MASTER

Timing the planning of transportation for logistical service providers
the case of ELC’s 3PL business

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Award date:
2023

Master Operations Management and Logistics (OML)

Master Thesis

"Timing the planning of transportation for logistical service providers: the case of ELC's 3PL business"

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Final version
Eindhoven, Friday 30th June, 2023

Preface

This research represents the final phase of my master's degree program at the University of Technology Eindhoven (TU/e) in Operations Management and Logistics. I am flattered by the opportunity to develop and implement an exact algorithm from scratch at Ewals Logistics Control to plan transportation more systematically. Furthermore, I am proud that the company is satisfied with the result and aims to use the algorithm in practice. Since multiple individuals made this opportunity possible, I dedicate the following paragraph to express my honest gratitude to these people for their contributions.

First, I am thankful to the European Supply Chain Forum (ESCF) for providing this opportunity, by which I was able as a student to hone my problem-solving abilities, analytical mindset, and understanding of logistics dynamics, and in this way, to prepare myself for a successful career. Next, I like to express my gratitude towards my supervisors/assessors at the TU/e. In particular, my first supervisor, Dr. Layla Martin, I hereby like to thank you for challenging me in every meeting to get the most out of this project with your on-point feedback. Similarly, I want to thank Dr. Collin Drent for his cooperation, as I can't take for granted to have had such a second supervisor that tried to be present at every meeting with the corresponding helpful suggestions for improvement. Furthermore, I am grateful for all the cooperation and support from Ewals Logistics Control. Having close contact with three supervisors at the company is not very common in a master's thesis. Still, it shows that the company took this project very seriously, by which I am even more proud to have delivered a successful result. This responsibility gave me many challenges during the project, but due to close collaborations, we successfully aligned all requirements with the possibilities and restrictions of this project. My company supervisors: Dario Palombo (manager), Stephan Verheijden (day-to-day supervisor), and Bruno Albino (Python sparring partner), all contribute differently to this collaboration, but I will reduce this elaboration to thank all of them for the opportunity for me to apply my knowledge and experiences in an innovative company that also provides a pleasant working atmosphere. Last but certainly not least, I thank all my friends and family for their lovely support during the last nine months.

Abstract

A systematic method to combine consignments into shipments enhances the efficiency of logistical service providers (LSPs) compared to relying on human judgment. Therefore a need arose at Ewals Logistics Control to develop a linear program that assists the continuous improvement (CI) and planning department in minimizing the cost (for their clients) by using the route optimization techniques of direct shipping, merging, milk runs, round trips, and cross-docking. This research combines these techniques in one model for inbound and outbound consignments simultaneously, by which we contribute to current literature as to our best knowledge this is never done before. To more systematically combine consignments into shipments, we batch the optimization and planning of consignments. For this, we propose to use fixed time window batching with different lengths and frequencies of the fixed-length planning horizon for each client, and extend on this by postponing consignments between these batches. The results show that LSPs, depending on the difference between the spot market and contract prices, improve efficiency (cost savings and manual work by the CI-analysts) by implementing the proposed processes and methodologies.

Keywords: *3PL business*, *merging*, *milk runs*, *round trips*, *cross-docking*, *linear programming*, *timing of planning*, *batching*, *fixed-length planning horizon (FLPH)*, *order postponement.*

Executive Summary

Currently, in ELC's 3PL business, planners book consignments at carriers and are combined based on 'rules'. The CI-analysts rule out the 'rules' by simply searching in the historical data for logistical improvements rather than any systematical tools aiding this process. Therefore, the company needed a solution to combine consignments more systematically using an (exact) algorithm rather than human judgment. In this research, we show a model that combines consignments (both inbound and outbound) using the CBC solver available within PuLP, implemented using Python in a Spyder environment. For this, we generalized the (un-)loading locations of the consignments to a 2-digit postal code area to quickly determine distances between locations without paying for expensive software that precisely calculates these distances. The model combines consignments using the route optimization strategies of merging, milk runs, round trips (i.e., backhauling), and cross-docking, which is (to our best knowledge) not combined in one model simultaneously yet in current literature. This shows the literature gap filled by this research. For the merging strategy, we investigated two heuristics for solving a one-dimensional bin-packing problem (BPP), from which we decided to continue with the First Fit Decreasing heuristic. Additionally, in this research, a "client" refers to a single plant of a 3PL client. We conduct separate logistical optimizations for each plant as our research primarily concentrates on one-to-many and many-to-one relationships. Furthermore, 3PL providers mainly optimize logistics for clients shipping business-to-business, by which the shipping sizes are significantly bigger than in the parcel industry. For example, at ELC on average consignments fill approximately 58% of the truck, showing the cost savings potential of combining consignments. Note, the distribution network in this research focuses on Europe only.

In the current consignment planning processes, planners book consignments immediately as they come in if they expect the consignment cannot be combined in the period to the booking deadline or can already be combined. We propose a solution in this research to batch consignments to elevate the cost savings potential for LSPs. We base these analyses on the data from a subset of clients in 2019 that industry experts assess as representative. Our literature review revealed that fixed time window batching (FTWB) most likely outperforms the use of variable time window batching (VTWB), by which we continued this research

with FTWB. Fixed time window batching with a frequency of once per day at 2 PM yields the highest cost savings, which is also the last possible moment to optimize as at 3 PM all consignments must have been sent to the carriers (for the consignments with one workday remaining to their collection date). However, our simulation model revealed that this leads to a capacity shortage at the planning department on some days during the year (i.e., 13 out of 261 of the workdays, not including holidays), by which we need to batch and optimize some of the clients earlier to ensure sufficient capacity at the planning department. For this, we show a procedure to approach a combination of lengths and frequencies of the fixed-length planning horizon (FLPH) that preserves most of the cost savings for all clients separately (i.e., above 90%) and ensures a more widespread planner workload by which we prevent a capacity shortage at the planning department. Different lengths and frequencies of the FLPH per client makes sense as the arrival of consignments differs significantly between clients.

For uncombined consignments in the current batch, our research considers postponing them to the next batch if possible regarding the deadline to send the consignment to the carrier. In the current way of working, planners postpone all uncombined consignments until the booking deadline. However, our results show that postponing all consignments only sometimes makes sense, depending on the difference between the spot market and contract prices. We base our postponement decision on the probability that a consignment can be combined in future batches until the booking deadline in merging, milk runs, round trips, or cross-docking. We determine this probability based on the relative frequency from historical data on whether similar consignments were possibly combined within the same amount of workdays till the booking deadline. We postpone consignments if this probability is above a specific cut-off value. For example, for milk runs, similar consignments are those from the same supplier/customer with a similar payable weight (with 2,000 kilograms of payable weight margin on both sides). For the downside of postponing consignments, we introduce a penalty cost that must outweigh the additional cost savings gained by postponing consignments. This penalty cost represents the possibility that a planner must book a consignment at a non-contracted carrier, which is generally more expensive (valid for 82.79% of the time between 01/2021 and 05/2023). As shown, this probability of booking transportation on the spot market increases with fewer workdays until the loading date. In the end, we found an approximately linear relationship between the difference of the spot market and contract prices and the probability cut-off value yielding the highest difference between additional gained cost savings and penalty cost. In other words, if the difference between the spot market and contract prices increases, the additional cost of booking a consignment at a non-contracted carrier increasingly outweighs the additional cost savings of that postponement. Investigating a more sophisticated probability calculation and implementing many-to-many relationships in the model are the leading suggestions for future research.

Acronyms

2PL second-party logistics.

3PL third-party logistics.

BPP bin-packing problem.

CI continuous improvement.

ECC Ewals Cargo Care.

ELC Ewals Logistics Control.

FLPH fixed-length planning horizon.

FTL full-truckload.

FTWB fixed time window batching.

LSPs logistical service providers.

LTL less-than-truckload.

VRP vehicle routing problem.

VTWB variable time window batching.

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Chapter 1 Introduction

As in the current market of logistical service providers (LSPs) margins are low, it became increasingly important to reduce costs to the minimum and remain competitive by providing unique services and reviewing competitors' services. Low margins result from a highly fragmented market by many LSPs and carriers existing in the market (Ojala et al., 2006). Moreover, the competition between LSPs increased even more by the lack of capacity in truck drivers (Allen, 2021) and the increase in transport volumes since the beginning of 2021. The war in Ukraine (Khudaykulova et al., 2022) resulted in an even more significant capacity shortage since many carriers were deploying Ukrainian truck drivers. Also, the price billed by carriers increased since the beginning of 2022 due to the increased gasoline prices (Khudaykulova et al., 2022). Because of that, clients of LSPs shift their demand. They not only focus anymore on price but also require the warrant that LSPs have a sufficient fleet with truck drivers and trailers (together with their subcontractors) to guarantee on-time shipments. Therefore, LSPs meet these client demands while reducing costs for their clients and themselves. This research improves this cost reduction process for LSPs by testing our proposed processes and methodologies on the case of Ewals Logistics Control (ELC) who currently plan their consignments immediately as they come in if they expect it cannot be combined later or can already be combined. By batching and waiting to plan these consignments, other consignments might come in in the meantime with which they can be combined (at a lower cost). This requires extensive research as our results showed that planning everything an hour before the booking deadline leads to a capacity shortage in the planning department. Additionally, postponing an uncombined consignment to the next batch might result in higher cost savings due to new possibilities to combine it. However, postponing the planning of a consignment might also result in higher costs due to possible capacity shortages at the contracted carrier by which an ad-hoc (i.e., more expensive) non-contracted carrier has to be booked. Besides, in the current way of optimizing the client networks, combining consignments is based on human judgment, likely resulting in sub-optimal planning.

1.1 Company description

We implement our exact algorithm at logistical service provider Ewals Logistics Control (ELC), a separate entity within Ewals Cargo Care (ECC). The following sections elaborate on both to better understand their differences and relation towards each other.

The company ECC has 1,950 employees and offers logistical solutions to businesses using its fleet of 3,400 trailers and 1,050 trucks. The focus of both ECC and ELC is business-to-business transportation, meaning larger shipping sizes than parcel shipping and fewer drop-off points. The logistical services of ECC are second-party logistics (2PL), where the focus mainly is on full-truckload (FTL). A 2PL provider is a carrier company that a client contacts directly to perform shipments for them. The carrier receives a schedule for when and where to (un-)load, without needing to optimize the logistics of their customer. Their most innovative invention is the Mega Huckepack trailer, by which they ship more efficiently (especially for the automotive sector, which is the largest sector for which they offer their services). ECC does not merely ship its goods via trailers and trucks. Instead, they deployed a multi-modal network (mainly within Europe) where a shipment can entail road, train track, and water transportation. To manage this entire network, they have 30 office locations in 14 different countries across Europe. On the contrary, the focus for ELC is mainly on road carriage.

The focus of ELC is on third-party logistics (3PL) services and is thus offering logistical solutions to clients which are much more complex than the services of ECC that just ship goods from A to B. So instead of being the carrier as in the case of ECC, ELC takes over the entire logistical decision-making of the client (referred to as the Control Tower service) to minimize their logistical cost. To continuously and systematically reduce these costs and remain competitive, the need arose for a transport network optimization algorithm which is the root of this research and aims to be used as a solution for the Control Tower to enhance efficiency in this optimization process. Moreover, this research investigates the timing of planning these consignments to optimize the algorithm's potential.

Although ELC is an entity within ECC, they focus on optimizing the logistics of their clients, which does not necessarily mean that ELC assigns ECC trailers and trucks more than those of other sub-contracted carriers. Therefore ELC acts as a neutral party when optimizing their clients' logistics. This Control Tower concept of ELC acts as a single contact point for the client and directs a trusted network of carrier partners for them. Figure 1.1 depicts the basics of this Control Tower service.

In the continuous improvement (CI) department, the CI-analysts continuously (manually) try to find improvements to their clients' logistical network. Suppose they find the improvements more systematically using an exact algorithm rather than human judgment. In that case, it

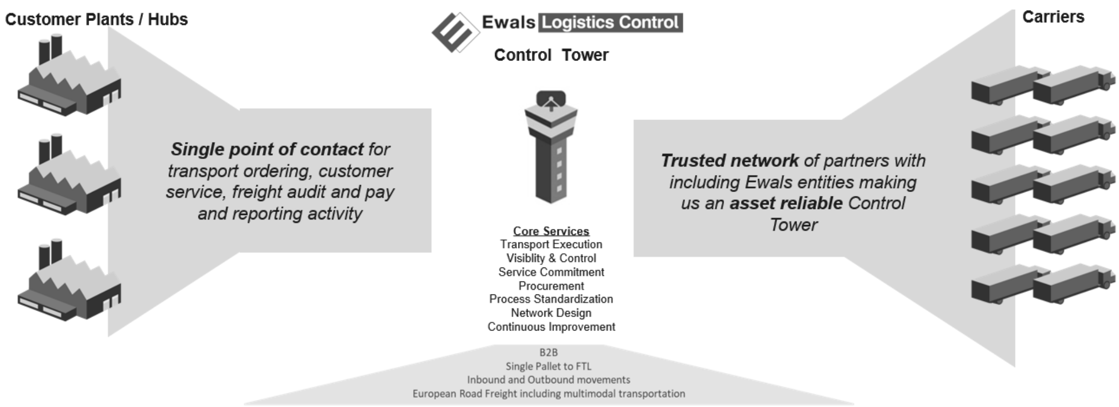

Figure 1.1: ELC Control Tower service

can lead to significant cost savings and reduced manual work by the CI-analysts. Optimization categories currently investigated by the CI-analysts for clients are:

1. Route optimization (including milk runs, round trips, and cross-docking, elaborated on in depth in Section 1.2)
2. Flow optimization (including loading frequency and lead-time extension)
3. Equipment optimization (including trailer type, loading optimization, and stackability)
4. Carrier optimization (including lane procurement, tendering, and carrier performance)

To limit the scope, this research focuses on the first category: route optimization.

1.2 Business case

The relevant processes are those associated with the CI-analysts and the 'planners'. The planners are responsible for matching consignments with carriers in the planning system, for example, by creating milk runs using pre-specified 'rules' with the associated consignments. The planners immediately plan the consignments as they come in for which the CI-analysts did not specify a rule. CI-analysts rule out these rules, which they find in their continuous search for optimizations in the categories mentioned above. An example of such a rule is: "Every time car manufacturer Rambo requires consignments to be shipped from suppliers Achep (door sup.), Brugip (tire sup.) and Criston (engine sup.) to Rambo, we make a milk run from Brugip to Achep to Criston to Rambo if they match regarding their (un-)loading dates, fit in one truck, etc.". CI-analysts manually find these kinds of optimizations by simply looking at the data and performing analyses (i.e., barely without any systematic tools). This research tackles the resulting shortcomings in efficiency (i.e., cost savings and manual work by the CI-analysts) by developing and implementing an exact algorithm. Figure 1.2 and Figure 1.3 depict the current and proposed improved processes.

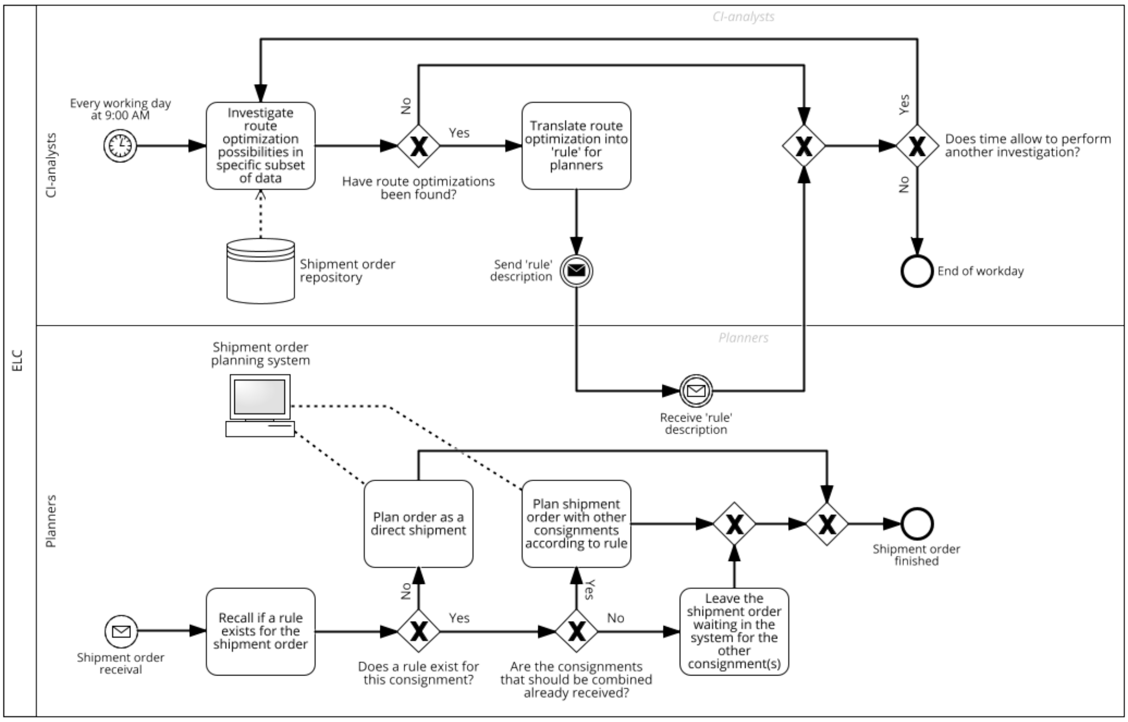

Figure 1.2: Current CI-analysts and planners processes

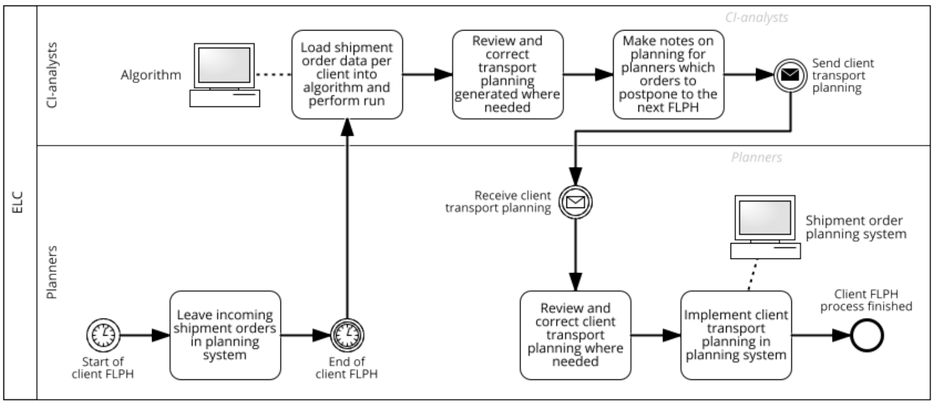

Figure 1.3: Future CI-analysts and planners processes proposed in this research

1.2.1 Milk runs optimization

Milk runs are consignment "pickups and deliveries at fixed times along fixed routes" (Baudin, 2005). In other words, a milk run co-loads shipments from different suppliers before shipping directly to the client from the last stop in the milk run. This means that a truck stops at multiple suppliers to collect the goods shipped towards the same client and have matching (un-)loading dates and fit in one truck. A milk run can also deliver to multiple customers one after another, starting at the client's site. The consignments' size in milk runs is relatively small compared to the trailer size (i.e., less-than-truckload (LTL)). This technique can lead to a significant amount of cost savings compared to shipping from all suppliers directly to the client, or from the client directly to all customers, particularly when suppliers are in close proximity to each other (and distant from the client). The planners are responsible for informing carriers when and where to (un-)load these consignments.

1.2.2 Round trips optimization

Round trips (i.e., backhauls) ship back another consignment to the first departure location. Getting back to the Rambo car manufacturer example, instead of booking a consignment between supplier Achep and Rambo (i.e., doors on pallets) and from Rambo to supplier Achep (i.e., empty pallets) as separate shipments, the total price is often lower if LSPs book a round trip (i.e., Achep-Rambo-Achep) at a single carrier. This is of critical importance as the distances between supplier/customer nodes and their clients, in general, are quite large for LSPs (i.e., often cross-border), and in that way the round trip discounts offered by the carriers can be significant. When LSPs perform a round trip, they often take 'empties' on the way back. For example, if a supplier always ships goods in crates to the client it is possible to take these (plus other) empty crates (i.e., empties) back to the supplier on the way back. LSPs pay round trip legs as FTL shipments as you limit the carrier in their routing optimization. However, LSPs receive discounts because carriers do not have to reposition their trucks themselves.

1.2.3 Cross-docking optimization

Van Belle et al. (2012) define that "cross-docking is a logistics strategy in which freight is unloaded from inbound vehicles and (almost) directly loaded into outbound vehicles, with little or no storage in between". It is a widely used concept in the transportation sector. LSPs chose the location of a cross-dock centrally to reduce the total distance driven and ultimately gain the most cost savings. ELC uses the so-called center of gravity analysis to find this location based on the distances to or from the cross-dock for suppliers and customers respectively and upon the volumes shipped between these locations. This research assumes fixed cross-dock locations (obtained from the center of gravity analysis) because ELC already intensively investigated this determination of the cross-dock location by this analysis. With this analysis, we prevent neglecting this determination leads the optimization to a local optimum (Mokhtarinejad et al., 2015). Moreover, incorporating location optimization in a model belongs "to the class of NP-hard problems" (Jakob & Pruzan, 1983).

In Chapter 2, we further review these techniques in the current literature and review papers that combine these techniques into one model. In a broad view, the reviewed papers all share that the vehicle routing problem (VRP) concept underlies their methodology, which is also fundamental to this research. “A vehicle routing problem (VRP) is one of visiting a set of customers using a fleet of vehicles, respecting constraints on the vehicles, customers, drivers, and so on. The goal is to produce a low-cost routing plan specifying for each vehicle, the order of the customer visits they make.” (Başligil et al., 2011).

1.3 Problem description

To overcome the mentioned efficiency shortcomings, we need a transport network optimization solution to plan consignments systematically with the objective to minimize cost. The solution allows the route optimization strategies of direct shipping, merging, milk runs, round trips, and cross-docking. Merging is an obvious but essential strategy combining consignments with the same collection and delivery locations and deadlines. As this combination of consignments can exceed the capacity of a truck, we review the literature regarding the bin-packing problem (BPP) in Chapter 2. Note, the CI-analysts and planners can change the solution generated, and the solution thus assists rather than replaces them.

