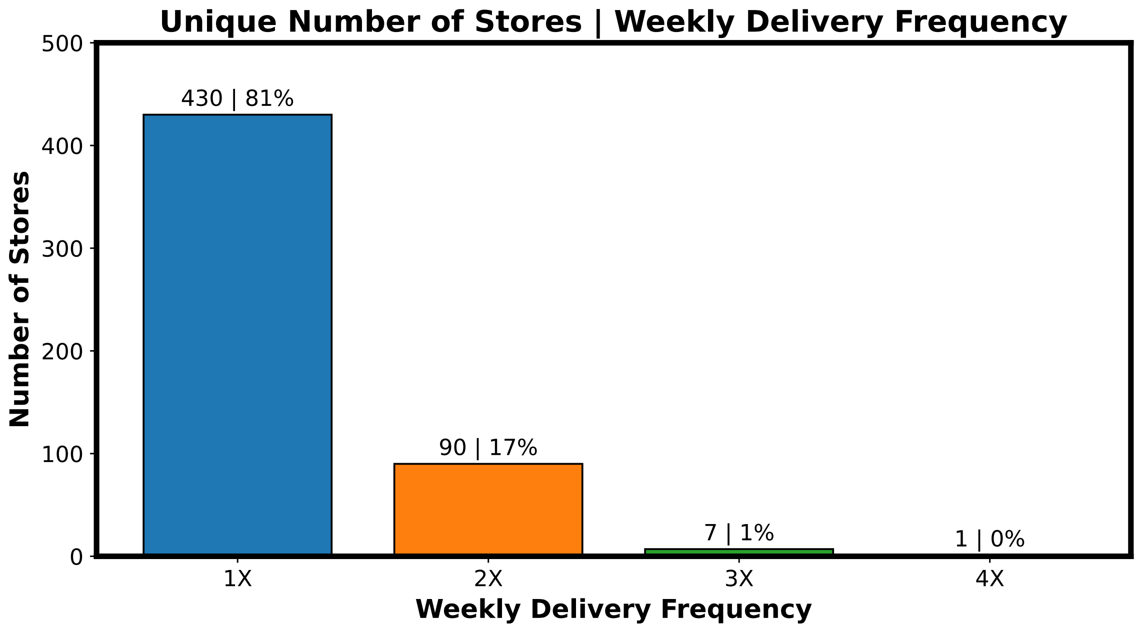


Figure 4.4: *Number of Stores per Weekly Delivery Frequency.*

The regular deliveries are distributed relatively evenly throughout the week, with Mondays and Thursdays seeing the fewest scheduled deliveries and Wednesdays seeing the greatest number. The distribution throughout the week is illustrated in Figure 4.5. Etos tries to keep deliveries evenly spaced throughout the week in order to keep driver and equipment utilization as high as possible and to take the human work capacity in our warehouse into account as much as possible.

In addition to the regular orders generated by the automated reorder process, each store also receives an extra order (which is generated separately) each week for promotional items. This order of promotional items is combined with the store's regularly scheduled delivery on either Wednesday, Thursday, or Friday so that the promotional product will be on hand early enough to display on the sales floor by Monday, the first day of the promotional week. Note that these promotional deliveries or not considered in Figure 4.5.

The reason why most of the stores are delivered at the end of the week has to do with our deliveries of promotional products and the weekend day. We want to bring these items to the stores as late as possible. In this way, we need to store the articles for the upcoming promotional period (starting on Monday) as shortly as possible. In addition, Etos realizes the majority of its sales during the weekend. This means that we have to be in the store with new stock before the peak days.

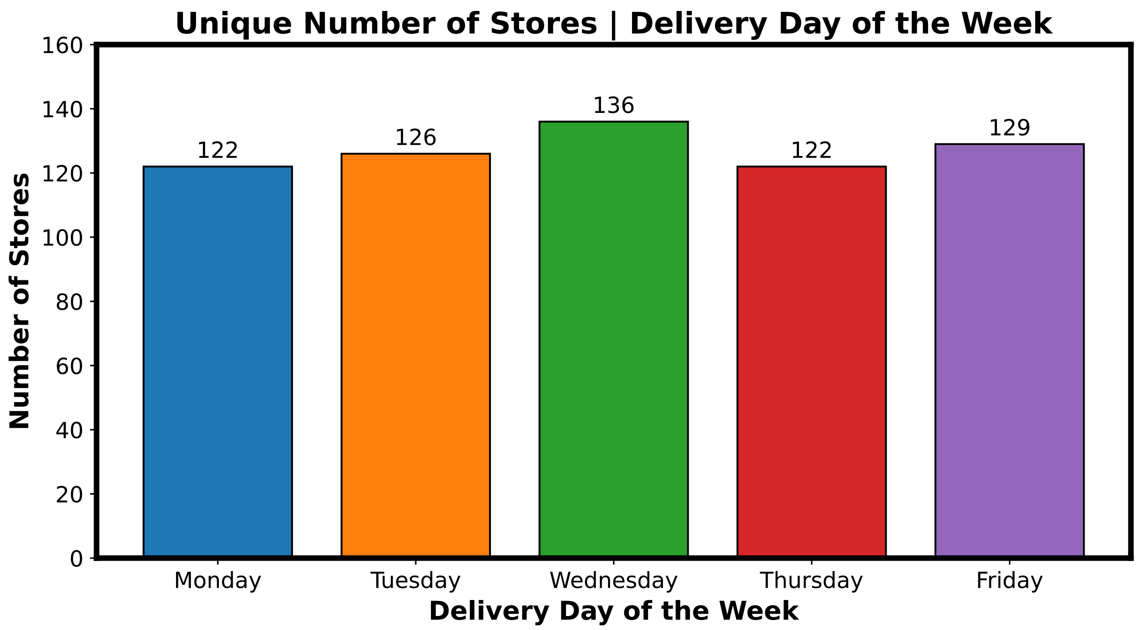


Figure 4.5: *Number of Stores per Delivery Day of the Week.*

Chapter 5

Data Collection

This section gives a description of the data that is used in this research. First, the data collection process is discussed in Section 5.1. Next, we describe how the data is cleaned and prepared such that it can be used by the optimization models in Section 5.2 and 5.3, respectively.

5.1 Data Extraction

The data in this research is collected from multiple sources provided and serviced by Etos. The main data sets contain both store and retail item data as well as historical orders for the year 2022. Every data set provides a unique primary key. The content of every data extraction is described in the upcoming paragraphs.

Store Attributes: The first data extraction contains information about the stores that Etos owns herself. Including the warehouse, the total number equals 551 unique locations. For each location, the extraction includes the longitude and latitude of the location, the travel distance and travel duration to the warehouse (driving with heavy-goods-vehicle), and the store storage area, expressed in square meters and the number of roll containers.

Store Transport Mode: For each individual location, the transport modes are retrieved as they are known according to our most recent information. Due to prescribed legislation, the transport capacity of each store is different and pre-determined. As a consequence, this data extraction contains the type of vehicle and its respective capacity. This distinction will be relevant at a later stadium for determining the freight volume to the stores and with which means of transportation these should be transported.

Store Order Deliveries: The store orders form the basis of the transport schedule. These store orders determine the quantity of specific retail items that have to be transported to the stores. For my research, we make use of historically delivered store orders. These have been selected based on their respective delivery date in the past.

Store Travel Matrix: Using the store longitude and latitude from the extraction of store attributes, a store travel matrix is constructed with the travel distance and travel duration between every possible combination of locations. These values will be of important use during the delivery frequency optimization and vehicle routing problem.

Store Time Window: In addition to retrieving vehicle information, the time window (earliest and latest time) of all individual stores are also retrieved. These times windows can mainly be determined by municipality restrictions. In all other cases, this is determined by the opening hours of the respective store.

Store Opening Hours: As stated in the previous section, store opening times are necessary for determining the time windows. As a result, this data extraction contains the store opening time and store closing time of every individual location.

Retail Item Dimensions: After the extraction of multiple store measures, retail item measures must also be included in the data collection. We start with the retail item dimensions (in CM). These values combined determine the volume of an individual product, which is of consequence for the type of shipment method.

Retail Item Pick Zone: Next to the extraction of the retail item dimensions, the extraction of the retail item pick zone in the warehouse is also included in the data collection. The different pick zones have an influence on the way of an individual item is picked and transported. As an example, items picked in single units are packed in CBL-23 crates while items picked in case units are packed directly onto roll containers. This distinction will be relevant at a later stadium for determining the means of transportation.

5.2 Data Cleaning

During the data collection, a lot of records were collected recorded from different data sources. Not all these data could be used in this research, because of the missing values or outlier values in part of the records. These non-useful values have been dropped or omitted for progress in various ways. Different discoveries are described in the upcoming paragraphs.

For example, 2 stores had to be manually supplemented with their coordinates (longitude and latitude), since they were unknown. Also, the store area and maximum container storage values were unknown for 14 stores. These are replaced with the value 3 since this is the minimum any store can handle at a single point in time. Stores that did not have a transport mode specified were assigned to the smallest transportation option available. In that way, one knows for sure the store is reachable without breaking any legislation.

Regarding store time windows, the store opening hours during the weekend are being removed since Etos does not supply its stores during the weekends. Furthermore, the final store opening and closing times were selected based on their most common occurrence. In addition, we reduced the store closing time by 1 hour and applied a maximum of 18:00 to ensure deliveries arrive on time and can still be useful on the day of delivery. At last, missing rows were given a start time of 9:00 and a closing time of 17:00, since these are the most common opening en closing hours of Etos stores in general.

In addition, retail items where one observed a maximum dimension greater than 180 centimeters, a minimum dimension greater than 60 centimeters, or a median dimension greater than 80 centimeters were removed from the selection of article, since none of them would fit on a psychical roll container (80cm x 60cm x 180cm). The exclusion of these items resulted in deleting approximately 5.35% of the total number of unique retail items.

Moreover, medical retail items are also excluded from the data extraction, since these are being transported via an external service. As a result, the exclusion of selected retail items result in the removal of approximately 11.5% of the store item deliveries (18,474,361 records remaining), throughout the period of 2022 up to and including week 36.

5.3 Data Preparations

After all necessary data sets have been cleaned and filtered for relevant articles and stores, they can be combined into a single data set that will be used for modeling and optimizing the Etos store delivery frequency. For the computation of an optimal result, we begin with the determination of the shipping method for every retail item. For this calculation, we use the retail item dimensions in combination with the retail item pick zone as specified and discussed in Section 5.1. Secondly, the order volume for every shipping method is calculated by multiplying and aggregating the retail item dimensions.

Chapter 6

Methodology

The current chapter presents the process of developing the research methods and theoretical optimization frameworks needed to complete the experimentation part of the current study. This chapter will discuss in detail the various stages of developing the methodology of the current study that follow one another to arrive at a definitive result.

To begin with, in Section 6.1 we will discuss the coherence of the two optimization models to come to a final result. Section 6.2 will discuss the model for determining the optimal delivery frequency. Section 6.3 will discuss the methodology for determining optimal routes using the Capacitated Vehicle Routing Problem with Time Windows (CVRPTW). Next, Section 6.4 will discuss which parameters apply and affect the outcome. Finally, in Section 6.5 we will discuss which software and packages were used for the technical implementation of the two optimization models.

6.1 Coherence of Both Optimization Models

The need for two different optimization models that together solve the problem arises from the fact that neither of the individual models is capable of answering the research question in full completeness. Ideally, we would like both models to communicate with each other for the most optimal and efficient result. However, due to time limitations and complexity, a sequential approach was chosen.

The first model determines the optimal delivery frequency based on a one-way journey from origin to destination, but in order to calculate realistic transport costs at the same time, we need the outcome of optimal routing. These can be calculated using the Capacitated Vehicle Routing Problem with Time Windows (CVRPTW) model described as second.

Based on the outcome of determining the optimal delivery frequency, we know the number of deliveries and the number of containers that Ahold Transport must carry out within the chosen periodic cycle. By dividing these two numerical values, we can also determine the number of load carriers (demand) per delivery. The output of the CVRPTW suggests on which day and at what time this delivery should actually take place.

This demand for an individual delivery is then passed as a parameter to the CVRPTW model as D_i (Demand at node i). From this point forward, together with the limited shelf space, backroom storage, limited vehicle capacity, and time constraints, we have all the data to solve the CVRPTW model and to arrive at an outcome of the (cumulative) total cost of transportation of Etos.

In the next two sections (Section 6.2 and 6.3), we take a closer look at the content of the individual methodologies and the mathematical formulation of upcoming models. I would also like to state in advance that both models apply to individual stores and that the CVRPTW is able to combine individual stores into an optimal route.

6.2 Store Delivery Frequency Optimization

Optimizing the store delivery frequency starts with designing an efficient fulfillment network. For the purpose of this thesis, this network should be based on relevant service requirements that have an impact on mainly transportation costs. As such, it is essential that the design will be an integrated effort of supply chain management to balance the needs and the possibilities.

After a careful review of the business processes, two factors, which play an important role in the determination of the delivery frequency have been found. Both, explicitly and logically obtained, factors are discussed in Subsections 6.2.1 and 6.2.2, respectively. Thereafter, the possible utilization of these two factors is discussed in the subsection detailing the mathematical formulation of delivery frequency optimization model.

6.2.1 Total Costs Minimization

The economic aspect of distribution management is one of the primary factors which plays a role in the determination of the delivery frequency in a company. Generally stated, it is not easy to find a model which deals only with the delivery frequency determination, because this topic is strictly related to a more general issue: developing an optimization model which aims to minimize the total costs of the supply chain considered.

In addition to this, the economic aspect, the minimization of the total costs, consists mainly of transportation costs. It is mathematically and logically demonstrated that as Sternbeck and Kuhn (2014) [12] state, a high delivery frequency corresponds to an increase in transportation costs, due to the many trips taken by the vehicles. Meanwhile, a low delivery frequency leads to lower transportation costs but higher holding and inventory costs and a different distribution of workload. Mathematically, the right balancing between these two measures leads to the perfect configuration of a delivery pattern.

The final objective is to present an equation, or a system of equations, in which the entire model is set, and it is successively implemented in an optimization model. Therefore, the goal of this equation is, mainly, to minimize the total cost of transportation. Once the model has been solved, many variables of the equation, or system of equations, are determined, including the demand variable regarding the delivery frequency.

6.2.2 Delivery Capacity

The capacity of delivery has been classified as a secondary factor that plays a role in the determination of delivery frequency because it represents such a constraint in the supply chain of the companies. The delivery capacity is defined as the maximum number of units at which a generic seller, such as a supplier or distribution center, can deliver its products to a generic buyer, a store for instance, into the supply chain. The delivery capability consists principally of the balance of two capacities: the transportation capacity and store storage capacity.

For example, if the capacity of delivery is not enough to handle the requested volume of demand, the company has the possibility to increase the delivery rate. It must be said that this way of thinking and acting is not always convenient. In fact, the real economic gain of this choice should be evaluated; sometimes it is preferable to adopt a lower delivery rate.

In conclusion, the company must evaluate the delivery frequency based on the advantages or disadvantages of the economic aspect to divide the moved load into more or fewer shipments, increasing or decreasing the delivery frequency, respectively, while satisfying demand and respecting capacity constraints.

Mathematical Formulation of Delivery Frequency Optimization

To utilize the possibilities of these two factors (discussed in Subsections 6.2.1 and 6.2.2 respectively) in any optimization, we compute an optimization model on the delivery frequency based on the defined volume calculations per shipping method from Section 5.3. For this utilization, we propose delivering the required goods through our internal carrier Ahold Transport and/or an external carrier PostNL. Both ways of transportation have an associated cost and the objective of this optimization is to minimize the total transportation costs accounting for the volume of demand given as input and the delivery capacities of both the transportation mode and maximum store storage capacity considered as constraints.

When trying to minimize the total transportation costs, the outcome of the model gives us, within the specified periodic cycle, output on the number of shipments that should theoretically be carried out for each carrier. The model also gives us output on the total number of containers and crates that have to be brought to each individual store. In addition, it is good to know that a maximum of 14 crates fit on a roll container and that a shipment can consist of several roll containers.

First of all, the model is introduced along with the sets and parameters, decision variables, and constraints that come with it. This mathematical elaboration is followed by a written explanation of the model.

Sets and Parameters

V_{RRC} : Total Volume Retail Items Shipped Through Containers
V_{CBL} : Total Volume Retail Items Shipped Through CBL-23 Crates
Q_{RRC} : Volume Capacity Container (in CM^3)
Q_{CBL} : Volume Capacity CBL-23 Crate (in CM^3)
Q_{Store} : Container Capacity of Store (in Units)
$Q_{Transport}$: Container Capacity of Transport Vehicle (in Units)
C_{AT} : Transportation Costs Ahold Transport
FC_{PNL} : Fixed Transportation Costs PostNL
VC_{PNL} : Variable Transportation Costs PostNL
PC : Periodic Cycle (in Weeks)

Decision Variables

$X_{AT} \in \mathbb{N}$: Number of Shipments Ahold Transport
$Y_{AT} \in \mathbb{N}$: Number of Containers Ahold Transport
$Z_{AT} \in \mathbb{N}$: Number of CBL-23 Crates Ahold Transport

$X_{PNL} \in \mathbb{N}$: Number of Shipments PostNL
$Z_{PNL} \in \mathbb{N}$: Number of CBL-23 Crates PostNL

Objective Function

$$\min(X_{AT} * C_{AT} + X_{PNL} * FC_{PNL} + Z_{PNL} * VC_{PNL}) \tag{6.2.1}$$

Constraints

$$Y_{AT} * Q_{RRC} \geq V_{RRC} \tag{6.2.2}$$

$$(Z_{AT} + Z_{PNL}) * Q_{CBL} \geq V_{CBL} \tag{6.2.3}$$

$$(Y_{AT} + Z_{AT}/14) \leq min(Q_{Store}, Q_{Transport}) * X_{AT} \tag{6.2.4}$$

$$Z_{PNL} \leq 14 * X_{PNL} \tag{6.2.5}$$

$$X_{AT} \leq PC * 5 \tag{6.2.6}$$

Explanatory Notes

The objective (6.2.1) is the minimization of the total transport cost. This value is formed by the summation of the transport costs of both Ahold Transport and PostNL, where the transport costs of Ahold Transport are composed of a one-way drive from the warehouse to the store accounting for the travel distance and travel duration and the transport costs of PostNL are composed of fixed costs plus a variable costs based on any additional CBL-23 crate. This process and calculation are then repeated for all stores considered.