This solution adds value to LSPs by not only being able to give a first estimation to new potential clients about possible cost savings they can expect when they start to use a Control Tower-like service. Instead, the solution can also give a strategic overview (like often recurring milk runs) and provide real-time planning. This also adds significant value to the clients as it likely saves them more cost. Subsequently, using this solution makes LSPs more competitive in their market by which they ultimately gain a bigger market share. This research fills the literature gap of implementing direct shipments, merging, milk runs, round trips, and cross-docking in one model for both inbound and outbound logistics simultaneously. Note, we only combine inbound and outbound consignments in round trips, as many-to-many relationships are out of this research’s scope. It is fully understood that combining consignments of different clients (i.e., many-to-many relationships) provides possibilities for making cost savings by consolidating them. However, to limit the scope, it is a suggestion for future research. Currently, ELC also does not combine consignments based on many-to-many relationships.

1.4 Research objectives

The goal of the mentioned model is to optimize the planning of the consignments that came in within a fixed-length planning horizon (FLPH), of which this research investigates the length and frequency (e.g., plan each workday at 11 AM and 2 PM for client A and collect consignments in between them). Suppose a consignment is uncombined within such an FLPH. In that case, we determine in this research whether we improve the planning by postponing this consignment to the next FLPH based on the probability of combining it in the future. This leads us to the main research objective of this research, formulated as:

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Besides, we derived two research sub-objectives that can only be investigated using the model implemented in Python. The first research sub-objective is to: "Determine a collection of lengths and frequencies of the fixed-length planning horizon (FLPH) for each client separately, preserving most cost savings while ensuring sufficient capacity at the planning department". Intuitively more cost savings can be achieved when the FLPH ends later and is less frequent, but in this way planners have a higher peak in their workload at the end of each FLPH.

The second sub-objective of our research focuses on: "Improving the consignment planning by postponing consignments between batches based on the probability that they can be combined in a future batch". In this research, we introduce a penalty cost for postponing consignments, that represents the probability of a capacity shortage at the contracted carrier (meaning a more expensive non-contracted carrier needs to be booked) as a function of the number of workdays before the loading date. Currently, the planners postpone all consignments to the workday before the loading date if it remains uncombined and for which they expect a consignment might arrive with which it can be combined (i.e., a 'rule' exists).

Chapter 2 Literature Review

This chapter reviews the literature regarding three different streams relevant to this research's consignment planning. These streams entail the available route optimization techniques in literature, frameworks incorporating them, and order batching.

2.1 Static 3PL routing strategies

To minimize transportation costs, Hosseini et al. (2014) outline the three transportation strategies of direct shipping, milk runs, and cross-docking. The name 'milk run' originates from how the milkman sold milk by walking by the customers' houses using a specified route (Korytkowski & Karkoszka, 2016). This is an example of a distribution milk run. At the same time, supplier milk runs exist (i.e., picking up goods to deliver to one end destination).

Another route optimization technique that significantly improves a transport network is backhauling (i.e., round trips), e.g., delivering goods in crates to the client and taking (other) empty crates back to the supplier after the delivery (Kodippili & Samarasekera, 2019). Yildiz et al. (2010) provide an example of how this concept of backhauling can be applied in business. However, they note a mismatch between the volumes in the initial shipment and the backhaul, proposing a solution to consolidate consignments on the same reversed route.

2.1.1 Milk runs

Performing milk runs is a common concept for internal plant logistics (Baudin, 2005). Thus, most papers addressing milk runs regard in-plant logistics. Xu (2003) was the first to introduce milk runs in a 3PL context. Xu (2003) provides an example of the potential benefits, where they reduced the total number of trips by 20%, the integrated logistics cost reduced by 30%, and the trailer utilization increased by 10%.

Milk runs likely make the delivery more efficient (i.e., fewer kilometers driven with fuller trucks, compared to only direct shipments) and faster as smaller quantities per supplier can be shipped per shipment (Klenk et al., 2012). Shipping smaller amounts ultimately lowers the inventory holding cost at locations such as assembly plants (Simić et al., 2021). Milk runs are mainly efficient for suppliers located near each other (Hosseini et al., 2014).

2.1.2 Backhauling

Backhauling reduces empty truck miles by hauling loads on the trip back to the first loading location (Jordan & Burns, 1984). Backhauling increases network and transportation efficiency and decreases emissions compared to one-way transportation (Kazancoglu et al., 2021). In backhauling LSPs often ship back 'empties' (e.g., empty crates that carried goods in the first haul). For example, Abejón et al. (2020) discuss backhauling empties. However, they are critical on the potential of backhauling empties, as in many situations, for example, empty crates from four FTL trucks can be shipped back with one FTL truck. The paper by Yano et al. (1987) shows that increased truck utilization in backhauls creates the most cost savings and is thus essential in the optimization for logistical service providers.

2.1.3 Cross-docking

The first company to successfully implement cross-docking in its distribution strategy is Walmart (Moghadam et al., 2014), significantly increasing its profit and market share. This increased profit is due to reduced store inventory and lead times. Cross-docking can lead to significant cost savings due to fewer kilometers driven. However, Mokhtarinejad et al. (2015) mention with uncertain demands cross-docking systems might be unsuccessful because no possibility to stock goods exists. These benefits especially arise in larger networks as this creates more possibilities to combine orders (Moghadam et al., 2014). Ko et al. (2006) state it is essential to use cross-docks to optimize 3PL distribution networks.

Making use of a cross-dock in a transport network optimization problem is essential as it has great potential to without increasing inventory reduce transportation costs and delivery time (Sung & Song, 2003). It is important to note that cross-docking uses most of its potential if smaller shipments of multiple suppliers close to each other are combined into full truckloads shipped to a single remote delivery location (Stephan & Boysen, 2011). This recipient is preferably far away from the cluster of suppliers to achieve the most cost savings.

2.1.4 Merging

This research investigates bin packing problem heuristics for the route optimization technique called 'merging'. Although the bin packing problem is simple to explain, it is NP-hard to solve (Fleszar & Hindi, 2002). Therefore it is unlikely an exact algorithm solves this problem to optimality in a reasonable time, and thus heuristics are widely used. Hereafter we discuss three of the most widely used heuristics.

A relatively easy heuristic to solve a one-dimensional bin packing problem is the First Fit Decreasing heuristic (Johnson, 1974). Though it is an easy heuristic, it proved to be effective in practice because the run time of this heuristic is bounded by $n \cdot log(n)$ (Panigrahy et al., 2011). Algorithm 1 in Appendix A provides the pseudo-code for this heuristic. We base the pseudo-code on the notation extracted from Carmona-Arroyo et al. (2021), see Table A.1 in Appendix A. Another heuristic available to solve a one-dimensional bin packing problem is the Best Fit Decreasing heuristic, which is also popular due to its simplicity and since it showed to be effective for generating good solutions quickly for more complex algorithms (Carmona-Arroyo et al., 2021). Algorithm 2 in Appendix A provides the pseudo-code for this heuristic. Gupta & Ho (1999) propose another heuristic called the Minimum Bin Slack heuristic. At each execution of this heuristic, they attempt to search for a collection of goods that fits the bin's capacity as much as possible (Fleszar & Charalambous, 2011). Fleszar & Hindi (2002) presents a recursive implementation of this heuristic. Algorithm 3 in Appendix A provides the procedure for this heuristic in pseudo-code.

2.2 Integrating approaches

Combining the solutions likely results in a sub-optimal solution if we solve the techniques using their methodologies separately. Therefore the route optimization techniques (i.e., milk runs, backhauling, and cross-docking) must be solved simultaneously in a 'framework'. Luckily, recent literature presented multiple meta-heuristic algorithms that solve similar vehicle routing-scheduling problems (Mokhtarinejad et al., 2015).

As a first example, Hosseini et al. (2014) create a programming model incorporating direct shipments, milk runs, and cross-docking. This paper also assesses this problem as NP-hard, and therefore heuristics (based on harmony search and simulated annealing) solve the model. The model by Hosseini et al. (2014) assumes consignments are LTL, while LSPs also combine FTL consignments in backhauls. This heuristic effectively reduced distribution costs and model computation time, especially for larger problems. Appendix B.1 provides the entire programming model by Hosseini et al. (2014).

The recent paper by Kocaoglu et al. (2020) also incorporates direct shipments, milk runs, and cross-docking into one hybrid distribution algorithm. Besides, they also acknowledge the need for this research to the existing literature by noting the need to propose an efficient solution for the mixed delivery problem (Kocaoglu et al., 2020). This paper concludes by mentioning that the hybrid algorithm provides a solution performing well in reducing the distribution cost and computation time, which shows the potential advantages of using the model by Kocaoglu et al. (2020). Note that these benefits arise especially for larger problems. Appendix B.2 provides the programming model by Kocaoglu et al. (2020).

At last, Ranjbaran et al. (2020) combine milk runs and backhauling into one model. The paper proposes solving the model to optimality for small-sized problems using a mixed integer linear program. For larger problems, they propose a heuristic algorithm. Ranjbaran et al.

(2020) conclude that the algorithms provide efficient and effective solutions for the problem. Appendix B.3 provides the programming model by Ranjbaran et al. (2020).

In Table 2.1 we compare the models from the discussed papers: Hosseini et al. (2014), Kocaoglu et al. (2020), and Ranjbaran et al. (2020), by comparing the route optimization techniques included and other characteristics, also against the model developed in this work.

Table 2.1: Model comparison of discussed models and this work

	Hosseini et al. (2014)	**Kocaoglu et al. (2020)**	**Ranjbaran et al. (2020)**	**This work**
Direct shipments	✓	✓	✓	✓
Milk runs	✓	✓	✓	✓
Backhauling			✓	✓
Cross-docking	✓	✓		✓
Objective function	Shipping cost minimization	Shipping cost minimization	Shipping cost minimization	Shipping cost minimization
Relationship type(s)	One-to-many Many-to-one Many-to-many	One-to-many	One-to-many Many-to-one	One-to-many Many-to-one
Inbound / Outbound	Inbound	Outbound	Inbound	Inbound Outbound
Heuristic / Exact algorithm	Heuristic algorithm	Heuristic algorithm	Exact algorithm (small instances) Heuristic algorithm (larger instances)	Exact algorithm
Context	General transportation network	3PL provider	Automotive industry	3PL provider
Model complexity	High	High	Very high	Very high

To our best knowledge, no model is available in literature combining milk runs, backhauling, and cross-docking simultaneously. Moreover, the discussed models focus either on inbound or outbound logistics only. So, it also remains open in the literature how to combine both in one model using the mentioned route optimization techniques.

2.3 Timing of consignment planning

To combine consignments, the planning of consignments must be batched. This concept has a lot of similarities with order batching in warehouses, wherein on each tour they determine the number of stops based on the capacity of the picking vehicle and the items to be picked. They batch orders until they reach the vehicle's capacity (Henn et al., 2012). In the context of this literature review, the tour of the picking vehicle refers to a truck passing by multiple nodes to deliver or pick up consignments to or at their delivery or collection location. Henn et al. (2012) mention that based on practical experiences they know that this leads to significant cost savings due to reduced labor hours and delivery lead time of customer orders.

Batching consignments can be based on variable time window batching (VTWB) or fixed time window batching (FTWB) (Van Nieuwenhuyse & de Koster, 2009). In VTWB the batch combines a fixed number of orders (Van Nieuwenhuyse & de Koster, 2009), and thus the batching time is variable. In FTWB the batch contains the consignments that arrived during a predetermined fixed interval. Van Nieuwenhuyse & de Koster (2009) perform an experiment that revealed that in order picking in warehouses in approximately 90% of the investigated settings the $E(W)_{\text{opt}}$ obtained for FTWB is slightly higher than the $E(W)_{\text{opt}}$ for VTWB, where $E(W)_{\text{opt}}$ refers to the optimal value of the customer order throughput time. This throughput time positively correlates with the total distance traveled through the warehouse to pick up the orders. For LSPs the main reason why shipping via a milk run or cross-dock instead of a direct shipment leads to lower prices billed by the carriers is because of a lower total distance driven (i.e., leading to a lower gasoline consumption, less trucker labor hours, etc.). This shows the connection to the order batching in warehouses. Therefore the result from Van Nieuwenhuyse & de Koster (2009) regarding the out-performance of the FTWB in comparison to VTWB can be generalized to LSPs, but do this with great caution due to the different settings. Note, Pardo et al. (2023) already recognize that batching alone does not capture the complete realistic picture of order batching, and therefore state that among others routing and assigning orders to pickers (i.e., trucks in a 3PL context) must also be included in the optimization process. To our best knowledge, current literature has not touched upon the consignment batching topic yet in a 3PL context. This research investigates the length and frequency of the fixed-length planning horizon (FLPH) underlying the FTWB.

Chapter 3 Consignment Planning

To investigate the timing of transportation planning for LSPs using batching and consignment postponements, we need to develop an exact algorithm to plan a set of inbound and outbound consignments simultaneously via direct shipping, milk runs, round trips, and cross-docking.

3.1 Methodology

Using the models from the literature presented in Chapter 2, we compose a mathematical model that is the basis for creating the model implemented in Python.

3.1.1 Problem statement

The objective is to plan consignments from their loading location to the unloading location such that costs are minimal for each client separately. These consignments are inbound or outbound and LSPs collect or deliver them at or to node 0, which represents the client location, hereafter also referred to as depot (captured in the set of nodes $V = \{0\} \cup V^{\text{in}} \cup V^{\text{out}}$, where V^{in} and V^{out} represent the set of loading and unloading nodes in inbound and outbound logistics respectively). The model optimizes all consignments in set $C = C^{\text{in}} \cup C^{\text{out}}$, where C^{in} and C^{out} represent the inbound and outbound consignments respectively. Inbound consignments go from a loading location (represented by the nodes $v \in V^{\text{in}}$) to the depot (node 0). Outbound consignments go from the depot (node 0) to an unloading location ($v \in V^{\text{out}}$). A sufficiently large set of trucks ($t \in T$) performs these shipments. These trucks can also pass by a set of inbound and outbound cross-docks, X^{in} and X^{out} respectively. For each client separately it differs if and which cross-docks can be used.

The combined payable weight in a shipment (w_c for $c \in C$) of consignments cannot exceed the truck capacity (r). Truck capacities differ between trucks, but since the availability of each different truck type at the carriers is unknown, we use the standard truck capacity in our model. To combine consignments in milk runs and cross-docks, we only consider consignments with a payable weight below b^{FTL}. We implement two distance rules to combine consignments in a milk run (with a maximum amount of stops: s), for which we take an inbound network as an example (i) the distance from a first to a second loading node is smaller than the distance from the first loading node to the depot (ii) the distance from a second loading node to the depot is smaller than the distance from the first loading node to the depot. Besides, the way we modeled this problem does not allow collections and deliveries in the two-digit postal code area of the depot in inbound and outbound milk runs, respectively. LSPs only make round trips if the loading location of the inbound consignment equals the unloading location of the outbound consignment. A cross-dock considers a consignment if it is in its service area.

Whether combining consignments is beneficial depends on the associated costs. The three different cost elements that occur between node p and q are (i) costs for shipment legs containing one consignment (i.e., direct shipments, pre-collection to $x \in X^{\text{in}}$, or distribution from $x \in X^{\text{out}}$) where the price depends on the payable weight w_c (i.e., $f_{p,q,c}$), (ii) $f^{\text{FTL}}_{p,q}$ is the cost for milk run shipping, direct FTL shipments (also in round trips), and linehauls (i.e., consolidated transportation leg) around the cross-dock, or (iii) k is the fraction of the shipping cost paid by shipping two consignments in a round trip (both paid as an FTL). If a consignment passes by a cross-dock ($x \in X^{\text{in}} \cup X^{\text{out}}$), LSPs also pay handling costs (h_x) per unit payable weight (w_c). Besides, if LSPs ship a consignment via a milk run, they pay an additional cost for stopping at these nodes (f^{stop}). Furthermore, in milk runs LSPs also pay an additional cost per kilometer that is driven more in comparison to a direct shipment from the first loading location to the last unloading location (f^{km}). We generalize the (un-)loading locations to a two-digit postal code area in combination with an alpha-2 ISO country code. To account for milk runs with stops within the same two-digit postal code, variables τ^{in}_t and τ^{out}_t count the amount of these stops per truck (incorporated in the cost function accordingly).

3.1.2 Descriptive statistics

This subsection performs a generic data analysis on the ELC data ($n = 148,166$ consignments) from 11 clients (or 33 plants, for which we optimize the logistics separately). Hereafter, if we refer to a client, we mean a client's plant. Whether we combine consignments, is based on the payable weight, calculated as $w_c = \max\left(a_c, CF^{\text{e}} \cdot e_c, CF^{\text{i}} \cdot i_c\right)$ where $c \in C$. This determination of the payable weight takes the maximum value of the gross weight a_c, the volume (e_c) transformed into a weight value with correction factor CF^{e}, and the loading meters (i_c) transformed into a weight value with correction factor CF^{i} for each consignment c in set C. The average payable weight in the data per consignment equals approximately 14,000 kg. The maximum allowed payable weight per trailer equals 24,000 kg, which shows the potential to combine consignments in trucks. The average payable weight ranges between approximately 1,500 kg and 23,000 kg at the client level.

In the data, 61.45% of all consignments regard inbound consignments and 38.55% regard outbound consignments. We also see this imbalance in the average amount of supplier and customer nodes per client: 65.67 supplier nodes (min: 3, max: 297) and 51.03 customer nodes (min: 0, max: 245). For each client there are on average approximately 2,800 inbound consignments in the data (min: 30, max: $13,494$) and 1,700 outbound consignments (min: 0, max: $10,820$). Per client per workday (on which at least one consignment arrives), on average 13.57 consignments arrive (min: 2.24, max: 55.98). For inbound consignments, this average equals 8.36 (min: 1.04, max: 40.92), and for outbound consignments 5.21 (min: 0, max: 22.68). However, even more important is to know to which extent these consignments are LTL compared to FTL, as FTL consignments can merely be included in direct shipments and round trips. Therefore, Figure 3.1 investigates the amount of LTL consignments coming in per workday per client (both inbound and outbound), as this to a large extent makes up for the algorithm's computation time. Among all consignments, the company currently ships 67.51% directly, 8.02% via a milk run, 22.59% in a round trip, and 1.88% using cross-docking. Each milk run on average contains 2.13 consignments, and each cross-docking shipment has on average 4.33 consignments. Besides, note that consignments only arrive on workdays.

Figures 3.2a and 3.2b show that the company mainly collects and delivers consignments in or to locations in central and western Europe. After their collection or before their delivery these consignments respectively arrive at or come from one of the depots (see Figure 3.3). The average distance between the loading and unloading locations of consignments is 736.29 kilometers, with a standard deviation of 535.82 kilometers. The longest distance is 3,880 kilometers from Ruse (Bulgaria) to Palmela (Portugal).

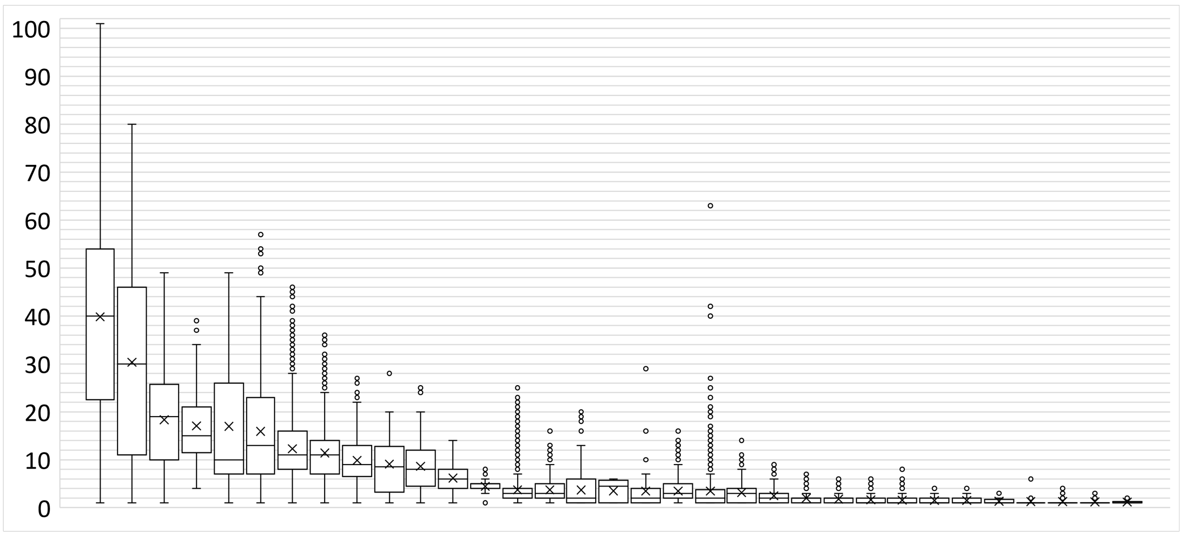
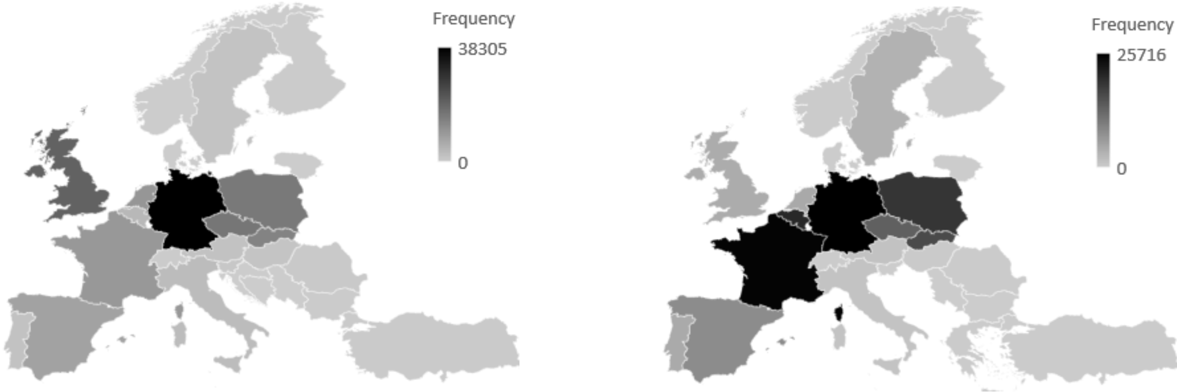


Figure 3.1: Number of LTL consignments (inbound and outbound) coming in per workday provided for each client (data from 2019 to 2022)



(a) Frequency of collections per country

(b) Frequency of deliveries per country

Figure 3.2: Frequency of collections and deliveries per European country

Figure 3.3: Depots

3.1.3 Mathematical model

In addition to the model's discussed parameters, we define our model decision variables in Table 3.2. For example, $\alpha^{\text{in}}_{c,t}$ is a binary decision variable equalling one if a consignment $c \in C^{\text{in}}$ is shipped via an inbound milk run with truck $t \in T$, and equals zero in all other cases. Table 3.3 defines the model auxiliary variables used for making constraints linear.

Table 3.1: Model parameters

$d_{p,q}$	distance from node p to node q in kilometers
$f_{p,q,c}$	shipping fee from node p to q relative to w_c of $c \in C$ (in €)
$f^{\text{FTL}}_{p,q}$	full truckload shipping fee from node p to node q (in €)
h_x	handling cost per unit w_c at cross-dock $x \in X^{\text{in}} \cup X^{\text{out}}$ (in €)
l_c	fixed loading date of consignment $c \in C$ in days
p_c	pick up location of consignment $c \in C^{\text{in}}$

Table 3.1 continued from previous page

u_c	unloading location of consignment $c \in C^{\text{out}}$
w_c	payable weight of consignment $c \in C$ in kilograms
z_c	fixed unloading date of consignment $c \in C$ in days
b^{FTL}	payable weight boundary above which we consider the consignments FTL
e	amount of slack in a round trip between unloading and loading in days
f^{km}	milk run fee per kilometer (in €)
f^{stop}	fee of an additional stop in a milk run (in €)
k	fraction of cost paid for round trips
r	truck payable weight capacity in kilograms
s	maximum amount of consignments in a milk run

Table 3.2: Model decision variables

$$\alpha^{\text{in}}_{c,t} = \begin{cases} 1, & \text{if truck } t \in T \text{ drives an inbound milk run with consignment } c \in C^{\text{in}} \text{ loaded at node } p_c \text{ and unloaded at } 0; \\ 0, & \text{otherwise} \end{cases}$$

$$\alpha^{\text{out}}_{c,t} = \begin{cases} 1, & \text{if truck } t \in T \text{ drives an outbound milk run with consignment } c \in C^{\text{out}} \text{ loaded at } 0 \text{ and unloaded at } u_c; \\ 0, & \text{otherwise} \end{cases}$$

$$\beta^{\text{in}}_{c} = \begin{cases} 1, & \text{if consignment } c \in C^{\text{in}} \text{ is shipped from node } p_c \text{ to } 0 \text{ via a direct inbound shipment;} \\ 0, & \text{otherwise} \end{cases}$$

$$\beta^{\text{out}}_{c} = \begin{cases} 1, & \text{if consignment } c \in C^{\text{out}} \text{ is shipped from } 0 \text{ to node } u_c \text{ via a direct outbound shipment;} \\ 0, & \text{otherwise} \end{cases}$$

$$\gamma^{\text{in}}_{p,q,t} = \begin{cases} 1, & \text{if truck } t \in T \text{ drives a milk run leg between node } p \in V^{\text{in}} \text{ and } q \in V^{\text{in}} \cup \{0\} \text{ in an inbound milk run;} \\ 0, & \text{otherwise} \end{cases}$$

$$\gamma^{\text{out}}_{p,q,t} = \begin{cases} 1, & \text{if truck } t \in T \text{ drives a milk run leg between node } p \in V^{\text{out}} \cup \{0\} \text{ and } q \in V^{\text{out}} \text{ in an outbound milk run;} \\ 0, & \text{otherwise} \end{cases}$$

$$\delta^{\text{in}}_{c_1,c_2} = \begin{cases} 1, & \text{if there is a round trip from } p_{c_1} \text{ to } 0 \text{ to } u_{c_2}\text{, with consignments } c_1 \in C^{\text{in}} \text{ and } c_2 \in C^{\text{out}}\text{, where } p_{c_1} = u_{c_2}; \\ 0, & \text{otherwise} \end{cases}$$

$$\delta^{\text{out}}_{c_2,c_1} = \begin{cases} 1, & \text{if there is a round trip from } 0 \text{ to } u_{c_2} \text{ to } 0\text{, with consignments } c_2 \in C^{\text{out}} \text{ and } c_1 \in C^{\text{in}}\text{, where } u_{c_2} = p_{c_1}; \\ 0, & \text{otherwise} \end{cases}$$

$$\varepsilon^{\text{in}}_{c,x,t} = \begin{cases} 1, & \text{if consignment } c \in C^{\text{in}} \text{ is shipped from } p_c \text{ to } 0 \text{ via cross-dock } x \in X^{\text{in}} \text{ with truck } t \in T \text{ in the second leg;} \\ 0, & \text{otherwise} \end{cases}$$

$$\varepsilon^{\text{out}}_{c,x,t} = \begin{cases} 1, & \text{if consignment } c \in C^{\text{out}} \text{ is shipped from } 0 \text{ to } u_c \text{ via cross-dock } x \in X^{\text{out}} \text{ with truck } t \in T \text{ in the first leg;} \\ 0, & \text{otherwise} \end{cases}$$

$$\pi^{\text{in}}_{x,t} = \begin{cases} 1, & \text{if truck } t \in T \text{ drives on the linehaul between node } x \in X^{\text{in}} \text{ and } 0; \\ 0, & \text{otherwise} \end{cases}$$

$$\pi^{\text{out}}_{x,t} = \begin{cases} 1, & \text{if truck } t \in T \text{ drives on the linehaul between node } 0 \text{ and } x \in X^{\text{out}}; \\ 0, & \text{otherwise} \end{cases}$$

τ^{in}_{t} = number of stops by truck $t \in T$ within the same postal code area as the previous stop in an inbound milk run

τ^{out}_{t} = number of stops by truck $t \in T$ within the same postal code area as the previous stop in an outbound milk run

Table 3.3: Model auxiliary variables

$\mu^{\text{in}}_{c,t}$	=	integer variable ensured to be 1 if $c \in C^{\text{in}}$ is in a milk run with truck $t \in T$ with one arc coming into node 0, 0 otherwise
$\mu^{\text{out}}_{c,t}$	=	integer variable ensured to be 1 if $c \in C^{\text{out}}$ is in a milk run with truck $t \in T$ with one arc coming into node u_c, 0 otherwise
$\sigma^{\text{in}}_{c,t}$	=	integer variable ensured to be 1 if $c \in C^{\text{in}}$ is in a milk run with truck $t \in T$ with one outgoing arc from node p_c, 0 otherwise
$\sigma^{\text{out}}_{c,t}$	=	integer variable ensured to be 1 if $c \in C^{\text{out}}$ is in a milk run with truck $t \in T$ with one outgoing arc from node 0, 0 otherwise
$\varphi^{\text{in}}_{p,t}$	=	integer variable ensured to be 1 if truck $t \in T$ departs from but never arrives in $p \in V^{\text{in}}$, 0 otherwise
$\varphi^{\text{out}}_{q,t}$	=	integer variable ensured to be 1 if truck $t \in T$ arrives in but never departs from $q \in V^{\text{out}}$, 0 otherwise
$\psi^{\text{in}}_{c_1,c_2,t}$	=	integer variable ensured to be 1 if truck $t \in T$ drives an inbound milk run with both $c_1, c_2 \in C^{\text{in}}$, 0 otherwise
$\psi^{\text{out}}_{c_1,c_2,t}$	=	integer variable ensured to be 1 if truck $t \in T$ drives an outbound milk run with both $c_1, c_2 \in C^{\text{out}}$, 0 otherwise
$\omega^{\text{in}}_{c_1,c_2,x,t}$	=	integer variable ensured to be 1 if truck $t \in T$ drives via inbound cross-dock $x \in X^{\text{in}}$ with both $c_1, c_2 \in C^{\text{in}}$, 0 otherwise
$\omega^{\text{out}}_{c_1,c_2,x,t}$	=	integer variable ensured to be 1 if truck $t \in T$ drives via outbound cross-dock $x \in X^{\text{out}}$ with both $c_1, c_2 \in C^{\text{out}}$, 0 otherwise

Using the notation from Table 3.1, Table 3.2 and Table 3.3, this research formulates the following model. The objective function minimizes the shipping cost of direct shipments (DS), milk runs (MR), round trips (RT), and cross-docking (CD) for each client separately.

$$
\begin{aligned}
&\text{———————Inbound———————} \\
\min C = \; & \sum_{c \in C^{\text{in}}} \beta^{\text{in}}_c \cdot f_{p_c,0,c} + && \leftarrow \text{DS} \\
& \sum_{t \in T} \sum_{p \in V^{\text{in}}} \varphi^{\text{in}}_{p,t} \cdot (f^{\text{FTL}}_{p,0} - d_{p,0} \cdot f^{\text{km}}) + \sum_{t \in T} \tau^{\text{in}}_t \cdot f^{\text{stop}} + && \leftarrow \text{MR} \\
& \sum_{t \in T} \sum_{p \in V^{\text{in}}} \left(\sum_{q \in \{0\} \cup V^{\text{in}} \setminus \{p\}} \gamma^{\text{in}}_{p,q,t} \cdot d_{p,q} \cdot f^{\text{km}} + \sum_{q \in V^{\text{in}} \setminus \{p\}} \gamma^{\text{in}}_{p,q,t} \cdot f^{\text{stop}} \right) + && \leftarrow \text{MR} \\
& \sum_{c_1 \in C^{\text{in}}} \sum_{c_2 \in C^{\text{out}}} k \cdot \delta^{\text{in}}_{c_1,c_2} \cdot (f^{\text{FTL}}_{p_{c_1},0} + f^{\text{FTL}}_{0,u_{c_2}}) + && \leftarrow \text{RT} \\
& \sum_{c \in C^{\text{in}}} \sum_{x \in X^{\text{in}}} \sum_{t \in T} \varepsilon^{\text{in}}_{c,x,t} \cdot (f_{p_c,x,c} + w_c \cdot h_x) + \sum_{t \in T} \sum_{x \in X^{\text{in}}} \pi^{\text{in}}_{x,t} \cdot f^{\text{FTL}}_{x,0} + && \leftarrow \text{CD} \\
&\text{———————Outbound———————} \\
& \sum_{c \in C^{\text{out}}} \beta^{\text{out}}_c \cdot f_{0,u_c,c} + && \leftarrow \text{DS} \\
& \sum_{t \in T} \sum_{q \in V^{\text{out}}} \varphi^{\text{out}}_{q,t} \cdot (f^{\text{FTL}}_{0,q} - d_{0,q} \cdot f^{\text{km}}) + \sum_{t \in T} \tau^{\text{out}}_t \cdot f^{\text{stop}} + && \leftarrow \text{MR} \\
& \sum_{t \in T} \sum_{q \in V^{\text{out}}} \left(\sum_{p \in \{0\} \cup V^{\text{out}} \setminus \{q\}} \gamma^{\text{out}}_{p,q,t} \cdot d_{p,q} \cdot f^{\text{km}} + \sum_{p \in V^{\text{out}} \setminus \{q\}} \gamma^{\text{out}}_{p,q,t} \cdot f^{\text{stop}} \right) + && \leftarrow \text{MR} \\
& \sum_{c_2 \in C^{\text{out}}} \sum_{c_1 \in C^{\text{in}}} k \cdot \delta^{\text{out}}_{c_2,c_1} \cdot (f^{\text{FTL}}_{0,u_{c_2}} + f^{\text{FTL}}_{p_{c_1},0}) + && \leftarrow \text{RT} \\
& \sum_{c \in C^{\text{out}}} \sum_{x \in X^{\text{out}}} \sum_{t \in T} \varepsilon^{\text{out}}_{c,x,t} \cdot (f_{x,u_c,c} + w_c \cdot h_x) + \sum_{t \in T} \sum_{x \in X^{\text{out}}} \pi^{\text{out}}_{x,t} \cdot f^{\text{FTL}}_{0,x} && \leftarrow \text{CD}
\end{aligned}
$$

Technique selection constraints

The model ships each consignment via one of the mentioned transportation techniques.

$$\sum_{t \in T} \alpha^{\text{in}}_{c,t} + \beta^{\text{in}}_{c} + \sum_{c_2 \in C^{\text{out}}} (\delta^{\text{in}}_{c,c_2} + \delta^{\text{out}}_{c_2,c}) + \sum_{x \in X^{\text{in}}} \sum_{t \in T} \varepsilon^{\text{in}}_{c,x,t} = 1 \qquad \forall c \in C^{\text{in}} \tag{1}$$

$$\sum_{t \in T} \alpha^{\text{out}}_{c,t} + \beta^{\text{out}}_{c} + \sum_{c_1 \in C^{\text{in}}} (\delta^{\text{out}}_{c,c_1} + \delta^{\text{in}}_{c_1,c}) + \sum_{x \in X^{\text{out}}} \sum_{t \in T} \varepsilon^{\text{out}}_{c,x,t} = 1 \qquad \forall c \in C^{\text{out}} \tag{2}$$

Constraints (1) and (2) ensure the model selects one transportation technique for inbound and outbound consignments: milk run, direct shipment, round trip, or cross-docking, respectively.

Milk run routing constraints

We implement the following milk run constraints to ensure the routing meets the requirements. The milk runs only allow a maximum number of stops and account for inner postal code trips. All consignments considered for milk runs have a payable weight below the b^{FTL} value.

$$w_c \cdot \alpha^{\text{in}}_{c,t} \leq b^{\text{FTL}} \qquad \forall t \in T, c \in C^{\text{in}} \tag{3}$$

$$w_c \cdot \alpha^{\text{out}}_{c,t} \leq b^{\text{FTL}} \qquad \forall t \in T, c \in C^{\text{out}} \tag{4}$$

$$\alpha^{\text{in}}_{c,t} = \mu^{\text{in}}_{c,t} \qquad \forall t \in T, c \in C^{\text{in}} \tag{5}$$

$$\alpha^{\text{out}}_{c,t} = \mu^{\text{out}}_{c,t} \qquad \forall t \in T, c \in C^{\text{out}} \tag{6}$$

$$\alpha^{\text{in}}_{c,t} = \sigma^{\text{in}}_{c,t} \qquad \forall t \in T, c \in C^{\text{in}} \tag{7}$$

$$\alpha^{\text{out}}_{c,t} = \sigma^{\text{out}}_{c,t} \qquad \forall t \in T, c \in C^{\text{out}} \tag{8}$$

$$\sum_{p \in V^{\text{in}}} \varphi^{\text{in}}_{p,t} \leq 1 \qquad \forall t \in T \tag{9}$$

$$\sum_{q \in V^{\text{out}}} \varphi^{\text{out}}_{q,t} \leq 1 \qquad \forall t \in T \tag{10}$$

$$\sum_{c \in C^{\text{in}}} \alpha^{\text{in}}_{c,t} \leq s \qquad \forall t \in T \tag{11}$$

$$\sum_{c \in C^{\text{out}}} \alpha^{\text{out}}_{c,t} \leq s \qquad \forall t \in T \tag{12}$$

$$\tau^{\text{in}}_{t} = \sum_{c \in C^{\text{in}}} \alpha^{\text{in}}_{c,t} - \sum_{p \in V^{\text{in}}} \sum_{q \in \{0\} \cup V^{\text{in}} \setminus \{p\}} \gamma^{\text{in}}_{p,q,t} \qquad \forall t \in T \tag{13}$$

$$\tau^{\text{out}}_{t} = \sum_{c \in C^{\text{out}}} \alpha^{\text{out}}_{c,t} - \sum_{p \in \{0\} \cup V^{\text{out}}} \sum_{q \in V^{\text{out}} \setminus \{p\}} \gamma^{\text{out}}_{p,q,t} \qquad \forall t \in T \tag{14}$$

Constraints (3) and (4) ensure to only consider LTL consignments for inbound and outbound milk runs respectively. Constraints (5) and (6) ensure that for each consignment in a milk run a truck arrives at its delivery location arriving from another node that is the pick-up location of that consignment or the pick-up/delivery location of another consignment for inbound and outbound transportation respectively. Constraints (7) and (8) ensure that for each consignment in a milk run a truck departs from that pick-up location to another node that is the delivery location of that consignment or the pick-up/delivery location of another consignment for inbound and outbound transportation respectively. Constraints (9) and (10) ensure route continuation for inbound and outbound milk runs respectively. Constraints (11) and (12) ensure respectively for inbound and outbound logistics that milk runs have an upper bound on the number of stops it contains. Constraints (13) and (14) determine per milk run truck how often it stops within the same postal code for inbound and outbound respectively.

Cross-docking routing constraints

If we ship a consignment via a cross-dock, we always ensure at least one transportation leg goes in, and one transportation leg goes out of that cross-dock for each consignment.

$$w_c \cdot \varepsilon^{\text{in}}_{c,x,t} \leq b^{\text{FTL}} \qquad \forall c \in C^{\text{in}}, x \in X^{\text{in}}, t \in T \tag{15}$$

$$w_c \cdot \varepsilon^{\text{out}}_{c,x,t} \leq b^{\text{FTL}} \qquad \forall c \in C^{\text{out}}, x \in X^{\text{out}}, t \in T \tag{16}$$

$$\varepsilon^{\text{in}}_{c,x,t} \leq \pi^{\text{in}}_{x,t} \qquad \forall c \in C^{\text{in}}, x \in X^{\text{in}}, t \in T \tag{17}$$

$$\varepsilon^{\text{out}}_{c,x,t} \leq \pi^{\text{out}}_{x,t} \qquad \forall c \in C^{\text{out}}, x \in X^{\text{out}}, t \in T \tag{18}$$

Constraints (15) and (16) ensure for inbound and outbound cross-docks respectively to only consider LTL consignments. Constraints (17) and (18) ensure a truck drives the consolidated leg from or to a cross-dock for inbound and outbound logistics respectively if we ship a consignment via this cross-dock.

Truck capacity constraints

For shipments with co-loading, we ensure the consignments fit in the truck.

$$\sum_{c \in C^{\text{in}}} w_c \cdot \alpha^{\text{in}}_{c,t} \leq r \qquad \forall t \in T \tag{19}$$

$$\sum_{c \in C^{\text{out}}} w_c \cdot \alpha^{\text{out}}_{c,t} \leq r \qquad \forall t \in T \tag{20}$$

$$\sum_{c \in C^{\text{in}}} w_c \cdot \varepsilon^{\text{in}}_{c,x,t} \leq r \qquad \forall t \in T, x \in X^{\text{in}} \tag{21}$$

$$\sum_{c \in C^{\text{out}}} w_c \cdot \varepsilon^{\text{out}}_{c,x,t} \leq r \qquad \forall t \in T, x \in X^{\text{out}} \tag{22}$$

Constraints (19), (20), (21), and (22) ensure the model respects the (payable weight) capacity of the trucks in inbound and outbound shipments for milk runs and cross-docking respectively.

Lead time constraints

We ensure shipments arrive and depart on time to satisfy client, supplier, customer, and carrier needs. Thus, if we co-load consignments, we ensure they match (un-)loading deadlines.

$$0 = (z_{c_1} - z_{c_2}) \cdot \psi^{\text{in}}_{c_1,c_2,t} \qquad \forall c_1 \in C^{\text{in}}, c_2 \in C^{\text{in}}, t \in T \tag{23}$$
$$0 = (l_{c_1} - l_{c_2}) \cdot \psi^{\text{out}}_{c_1,c_2,t} \qquad \forall c_1 \in C^{\text{out}}, c_2 \in C^{\text{out}}, t \in T \tag{24}$$
$$0 = (z_{c_1} - z_{c_2}) \cdot \omega^{\text{in}}_{c_1,c_2,x,t} \qquad \forall c_1, c_2 \in C^{\text{in}}, t \in T, x \in X^{\text{in}} \tag{25}$$
$$0 = (l_{c_1} - l_{c_2}) \cdot \omega^{\text{out}}_{c_1,c_2,x,t} \qquad \forall c_1, c_2 \in C^{\text{out}}, t \in T, x \in X^{\text{out}} \tag{26}$$
$$0 \leq \delta^{\text{in}}_{c_1,c_2} \cdot (l_{c_2} - z_{c_1}) \leq e \qquad \forall c_1 \in C^{\text{in}}, c_2 \in C^{\text{out}} \tag{27}$$
$$0 \leq \delta^{\text{out}}_{c_2,c_1} \cdot (l_{c_1} - z_{c_2}) \leq e \qquad \forall c_1 \in C^{\text{in}}, c_2 \in C^{\text{out}} \tag{28}$$

Constraints (23), (24), (25), and (26) ensure for milk runs and cross-docking respectively that the consignments can be combined regarding their (un-)loading dates for inbound and outbound respectively. Constraints (27) and (28) ensure for round trips there is a maximum amount of workdays allowed between the unloading and loading of the consignments on the first and second round trip leg respectively.