Furthermore, constraints 6.2.2 and 6.2.3 ensure that all the volume of the retail item orders is being shipped to each individual store for both shipping methods respectively. Constraint 6.2.4 ensures that the number of containers and CBL-23 crates we ship to the store does not exceed the minimum capacity of the store or the transport vehicle. Thereby we must take into account that a maximum of 14 CBL-23 crates fit on a single container. Constraint 6.2.5 determines the number of shipments carried out by PostNL, where we must again take into account that a maximum of 14 CBL-23 crates fit on a single container. At last, constraint 6.2.6 ensures the maximum number of shipments that can be carried out by Ahold Transport is less than or equal to the number of working days within the periodic cycle (10 days in a periodic cycle of 2 weeks).

6.3 Capacitated Vehicle Routing Problem with Time Windows

Freight transportation is one of the most critical activities in supply chain management. This importance comes from the fact that it brings more than half of the total logistics cost. The contribution of the freight transportation cost to the total cost can be decreased by better utilization of the resources, which can be suggested by better routing and scheduling approaches to the problems.

In general, in this paper one considers the Capacitated Vehicle Routing Problem with Time Windows (CVRPTW), in which vehicles with finite capacities are allowed to start servicing customers with their volume of demand after and before the earliest and latest time window bounds, respectively. Furthermore, The CVRPTW aims at designing a set of vehicle routes through several store locations with minimum transportation costs, under the conditions that each route starts and ends at the depot and each store must be visited only once by one vehicle.

The general definitions and overall complexity are also discussed in Section 3.8. In this section, we take a closer look at the mathematical formulation. First of all, the model is introduced along with the sets and parameters, decision variables, and constraints that come with it. This mathematical elaboration is followed by a written explanation of the model.

Mathematical Formulation of Capacitated Vehicle Routing Problem with Time Windows

The CVRPTW model is given by a heterogeneous set of vehicles, a set of store deliveries and a directed graph G. The graph consists of $n + 1$ vertices where the locations are denoted as $StoreID + X$, where the letter X can be variable from the letter A to letter J (every letter represents a unique working day in periodic cycle, with a maximum of 10). The warehouse is represented by the vertex $1234A$. The set of vertices excluding the depot is denoted as N'. The set of arcs (denoted as A) represents connections between the depot and the customers and among the customers.

All routes originate from the warehouse and terminate at the warehouse (vertex $1234A$). With each arc $(i, j) \in A$, we associate a cost $C_{i,j}$. Each vehicle has a finite capacity Q_i and each store i has a demand D_i and strict earliest start time E_i and latest end time L_i. A new route (with a possible new truck) is created when the maximum capacity of the truck is reached. The model uses an unlimited number of trucks because we make the assumption that the goods can always be delivered to each and every store.

First of all, the model is introduced along with the sets and parameters, decision variables, and constraints that come with it. This mathematical elaboration is followed by a written explanation of the model.

Sets and Parameters

$G = (N, A)$
N : Nodes
A : Arcs
0 : Warehouse

$A = \{(i, j) : i, j \in N\}$
$N = \{0, 1, ..., N\}$
$N' = \{1, ..., N\}$

$T_{i,j}$: Travel duration of going from node i to node j
$K_{i,j}$: Kilometer allowance of going from node i to node j
$C_{i,j}$: Cost of going from node i to node j. $C_{i,j} = K_{i,j} + T_{i,j}$

D_i : Demand at node i
Q_i : Vehicle Capacity at node i
S_i : Service time at node i
E_i : Earliest arrival time at node i
L_i : Latest arrival time at node i

Decision Variables

$$X_{i,j} = \begin{cases} 1, & \text{if arc } (i,j) \text{ is used} \\ 0, & \text{otherwise} \end{cases}$$

$Y_i \in \mathbb{N}$: Load of Vehicle arriving at node i
$A_i \in \mathbb{N}$: Arrival time at node i

Objective Function

$$\min \sum_{i \in N} \sum_{j \in N} C_{i,j} * X_{i,j} \tag{6.3.1}$$

Constraints

$$\sum_{i \in N} X_{i,j} = 1 \qquad \forall j \in N' \tag{6.3.2}$$

$$\sum_{i \in N} X_{j,i} = 1 \qquad \forall j \in N' \tag{6.3.3}$$

$$\sum_{j \in N} X_{0,j} = \sum_{i \in N} X_{i,0} \tag{6.3.4}$$

$$\sum_{i \in N} X_{i,j} = \sum_{i \in N} X_{j,i} \qquad \forall j \in N \tag{6.3.5}$$

$$D_i \leq Y_i \leq Q_i \qquad \forall i \in N' \tag{6.3.6}$$

$$X_{i,j} * (Y_i - D_i - Y_j) = 0 \qquad \forall i \in N', j \in N', i \neq j \tag{6.3.7}$$

$$E_i \leq A_i \leq L_i - S_i \qquad \forall i \in N' \tag{6.3.8}$$

$$X_{i,j} * (A_i + S_i + T_{i,j} - A_j) \leq 0 \qquad \forall i \in N', j \in N', i \neq j \tag{6.3.9}$$

Explanatory Notes

The objective (6.3.1) is the minimization of the total transport cost. This value is formed by the travel distance and travel duration traveled by all delivery vehicles within the proposed routes.

Furthermore, Constraints 6.3.2 and 6.3.3 ensure that each store is visited exactly once. Constraint 6.3.4 ensures that the number of vehicles leaving the warehouse is equal to the number of vehicles arriving at the warehouse. Constraint (6.3.5) ensures that the in-flow equals the out-flow of all the visited stores.

Constraints 6.3.6 and 6.3.7 ensure the demand equalities of the vehicle. A vehicle's load arriving at store j is equal to the vehicle's load arriving at store i minus the demand at store i, where the vehicle's load is always greater or equal to the demand of store i and less than or equal to the vehicle capacity of the store i.

Constraints 6.3.8 and 6.3.9 ensure the time equalities of the vehicles arriving at the stores. The arrival time at store j must be between the specified time window and must also keep in mind the travel duration between store i and store j and the service time at store i.

6.4 Parameter Settings

For the implementation of the methodology of the Capacitated Vehicle Routing Problem with Time Windows (CVRPTW) we have accounted for a small number of parameters representing some fixed values for the results of the optimization. To begin with, the hourly rate and cost per driven kilometer are fixed and determined by Ahold Transport. Next, the costs per package and any additional cases carried out by PostNL also have a fixed cost rate.

In addition to a fixed rate for determining the (cumulative) total transport costs, we also use a fixed minimum number for the storage of containers ('MaxStorageContainers') in the stores and the maximum volume per container or CBL-23 crate for optimization, namely 3 containers. The number that determines the minimum number of containers to be stored ('MaxStorageContainers') is experimented with and discussed in Section 7.7. The maximum number of roll containers in store storage is determined by the back room space of each individual Etos store.

For the maximum volume of a roll container, we use the same value as the warehouse currently has applied in its Warehouse Management System (WMS). For the maximum volume of a CBL-23 crate, we use the inner dimensions but take into account an air percentage of 33%. This value was determined on the basis of observation in the distribution center, various discussions with experts by experience, and an evaluation of an experiment discussed in Section 7.8. As a result, both determinations of values correspond most closely to reality and provide an accurate approximation of the optimization results.

Important Note: At last, for each experiment and associated evaluation discussed in Chapter 7, we use a periodic cycle of 2 weeks and 33% percentage of air in the CBL-23 load carriers, unless stated otherwise. For the most innovative and cost-saving change, a periodic cycle of 10 working days has been chosen that differs from the current one, namely 1 week (5 working days). Thereby, a broader periodic cycle gives more room for the calculation and optimization of the research problem.

6.5 Software and Packages Used

The implementation of all the data preparations (Section 5.3) and the optimization models were performed using the combination of the programming language Python and the Gurobi Optimizer V9.5.2. The Gurobi Optimizer is a state-of-the-art solver for mathematical programming. The solvers in the Gurobi Optimizer were designed from the ground up to exploit modern architectures and multi-core processors, using the most advanced implementations of the latest algorithms.

The Gurobi Optimizer is considered one of the most diverse optimization software that can solve a wide range of problem types. These include linear programming, mixed integer linear programming, mixed integer quadratically constrained programming, and many more. It is accessible by importing the Gurobi library in Python.

In addition, all computations were performed on an HP notebook with an I7 processor, an 8-core CPU, and 16GB of RAM.

Chapter 7

Evaluation of Results

In Chapter 6, we have outlined and introduced the methodology related to the research problem. In this section, we discuss the results obtained by the different models. To begin with, we will discuss the application of the Capacities Vehicle Routing Problem with Time Windows (CVRPTW) to the actual historic deliveries planned by Ahold Transport in Section 7.1. Next, we will discuss the complexity and performance of the CVRPTW related to the size of the instances and an evaluation of the actual application of the CVRPTW in Sections 7.2 and 7.3, respectively.