Auxiliary constraints

To linearize the model, we require the following constraints.

$$\alpha^{\text{in}}_{c,t} + \sum_{p \in V^{\text{in}}} \gamma^{\text{in}}_{p,0,t} - 1 \leq \mu^{\text{in}}_{c,t} \geq 0 \qquad \forall c \in C^{\text{in}}, t \in T \tag{29}$$
$$\alpha^{\text{out}}_{c,t} + \sum_{p \in \{0\} \cup V^{\text{out}} \setminus \{u_c\}} \gamma^{\text{out}}_{p,u_c,t} - 1 \leq \mu^{\text{out}}_{c,t} \geq 0 \qquad \forall c \in C^{\text{out}}, t \in T \tag{30}$$
$$\alpha^{\text{in}}_{c,t} + \sum_{q \in \{0\} \cup V^{\text{in}} \setminus \{p_c\}} \gamma^{\text{in}}_{p_c,q,t} - 1 \leq \sigma^{\text{in}}_{c,t} \geq 0 \qquad \forall c \in C^{\text{in}}, t \in T \tag{31}$$
$$\alpha^{\text{out}}_{c,t} + \sum_{q \in V^{\text{out}}} \gamma^{\text{out}}_{0,q,t} - 1 \leq \sigma^{\text{out}}_{c,t} \geq 0 \qquad \forall c \in C^{\text{out}}, t \in T \tag{32}$$

$$\sum_{q\in V^{\text{in}}\setminus\{p\}} \gamma^{\text{in}}_{p,q,t} - \sum_{a\in V^{\text{in}}\setminus\{p\}} \gamma^{\text{in}}_{a,p,t} \leq \varphi^{\text{in}}_{p,t} \geq 0 \qquad \forall p \in V^{\text{in}}, t \in T \tag{33}$$

$$\sum_{p\in V^{\text{out}}\setminus\{q\}} \gamma^{\text{out}}_{p,q,t} - \sum_{b\in V^{\text{out}}\setminus\{q\}} \gamma^{\text{out}}_{q,b,t} \leq \varphi^{\text{out}}_{q,t} \geq 0 \qquad \forall q \in V^{\text{out}}, t \in T \tag{34}$$

$$\alpha^{\text{in}}_{c_1,t} + \alpha^{\text{in}}_{c_2,t} - 1 \leq \psi^{\text{in}}_{c_1,c_2,t} \geq 0 \qquad \forall c_1 \in C^{\text{in}}, c_2 \in C^{\text{in}}, t \in T \tag{35}$$

$$\alpha^{\text{out}}_{c_1,t} + \alpha^{\text{out}}_{c_2,t} - 1 \leq \psi^{\text{out}}_{c_1,c_2,t} \geq 0 \qquad \forall c_1 \in C^{\text{out}}, c_2 \in C^{\text{out}}, t \in T \tag{36}$$

$$\varepsilon^{\text{in}}_{c_1,x,t} + \varepsilon^{\text{in}}_{c_2,x,t} - 1 \leq \omega^{\text{in}}_{c_1,c_2,x,t} \geq 0 \qquad \forall c_1, c_2 \in C^{\text{in}}, t \in T, x \in X^{\text{in}} \tag{37}$$

$$\varepsilon^{\text{out}}_{c_1,x,t} + \varepsilon^{\text{out}}_{c_2,x,t} - 1 \leq \omega^{\text{out}}_{c_1,c_2,x,t} \geq 0 \qquad \forall c_1, c_2 \in C^{\text{out}}, t \in T, x \in X^{\text{out}} \tag{38}$$

Constraints (29) until (38) ensure the auxiliary variables can only be 0 or 1. As an example, the model ensures the variable $\omega^{\text{out}}_{c_1,c_2,x,t}$ to be 1 if truck $t \in T$ drives via outbound cross-dock $x \in X^{\text{out}}$ containing both $c_1, c_2 \in C^{\text{out}}$, 0 otherwise.

Domain restriction constraints

Lastly, we limit the values of the decision variables to what they represent.

$$\alpha^{\text{in}}_{c_1,t}, \alpha^{\text{out}}_{c_2,t}, \beta^{\text{in}}_{c_1}, \beta^{\text{out}}_{c_2}, \gamma^{\text{in}}_{p_1,q_1,t}, \gamma^{\text{out}}_{p_2,q_2,t}, \delta^{\text{in}}_{c_1,c_2}, \delta^{\text{out}}_{c_2,c_1}, \varepsilon^{\text{in}}_{c_1,x_1,t}, \varepsilon^{\text{out}}_{c_2,x_2,t}, \pi^{\text{in}}_{x_1,t}, \pi^{\text{out}}_{x_2,t} \in \{0,1\} \quad \forall p_1 \in V^{\text{in}},$$
$$q_1 \in \{0\}\cup V^{\text{in}}, p_2 \in \{0\}\cup V^{\text{out}}, q_2 \in V^{\text{out}}, t \in T, c_1 \in C^{\text{in}}, c_2 \in C^{\text{out}}, x_1 \in X^{\text{in}}, x_2 \in X^{\text{out}} \tag{39}$$

$$\mu^{\text{in}}_{c_1,t}, \mu^{\text{out}}_{c_2,t}, \sigma^{\text{in}}_{c_1,t}, \sigma^{\text{out}}_{c_2,t}, \tau^{\text{in}}_t, \tau^{\text{out}}_t, \varphi^{\text{in}}_{p,t}, \varphi^{\text{out}}_{q,t}, \psi^{\text{in}}_{c_1,c_1,t}, \psi^{\text{out}}_{c_2,c_2,t}, \omega^{\text{in}}_{c_1,c_1,x_1,t}, \omega^{\text{out}}_{c_2,c_2,x_2,t} \in \mathbb{Z} \quad \forall p \in V^{\text{in}},$$
$$q \in V^{\text{out}}, t \in T, c_1 \in C^{\text{in}}, c_2 \in C^{\text{out}}, x_1 \in X^{\text{in}}, x_2 \in X^{\text{out}} \tag{40}$$

Constraint (39) limits the values the binary variables take to 0 and 1. Constraint (40) limits the values the auxiliary variables take to integer values.

3.2 Numerical design

This research implements the model using Python 3.7 in a Spyder environment (processor: Intel(R) Core(TM) i7-7700HQ CPU @ 2.80GHz 2.81 GHz) and uses the open-source linear program solver CBC in PuLP so that ELC can solve the model instances free of charge. PuLP offers a *warmStart* function that inserts an initial solution into the model to find the best solution faster. The initial solution inserted is shipping all consignments directly. This is also the solution for calculating the baseline cost savings. Note, how ELC documented how they planned each consignment specifically made it hard to compare the solution of this model to the actual planning, and we thus compare it against a simple base solution to at least show the effects of changing characteristics of the model on the cost savings potential. Table 3.4 provides the model parameter values used.

Table 3.4: Model parameter values

Parameter	Description	Value
b^{FTL}	Payable weight boundary above which we consider consignments FTL	20,000
e	Amount of slack in a round trip between unloading and loading in workdays	0
f^{km}	Milk run fee per kilometer (in €)	1
f^{stop}	Fee of an additional stop in a milk run (in €)	60
k	Fraction of cost paid for round trips	0.93
r	Truck payable weight capacity in kilograms	24,000
s	The maximum amount of consignments in a milk run	4

In order to comply with carrier contracts, planners send out the majority of consignments to carriers prior to 3 PM on each workday. Therefore for the analyses in this chapter, each model instance uses consignments that came in before 2 PM (the previous 24 hours) to allow some time to run the code, potentially adjust the planning, and send the consignments to the carriers. Chapter 4 investigates different planning moments and frequencies. However, for the analyses in this chapter, we take the most extended batching duration, as the next analyses aim to investigate and potentially reduce the run-time for the most complex model instances. Logically speaking, the most extended time frames of batching also have the most consignments and are thus harder to solve. Batching for an entire workday is the upper bound as otherwise planning deadlines are potentially not met, as some consignments that come in before 3 PM have their collection date the day after. In the current way of working, planners plan consignments coming in after 3 PM with a collection date the next workday as ad-hoc direct consignments, which this research thus excludes from the data used.

From a business perspective, a model instance must be solved within a reasonable time so that this model can be used in the daily processes of LSPs. Industry experts assessed a maximum duration per model instance of approximately 20 minutes run-time as reasonable. Therefore we reduce the run-time of the model instances taking longer than 20 minutes to solve. The downside of using the CBC solver over paid linear program solvers (like Gurobi) is that it also requires time to create the variables and constraints, which gives in on the amount of time left to solve the model instances in a reasonable amount of time. Moreover, it is also slower to get to the best solution.

The element that contributes most to the complexity and run-time of the model instances is the amount of milk run trucks and trunkload trucks (i.e., the trucks driving the consolidated transportation leg from or to the cross-dock) inserted into the model. As mentioned in

Subsection 3.1.1, the model inserts a sufficiently large set of trucks. For example, if the payable weight of 30 consignments for a model instance does not exceed the b^{FTL} parameter value, the most extreme case is 15 milk runs containing two consignments each. Therefore we made a rule to insert half of the amount of milk run trucks to the model as there are consignments in the model instance having a payable weight below b^{FTL} (rounded down). However, this also means if the number of consignments below this threshold grows, the corresponding complexity and run-time of the model will grow exponentially. This proves the need for a maximum amount of milk run trucks. Similarly, industry experts mentioned that cross-docking is never profitable if less than three consignments are in the trunkload truck. Therefore, for each model instance where cross-docking is possible, the number of trunkload trucks inserted into the model is a third of the number of consignments that have a payable weight below b^{FTL} (rounded down). Here we also need a maximum amount of (trunkload) trucks to limit the complexity and run-time of the model instances.

Therefore we perform an analysis hereafter to settle a maximum amount of milk run trucks (see Subsection 3.2.1) and trunkload trucks (see Subsection 3.2.2) inserted into the model, without giving in to the cost savings potential too much (preserving at least 95% of the cost savings), while making sure the run-time reaches on average at most 20 minutes for the most complex model instances (i.e., initially exceeding the reasonable run-time of 20 minutes). As all clients can perform milk runs, the analysis regarding the maximum amount of milk run trucks is done first. Afterward, we perform a similar analysis for the clients that can ship via cross-docks to determine the maximum amount of trunkload trucks. For these analyses, this research uses one year of historical data in which both clients are available that can and cannot ship via a cross-dock. As cross-docking clients are only present in the data of 2019, we take the historical data from that entire year.

3.2.1 Algorithmic parameter tuning: milk run trucks

As a first step, we determine which model instances (not including cross-docking) take longer than 20 minutes to solve. In the sample, this is 5.91% of the model instances (185 out of 3,131). The five largest clients (i.e., regarding the average daily amount of LTL consignments) from Figure 3.1 are in the sample, and thus in the current business this percentage is even lower, as these they are no longer clients. Figure 3.4 shows the number of LTL consignments for these model instances that were not solved in 20 minutes, with an average of 30.51 LTL consignments. In the sample, for each LTL consignment there are on average 0.56 FTL consignments, not captured in Figure 3.4. The number of LTL consignments does not solely represent the complexity of a model instance, also characteristics like the depot location.

Afterward, we use a random sample of 30 model instances (from these 185 model instances that take longer than 20 minutes to solve) in the analysis for determining the maximum

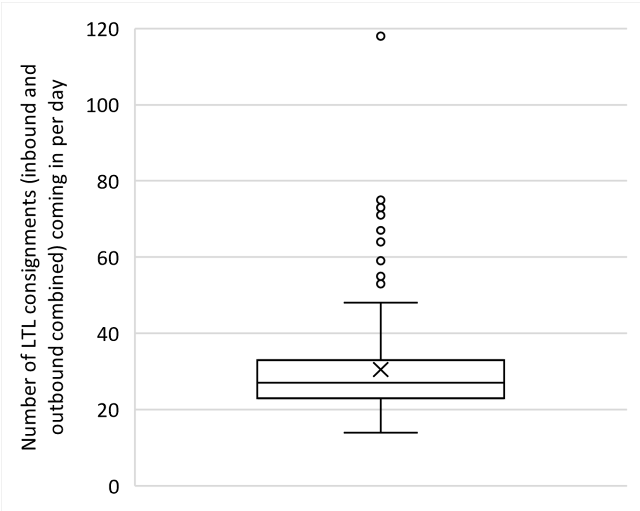


Figure 3.4: Number of LTL consignments (inbound and outbound) coming in per workday for milk run model instances taking longer than 20 minutes to solve

amount of milk run trucks inserted into the model. This sample size is relatively small as these model instances have to be solved for multiple values of the number of milk run trucks in this analysis. Therefore, this analysis requires significant run-time (as the model instances are complex). This analysis is based on two metrics: the average cost savings obtained for each model instance solved and the average run-time per model instance. For the first metric, the average cost savings, there is no need to increase the number of milk run trucks in the model (and the corresponding complexity and run-time) if there is no increase in the obtained cost savings. Moreover, the obtained additional cost savings must outweigh the additional run-time, and therefore we settle for obtaining at least 95% of the potential cost savings in the sample. As discussed, we aim to stay below 20 minutes for the average run-time of these model instances. We do not aim to reduce the maximum run-time below this threshold as outliers are in-evident in these settings and otherwise we limit thousands of model instances based on the run-time of one model instance (with a likely loss in the cost savings potential).

Figure 3.5 shows for this sample that the run-time grows exponentially if the number of milk run trucks inserted into the model increases. Besides, we see that the average cost savings per model instance flatten out when including more milk run trucks. Please note that the cost savings achieved through the use of zero milk run trucks are a result of creating round trips. The amount of milk run trucks preserving above 95% of the cost savings (i.e., 97.32%) and on average solves the model instances within 20 minutes (i.e., average: 2.86 minutes, standard deviation: 4.36 minutes) is four milk run trucks. If LSPs allow an average run-time time of approximately 30 minutes for the most complex milk run model instances (not containing cross-docking), consider increasing this maximum amount of milk run trucks inserted into the model to five trucks (which for this sample preserves 100% of the cost savings). Using four milk run trucks for each model instance also allows that for the cross-docking model instances there is still some allowance for additional complexity and the corresponding run-time. Therefore we decided to continue all analyses with four milk run trucks inserted into the model instances.

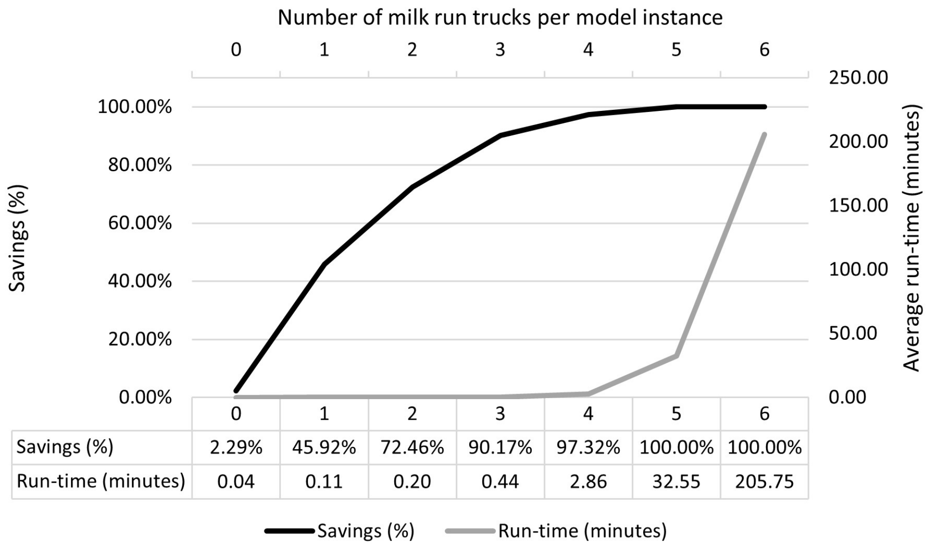


Figure 3.5: Number of milk run trucks determination (percentages relative to cost savings of six milk run trucks)

3.2.2 Algorithmic parameter tuning: cross-docking trucks

Using four milk run trucks for each model instance, we now investigate which model instances (that can also use cross-docks) take longer than 20 minutes to solve. In the sample, this is 4.59% of the model instances (32 out of 697). Figure 3.6 visualizes the number of LTL consignments for these model instances that were not solved within 20 minutes, with an average of 36.91 LTL consignments. Afterward, we use these model instances to determine the maximum number of trunkload trucks inserted into the model (see Figure 3.7). This analysis is based on the same two metrics as in the milk run analysis, namely the average cost savings (for which we again aim to preserve at least 95%) and average run-time.

The first thing in Figure 3.7 catching our attention is the V-shaped function of the run-time, as it is counterintuitive that adding the route optimization technique cross-docking to the model at first decreases the run-time. However, when considering the complexity of milk runs, it does make sense. To illustrate this concept, we take a real example from a client in Palmela, Portugal that had a lot of suppliers in Germany and the Czech Republic that were mainly shipping consignments with a relatively low size ($\sim$ 2,000 kilograms of payable weight), for which they also installed a cross-dock in respectively both countries. Many routing options exist if LSPs merely ship these consignments via milk runs, significantly contributing

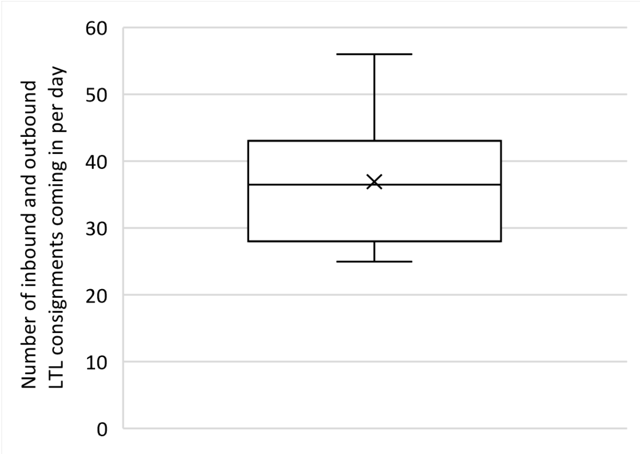


Figure 3.6: Number of LTL consignments (inbound and outbound) coming in per workday for milk run and cross-docking model instances taking longer than 20 minutes to solve

to the run-time. However, if LSPs also 'simply' ship these consignments via a cross-dock, the routing is fixed and much more straightforward, namely the pre-collection and the trunkload. Therefore, if cross-docking is the cheaper option, the linear program solver (i.e., PuLP) enters the direction towards this best solution faster and thus results in a decrease in the run-time. Besides, with one trunkload truck, we already obtain 99.50% of the maximum potential cost savings for these most complicated model instances, with the lowest possible run-time when including cross-docking (average: 4.41 minutes, standard deviation: 2.29 minutes). Therefore, we decide to include one truckload truck (per cross-dock) in the model.

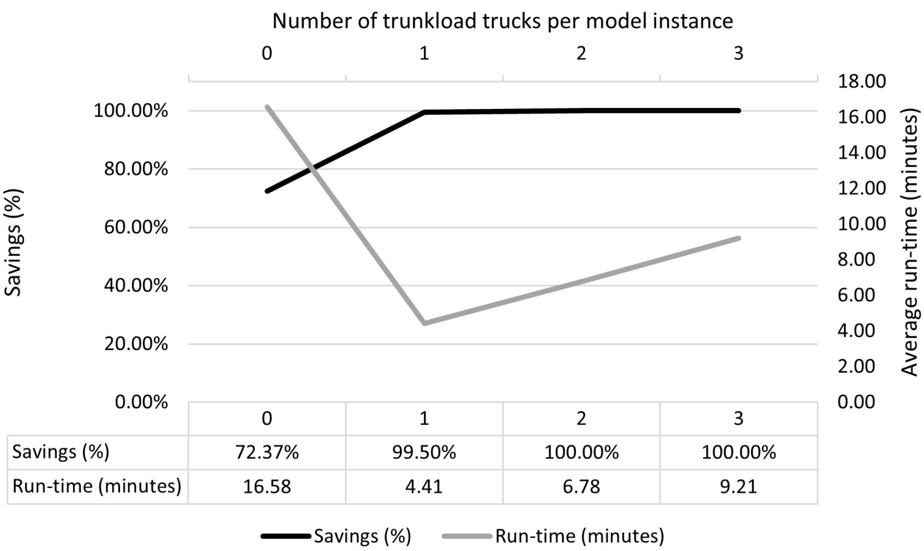
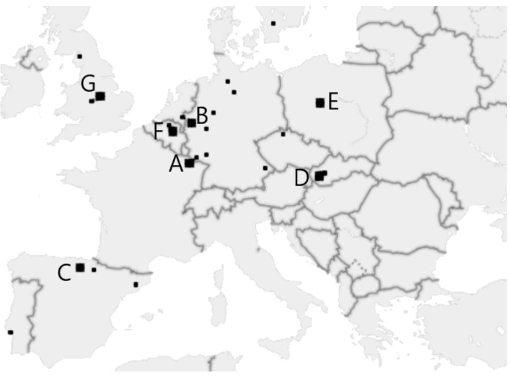


Figure 3.7: Number of trunkload trucks determination (percentages relative to cost savings of three trunkload trucks per cross-dock)

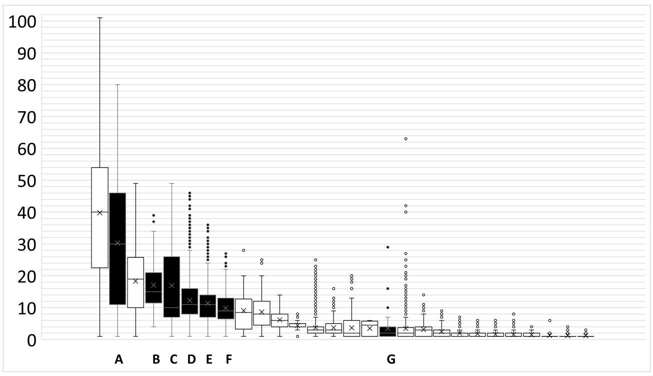
In summary, to obtain at least 95% of the cost savings and to ensure the run-time of the most complex model instances is on average below 20 minutes, this research shows to use at most four milk run trucks and one trunkload truck (per cross-dock).

3.2.3 Experimental setup

In the analyses in the following chapters we among other things investigate multiple FLPH lengths and frequencies. Therefore it takes too much run-time to include all clients in the analyses to retrieve results within a reasonable time. Therefore, this research uses a representative subset of clients from the same 2019 data (7 out of 28 clients). Recall we use the data of 2019 as this contains data from clients that can also ship via a cross-dock, which is not the case in other years. The clients in the subset have a label with a letter from 'A' to 'G'. Industry experts value the chosen subset as representative as it contains data from clients spread over Europe (see Figure 3.8a). This is essential as for example for the clients in Spain there are much more possibilities for milk run routings than for clients in the center of Europe (e.g., a milk run from Poland to France to a depot in Germany will never be feasible, while from Poland to France to a client in Spain is feasible). Therefore solving similar model instances for clients in 'the corners of Europe' is taking longer than for clients in the center. Furthermore, it contains clients that can (clients 'B' and 'C') and cannot ship via a cross-dock. In the subset, 2 out of 7 clients can ship via a cross-dock (portion ≈ 0.29), whereas in the 2019 data, 8 out of 28 clients can ship via a cross-dock (portion ≈ 0.29). Lastly, the number of LTL consignments coming in per workday from the clients in this subset are both large and small (see Figure 3.8b).



(a) Subset depots (i.e. large markers are included clients, small: excluded clients)



(b) Number of inbound and outbound LTL consignments coming in per workday per client (for subset see letters)

Figure 3.8: Characteristics of the chosen subset of clients

3.3 Numerical experiments

Using the mentioned subset data, we perform multiple numerical experiments hereafter.