Afterward, in Section 7.4, we will discuss the heuristic approach to produce a feasible solution that is good enough to quickly solve a particular problem and achieve immediate goals, but not necessarily an optimal solution. At last, we will evaluate results on the total cumulative cost of transportation in Section 7.5, results on the number of planned deliveries in Section 7.6, results on the number of store storage containers in Sections 7.7, results on the percentage of air in CBL-23 crates in Section 7.8 and results on the inclusion of PostNL deliveries in Section 7.9.

7.1 Baseline Results Vehicle Routing Problem

To begin with, we start with the interpretation of the results computed using the actual historic outbound deliveries to all 550 Etos stores throughout the Netherlands. Figure 7.1.1 illustrates the cumulative transport costs of the historic deliveries planned by Ahold Transport and the historic deliveries computed using the methodology of the Capacitated Vehicle Routing Problem With Time Windows (CVRPTW) model. In both latter calculations, the number of roll containers has been used as input for demand.

The results show that at the start of the year the methodology of CVRPTW (orange) is about 15% higher compared to Ahold Transport (blue). Cumulatively, this percentage decreases to 8.7% in week 36 of 2022. This percentage is equal to approximately €XXX,XXX.

These results evaluate the methodology behind my implementation of Capacitated Vehicle Routing Problem With Time Windows as discussed in Section 6.3. By comparing the results with the routing calculations of Ahold Transport, we can check how well the implemented methodology works against the computation of the executing party.

Intuitively, it makes sense that my model comes out higher compared to Ahold Transport. The main reason for this is that Ahold Transport has the ability to combine the transport of Etos with other Ahold entities (Albert Heijn and Gall & Gall). As an example, it is, therefore, possible to deploy a single truck for multiple entities and distribute the costs evenly based on their fraction of physical contents. This ensures a more efficient way of planning and optimal use of transport vehicles.

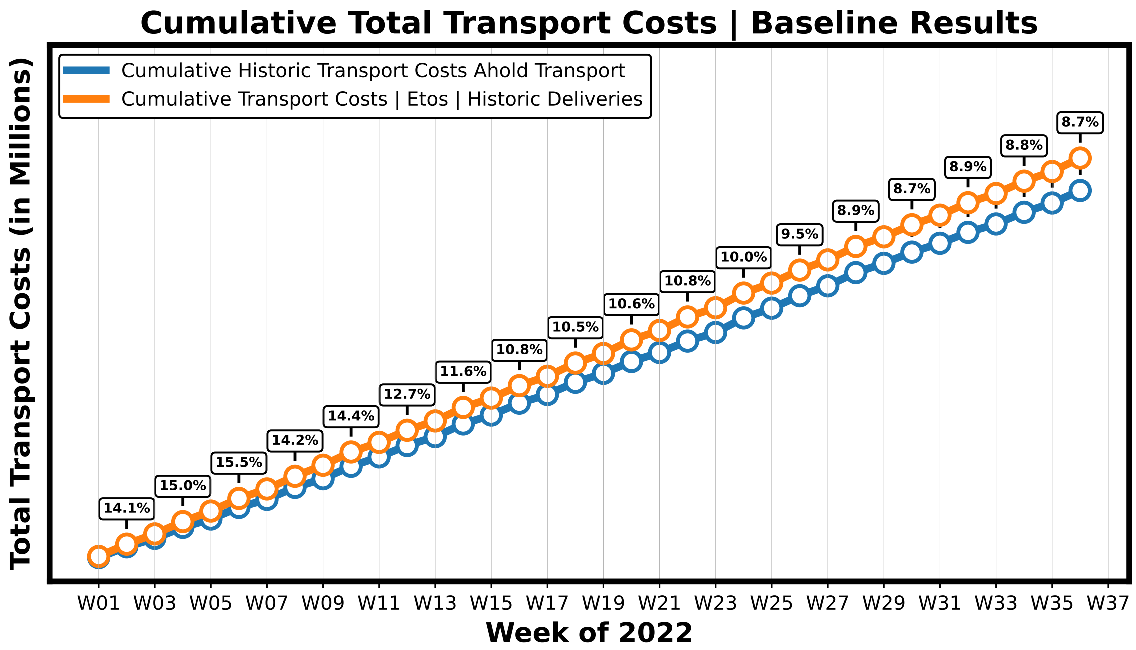


Figure 7.1.1: *Cumulative Transport Costs of Historic Deliveries Planned by Ahold Transport and Capacitated Vehicle Routing Problem with Time Windows Model.*

7.2 Complexity Mixed Integer Programming Models

In the use case of Mixed Integer (Quadratically Constrained) Programming optimization models, one can use the evaluation of the MIPGap to evaluate on the complexity of the model. The MIPGap value refers to at least the gap value that Gurobi has to reach before declaring optimality. The current relative optimality gap is computed as follows: $|(ObjBound - ObjVal)|/|ObjVal|$, where $ObjBound$ and $ObjVal$ are the MIP objective bound and incumbent solution objective, respectively.

Gurobi will not always terminate with the exact MIPGap set by the user. Gurobi does not search for feasible points that are exactly in the gap set by the user but rather tries to find the best point it can reach and terminates when the MIPGap requirement is met.

In the process of verifying the correctness of the model using the evaluation of the MIP-Gap value, a run of the Capacitated Vehicle Routing Problem with Time Windows was performed where the parameter 'TimeLimit' was set to a value equal to 36000 seconds (10 hours). For comparison and verification, we established 4 different sets of data instances of different sample sizes of Etos stores which were used for optimality calculations. The results in Figure 7.2.1 show that the size of the input instances has a major impact on the opportunity of reaching optimality. This information will be discussed further in Section 7.4, where we will discuss a heuristic approach to better scale the computations.

The MIPGap value after 36000 seconds was still around 37%. If we then take a sample of 20% of the total number of stores (100 stores), we observe that the MIPGap value decreases to 4% after the total run time has passed. In case the vehicle routing problem is solved for 50 stores, we observe a MIPGap value equal to 2.5% after 750 seconds. At last, when trying an instance where the sample size equals 25 stores, we reach optimality after 3 seconds.

Furthermore, Figure 7.2.1 illustrates that in case the number of large instances of data sets, the data presolve preparations take a significantly larger amount of time ($\approx$ 800 seconds), where all the other samples start from almost the beginning of time. Moreover, the illustration shows that after $\approx$ 750 seconds, the MIPGap value does not decrease as significantly as from the start of the optimality calculations and remains fairly the same thought the rest of the optimization.

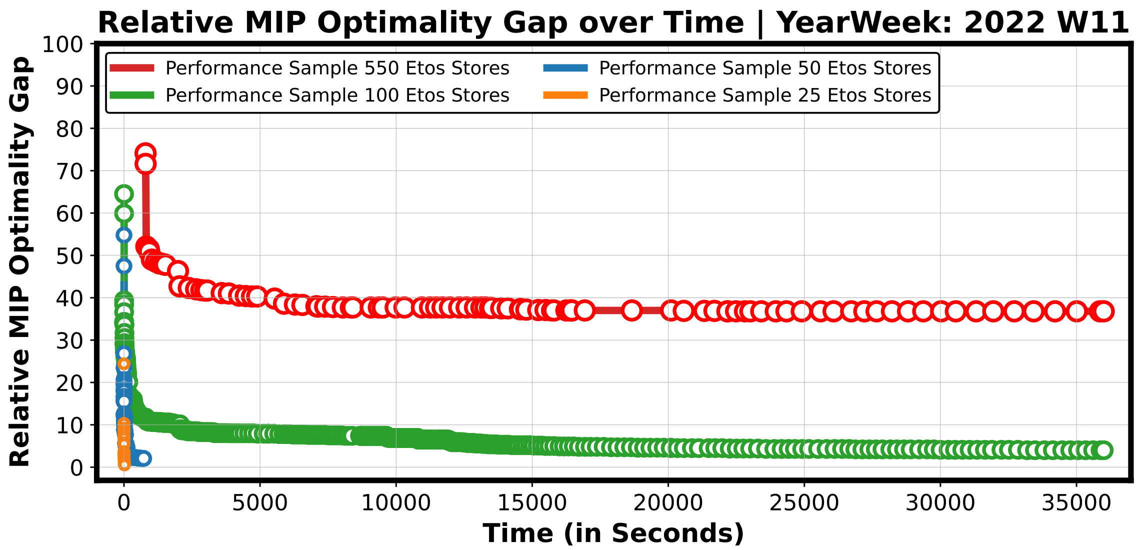


Figure 7.2.1: *Relative MIP Optimality Gap over Time of CVRPTW.*

As mentioned in the literature review (Section 3.8.6), the VRP is one of the most difficult problems to solve. The problem is quite close to the Traveling Salesman Problem (TSP). TSP is a well-known NP-Hard problem, where only one vehicle or person visits all the stores. However, The Vehicle Routing Problem (VRP) is more complicated than Traveling Salesman Problem (TSP). Furthermore, Savelsbergh (1985) [15] had shown that even finding a feasible solution to the VRPTW when the number of vehicles is fixed is itself an NP-Complete problem. In conclusion, we may state that the complexity of the capacitated vehicle routing problem with time windows increases as the set of data instances increases.

7.3 Evaluation of Application CVRPTW

With the current sample sizes of the large-scale data sets of store instances given to the model of the CVRPTW, one does not always achieve an optimal result. As a result, in exceptional cases, the model returns an erroneous route. Results in the output show this happens in less than 1% of the cases. We see this observation since we are solving a non-linear (quadratically constrained) optimization problem for which there are no optimality guarantees. To address this observation and proof this erroneous route is related to methodology of the quadratically constrained mixed integer programming model with respect to the input size, an example is outlined and discussed. This example addresses both the erroneous route and the correct application.

In a large-scale situation, an example of this erroneous route is illustrated in Table 7.3.1 and Figure 7.3.1. From the table, we observe the Etos store in both Hilversum (6322) and Utrecht (7780) is visited twice during this single route. This result violates constraints 6.3.2 and 6.3.3, which states that a store may receive a maximum of 1 delivery during a route due to store storage capacity constraints. In conclusion, this result in infeasible and not optimal.

However, to demonstrate that the CVRPTW model has been formulated correctly, this exact same set of specific instances (Etos stores from Table 7.3.1) was given to the same model formulation. The result of this sub-optimization is shown in Table 7.3.2 and Figure 7.3.2. From Table 7.3.2 one can observe every single store is visited once during a single route. In case a store requires multiple deliveries during the periodic cycle, multiple routes are created for those stores (i.e. 6322 and 7780). In conclusion, this result in both feasible and optimal.

Route	Origin	To	Destination
1	Etos Warehouse	→	7584 | Etos Amsterdam
1	7584 | Etos Amsterdam	→	6310 | Etos Amsterdam
1	6310 | Etos Amsterdam	→	7780 | Etos Utrecht
1	7780 | Etos Utrecht	→	6322 | Etos Hilversum
1	6322 | Etos Hilversum	→	6327 | Etos Kortenhoef
1	6327 | Etos Kortenhoef	→	7780 | Etos Utrecht
1	7780 | Etos Utrecht	→	6322 | Etos Hilversum
1	6322 | Etos Hilversum	→	Etos Warehouse

Table 7.3.1: *Numeric Example of Wrong Route As Result of Relative MIP Optimality Gap.*

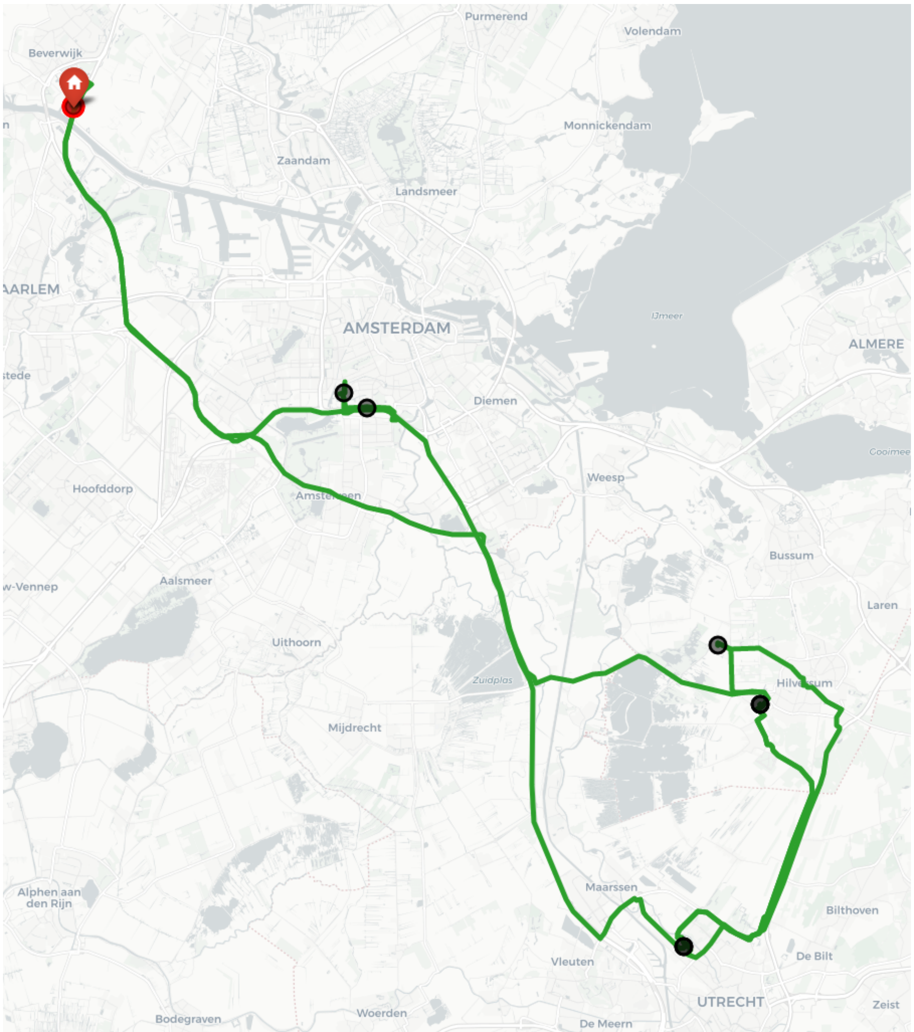


Figure 7.3.1: *Visual Example of Wrong Route As Result of Relative MIP Optimality Gap.*

Route	Origin	To	Destination
1	Etos Warehouse	→	7584 | Etos Amsterdam
1	7584 | Etos Amsterdam	→	6310 | Etos Amsterdam
1	6310 | Etos Amsterdam	→	7780 | Etos Utrecht
1	7780 | Etos Utrecht	→	6322 | Etos Hilversum
1	6322 | Etos Hilversum	→	Etos Warehouse
2	Etos Warehouse	→	7780 | Etos Utrecht
2	7780 | Etos Utrecht	→	6322 | Etos Hilversum
2	6322 | Etos Hilversum	→	6327 | Etos Kortenhoef
2	6327 | Etos Kortenhoef	→	Etos Warehouse

Table 7.3.2: *Numeric Example of Correct Route As Result of Relative MIP Optimality Gap.*

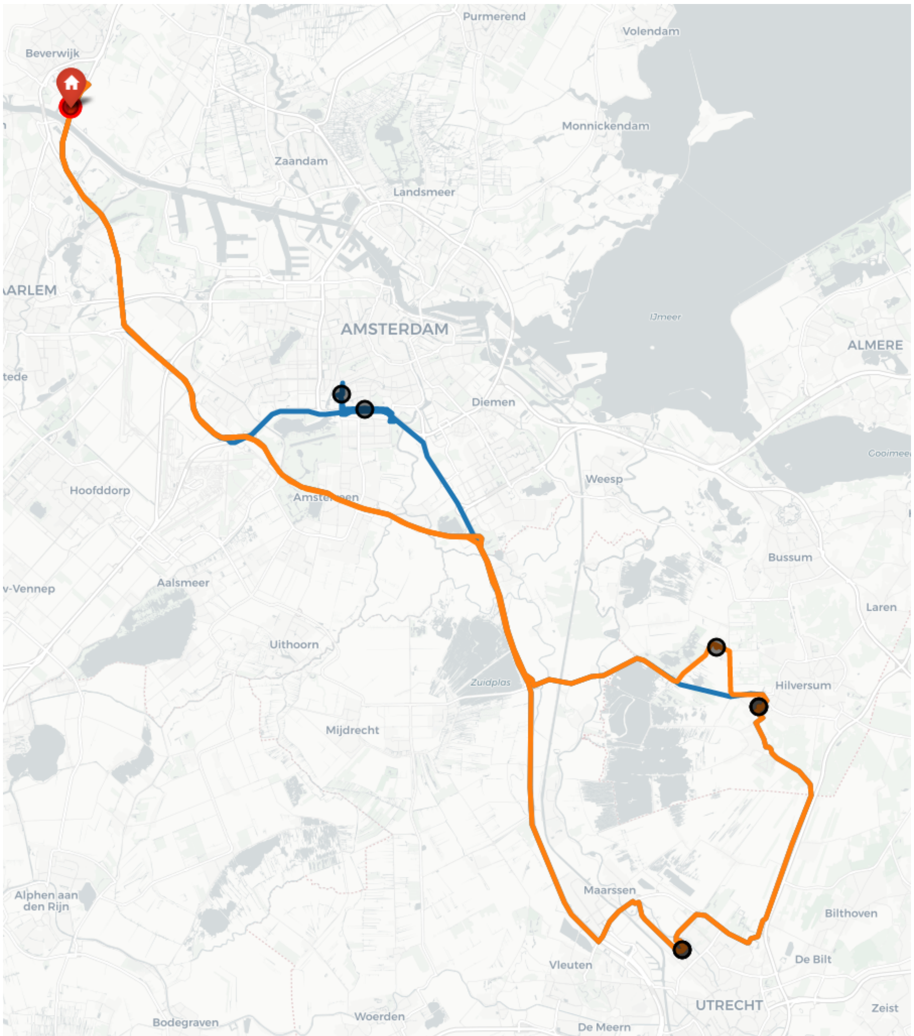


Figure 7.3.2: *Visual Example of Correct Route As Result of Relative MIP Optimality Gap.*

7.4 Heuristic Approach

If we look back at Section 7.2 and Section 7.3, one can conclude that the methodology behind Capacitated Vehicle Routing Problem with Time Windows (CVRPTW) works faster and more optimally with smaller sizes of data set instances. This decreases the number of instances of a single run and benefits the MIPGap without compromising the results. From this point forward, it is good to know that all results displayed and discussed make use of this heuristic approach with the distinction and approximation below.