3.3.1 Merging optimization

Before initiating the model presented in Subsection 3.1.3, performing the so-called 'merging' optimization is essential. Merging includes combining consignments with the same collection and delivery addresses and deadlines. These consignments come in separately from the client (their suppliers or customers) as sometimes they come from a different business unit or a batch production. If we have more than two consignments that can be merged that exceed the payable weight limit of a single truck, we need a method to assign these consignments to trucks. This is an example of the generic bin-packing problem (BPP), for which literature presents multiple heuristics (see Chapter 2).

Result 3.1 *Our simulation revealed that the First Fit Decreasing and Best Fit Decreasing heuristics perform equally in reducing the consignment set using the merging technique.*

The two most commonly used heuristics in current literature that proved to be fast and effective for generating good solutions are the First Fit Decreasing and Best Fit Decreasing heuristics. Both heuristics perform the same with a decrease of 5.19% in the number of consignments. This equal performance is not surprising, as the vast majority of consignments eligible to be merged fit together in a single truck, which removes the heuristic's purpose of allocating consignments to different bins. As the First Fit Decreasing heuristic bounds the run-time by $n \cdot \log(n)$, this research continues to work with this heuristic.

3.3.2 Sensitivity analyses

Hereafter we investigate the parameter values chosen by industry experts for the parameters mentioned in Table 3.4 using sensitivity analyses. This research starts by investigating the impact on the cost savings, by changing the value above which we label consignments FTL.

Result 3.2 *The payable weight boundary value of 20,000 kilograms above which we consider consignments FTL, that we use in the model and is in line with the current way of working, ensures obtaining (approximately) the maximum cost savings possible.*

Intuitively, we expect more cost savings when considering more consignments to include in milk runs and cross-docks. Figure 3.9 confirms this expectation and shows that we obtain higher cost savings if we enhance the value above which consignments are considered FTL. However, Figure 3.9 shows that it takes some time to obtain significant cost savings, which is because if the b^{FTL} parameter value is at for example 4,000 kilograms, we need at least six consignments to use the capacity of a truck fully (infeasible for milk runs). From a value of 22,000 and higher, the model instances took undesirably long to solve and are therefore excluded from the sensitivity analysis. Note, the cost savings curve in Figure 3.9 flattens out, by which we conclude that we do not expect a significant increase in cost savings when increasing the current b^{FTL} value of 20,000, making the chosen parameter value reasonable.

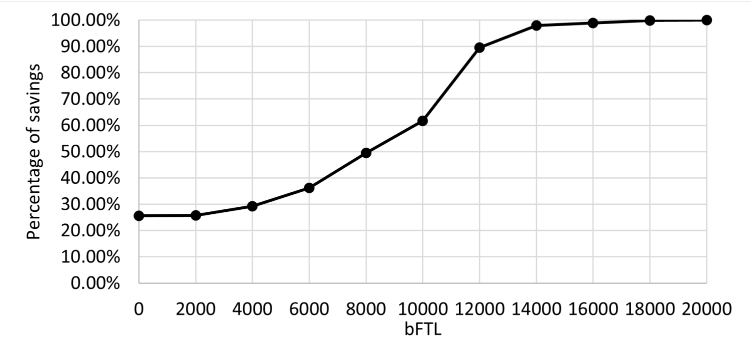


Figure 3.9: Sensitivity analysis b^{FTL} (percentages relative to b^{FTL} of 20,000)

Furthermore, this research investigates the impact of allowing more time in round trips between the (un-)loading of the different transportation legs.

Result 3.3 *Allowing (more) days between the unloading and loading of the first and second transportation leg in round trips respectively, merely increases the cost savings obtained.*

Recall, parameter e denotes the number of workdays between the first consignment's unloading and the second consignment's loading in a round trip. In general, we expect more opportunities for round trips to emerge when we increase this value, as in the current business these dates have to match precisely. As a result, we obtain 0.50% higher cost savings by a parameter value of one compared to a value of zero. This research values this difference as relatively low, showing that suppliers and customers are already successfully aligned to ensure they match their (un-)loading dates if a round trip is possible.

Next, we also investigate the impact of changing the cost parameter values, being the kilometer milk run fee, the milk run stop fee, and the fee fraction paid in round trips.

Result 3.4 *Intuitively, increasing the fees paid (or similarly decreasing the discounts) in milk runs and round trips decreases the gained cost savings.*

Firstly, in milk runs we pay a cost per kilometer for each kilometer that is driven more in comparison to a direct shipment from the first loading location to the last unloading location (i.e., denoted with parameter f^{km}). Intuitively, if this fee decreases, we expect higher cost savings caused by more milk runs made and lower costs, proven by the sensitivity result in Figure 3.10. We note that the curve of the cost savings is not linear and flattens out, meaning that above a kilometer fee of €1.25, we approach a situation in which shipping consignments directly is approximately equally expensive as milk run shipping. We also see this in the run-time of the model instances that exploded when solving them with a f^{km} of €1.50. Secondly, for each additional stop in a milk run LSPs pay a fee. As expected the cost savings and the number of consignments in milk runs decrease with an increase of this fee (see Figure 3.11). Thirdly, parameter k denotes the percentage paid in round trips. Intuitively, a higher discount results in more round trips made, which results in higher cost savings (confirmed in Figure 3.12).

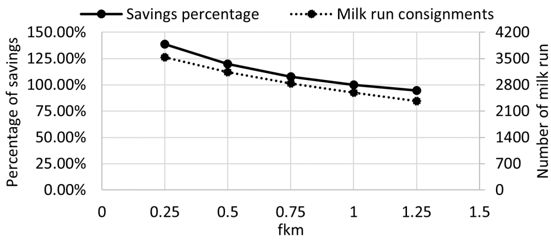


Figure 3.10: Sensitivity analysis f^{km} (percentages relative to f^{km} of €1.00)

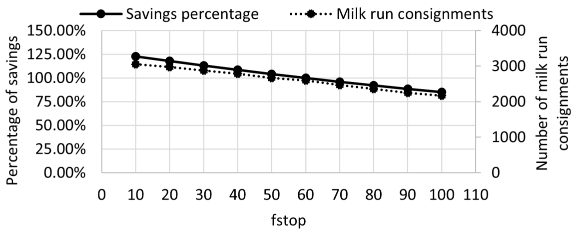


Figure 3.11: Sensitivity analysis f^{stop} (percentages relative to f^{stop} of €60.00)

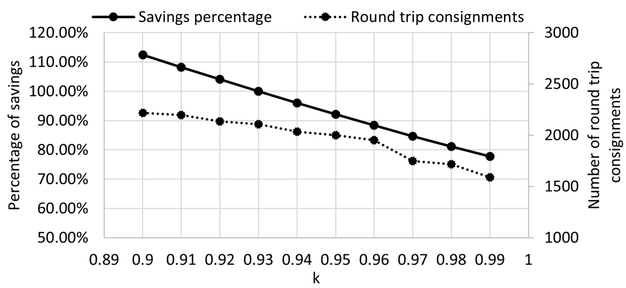


Figure 3.12: Sensitivity analysis k (percentages relative to k of 93%)

The last sensitivity analysis investigates the impact on cost savings by altering the number of stops allowed in milk runs.

Result 3.5 *As expected, cost savings increase with more consignments included in milk runs.*

More than four stops in a milk run is infeasible as otherwise the lead times cannot be reached. Therefore we investigated parameter s on the values two to four (see Figure 3.13). The number of consignments included in milk runs has a similar relationship as the cost savings, which both increase intuitively when increasing the number of milk run stops allowed.

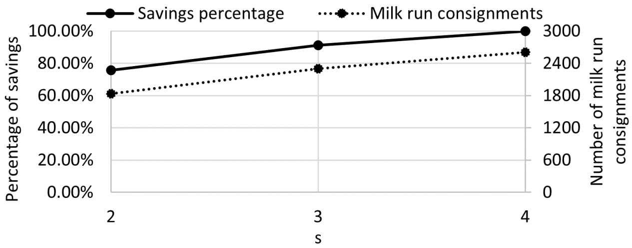


Figure 3.13: Sensitivity analysis s (percentages relative to s of 4 stops)

Note, a sensitivity analysis for parameter r is infeasible for two reasons. At first, a truck capacity lower than 24,000 kilograms payable weight requires to split FTL consignments. In practice, if the truck capacity decreases, suppliers and customers likely tend to place the remaining payable weight in the next truck for which they wait again to be an FTL. As there is no method available to split the consignments, as there is nothing known about how the ordering of suppliers or customers will change if the capacity decreases, this analysis is infeasible. Secondly, determining the effects of a truck capacity higher than 24,000 kilograms payable weight is also infeasible as these weights have no cost structure.

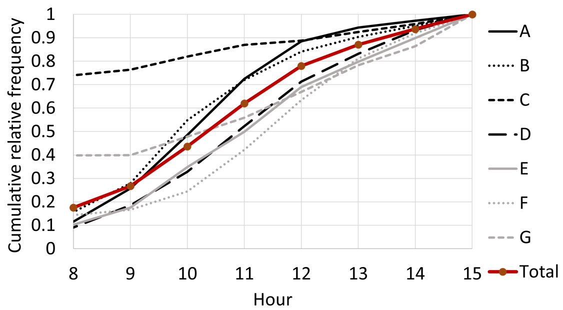
Chapter 4 Timing of Planning

If we batch as late as possible and longer (i.e., less frequent), more opportunities arise to combine these consignments. However, infrequent batching results in higher peaks in the workload of the planners. Therefore, to make an informed decision on the most preferred timing of planning per client, we in this chapter investigate the impact of this timing on the total cost savings and the number of consignments per optimization moment (i.e., workload). As for each model instance the run-time was below the reasonable run-time of 20 minutes, there is no need to elaborate further on this. However, we included this analysis in Appendix C for completeness. The solution we present satisfies the workload capacity of the planners and preserves most of the cost savings.

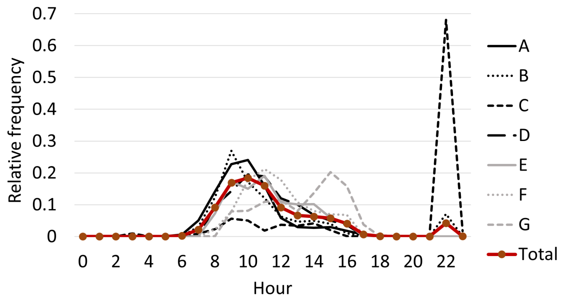
4.1 Methodology

As discussed, planners send consignments with a loading date the next workday to carriers before 3 PM. Therefore it was decided the last possible moment during the day to run the model is at 2 PM to allow for some run-time, time for adjusting the planning, and to get in touch with the carriers regarding these shipments. Planners plan consignments arriving after this 3 PM deadline as ad-hoc direct shipments if their loading date is the next workday, otherwise they can also be planned later. Therefore the most obvious frequency of planning consignments is once per day at 2 PM, with a corresponding length of the FLPH of 24 hours. Logically, this timing of planning results in the highest possible cost savings investigated, of which Subsection 4.2.1 investigates the workload impact. In Subsection 4.2.2 we enhance this investigation by incorporating more planning frequencies at different points in time. In other words, we investigate the impact of optimizing once per workday at 10 AM, 11 AM, 12 PM, and 1 PM (per client separately). For example, if we optimize once per day at 12 PM, planners book the consignments arriving between 12 PM and 2 PM as direct shipments. Also the consignments arriving between 2 PM and 3 PM with a loading date the next workday are booked as a direct shipment. Together with industry experts we decided to also investigate a frequency of two and three times a day as a planning frequency. These planning moments are chosen such that the workload for the planners in each FLPH is approximately similar.

For this we use the cumulative function of the 'Total' line in Figure 4.1a, where we depict for each hour the percentage of consignments that have arrived from the subset so far for the current workday (until 3 PM). For each workday we take 3 PM as the point at which 100% of the relevant consignments arrived. As a result, we decided to investigate planning twice a day at 10 AM and 12 PM, 11 AM and 1 PM, 11 AM and 2 PM. The planning moments are at 10 AM, 12 PM, and 2 PM for planning three times a day.



(a) Cumulative relative frequency of consignment arrival per working hour (relevant until 3 PM) per client in the subset (total: average of subset)



(b) Relative frequency of consignment arrival per hour per client in the subset (total: average of subset)

Figure 4.1: Characteristics of consignment arrivals of clients in the subset

Note, the arrival process (see Figure 4.1b) of the consignments differs significantly per client, which shows the need to determine the timing of planning separately for each subset client.

4.2 Numerical experiments

Hereafter we elaborate on the processes that account for the planners' workload in the new way of working using the algorithm, together with an estimation of the duration per consignment it takes to perform these tasks. Determining this estimation is difficult but essential to investigate the impact of timing the planning moments for each client separately. The first planners' task is to retrieve the planning from the algorithm, including: importing a data set from the planning system of the consignments to be optimized and running the code (approximated at 30 seconds per consignment). Secondly, planners need to review, and if necessary change accordingly, the planning schedule advised by the algorithm (approximated at 5 seconds per consignment). Furthermore, planners book the consignment at the carrier according to the (adjusted) planning (approximated together with the planning department: 30 seconds per consignment). At last, is the consignment follow-up, in which for example suppliers request to change the collection date. However, to a certain extent planners in the current way of working postpone this task until after 3 PM, by which they focus on planning the consignments solely during peak moments of consignment arrivals (approximated at 25 seconds per consignment, excluding required time out of peak hours).

In conclusion, each consignment requires 90 seconds on average to be planned. In other words, the planners have a maximum capacity to plan 40 consignments per hour. We make an exception for the time slot between 12 PM and 1 PM, where we assume planners have 50% of their capacity (i.e., 20 consignments per hour) due to lunch break. In 2019 ELC had eight planner FTEs. The subset of clients discussed previously makes up 61.50% of the total consignments planned in 2019. This results in a total capacity of 196 consignments per hour (i.e., $\lfloor 40 \cdot 8 \cdot 0.6150 \rfloor$) at the planning department in 2019. Similarly, the capacity between 12 PM and 1 PM is 98 consignments per hour. Suppose the number of consignments coming in exceeds this capacity. In that case, planners use the next hour as a buffer if sufficient capacity is available and the discussed 3 PM mark is not yet reached.

4.2.1 Baseline solution

If we have a planning frequency of once per workday at 2 PM for each client separately, we receive the highest cost savings compared with all other investigated lengths and frequencies of the FLPH. However, this yields an enormous peak in the workload of the planners between 2 PM and 3 PM. Hence we need to verify if this 'baseline solution' results in capacity shortages in the planning department.

Result 4.1 *Optimizing and planning all consignments between 2 PM and 3 PM for all clients results in capacity shortages at the planning department for multiple workdays during the year.*

We retrieved this result by simulating for each workday in 2019 and check if planners can plan all consignments between 2 PM and 3 PM. As a result, 13 out of 261 of the workdays had a capacity shortage. However, this must strictly be 0 as there are agreements with carriers that do not allow the booking of consignments loaded the next workday after 3 PM (without having to pay ad-hoc shipping prices that can be significantly higher, see Section 5.2). Therefore in Subsection 4.2.2 we investigate a different approach to preserve most of the cost savings while spreading out the workload of the planners by which the capacity constraints are met.

4.2.2 Experimental solution

This subsection presents for each client in the subset for each timing of planning the impact on the cost savings (see Table 4.1) and the workload per planning moment (see Table 4.2).

Cost savings

As LSPs optimize their clients' logistics individually as well as possible, optimizing the total cost savings is undesirable. Therefore, for each client separately we need to preserve the most cost savings, and for that purpose we provide for each timing of planning the percentage of cost savings obtained in comparison with the cost savings obtained from planning everything at 2 PM (see Table 4.1). Besides, clients differ significantly in the yearly total cost savings they achieve. For example, the average payable weight of the consignments of client 'D' in 2019 equals approximately 12,000 and 23,000 for client 'G', by which most consignments of client 'G' only obtain cost savings by including them in round trips. Therefore, we get approximately five times higher cost savings for client 'D' compared to 'G' in absolute terms. Note, the payable weight is only one factor influencing the cost savings. Other factors that influence the cost savings are the number of consignments, the distance between the (un-)loading locations, the presence of both inbound and outbound consignments, etc. Furthermore, we note it differs significantly between clients per timing of planning if they preserve most of the savings, showing the potential of timing the planning of clients differently.

Table 4.1: Cost savings percentage (baseline: 2 PM) per timing of planning for subset clients

Client	10 AM & 12 PM & 2 PM	10 AM & 12 PM	11 AM & 1 PM	11 AM & 2 PM	10 AM	11 AM	12 PM	1 PM	2 PM
A	54.64%	54.21%	74.58%	74.93%	31.78%	69.22%	97.82%	99.05%	100.00%
B	87.88%	78.81%	89.40%	94.21%	52.10%	67.82%	84.09%	93.60%	100.00%
C	97.58%	68.01%	80.64%	98.11%	63.33%	68.39%	69.16%	81.25%	100.00%
D	81.43%	57.32%	76.06%	89.39%	30.84%	47.78%	66.18%	85.69%	100.00%
E	90.66%	72.62%	82.88%	92.19%	45.16%	55.69%	76.57%	89.32%	100.00%
F	49.36%	44.53%	53.51%	57.92%	32.56%	43.64%	55.79%	90.79%	100.00%
G	91.43%	80.88%	90.79%	95.58%	60.43%	70.92%	85.16%	94.43%	100.00%

Planner workload

To spread out the planners' workload by choosing different planning moments for each client (ensuring no capacity shortages), it is essential to determine the average number of consignments planned per planning moment (see Table 4.2). This way, we use this table to determine the average workload per hour and choose the planning moments for clients such that it spreads out the workload as much as possible while preserving the most cost savings.

After a couple of iterations of changing the timing of planning for each client separately, while preserving most cost savings for each client (i.e., at least 90%), we obtained the solution mentioned in Table 4.3 that created a more widespread planning of consignment over the workday (see Table 4.4). Although it seems like an uneven spread workload, having most workload closer to 3 PM makes sense to create most possibilities to combine consignments. Furthermore, the lower workload between 12 PM and 1 PM allows the planners to have a proper lunch break. In this procedure we started with planning each client at 2 PM.

Table 4.2: Average number of consignments per timing of planning for each client in subset

Client	10 AM & 12 PM & 2 PM	10 AM & 12 PM	11 AM & 1 PM	11 AM & 2 PM	10 AM	11 AM	12 PM	1 PM	2 PM
A	10 AM: 6.57 12 PM: 5.5 2 PM: 0.67	10 AM: 6.57 12 PM: 5.5	11 AM: 10.06 1 PM: 2.31	11 AM: 10.06 2 PM: 2.67	10 AM: 6.57	11 AM: 10.06	12 PM: 12.04	1 PM: 12.35	2 PM: 12.71
B	10 AM: 11.48 12 PM: 5.94 2 PM: 2.26	10 AM: 11.48 12 PM: 5.94	11 AM: 14.97 1 PM: 3.79	11 AM: 14.97 2 PM: 4.75	10 AM: 11.43	11 AM: 14.95	12 PM: 17.34	1 PM: 18.25	2 PM: 19.21
C	10 AM: 13.91 12 PM: 1.42 2 PM: 1.61	10 AM: 13.91 12 PM: 1.42	11 AM: 14.97 1 PM: 1.2	11 AM: 14.97 2 PM: 1.95	10 AM: 13.91	11 AM: 14.97	12 PM: 15.31	1 PM: 16.15	2 PM: 16.9
D	10 AM: 7.78 12 PM: 7.78 2 PM: 4.47	10 AM: 7.78 12 PM: 7.78	11 AM: 11.73 1 PM: 6.28	11 AM: 11.73 2 PM: 8.32	10 AM: 7.79	11 AM: 11.72	12 PM: 15.53	1 PM: 17.94	2 PM: 19.94
E	10 AM: 7.42 12 PM: 5.84 2 PM: 3.58	10 AM: 7.42 12 PM: 5.84	11 AM: 9.98 1 PM: 5.11	11 AM: 9.98 2 PM: 6.84	10 AM: 7.42	11 AM: 9.98	12 PM: 13.23	1 PM: 15.07	2 PM: 16.79
F	10 AM: 2.4 12 PM: 3.36 2 PM: 2.47	10 AM: 2.4 12 PM: 3.36	11 AM: 3.93 1 PM: 3.37	11 AM: 3.93 2 PM: 4.29	10 AM: 2.4	11 AM: 3.93	12 PM: 5.76	1 PM: 7.3	2 PM: 8.22
G	10 AM: 6.14 12 PM: 1.98 2 PM: 2.03	10 AM: 6.14 12 PM: 1.98	11 AM: 6.98 1 PM: 2.31	11 AM: 6.98 2 PM: 3.15	10 AM: 6.14	11 AM: 6.98	12 PM: 8.12	1 PM: 9.3	2 PM: 10.13

Afterward, we iteratively changed the planning moment(s) of the clients, which still preserved 90% of the cost savings while spreading out the workload of the planners.

Table 4.3: Experimental solution: timing of planning with preserved cost savings

Client	Planning timing	Savings
A	1 PM	99.05%
B	11 AM & 2 PM	94.21%
C	10 AM & 12 PM & 2 PM	97.58%
D	2 PM	100%
E	11 AM & 2 PM	92.19%
F	1 PM	90.79%
G	1 PM	94.43%

Table 4.4: Average number of consignments planned per hour per client

Client	10AM	11AM	12PM	1PM	2PM
A				12.4	0.36
B		14.97			4.75
C	13.91		1.42		1.61
D					19.9
E		9.98			6.84
F				7.3	0.92
G				9.3	0.83
Sum	13.91	24.95	1.42	29	35.3

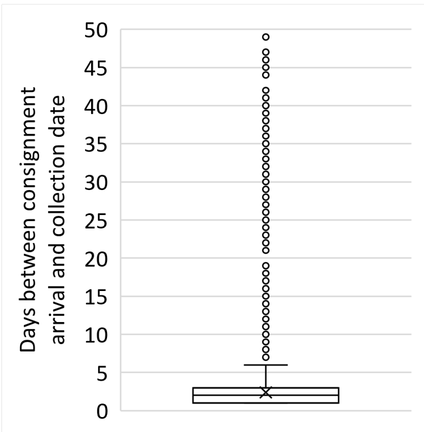
What remains is to determine whether this collection of lengths and frequencies of the FLPH ensures sufficient capacity at the planning department to book the consignments.