In order to reduce both the complexity of modeling and the model's run time, it was decided to divide the Etos stores into different groups. Firstly, For the final determination of groupings, it was decided to locate the Etos stores based on their geographical location. This creates 12 different groups, all with a relatively useful size.

Secondly, to further reduce the sizes of the data set instances, the stores within these 12 distinct groups are divided according to a predetermined delivery day. This predetermined delivery day was applied according to Table 7.4.1. This allows for an individual CVRPTW on a weekday, but multiple CVRPTWs within a region (province).

Cumulative Number of Delivery	**Week**	**Delivery Day**
1	1	Monday
2	1	Wednesday
3	1	Friday
4	1	Tuesday
5	1	Thursday
6	2	Monday
7	2	Wednesday
8	2	Friday
9	2	Tuesday
10	2	Friday

Table 7.4.1: *Predetermined Delivery Day Based on Number of Delivery During Periodic Cycle.*

From Table 7.4.1, we observe it was decided to keep a fixed pattern related to the lead-time of delivering new goods to the stores. The main takeaway from this table is that deliveries are as planned as possible at the start of the week and, if possible, maintain a 2-day lead time.

7.5 Results on Transportation Costs

In this section, we will evaluate the results related to the total cumulative cost of transportation. These have been computed using the sequential methodologies and their coherence as discussed in Sections 6.1 and the heuristic approach from Section 7.4. For the final results and evaluation, we used the parameters discussed in Section 6.4.

Figure 7.5.1 illustrates the final results for the cumulative total transport costs of different experiments. For the final results, we included the multiple computations, mentioned in the legend of Figure 7.5.1 and the next paragraphs, and will evaluate on the difference between the cumulative outcomes. It is good to repeat that the results in Figure 7.5.1 are based on the applied elaborations described in Section 7.4 and using the parameter settings as described in Section 6.4.

Figure 7.5.1 also includes the cumulative transport costs of the actual historic deliveries planned by Ahold Transport and computed using the methodology of the Capacitated Vehicle Routing Problem With Time Windows (CVRPTW) model. These have been evaluated in Section 7.1 and will be used as a reference for the optimization of the delivery frequency and solving the vehicle routing problem associated with this delivery frequency.

In addition, it was decided to simulate the results over the first 36 weeks of the year in order to gain a better understanding of the potential cost savings over time. On one hand, it is possible to compare a specific periodic cycle of 2 weeks with the historical observations, but cumulatively it becomes more insightful what the impact can be of the proposed sequential methodology.

First and foremost, Figure 7.5.1 illustrates the results of the interaction between the delivery frequency optimization and the Capacitated Vehicle Routing Problem With Time Windows for both a periodic cycle of 1 week (purple) and 2 weeks (green). From the illustration, we observe that cumulatively, up to and including week 36 of 2022, the total transportation costs have decreased by 26.5% (€XXX,XXX) for a periodic cycle of 1 week and even decreased by 38.6% (€X,XXX,XXX) for a periodic cycle of 2 weeks.

When we look at the difference between the periodic cycles, we see that a periodic cycle of 2 weeks causes a decrease of 16.5% (€XXX,XXX) percent compared to a periodic cycle of 1 week.

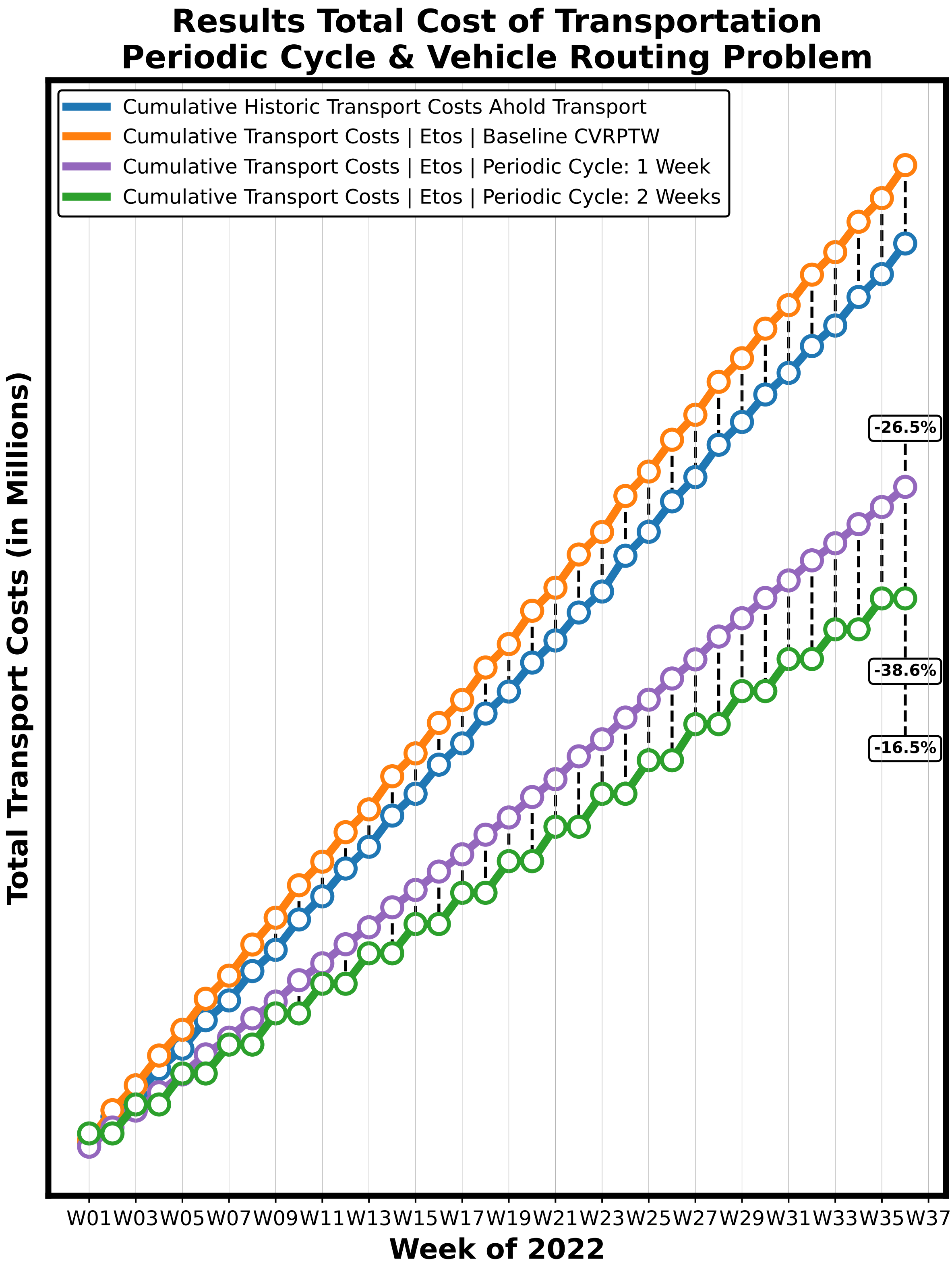


Figure 7.5.1: *Results Total Cost of Transportation of Etos Periodic Cycle & Capacitated Vehicle Routing Problem with Time Windows.*

7.6 Results on Number of Deliveries

From the delivery frequency optimization methodology proposed and implementation as described in Section 6.2, we can visualize the effect on the (cumulative) number of deliveries carried out by Ahold Transport, the transport company responsible for all transport movements of the various entities within Ahold. The results are illustrated in Figure 7.6.1.

In the current situation, Etos brings new goods to the stores once a week. For the optimization of the delivery frequency, a new periodic cycle of 2 weeks has been chosen and proposed. This periodic cycle of 2 weeks is also used for the optimization of the cumulative number of deliveries visible in Figure 7.6.1.

From the illustration, we observe striking results regarding the number of deliveries that had to be carried out by Ahold Transport. First of all, if an external carrier such as PostNL is not used, we see that the cumulative number of deliveries up to and including week 36 of 2022 has decreased by 22.9% compared to the current delivery schedule. When PostNL is one of the transportation options, we see a cumulative decrease of 47.3% compared to the current delivery schedule. When we then look at the difference between whether or not PostNL deliveries are allowed, we see that the number of deliveries that had to be carried out by Ahold Transport decreases by 31.6% if we were to deliver goods via PostNL to the Etos stores.

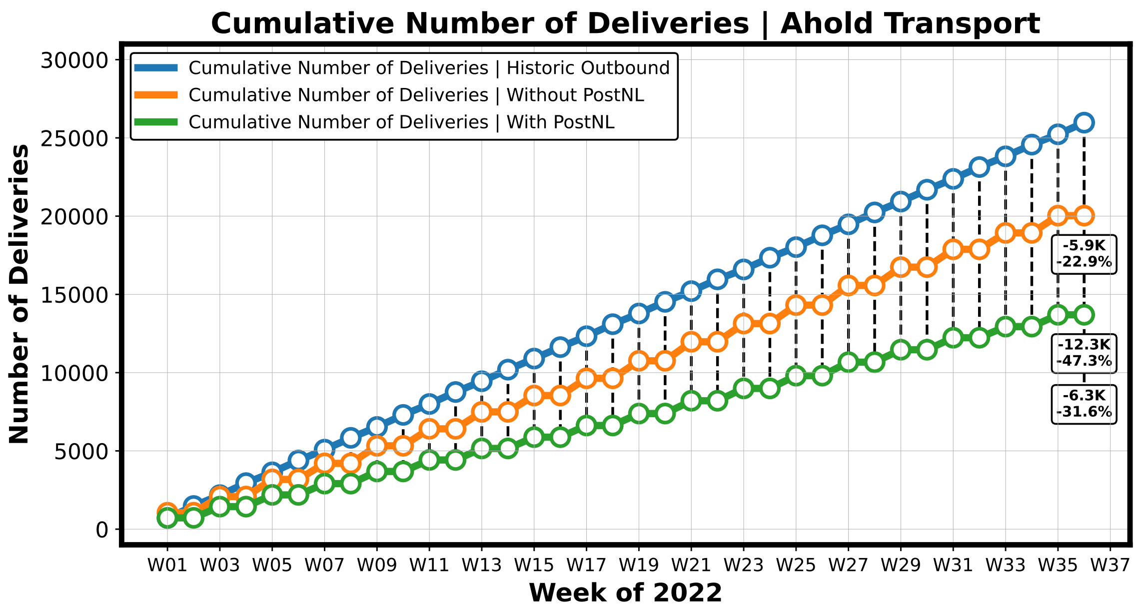


Figure 7.6.1: *Cumulative Number of Deliveries of Ahold Transport.*

7.7 Maximum Number of Store Storage Containers

An important parameter that can influence the determination of the total transport costs of Etos is the parameter 'MaxStorageContainers'. This parameter is responsible for the minimum number of containers a store can store in its storage area in the back of the store. For the final results, we conducted a small experiment with different values of this parameter 'MaxStorageContainers'. The results of this experiment are illustrated in Figure 7.7.1.

From the illustration, we see that for the first 7 weeks of 2022 the difference between the cumulative transport costs for Etos is minimal. In week 7, a 'MaxStorageContainers' value equal to 5 is only 2.5% lower compared to a 'MaxStorageContainers' value equal to 3. Moreover, a 'MaxStorageContainers' value equal to 8 is 8.8% lower compared to a 'MaxStorageContainers' value equal to 3. Furthermore, from the 'StoreLibrary' file provided by Etos (a file containing the storage area information of Etos stores), we observed 58 stores (10.5%) have a 'MaxStorageContainers' lower than 3 containers, 138 stores (25.1%) have 'MaxStorageContainers' lower than 5 and 290 stores (52.7%) have a 'MaxStorageContainers' lower than 8.

In conclusion, a 'MaxStorageContainers' value equal to 3 was chosen for the final computation of the (cumulative) total cost of transportation. The differences between all three possibilities were significantly small, but the larger two values were realistically too high.

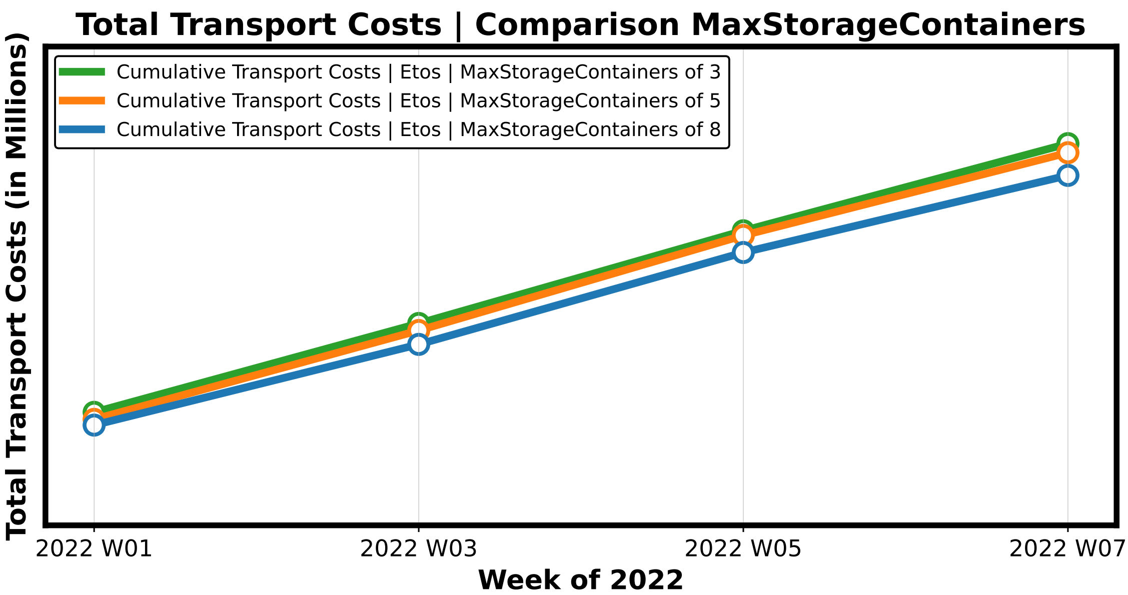


Figure 7.7.1: *Effect Parameter 'MaxStorageContainers' on Total Transport Costs.*

7.8 Percentage of Air in CBL-23 Crate

One of many possible important distinction that can influence the determination of the (cumulative) total cost of transportation of Etos is percentage of air we take into consideration when order picking the goods that need to be packed in the CBL-23 load carrier crates and shipped to the Etos stores. The results of different parameter values can be observed in Figure 7.8.1.

From the illustration, which plots the cumulative total cost of transportation up to and including week 36 of 2022 for different percentages of air and the historic outbound planned by Ahold Transport (red), we observe a noticeable, influential difference in total transport costs. In earlier discussed results from Section 7.5, the percentage of air is equal to 33% for the final computation of results. Both these lines are presented in green.

From the illustration we observe that, by the end of week 36 of 2022, the cumulative total transportation costs have decreased by 38.6% (€X,XXX,XXX) when considering 33% of air. When we take into account 66% air, this reduction in transport costs is only equivalent to 15.1% (€XXX,XXX). Finally, for a common middle ground, which is 50% air, the reduction in transport costs is equivalent to 30.8% (€XXX,XXX). All reductions are compared the historic outbound planned by Ahold Transport (red).

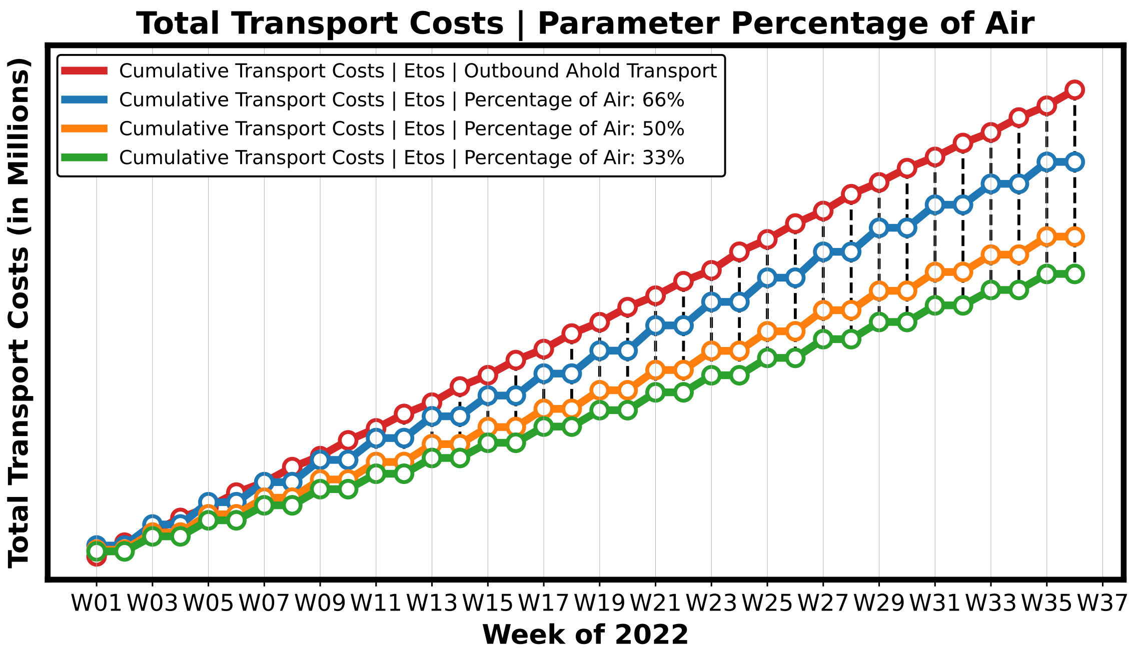


Figure 7.8.1: *Effect Parameter 'PercentageAirCBL23' on Total Transport Costs.*

7.9 Inclusion of PostNL Deliveries

Another important distinction that can influence the determination of the (cumulative) total cost of transportation of Etos is the inclusion of possible PostNL Deliveries. For the results and evaluation of this inclusion, we will take observations from Figure 7.9.1.

From the illustration, which plots the cumulative total transport costs up to and including week 36 of 2022 for the inclusion (green) and exclusion (orange) of PostNL deliveries, we observe a noticeable difference in total transport costs.