Result 4.2 *A collection of lengths and frequencies of the fixed-length planning horizon exists for each client separately, preserving most cost savings while ensuring sufficient capacity at the planning department to book the consignments. This shows that batching is feasible for logistical service providers and is critically important to combine consignments into shipments when using the consignment planning model presented in this research.*

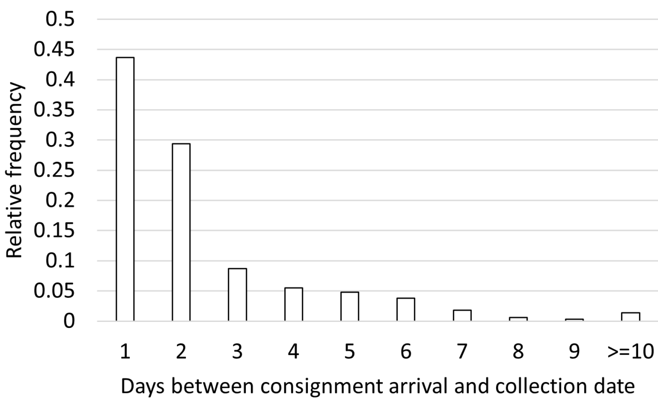
The presented timing of planning for each client results in zero workdays having planning capacity shortages (simulated again for each workday in 2019). Therefore we use this set of planning moments in the analyses performed in the next chapter. Implementing consignment batching in the current way of working requires significant changes in the planners' processes and causes some challenges, but the company is eager to tackle these. Moreover, with this analysis we show that batching is feasible regarding the workload capacity, and therefore incorporating this algorithm in the daily processes is essential to overcome the discussed efficiency shortcomings, without having to rely on human judgment in consignment planning.

Chapter 5 Consignment Postponement

To improve the consignment planning, we consider postponing consignments to the next FLPH if they did not reach their planning deadline yet (one workday before the collection date) and are uncombined. In this chapter, we determine probabilities for consignments for combining it in future FLPHs based on the relative frequency from historical data. This research assumes the relative frequency of a scenario in historical data represents the likelihood of its occurrence in the future. Figure 5.1 depicts the number of workdays between consignment arrival and collection. The sub-figures prove postponing consignments between FLPHs will not occur rarely, instead is of significant importance to gain more cost savings.



(a) Box-plot for number of workdays from arrival to loading, average: 2.38



(b) Bar-chart regarding the number of workdays between consignment arrival and collection date

Figure 5.1: Number of workdays between consignment arrival and collection (subset data)

5.1 Methodology

This research bases the calculation of the probabilities of combining a consignment in the future (p^{combine}) on a training data set, which is part of the subset data, for which we introduce a notation in Table 5.1. We generate the results based on a test data set, also part of the subset data, and split the data into the train and test data using the rule from Dangeti (2017) stating that: "in practice, data usually will be split randomly 70-30 or 80-20 into train and test datasets respectively in statistical modeling, in which training data utilized for building the model and its effectiveness will be checked on test data". We, therefore, take the average and split the data in a train and test set based on the ratio 75-25.

An assumption that industry experts evaluate as valid is that each supplier ships just one product type, but the consignments can differ significantly in size (i.e., payable weight), so we generalize them to a certain payable weight to find similar consignments in the train data. For this purpose, we use a margin of 2,000 kilograms of payable weight on both the positive and negative sides. Industry experts determined this margin and assess these consignments as similar. For example, suppose we currently have a consignment that is eligible to be postponed with a payable weight of 16,200 kilograms. In that case, we treat consignments from the same supplier/customer similar if they have a payable weight between 14,200 and 18,200 kilograms. If the consignment, for example, has three workdays to its collection date, we have two workdays left until the planning deadline in which consignments can arrive to combine it with. Then we check in the train data for each similar consignment if a consignment arrived in the two workdays after its arrival that can be combined in a merging, milk run, cross-dock, or round trip. We capture the frequency of this occurrence in the parameters n^{merge}, $n^{\text{milk run}}$, $n^{\text{cross-dock}}$, and $n^{\text{round trip}}$ respectively, in which we also consider the consignments to fit in a truck. For significance we only calculate the relative frequency if at least ten similar consignments are available, otherwise it returns a probability of zero. This means that the total amount of similar consignments t^{merge}, $t^{\text{milk run}}$, $t^{\text{cross-dock}}$,

Table 5.1: Notation of variables and parameters used in probability calculation

$\kappa^{\text{merge}}, \kappa^{\text{milk run}}, \kappa^{\text{cross-dock}}, \kappa^{\text{round trip}} =$	$\begin{cases} 1, & \text{if at least ten consignments are available in the training data from the same} \\ & \text{supplier/customer with a payable weight within the corresponding range;} \\ 0, & \text{otherwise} \end{cases}$
$n^{\text{merge}} =$	number of similar consignments in the payable weight range that can be merged with a consignment from the same supplier/customer in the days till the booking deadline of the consignment at hand
$n^{\text{milk run}} =$	number of similar consignments in the payable weight range that can be combined with a consignment from another supplier/customer in the days till the booking deadline of the consignment at hand respecting the capacity of a truck and the distance rules defined for milk runs
$n^{\text{cross-dock}} =$	number of similar consignments in the payable weight range that can be combined with a consignment from another supplier/customer in the days till the booking deadline of the consignment at hand if they are in the service area of the cross-dock and respect the capacity of a truck
$n^{\text{round trip}} =$	number of similar consignments in the payable weight range that can be combined with a consignment from another supplier/customer in the days till the booking deadline of the consignment at hand if the two consignments are on a reversed route and are at least 16000 kilograms of payable weight
$t^{\text{merge}} =$	total number of similar consignments in the payable weight range
$t^{\text{milk run}} =$	total number of similar consignments in the payable weight range
$t^{\text{cross-dock}} =$	total number of similar consignments in the payable weight range and in a cross-dock service area
$t^{\text{round trip}} =$	total number of similar consignments in the payable weight range with a minimum of 16,000 kilograms

or $t^{\text{round trip}}$ has to be higher than ten to calculate the probability to combine it in a merging, milk run, cross-dock, or round trip respectively. As business-to-business relationships are relatively stable, enough similar consignments are available for most consignments. For this, binary variables κ^{merge}, $\kappa^{\text{milk run}}$, $\kappa^{\text{cross-dock}}$, and $\kappa^{\text{round trip}}$ return one if at least ten similar consignments are available for combining the consignment at hand in merging, milk runs, cross-docking, or round trips respectively, zero otherwise.

In milk runs, cross-docking, and round trips to combine a consignment we await the arrival of a consignment from a different supplier or customer, but for merging we determine the probability based on the probability of an arrival from the same supplier or customer (p^{merge}, see formula (41)). For merging the collection and delivery date of both consignments must match. For milk runs and cross-docking, the delivery or collection date must match depending on the flow type (i.e., inbound or outbound respectively). For round trips at least one collection date must match the delivery date of the other consignment. In other words, in terms of cost it is all the same for LSPs if they first ship the inbound or outbound consignment in round trips. For milk runs we use the same distance rules in the probability calculation ($p^{\text{milk run}}$, see formula (42)) as discussed for the creation of the variables in Subsection 3.1.1. For the probability calculation of cross-docking ($p^{\text{cross-dock}}$, see formula (43)) the consignments considered to be combined have to be in the service area of a cross-dock. For the probability calculation of round trips ($p^{\text{round trip}}$, see formula (44)) we use the rule to only consider consignments for round trips if they exceed a payable weight of 16,000 kilograms. The discount received below this payable weight boundary is lower than the additional cost of paying a round trip as an FTL shipment (while the consignment is LTL).

At last, formula (45) combines the probabilities for each route optimization technique into one probability (p^{combine}) that is used in the consignment postponement decision process. As the ways in which the route optimization techniques save cost in comparison with direct shipping differ significantly, we assume in this research that the probabilities are mutually exclusive. The route optimization techniques having the most similarities are milk runs and cross-docking, but industry experts know from experience that the consignment characteristics of consignments in these strategies differ significantly from each other. For example, in general, consignments included in milk runs have a significantly higher payable weight than in cross-docking, showing a justification for the aforementioned assumption.

$$p^{\text{merge}} = \frac{n^{\text{merge}}}{t^{\text{merge}}} * \kappa^{\text{merge}} \tag{41}$$

$$p^{\text{cross-dock}} = \frac{n^{\text{cross-dock}}}{t^{\text{cross-dock}}} * \kappa^{\text{cross-dock}} \tag{43}$$

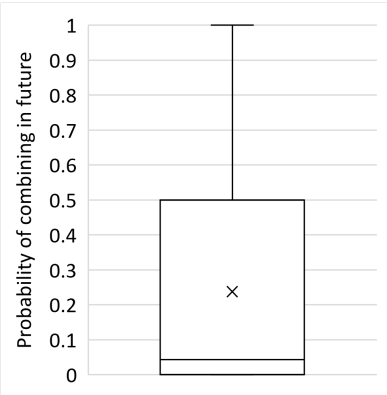
$$p^{\text{milk run}} = \frac{n^{\text{milk run}}}{t^{\text{milk run}}} * \kappa^{\text{milk run}} \tag{42}$$

$$p^{\text{round trip}} = \frac{n^{\text{round trip}}}{t^{\text{round trip}}} * \kappa^{\text{round trip}} \tag{44}$$

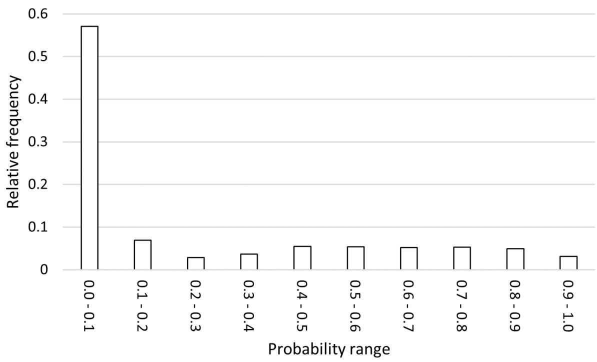
$$p^{\text{combine}} = 1 - ((1 - p^{\text{merge}}) * (1 - p^{\text{milk run}}) * (1 - p^{\text{cross-dock}}) * (1 - p^{\text{round trip}})) \tag{45}$$

5.1.1 Descriptive statistics: probabilities

Figures 5.2a and 5.2b depict the calculated probabilities for the consignments for which a first postponement is feasible (in the train data) in terms of the planning deadline. We note that the majority of the probabilities is around 0, which makes sense because as mentioned in Subsection 3.1.2 ELC ships 67.51% of the consignments via a direct shipment.



(a) Box-plot calculated probabilities



(b) Bar-chart calculated probabilities categorized per 10%

Figure 5.2: Probability of combining a consignment with another until the planning deadline

5.2 Numerical design

The penalty cost that we introduce for the downside of postponing consignments consists of three factors, namely: the probability that a consignment has to be booked (ad-hoc) at a non-contracted carrier, the percentage difference between prices at the contracted carriers and the prices on the spot market (i.e., at non-contracted carriers), and the absolute cost at the contracted carrier for the consignment. We multiply the first two percentages by the third factor, the absolute cost, to arrive at the absolute value of the penalty cost. This penalty cost ultimately exceeds the additional cost savings due to the postponement.

5.2.1 Ad-hoc shipment probability

Intuitively, the probability of having to book ad-hoc decreases with the number of workdays to the loading date and is determined from historical data (see Figure 5.3). Booking earlier than six workdays before collection never resulted in a shortage at the contracted carrier.

5.2.2 Spot market and contract price difference

On average, spot market prices are 8.59% higher than contract rates. However, Figure 5.4 shows that this difference varies significantly over time. Therefore, Section 5.3 determines

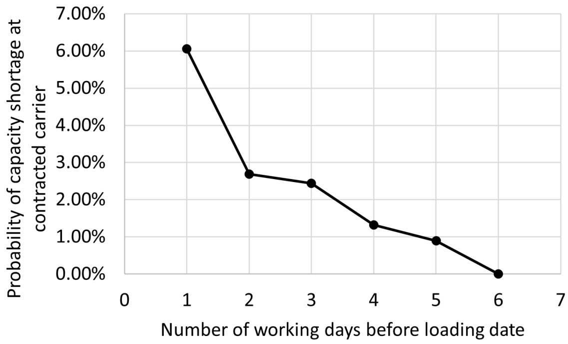


Figure 5.3: Probability of capacity shortage at contracted carrier as a function of the number of workdays till the loading date

the probability cut-off value yielding the highest net cost savings for multiple scenarios of this price difference. For example, Figure 5.4 shows that there is a peak around Christmas, caused by truck drivers taking holidays by which capacity shortages arise at the carriers causing higher prices. Another thing that stands out is that since the end of 2022 we see that the spot market prices are lower than the contract prices. This is a general tendency of the market to recover itself, forcing future contract rates to be lower.

Note, due to the contracts, carriers only allow LSPs to book transportation on the spot market when there is a capacity shortage. However, a negative percentage difference implies excessive capacity (also at the contracted carriers), by which capacity shortages only rarely occur in these periods. If LSPs can shift to the spot market freely, it is interesting to investigate the additional cost savings it gains in these scenarios. However, since this is not the case, Section 5.3 investigates different scenarios ranging from a price difference of 5%

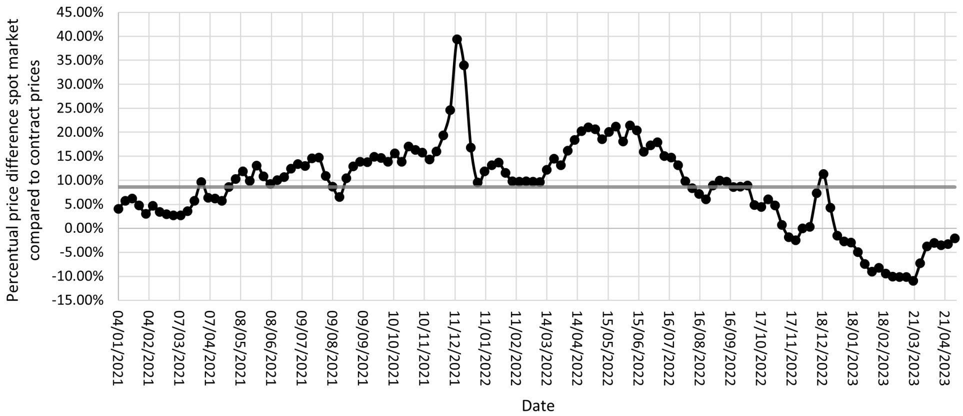


Figure 5.4: Percentage difference between transport prices on the spot market and contract rates over time (01/2021 - 04/2023), average (i.e., 8.59%) depicted in grey

to the most extreme case (i.e., 40%) with steps of 5%. We also investigate a scenario with the average price difference of 8.59%.

5.3 Numerical experiments

Below the probability cut-off we do not consider consignments for postponement. Intuitively, the number of postponements decreases with an increasing probability cut-off (see Figure 5.5).

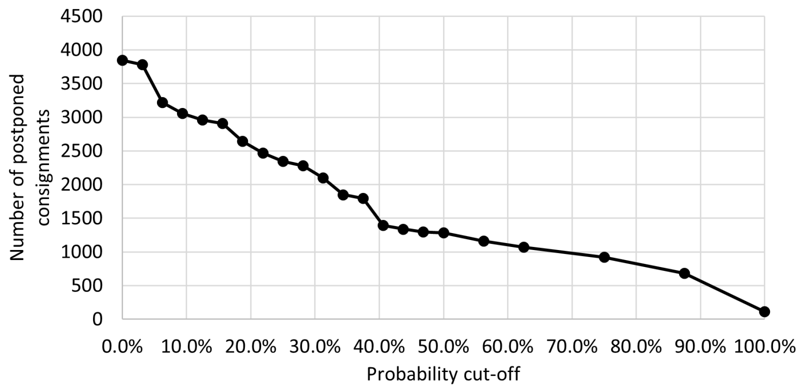


Figure 5.5: Relationship between probability cut-off and number of postponements

To determine the probability cut-off value yielding the highest net cost savings for different scenarios of the spot market and contract price difference, we take the maximum result of subtracting the additionally generated penalty cost from the additional cost savings obtained by postponing consignments for different cut-off values. Figure 5.6 depicts the additional

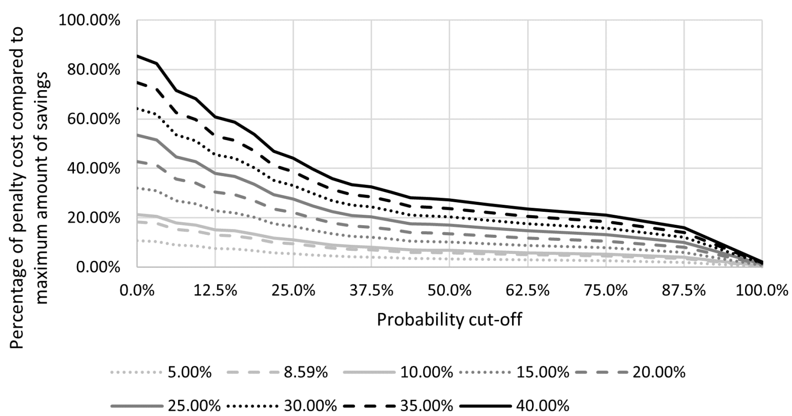


Figure 5.6: Percentage of additional penalty cost compared to the maximum amount of additional cost savings (i.e., cut-off at 0.0%) for multiple percentage differences between spot market and contract prices as a function of the probability cut-off

penalty cost for the different scenarios. Intuitively the additional penalty costs are higher if the difference between spot market and contract prices increases, but also if the number of postponed consignments increases (i.e., a decrease in the probability cut-off value). As an example to Figure 5.6, if the market enters the extreme scenario of a difference between the spot market and contract prices of 40%, the additional generated cost savings are almost nullified by the additional penalty cost (i.e., for 85.49%, meaning only 14.51% of the additional cost savings are preserved). Figure 5.7 depicts the additional cost-saving curve (without subtracting the penalty cost) that intuitively decreases when we increase in the probability cut-off value. Figure 5.7 reveals that this research tests more cut-off values below 50% than above it, which is because in a first run we found out that for each scenario the cut-off value yielding the highest net cost savings is below 50%. Subsequently, we test cut-off values to 50% with steps of 3.125%, and cut-offs at 56.25%, 62.5%, 75%, 87.5%, and 100%.

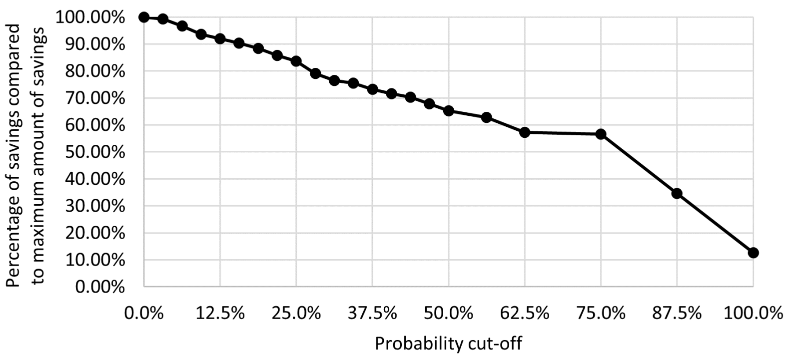


Figure 5.7: Percentage of additional cost savings compared to the maximum amount of additional cost savings (i.e., cut-off at 0.0%) for multiple percentage differences between spot market and contract prices as a function of the probability cut-off

What remains is to combine Figure 5.6 and Figure 5.7 and to determine for each scenario the probability cut-off value yielding the highest net cost savings (which is the highest difference between the additional cost savings and penalty cost, indicated with a dot in Figure 5.8).

Result 5.1 *The current way of working, of postponing consignments independent of the difference between spot market and contract prices, does not result in the highest possible net cost savings if this difference is at or above 10%.*

For the scenarios on and below the average (i.e., 5%, 8.59%), Figure 5.8 depicts the cut-off value yielding the highest net cost savings is at 0.0%, meaning it always makes sense to postpone a consignment. This is intuitive as in this case the penalty cost per consignment is relatively low compared with the additional savings gained by postponing that consignment. Currently, planners postpone all uncombined consignments for which this is possible regarding

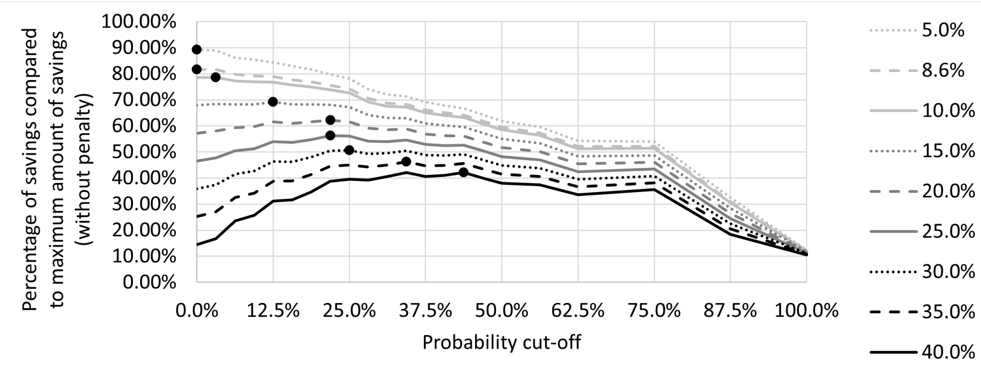


Figure 5.8: Percentage of additional net cost savings (penalty cost subtracted) compared to the maximum amount of cost savings (without subtracting penalty cost) for multiple differences between spot market and contract prices as a function of the probability cut-off, the dots depict the probability cut-off value yielding the highest net cost savings

their loading date, independent of the difference between spot market and contract prices. Therefore, to ensure higher cost savings, we suggest using the probability calculation presented once the price difference between spot market and contract prices is at or above 10% using the corresponding probability cut-off value yielding the highest net cost savings. If the percentage difference between the spot market and contract prices increases, so does the probability cut-off value yielding the highest net cost savings. Taking the extreme case of a 40% difference between the spot market and contract prices, we obtain the most net cost savings for this subset by putting the probability cut-off at 43.75%. Similarly, in this scenario the risk of having to book at an expensive non-contracted carrier outweighs the additional cost savings that we gain by postponing that consignment for those that have a probability to be combined below 43.75%.

Result 5.2 *Using the consignment postponement decision process presented, logistical service providers gain significant additional cost savings. In the extreme case of a difference between the spot market and contract prices of 40%, these additional cost savings are improved by a staggering amount of approximately 290%.*

For each scenario of the difference between spot market and contract prices, Figure 5.9 depicts the loss of net cost savings in percentages by always postponing all consignments in comparison with using the probability cut-off values given in Figure 5.8. Figure 5.9 shows an approximately exponential relationship for which we cannot fit a trend line as the lost cost savings for the price differences of 5.00% and 8.59% are zero. These results show that the postponement decision is entirely dependent on the market. Subsequently, LSPs significantly enhance their gained cost savings in their timing of planning consignments by using the correct probability cut-off value. Since the beginning of 2021 the price difference between spot market and contract prices was 10% or higher at 45.08% of the time, meaning that in almost 50% of the time the current way of working did not result in the highest net cost savings.

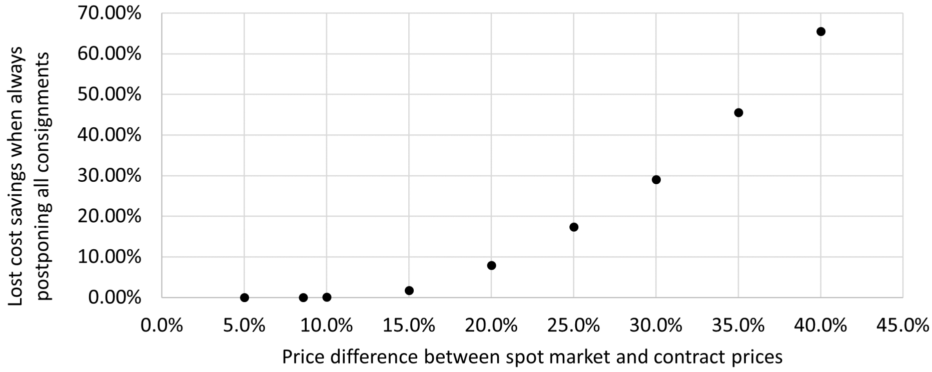


Figure 5.9: Relationship between percentage difference between spot market and contract prices and the lost cost savings by always postponing all consignments

Result 5.3 *An approximately linear relationship exists between the difference of spot market and contract prices and the probability cut-off value yielding the highest net cost savings.*

We found an approximately linear relationship with an R-squared value of 96.56% by fitting a trend line to the data presented in Figure 5.10, which we assess as a good fit. The slope of the relationship shows that each 1% increase in the difference between spot market and contract prices results in a 1.23% increase in the probability cut-off value yielding the highest net cost savings starting at a price difference of 6.26%. This relationship provides LSPs with an explicit approximation of the probability cut-off to ensure the highest net cost savings in different scenarios of the difference between the spot market and contract prices.

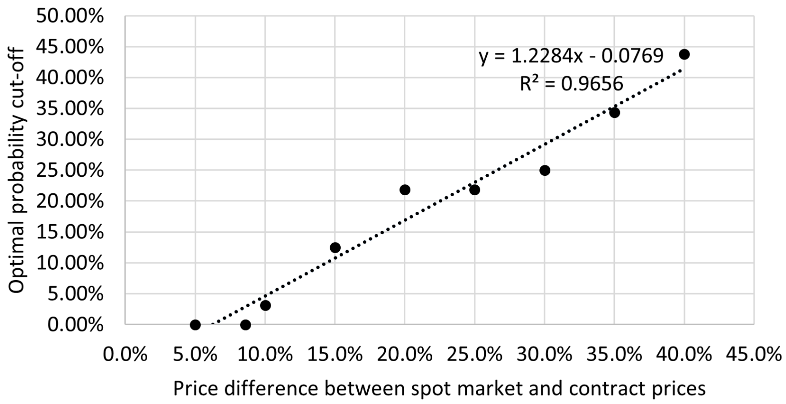


Figure 5.10: Relationship between percentage difference between spot market and contract prices and the probability cut-off value yielding the highest net cost savings

Chapter 6 Conclusion and Discussion

This research presents a model that enables LSPs to overcome the efficiency shortcomings (i.e., in cost savings and manual work by the CI-analysts) resulting from a consignment planning based on human judgment. This model fills the literature gap to simultaneously plan inbound and outbound consignments using the route optimization techniques of direct shipping, merging, milk runs, round trips, and cross-docking. To elevate the potential of this model, we show that batching consignments is essential but requires a significant change in the planning processes. Although batching results in higher peaks in the workload of the planners, we show that a collection of lengths and frequencies of the FLPH exists for each client separately, which preserves most of the cost savings while ensuring sufficient capacity in the planning department. Moreover, we show that (the current way of working of) postponing all consignments does not always make sense, depending on the difference between the spot market and contract prices. Therefore we calculate probabilities of whether a consignment can be combined in a future batch and postpone the consignment if it exceeds the determined cut-off value yielding the highest net cost savings.

6.1 Conclusion

In this research, we implemented the presented linear program in Python, which generally solves model instances within a reasonable run-time of at most 20 minutes. Before running the model instances, we showed to use the First Fit Decreasing heuristic to reduce the consignment set with the merging optimization technique. Furthermore, we showed with the sensitivity analysis for the b^{FTL} parameter that the chosen parameter value makes sense as almost no increase in cost savings is expected with a higher parameter value, which thus shows that the conclusions drawn are robust. Besides, we demonstrated that clients, suppliers, and customers are already aligned well in sending consignments to be included in round trips with the sensitivity analysis regarding the e parameter.

As consignments come in independently from each other, we propose to batch consignments to realize cost savings by combining the consignments. From a cost savings perspective, it is most preferred to batch using a fixed-length planning horizon (FLPH) of 24 hours starting each workday at 2 PM. However, doing this for all clients resulted in a capacity shortage in the planning department. Therefore, we showed an approach to arrive to a combination of different lengths and frequencies of the FLPH for the clients in the subset, which preserves 90% of the cost savings for each client separately and does not cause any capacity problems at the planning department. Different lengths and frequencies of the FLPH per client make sense as it differs significantly between them how many cost savings we achieve with each timing of planning (as shown in Table 4.1). This is because clients differ significantly in their timing of sending consignments. Still, the new proposed way of using batching requires a hands-on approach by the company as it requires some significant changes within the CI- and planning department, of which they are aware and are open to change.

Next, we investigated if postponing consignments to the next batch results in additional cost savings, for which we calculate probabilities for each eligible postponement using the relative frequency from historical data. For the downside of postponing consignments, we proposed to incur a penalty cost representing the probability that a non-contracted carrier has to be booked once the loading date of a consignment gets closer. One of the factors of this penalty cost is the difference between the spot market and contract prices which differs significantly over time. Therefore, we determined for multiple scenarios (i.e., being a particular percentage difference between the spot market and contract prices) the probability cut-off value yielding the highest net cost savings below which consignments are not considered for postponement. Suppose the difference between the spot market and contract prices is 10% or higher (valid for 45.08% of the time since the beginning of 2021). In that case, the current way of working of ELC (i.e., always postponing every consignment) does not result in the highest net cost savings. In other words, we presented a way for LSPs to improve efficiency in terms of cost savings (up to 290% for our sample) by postponing consignments depending on the difference between spot market and contract prices. Lastly, we show that the probability cut-off value yielding the highest net cost savings increases approximately linearly with this price difference percentage. In particular, for each percentage increase in the difference between the spot market and contract prices, there is an increase in the probability cut-off value yielding the highest net cost savings of 1.23% starting at 6.26%.

In conclusion, when LSPs take the model into practice in combination with batching (using a separate FLPH for each client) and the decision process shown to postpone consignments, LSPs significantly improve their efficiency in the consignment planning processes.

6.2 Discussion

As this research is a first attempt to simultaneously plan inbound and outbound consignments with the discussed route optimization techniques, decisions were made to leave elements out of the research scope and are thus suggested for future research. At first, the model does not allow many-to-many relationships, which limits the solution space. On the one hand, this enabled us to use an exact algorithm instead of a heuristic solution, as many-to-many relationships increase the model complexity significantly. However, on the other hand, not including this feature might reduce the cost savings potential of the solutions generated. Our gut feeling is that an exact algorithm in that case is inadequate, and we recommend a heuristic approach if future research aims to include these many-to-many relationships, possibly in combination with geo-clustering. Furthermore, the data did not allow us to easily compare the solutions generated by the model against the real way how it was shipped. Using the current baseline solution of shipping all consignments directly limits us in our research to compare the model's performance with the solutions generated by ELC's planning department. So, we suggest to investigate this in future research. Besides, Subsection 3.2.3 elaborated extensively on the approach used to arrive at a subset of clients representing the entire client base. However, whether all conclusions also apply to all other former and current clients remains to be discovered, and we suggest investigating this in future research.

Furthermore, using knowledge from experts in the 3PL-industry and in particular the research by Van Nieuwenhuyse & de Koster (2009), this research assumes variable time window batching (VTWB) is outperformed by fixed time window batching (FTWB) in this setting. This assumption is a limitation of our research and is therefore suggested to be investigated in future research. Moreover, in Subsection 4.2.2 we present an approach to determine the lengths and frequencies of the FLPHs for all clients in the subset. However, a more sophisticated approach might preserve more cost savings for each client. Note, this is more complex than simply making a linear program similar to the one presented in Section 3.1, as clients require LSPs to optimize their cost savings individually, instead of the total cost savings over all clients. Additionally, if future research predicts the workload for the next workday on a daily basis, LSPs improve their efficiency by changing the timing of planning at each moment accordingly. For example, if a low workload is expected, batching all clients until 2 PM might not result in capacity shortages at the planning department while ensuring the highest possible cost savings.

Also, a limitation of this research is that at the moment of postponing consignments, it is unknown how much additional cost savings we achieve due to this decision. For this, we explored whether approximate dynamic programming can help predict the additional cost savings achieved in the future by postponing the consignment. However, this was not feasible due to bimodal distributions in, for example, the payable weight of consignments. Therefore, we suggest future research to investigate a more sophisticated approach to postpone consignments. Furthermore, this research does not investigate using a probability cut-off value yielding the highest net cost savings in real time depending on the current difference between spot market and contract prices. It is thus a limitation and recommendation for future research. In addition to this, suppose the collection date is much later than the arrival of the consignment, we suggest future research to forecast the difference between the spot market and contract prices to determine a more accurate probability (cut-off value).

6.3 ELC recommendations

First and foremost, we suggest to ELC and other LSPs to consider all research limitations with their corresponding suggestions for future research (presented in Section 6.2). Furthermore, to ensure a successful implementation of the research solutions in the processes of ELC, we recommend the company to put into practice the new proposed way of working as presented in Figure 1.3. One of these newly proposed processes is batching using a FLPH, for which we recommend repeating the analyses from Chapter 4 to determine the lengths and frequencies of the FLPHs for the current clients. Moreover, to fully utilize the cost savings potential of the FLPH model, we suggest (depending on the price difference between spot market and contract prices) using the relative frequency probabilities in the consignment postponement decision. If this probability is at or above the determined probability cut-off value yielding the highest net cost savings, we recommend postponing this consignment to the next FLPH.

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Appendix A Bin Packing Problem (BPP) notation and heuristics

Table A.1: Bin packing problem notation copied from Carmona-Arroyo et al. (2021)

n	number of items
c	bin capacity
opt	number of bins in the optimal solution
w_i	weight of the item $i(i = 1, ..., n)$
$l(j)$	accumulated weight in bin j
Z	list of items sorted in decreasing order according w_i
Sol	solution, i.e., complete assignment of items to bins
m	number of bins in the solution
$s(j)$	free space in the bin j, i.e., $c - l(j)$
N	set of n items
W	set of n weights

Algorithm 1: First Fit Decreasing heuristic pseudo-code

```
Data: Z, c
Result: m
for each item i ∈ Z do
    for each bin j ∈ Sol do
        if w_i + l(j) ≤ c then
            Pack item i in bin j;
            Update l(j);
            Break for
    if item i was not packed in any available bin then
        Create a new bin for item i
```

Algorithm 2: Best Fit Decreasing heuristic pseudo-code

```
Data: Z, c
Result: m
for each item i ∈ l do
    best_bin = Φ;
    for each bin j ∈ Z do
        if w_i + l(j) ≤ c and l(j) > l(best_bin) then
            best_bin = j
    if no bin has enough capacity to pack i then
        Create a new bin to pack i
    else
        Pack item i in the fullest bin (best_bin);
        Update l(j)
```

Algorithm 3: Minimum Bin Slack heuristic pseudo-code

```
Data: q = 1
Result: A*
for r = q to n do
    Let i be the r-th element ∈ Z;
    if w_i ≤ s(A) then
        A = A ∪ {i};
        Apply MBS(r + 1);
        A = A \ {i};
        if s(A*) = 0 then
            End
if s(A) ≤ s(A*) then
    A* = A
```

Appendix B Literature models

B.1 Hosseini et al. (2014)

Table B.1: Decision variables of Hosseini et al. (2014)

u_{ij}	=	$\begin{cases} 1, & \text{if load from } PS_i \text{ to } AP_j \text{ is sent directly}; i \in V1, j \in V3 \\ 0, & \text{otherwise} \end{cases}$
y_{ij}^{k}	=	$\begin{cases} 1, & \text{if load from } PS_i \text{ to } AP_j \text{ is sent through } CD_k; i \in V1, k \in V2, j \in V3 \\ 0, & \text{otherwise} \end{cases}$
m_{ik}	=	$\begin{cases} & \text{the number of trucks on link } ik \text{ from } PS_i \text{ to } CD_k; i \in V1, k \in V2 \\ 0, & \text{otherwise} \end{cases}$
n_{kj}	=	$\begin{cases} & \text{the number of trucks on link } kj \text{ from } CD_k \text{ to } AP_j; k \in V2, j \in V3 \\ 0, & \text{otherwise} \end{cases}$
z_{ijr}	=	$\begin{cases} 1, & \text{if load from } PS_i \text{ to } AP_j \text{ is sent through a milk run trip by truck } r; i \in V1, j \in V3, r \in V4 \\ 0, & \text{otherwise} \end{cases}$
d_{ijr}	=	$\begin{cases} 1, & \text{if there is a milk run trip by truck } r \text{ starting from } PS_i \text{ and terminating at } AP_j; i \in V1, j \in V3, r \in V4 \\ 0, & \text{otherwise} \end{cases}$
f_{ijr}	=	$\begin{cases} 1, & \text{if there is a milk run trip by truck } r \text{ passing } PS_i \text{ and terminating at } AP_j; i \in V1, j \in V3, r \in V4 \\ 0, & \text{otherwise} \end{cases}$
h_{ijr}	=	$\begin{cases} 1, & \text{if there is a milk run trip by truck } r \text{ ending in } PS_i \text{ before terminating at} AP_j; i \in V1, j \in V3, r \in V4 \\ 0, & \text{otherwise} \end{cases}$
x_{igr}^{j}	=	$\begin{cases} 1, & \text{if there is a milk run trip in which truck } r \text{ moves from } PS_i \text{ to node g and terminates at} AP_j; i \in V1, g \in W, j \in V3, r \in V4, i \neq g \\ 0, & \text{otherwise} \end{cases}$

Table B.2: Parameters of Hosseini et al. (2014)

$V1$	$\{i \mid i = 1, 2, ..., \lvert V1 \rvert\}$ set of part suppliers (PS)	W	$\{g \mid g \in \{V1 \cup V3\}\}$
$V2$	$\{k \mid k = 1, 2, ..., \lvert V2 \rvert\}$ set of cross-docks (CD)	S_{ij}	flow from PS_i to AP_j
$V3$	$\{j \mid j = 1, 2, ..., \lvert V3 \rvert\}$ set of assembly plants (AP)	A	truck capacity
$V4$	$\{r \mid r = 1, 2, ..., \lvert V4 \rvert\}$ set of trucks	C_{qp}	cost of a truck from node q to node p

Using the notation from Table B.1 and Table B.2, Hosseini et al. (2014) formulated the problem as the following integer programming model.

Objective function:

$$\min \sum_{i\in V1}\sum_{j\in V3} u_{ij}C_{ij} + \sum_{i\in V1}\sum_{k\in V2} m_{ik}C_{ik} + \sum_{k\in V2}\sum_{j\in V3} n_{kj}C_{kj} + \sum_{i\in V1}\sum_{j\in V3}\sum_{g\in W}\sum_{r\in V4} x^j_{igr}C_{ig}$$

Constraints:

$$u_{ij} + \sum_{k\in V2} y^k_{ij} + \sum_{r\in V3} z_{ijr} = min\{1, S_{ij}\} \qquad \forall i\in V1, j\in V3 \quad (1)$$

$$d_{ijr} + f_{ijr} + h_{ijr} = z_{ijr} \qquad \forall i\in V1, j\in V3, r\in V4 \quad (2)$$

$$\sum_{i\in V1} d_{ijr} - \sum_{i\in V1} h_{jr} = 0 \qquad \forall j\in V3, r\in V4 \quad (3)$$

$$f_{ijr} \le \sum_{i\in V1} d_{ijr} \qquad \forall i\in V1, j\in V3, r\in V4 \quad (4)$$

$$f_{ijr} \le \sum_{i\in V1} h_{ijr} \qquad \forall i\in V1, j\in V3, r\in V4 \quad (5)$$

$$d_{ijr} + \sum_{g\in V1} x^j_{gir} \le 1 \qquad \forall i\in V1, j\in V3, r\in V4, i\ne g \quad (6)$$

$$d_{ijr} + x^j_{ijr} \le 1 \qquad \forall i\in V1, j\in V3, r\in V4 \quad (7)$$

$$f_{ijr} + x^j_{ijr} \le 1 \qquad \forall i\in V1, j\in V3, r\in V4 \quad (8)$$

$$h_{ijr} - x^j_{ijr} = 0 \qquad \forall i\in V1, j\in V3, r\in V \quad (9)$$

$$h_{ijr} + \sum_{g\in V1} x^j_{igr} \le 1 \qquad \forall i\in V1, j\in V3, r\in V4, i\ne g \quad (10)$$

$$\sum_{g\in V1} x^j_{igr} + \sum_{g\in V1} x^j_{gir} + x^j_{ijr} = 2f_{ijr} + 2h_{ijr} + d_{ijr} \qquad \forall i\in V1, j\in V3, r\in V4, i\ne g \quad (11)$$

$$\sum_{i\in B}\sum_{g\in B} x^j_{igr} \le |B| - 1 \qquad \forall B\subseteq M_{jr}, j\in V3, r\in V4, i\ne g \quad (12)$$

$$\sum_{i\in V1}\sum_{j\in V2} h_{ijr} \le 1 \qquad \forall r\in V4 \quad (13)$$

$$\sum_{i\in V1}\sum_{g\in W} x^j_{igr}\cdot S_{ij} \le A \qquad \forall j\in V3, r\in V4, i\ne g \quad (14)$$

$$\sum_{j\in V3} y^k_{ij}\cdot S_{ij} \le m_{ik}\cdot A \qquad \forall i\in V1, k\in V2 \quad (15)$$

$$\sum_{i\in V1} y^k_{ij}\cdot S_{ij} \le n_{kj}\cdot A \qquad \forall k\in V2, j\in V3 \quad (16)$$

$$u_{ij}, y^k_{ij}, z_{ijr}, d_{ijr}, f_{ijr}, h_{ijr}, x^j_{igr} \in \{0,1\} \qquad \substack{\forall i\in V1, k\in V2, j\in V3,\\ g\in W, r\in V4, i\ne g} \quad (17)$$

$$m_{ik}, n_{kj} \in Z^* \qquad \forall i\in V1, k\in V2, j\in V3 \quad (18)$$

The objective function minimizes the sum of costs for direct, indirect via a cross-dock, and milk run transportation. Constraint (1) ensures to ship shipment S_{ij} via direct, indirect, or milk run transportation. Constraint (2) ensures that part supplier PS_i in a milk run to

AP_j (by truck r) is on either position d_{ijr}, f_{ijr} or h_{ijr}. Constraint (3) ensures a milk run contains at least two suppliers (d and h). Constraints (4) and (5) ensure in a milk run that at least one supplier occupies position f if two other suppliers occupy positions d and h in that milk run. Constraints (6) and (7) ensure that when in a milk run a supplier occupies position d, no trucks visit this supplier, and the truck leaving this supplier's site can only go to another supplier, not the assembly plant. Constraint (8) ensures when a supplier occupies position f, the departing truck cannot go to an assembly plant (i.e., only allowed when the supplier occupies position h). Constraints (9) and (10) ensure the departing truck from the supplier's position h only goes to the assembly plant. Constraint (11) determines the milk run routing of a truck carrying the loads toward the same assembly plant. Constraint (12) ensures for every subset of M, the amount of shipments around suppliers occupying position f is strictly smaller than the subset size. Constraints (4), (5), and (12) are sub-tour elimination constraints. Constraint (13) ensures trucks are in one milk run at a time. Constraint (14) ensures the capacity of the trucks is not exceeded. Constraints (15) and (16) ensure the trucks used for shipments through the cross-docks do not exceed their capacity. Constraints (17) and (18) limit the values of the variables.

B.2 Kocaoglu et al. (2020)

Table B.3: Decision variables of Kocaoglu et al. (2020)

$$X_{ijv} = \begin{cases} 1, & \text{if vehicle } v \text{ travels from customer } i \text{ to customer } j; i \in N_0, j \in N_0, i \neq j, v \in V \\ 0, & \text{otherwise} \end{cases}$$

$$Z_{jv} = \begin{cases} 1, & \text{if vehicle } v \text{ travels directly to customer } j; j \in N, v \in V \\ 0, & \text{otherwise} \end{cases}$$

$$Y_j = \begin{cases} 1, & \text{if customer } j \text{ demand is transported with cross-docking}; j \in N \\ 0, & \text{otherwise} \end{cases}$$

M = number of trucks used for shipment from the manufacturer/supplier to the cross-docking center

Table B.4: Indices and parameters of Kocaoglu et al. (2020)

N_0	$\{i, j = 0, 1, ..., n\}$ set of nodes with manufacturer/supplier	S	truck capacity for cross-docking center
N	$\{i, j = 1, 2, ..., n\}$ set of customer nodes	D	milk run tour length (km)
V	$\{V = 1, 2, ..., v\}$ set of vehicles	L_v	$\{v = 1, 2, ..., v\}$ rental cost of vehicle
K	cross-docking center (CDC)	O	fixed cost of transportation from the manufacturer/supplier to a CDC
K_v	$\{v = 1, 2, ..., v\}$ the maximum loading capacity of the vehicles (m^3)	W	milk run stop cost (time it takes to deliver the product to the customer)
d_j	the volume of customer j shipments (m^3), $j \in N$	T	direct shipment cost from the cross-docking center to customers
C_ij	total distance between customer i and customer j (km)	P	cost per unit of gasoline consumed per km

Using Table B.3 and Table B.4, Kocaoglu et al. (2020) formulated the following model.