By the end of week 36 of 2022, adding the ability to deliver goods via PostNL will, accounting for a periodic cycle of 2 weeks, reduce the cumulative total transportation costs by 12.6%. This reduction is equivalent to approximately €XXX,XXX.

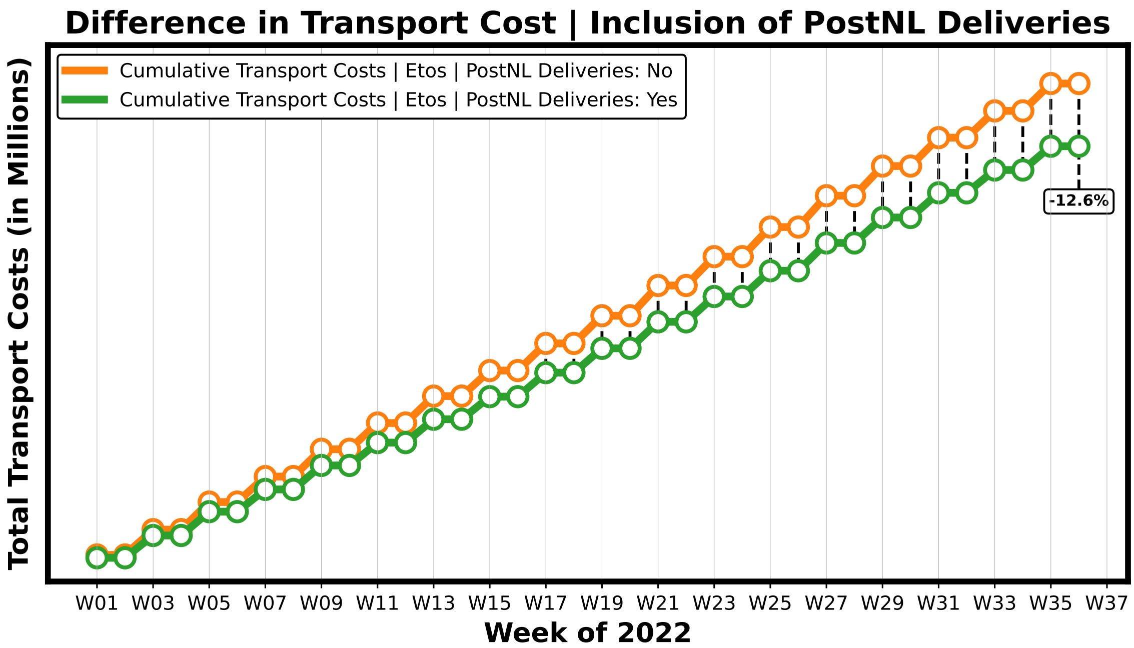


Figure 7.9.1: *Difference in Transport Costs with Inclusion of PostNL Deliveries.*

Chapter 8

Conclusion and Recommendations

The goal of this research was to investigate the effect of the delivery frequency on the (cumulative) total cost of transportation of Etos, which was calculated by the methodology of the delivery frequency and the Capacitated Vehicle Routing Problem with Time Windows (CVRPTW). A combination and interaction of two Mixed Integer (Quadratically Constrained) Programming optimization models that are solved using Gurobi was developed to answer these questions. These models have been used sequentially to solve the problem where we used different input values for the periodic cycle, the minimum number of storage containers, the percentage of air in load carriers, and the inclusion of PostNL deliveries to evaluate the predicted outcome of the (cumulative) total cost of transportation.

It turned out that, with the current data cleaning, data preparations, and parameter settings, these sequentially Mixed Integer (Quadratically Constrained) Programming optimization models were able to produce insightful results using a heuristic approach for the data set instances. This heuristic approach was chosen to produce a working solution within a reasonable time frame. Instead of looking for a perfect solution, heuristic strategies look for a quick solution that falls within an acceptable range of accuracy. Because a heuristic approach emphasizes speed over accuracy, it is often combined with optimization algorithms to improve results. This heuristic approach was taken with care and had a positive effect on the predicted outcome of the total (cumulative) cost of transportation.

Based on the results, we would like to make a number of recommendations to Etos. First and foremost, a new evaluation of the periodic cycle parameter, the volume parameter, and the inclusion of PostNL deliveries could have a major impact on its cost of transportation. An evaluation of the results, as discussed in Sections 7.5, 7.8 and 7.9 respectively, shows that significant savings can be made when the combination of these parameters and interactions is used correctly.

In addition, when we propose a new periodic cycle of bi-weekly deliveries, we see a cost of transportation cost decrease of 38.6% compared to Ahold Transport's current schedule. Consequently, as a result of a newly proposed efficient planning, it is also possible to reduce the number of transport rides of Ahold Transport, and thus the number of kilometers and transport movements, by 47.3%. In addition to this latter conclusion, it is of great influence to add the possibilities of PostNL deliveries to its flow of goods from the warehouse to its stores.

Chapter 9

Limitations and Future Research

In analyzing the delivery frequencies and scheduling the possible routes for all the stores of Etos, this thesis has uncovered multiple primary areas for future research, all of which can have significant impacts on the operations and costs of a retail supply chain independent of the delivery schedules of its stores.

To conclude this research, we may state different topics of limitations and alterations which are subject to future research and will be discussed in this chapter. Most topics are devoted to the quality of the data and various optimizations that could be applied in the future.

9.1 Quality of Data Extractions

Data quality is a measure of the condition of data based on factors such as accuracy, completeness, consistency, reliability, and whether it's up to date. The emphasis on data quality has increased as data processing has become more intricately linked with business operations and organizations increasingly use data analytics to help drive business decisions. Data quality management is a core component of the overall data management process, and data quality improvement efforts are often closely tied to data governance programs that aim to ensure data is formatted and used consistently throughout an organization.

This thesis brought to light that bad data can have significant business consequences for companies. Poor-quality data is often pegged as the source of operational snafus, inaccurate analytics, and ill-conceived business strategies. Examples of the economic damage that data quality problems can cause include the exclusion of retail items because their dimensions exceed transportation limits, and lost sales opportunities because of erroneous or incomplete customer records.

9.2 Intermediate Lead Time Optimization

To begin with, the underlying lead times between two deliveries may also be the subject of further investigation. The current study does not take into account a minimum number of days between deliveries. This can have consequences for the number of delivery locations per day and their geographical location, respectively.

9.3 Store Storage Capacities

Secondly, this research is highly dependent on the values specified in the so-called 'Store-Library' of Etos. In this file, all physical store properties are documented and maintained, including the store storage capacities. However, while using this data, it appeared that there was a lot of misconception about the interpretation of the numbers. Research has shown that not all values are correct or that values are missing. In order to improve the possible theoretical solution compared to reality, it would be desirable to conduct a new inquiry into the most recent, actual numbers related to the store storage capacities.

9.4 Distribution of Demand

Thirdly, under the current implementation of my research problem, the demand for the number of load carriers to the stores is evenly distributed over the number of proposed deliveries. As an example, if the Etos store in Leidschendam has a store storage capacity of 9, and requires 21 load carriers in the periodic cycle of 2 weeks, we proposed 3 deliveries. Consequently, the demand for each delivery will be 7 load carriers each time. However, one could think it might be more efficient to deliver different quantities for every single delivery, accounting for the maximum store storage capacity. Future research could show whether this statement applies to my research topic.

9.5 Percentage of Air in Load Carriers

In addition, under the current implementation of my research problem, we use a fixed percentage of air in the load carriers that have to be transported to the stores. In future applications, the retail items can also be packed optimally using the algorithm applications of the bin packing problem. This optimization problem tries to minimize the total number of used bins.

9.6 Delivery Day and Delivery Time Optimization

Moreover, in relation to lead time optimization, any optimization towards the optimal delivery day and delivery time during the week and day, respectively, also has great potential. In this way, Etos can maintain an equal distribution over the week, which can be of great importance to the external carrier.

9.7 Workload Optimization Warehouse

Furthermore, this equal distribution over the week is just as important for the Etos warehouse. The warehouse also has to deal with its own capacity restrictions, both humanly and psychically. These constraints are currently not included in the optimization. Since this topic of future research is mainly related to lead time optimization and delivery day and time optimization, this combination of additions would be of great practical added value for Etos her supply chain.

9.8 Retail Item Store Stock Level

Currently, the current stock levels of articles in the stores and the rotational speed at which these goods are sold are also not taken into account. In this way, insight is not used when an article can go out of stock. Implementing this information to the optimization could consider when the next delivery should be scheduled in the future. Therefore, this topic is parallel to the lead time optimization described in Section 9.2.

9.9 Algorithmic Applications

At last, there are many perspectives related to the optimization algorithms that are worthy of receiving further investigation. One could think of the application of multiple but different algorithms. The more successful implementations of Tabu Search are more likely to create better initial solutions and neighborhood structures.

Alternative strategies for generating an initial solution, more sophisticated neighborhood exploration, different memory structures, different aspiration criteria, and more sophisticated diversification and intensification methods can be developed. One should also take the trade-off between the complexity of the algorithm and the computational effort that this algorithm requires into consideration.

Another future option can focus on the setting where only a subset of customers has fixed time windows. A study on developing more sophisticated approximation methods and doing extensive parameter tuning of these methods can be conducted.

Chapter 10

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Etos

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