Objective function:

$$\min \sum_{i=0,j\in N}\sum_{v\in V} Z_{jv}\cdot(L_v+C_{ij}\cdot P_v)+\sum_{i=0,j\in N}\sum_{v\in V} X_{ijv}\cdot(L_v+C_{ij}\cdot P_v)+\sum_{i\in N}\sum_{j\in N}\sum_{v\in V} X_{ijv}\cdot C_{ij}\cdot P_v$$

$$+\sum_{i\in N_0}\sum_{j\in N}\sum_{v\in V} W\cdot X_{ijv}+M\cdot O+\sum_{j\in N} T\cdot Y_j$$

Constraints:

$$\sum_{i\in N_0}\sum_{v\in V} X_{ijv}+\sum_{v\in V} Z_{jv}+y_j=1 \qquad \forall j\in N, i\neq j \tag{19}$$

$$\sum_{i\in N_0}\sum_{j\in N} d_j\cdot X_{ijv}\leq K_v \qquad \forall v\in V, V=1,2,3,...,v, i\neq j \tag{20}$$

$$\sum_{i\in S}\sum_{j\in S\setminus\{i\}} X_{ijv}|S|=1 \qquad \forall S\subset N, |S|\geq 2, V=1,2,3,...,v \tag{21}$$

$$\sum_{v\in V} X_{ijv}+\sum_{v\in V} Z_{iv}+Y_i\leq 1 \qquad \forall i\in N, j=0 \tag{22}$$

$$\sum_{v\in V} X_{jiv}+\sum_{v\in V} Z_{iv}+Y_i\leq 1 \qquad \forall i\in N, j=0 \tag{23}$$

$$\sum_{j\in N} X_{jiv}+\sum_{j\in N} Z_{jv}\leq 1 \qquad \forall v\in V, i=0, j\neq 0, i\neq j \tag{24}$$

$$\sum_{i\in N_0} X_{ijv}-\sum_{l\in N_0} X_{jlv}=0 \qquad \forall j\in N, v\in V, i\neq j, 1\neq j \tag{25}$$

$$d_i\cdot\sum_{i\in N} Z_{iv}\leq K_v \qquad \forall i\in N, v\in V, V=1,2,3,...,v \tag{26}$$

$$\sum_{j\in N} d_j\cdot Y_j\leq M\cdot S \qquad \forall s\in S \tag{27}$$

$$\sum_{i\in N_0}\sum_{j\in N_0} C_{ij}\cdot X_{ijv}\leq D \qquad \forall v\in V, i\neq j \tag{28}$$

$$\sum_{j\in N} Y_j\leq N \tag{29}$$

$$X_{ijv}\in\{0,1\} \tag{30}$$

$$Z_{iv}\in\{0,1\} \tag{31}$$

$$Y_{iv}\in\{0,1\} \tag{32}$$

The objective function minimizes the total distribution costs. Constraint (19) ensures to satisfy customer demands via direct shipment, milk run, or cross-docking. Constraint (20) ensures the vehicle capacity is not exceeded in a milk run. Constraint (21) ensures sub-tour elimination. Constraints (22) and (23) ensure only one of the distribution strategies is available. Constraint (24) ensures a vehicle is not in a direct shipment and milk run. Constraint (25) ensures only one vehicle is used in a milk run. Constraint (26) ensures a vehicle is allocated to each direct shipment. Constraint (27) ensures that the total load shipped to the cross-dock equals the demand. Constraint (28) ensures a maximum milk run length. Constraint (29) ensures that the amount of loads assigned to the cross-dock is the maximum number of customers at most. Constraints (30), (31), and (32) ensure that the decision variables only take binary values 0 or 1.

B.3 Ranjbaran et al. (2020)

Table B.5: Decision variables of Ranjbaran et al. (2020)

X_{ijk}	$= \begin{cases} 1, & \text{if the vehicle } k \text{ moves from node } i \text{ to node } j \\ 0, & \text{otherwise} \end{cases}$	$D_{m,k}$	number of pallets of order m that is delivered by vehicle k
Y_{ik}	$= \begin{cases} 1, & \text{if node } i \text{ is visited by vehicle } k \\ 0, & \text{otherwise} \end{cases}$	$U_{i,k}$	occupied length of the container of vehicle k , when it leaves node i
$\Delta_{m,k}$	$= \begin{cases} 1, & \text{if order } m \text{ is picked up by vehicle } k \\ 0, & \text{otherwise} \end{cases}$	$W_{i,k}$	total weight of pallets in vehicle k when it leaves node i
$\sigma_{mb,k}$	$= \begin{cases} 1, & \text{if the big order } mb \text{ (split) is directly shipped by vehicle } k \\ 0, & \text{otherwise} \end{cases}$	$T_{i,k}$	time vehicle k arrives at node i
$P_{m,k}$	= number of pallets of order m that is picked up by vehicle k		

Table B.6: Sets and parameters of Ranjbaran et al. (2020)

K	vehicle's set (k)	f_m	the flow of order m (number of pallets)
I	node's set (i, j), where the first node is dummy	O_m	the origin of order m
M	order's set (m, m')	D_m	the destination of order m
$MB \in M$	big order's set (mb)	$O_i^{'}$	orders with the origin of node i
$BM1 - BM5$	five (relatively) large numbers	$D_i^{'}$	orders with the destination of node i
L_k	the container length of vehicle k	$comp_{m,m'}$	compatibility (1) or incompatibility (0) of orders m and m'
WC_k	weight capacity of vehicle k	lb_m	time window's lower bound for the pickup of order m
w_m	pallet weight of order m	ub_m	time window's upper bound for the delivery of order m
$Nw_{m,k}$	number of pallets of order m that can be put on the width of vehicle k	$c_{i,j,k}$	transportation cost from node i to node j by vehicle k
$Nh_{m,k}$	pallet amount of order m that can be stacked on each other in vehicle k	$t_{i,j,k}$	transportation time from node i to node j by vehicle k
pw_m	pallet width of order m	ns	number of suppliers
LT_m	pallet loading time of order m	na	number of assembly plants
UT_m	pallet unloading time of order m	nk	an upper bound on the number of vehicles

Using Table B.5 and Table B.6, Ranjbaran et al. (2020) formulated the following program.

Objective function:

$$\min \sum_{i \in I} \sum_{j \in I} \sum_{k \in K} c_{i,j,k} \cdot X_{i,j,k}$$

Constraints:

$$\sum_{j \in I} X_{1,j,k} \leq 1 \qquad \forall k \in K \quad (33)$$

$$\sum_{i \in I} X_{i,1,k} \leq 1 \qquad \forall k \in K \quad (34)$$

$$\sum_{j \in I} \sum_{k \in K} X_{1,j,k} \leq nk \quad (35)$$

$$\sum_{i \in I} X_{i,j,k} = \sum_{i \in I} X_{j,i,k} \qquad \forall j \in I, k \in K \quad (36)$$

$$\sum_{j \in I} X_{i,j,k} = Y_{i,k} \quad \forall i \in I, k \in K \quad (37)$$

$$\sum_{k \in K} Y_{i,k} \geq 1 \quad \forall i \in I \quad (38)$$

$$\sum_{k \in K} X_{i,i,k} = 0 \quad \forall i \in I \quad (39)$$

$$X_{i,j,k} + X_{j,i,k} \leq 1 \quad \forall i \in I, j \in I, k \in K \quad (40)$$

$$\sum_{\substack{i \in I, i \neq 1, \\ i \leq ns+1}} \sum_{\substack{j \in I, j \geq ns+2, \\ j \leq ns+na+1}} X_{i,j,k} \leq 1 \quad \forall k \in K \quad (41)$$

$$\sum_{\substack{i \in I, i \geq ns+2, \\ i \leq ns+na+1}} \sum_{\substack{j \in I, \\ j \geq ns+na+2}} X_{i,j,k} \leq 1 \quad \forall k \in K \quad (42)$$

$$\sum_{\substack{i \in I, \\ i \geq ns+na+2}} \sum_{\substack{j \in I, j \neq 1, \\ j \leq ns+1}} X_{i,j,k} = 0 \quad \forall k \in K \quad (43)$$

$$\sum_{\substack{i \in I, i \neq 1 \\ i \leq ns+1}} \sum_{\substack{j \in I, \\ j \geq ns+na+2}} X_{i,j,k} = 0 \quad \forall k \in K \quad (44)$$

$$\sum_{\substack{i \in I, i \geq ns+2, \\ i \leq ns+na+1}} \sum_{\substack{j \in I, j \neq 1, \\ j \leq ns+1}} X_{i,j,k} = 0 \quad \forall k \in K \quad (45)$$

$$\sum_{\substack{i \in I, \\ i \geq ns+na+2}} \sum_{\substack{j \in I, j \geq ns+2, \\ j \leq ns+na+1}} X_{i,j,k} = 0 \quad \forall k \in K \quad (46)$$

$$P_{m,k} \leq f_m \cdot Y_{i,k} \quad \substack{\forall i \in I, i \neq 1, \\ k \in K, m \in O_i'} \quad (47)$$

$$\sum_{k \in K} P_{m,k} = f_m \quad \forall m \in M \quad (48)$$

$$D_{m,k} \leq f_m \cdot Y_{i,k} \quad \substack{\forall i \in I, i \neq 1, \\ k \in K, m \in D_i'} \quad (49)$$

$$P_{m,k} = D_{m,k} \quad \forall k \in K, m \in M \quad (50)$$

$$\sum_{m \in O_i'} P_{m,k} + \sum_{m \in D_i'} D_{m,k} \geq Y_{i,k} \quad \substack{\forall i \in I, i \neq 1, \\ k \in K} \quad (51)$$

See below ... (52)

$$U_{i,k} \leq L_k \quad \forall i \in I, k \in K \quad (53)$$

See below ... (54)

$$W_{i,k} \leq WC_k \quad \forall i \in I, k \in K \quad (55)$$

$$\Delta_{m,k} + \Delta_{m',k} \leq comp_{m,m'} + 1$$

$$\forall m \in M, m' \in M, k \in K \quad (56)$$

$$\left\lceil \frac{P_{m,k}}{Nw_{m,k} \cdot Nh_{m,k}} \right\rceil pw_m \leq L_k \cdot \Delta_{m,k}$$

$$\forall m \in M, k \in K \quad (57)$$

$$P_{m,k} \geq \Delta_{m,k} \quad \forall m \in M, k \in K \quad (58)$$

$$\sum_{k \in K} \Delta_{m,k} = 1 \quad m \in M - MB \quad (59)$$

$$\Delta_{m,k} \leq (1 - \Delta_{mb,k}) + (1 - \sigma_{mb,k})$$

$$\forall m \in M, mb \in MB, m \neq mb, k \in K \quad (60)$$

$$\sigma_{mb,k} \leq \Delta_{mb,k} \quad mb \in MB, k \in K \quad (61)$$

$$\sum_{k \in K} \sigma_{mb,k} = \sum_{k \in K} \Delta_{mb,k} - 1 \quad mb \in MB \quad (62)$$

See below ... (63)

$$T_{j,k} \geq T_{i,k} - (1 - \Delta_{m,k}) \cdot BM4$$

$$\forall k \in K, m \in M, i = O_m, j = D_m \quad (64)$$

$$T_{i,k} \geq lb_m \Delta_{m,k} \quad \forall m \in M, i = O_m, k \in K \quad (65)$$

$$T_{i,k} \leq ub_m + (1 - \Delta_{m,k}) \cdot BM5$$

$$\forall m \in M, i = D_m, k \in K \quad (66)$$

$$X_{i,j,k}, Y_{i,k}, \gamma_k, \Delta_{m,k}, z_{i,j,k}, \sigma_{mb,k} \in \{(0,1)\}$$

$$P_{m,k}, D_{m,k} \in Z$$

$$U_{i,k}, W_{i,k}, T_{i,k} \geq 0 \quad (67)$$

$$U_{i,k} + \sum_{m \in O_j'} \left\lceil \frac{P_{m,k}}{Nw_{m,k} \cdot Nh_{m,k}} \right\rceil pw_m - \sum_{m \in D_j'} \left\lceil \frac{D_{m,k}}{Nw_{m,k} \cdot Nh_{m,k}} \right\rceil pw_m \leq U_{j,k} + (1 - X_{i,j,k}) \cdot BM1$$

$$\forall i \in I, j \in I, j \neq 1, i \neq j, k \in K \quad (52)$$

$$W_{i,k} + \sum_{m \in O'_j} w_m P_{m,k} - sum_{m \in D'_j} w_m D_{m,k} \leq W_{j,k} + (1 - X_{i,j,k}) \cdot BM2$$

$$\forall i \in I, j \in I, j \neq 1, i \neq j, k \in K \quad (54)$$

$$T_{i,k} + \sum_{m \in O'_i} LT_m P_{m,k} + \sum_{m \in D'_i} UT_m D_{m,k} + t_{i,j,k} \leq T_{j,k} + (1 - X_{i,j,k}) \cdot BM3$$

$$\forall i \in I, j \in I, j \neq 1, i \neq j, k \in K \quad (63)$$

The objective function minimizes the transportation cost. Constraints (33) and (34) ensure a vehicle drives at most once to j from node 1 and from i to node 1, respectively. Constraint (35) ensures the upper bound for the number of vehicles is not exceeded. Constraint (36) ensures an entering vehicle always leaves. Constraint (37) ensures vehicles visiting a node exit it just once. Constraint (38) ensures visiting each node at least once. Constraint (39) ensures trucks don't drive from one node to the same node in a loop. Constraint (40) prevents backward movements. Constraint (41) ensures a vehicle moves from the suppliers to the assembly plants at most once. Constraint (42) ensures a vehicle moves from assembly plants to suppliers' dummy nodes at most once. Constraints (43) and (44) ensure a vehicle cannot move from the supplier's dummy nodes to supplier nodes and from supplier nodes to the supplier's dummy nodes, respectively. Constraint (45) ensures a vehicle cannot go from assembly plants to suppliers. Constraint (46) ensures a vehicle cannot go from suppliers' dummy nodes to assembly plants. Constraint (47) ensures a vehicle picks up orders when it visits the origin of that order. Constraint (48) prevents abandoned pallets. Constraint (49) ensures a vehicle delivers orders when it visits the delivery node of that order. Constraint (50) ensures the number of picked-up pallets matches the number of delivered pallets. Constraint (51) ensures at least one pallet is picked up from or delivered to that node when it is visited. Constraint (52) calculates the occupied length of a vehicle when it leaves a node. Constraint (53) ensures that a vehicle's total occupied length does not exceed capacity. Constraints (54) and (55) have the same function as constraints (52) and (53) but then for weight instead of length. Constraint (56) ensures that incompatible orders are not in the same vehicle. Constraints (57) and (58) ensure the number of pallets picked up by a vehicle respects the minimum and maximum number allowed, respectively. Constraint (59) ensures LTL orders are not split. Constraints (60), (61), and (62) ensure the split of orders that exceed the capacity of the largest vehicle, such that the orders are FTL except probably one that is LTL. In constraint (63), each vehicle's arrival time at a node is calculated. Constraint (64) ensures each pickup node is visited before the delivery node of an order. Constraints (65) and (66) ensure to respect time windows for orders. Constraint (67) ensures the variables only take their allowed values.

Appendix C Timing of planning: run time

Table C.1: Average run time in seconds per timing of planning for each client in the subset

Client	10 AM & 12 PM & 2 PM	10 AM & 12 PM	11 AM & 1 PM
A	10 AM: 7.77 (min: 0, max: 164.15, SD: 18.42) 12 PM: 4.5 (min: 0, max: 58.31, SD: 8.45) 2 PM: 0.06 (min: 0, max: 1.07, SD: 0.15)	10 AM: 7.37 (min: 0, max: 160.83, SD: 17.67) 12 PM: 5.02 (min: 0, max: 54.46, SD: 9.2)	11 AM: 27.88 (min: 0, max: 377.23, SD: 61.57) 1 PM: 0.83 (min: 0, max: 13.35, SD: 1.84)
B	10 AM: 4.56 (min: 0.1, max: 90.71, SD: 12.56) 12 PM: 1.37 (min: 0, max: 24.51, SD: 3.49) 2 PM: 0.78 (min: 0, max: 28.61, SD: 3.73)	10 AM: 4.56 (min: 0.11, max: 88.6, SD: 12.34) 12 PM: 2.33 (min: 0, max: 24.81, SD: 4.33)	11 AM: 23.81 (min: 0.11, max: 1,023.92, SD: 129.82) 1 PM: 1.38 (min: 0, max: 25.29, SD: 3.93)
C	10 AM: 16.31 (min: 0, max: 281.19, SD: 38.99) 12 PM: 0.45 (min: 0, max: 21.54, SD: 2.66) 2 PM: 1.8 (min: 0, max: 54.75, SD: 8.49)	10 AM: 15.09 (min: 0, max: 258.7, SD: 35.9) 12 PM: 0.88 (min: 0, max: 21.61, SD: 3.0)	11 AM: 16.14 (min: 0, max: 259.4, SD: 36.23) 1 PM: 0.99 (min: 0, max: 41.68, SD: 5.21)
D	10 AM: 1.78 (min: 0, max: 17.34, SD: 2.35) 12 PM: 1.46 (min: 0, max: 13.2, SD: 1.74) 2 PM: 0.6 (min: 0, max: 7.67, SD: 0.96)	10 AM: 1.79 (min: 0, max: 17.44, SD: 2.38) 12 PM: 3.35 (min: 0, max: 24.23, SD: 3.38)	11 AM: 3.78 (min: 0, max: 53.34, SD: 5.0) 1 PM: 1.69 (min: 0, max: 20.46, SD: 2.27)
E	10 AM: 1.87 (min: 0, max: 34.51, SD: 3.52) 12 PM: 1.17 (min: 0, max: 10.86, SD: 1.52) 2 PM: 0.52 (min: 0, max: 8.75, SD: 0.98)	10 AM: 1.54 (min: 0, max: 20.84, SD: 2.22) 12 PM: 2.12 (min: 0, max: 12.19, SD: 2.27)	11 AM: 2.5 (min: 0, max: 20.62, SD: 2.8) 1 PM: 1.17 (min: 0, max: 9.76, SD: 1.43)
F	10 AM: 0.65 (min: 0, max: 9.82, SD: 1.34) 12 PM: 1.15 (min: 0, max: 15.8, SD: 1.99) 2 PM: 0.62 (min: 0, max: 8.97, SD: 1.16)	10 AM: 0.64 (min: 0, max: 9.99, SD: 1.32) 12 PM: 2.62 (min: 0, max: 17.97, SD: 2.82)	11 AM: 1.47 (min: 0, max: 19.36, SD: 2.55) 1 PM: 1.56 (min: 0, max: 10.55, SD: 2.08)
G	10 AM: 0.25 (min: 0, max: 2.4, SD: 0.48) 12 PM: 0.07 (min: 0, max: 1.98, SD: 0.2) 2 PM: 0.07 (min: 0, max: 2.23, SD: 0.23)	10 AM: 0.25 (min: 0, max: 2.42, SD: 0.48) 12 PM: 0.14 (min: 0, max: 2.37, SD: 0.32)	11 AM: 0.28 (min: 0, max: 2.63, SD: 0.5) 1 PM: 0.12 (min: 0, max: 2.41, SD: 0.31)
Client	**11 AM & 2 PM**	**10 AM**	**11 AM**
A	11 AM: 31.61 (min: 0, max: 386.13, SD: 70.12) 2 PM: 0.98 (min: 0, max: 17.02, SD: 2.36)	10 AM: 20.14 (min: 0, max: 228.32, SD: 36.64)	11 AM: 34.82 (min: 0, max: 360.91, SD: 70.45)
B	11 AM: 23.74 (min: 0.1, max: 1,020.65, SD: 129.42) 2 PM: 1.51 (min: 0, max: 25.36, SD: 4.25)	10 AM: 9.64 (min: 0.11, max: 91.5, SD: 14.64)	11 AM: 25.68 (min: 0.11, max: 618.96, SD: 96.89)
C	11 AM: 17.19 (min: 0, max: 265.88, SD: 37.53) 2 PM: 1.75 (min: 0, max: 51.58, SD: 7.99)	10 AM: 17.52 (min: 0, max: 259.27, SD: 37.88)	11 AM: 18.02 (min: 0, max: 257.14, SD: 37.86)
D	11 AM: 3.79 (min: 0, max: 53.35, SD: 5.02) 2 PM: 1.85 (min: 0, max: 31.96, SD: 3.06)	10 AM: 8.39 (min: 0, max: 35.31, SD: 5.67)	11 AM: 9.1 (min: 0, max: 88.93, SD: 8.0)
E	11 AM: 3.07 (min: 0, max: 20.45, SD: 3.59) 2 PM: 1.33 (min: 0, max: 9.65, SD: 1.58)	10 AM: 6.82 (min: 0, max: 117.87, SD: 8.53)	11 AM: 6.59 (min: 0, max: 43.76, SD: 5.16)
F	11 AM: 1.47 (min: 0, max: 19.21, SD: 2.53) 2 PM: 1.57 (min: 0, max: 10.38, SD: 2.09)	10 AM: 4.81 (min: 0, max: 20.71, SD: 4.09)	11 AM: 4.82 (min: 0, max: 21.52, SD: 4.12)
G	11 AM: 0.27 (min: 0, max: 2.45, SD: 0.49) 2 PM: 0.12 (min: 0, max: 2.37, SD: 0.31)	10 AM: 0.4 (min: 0, max: 3.05, SD: 0.61)	11 AM: 0.39 (min: 0, max: 3.31, SD: 0.61)
Client	**12 PM**	**1 PM**	**2 PM**
A	12 PM: 54.1 (min: 0, max: 890.53, SD: 124.07)	1 PM: 56.61 (min: 0, max: 1,016.59, SD: 132.82)	2 PM: 61.95 (min: 0, max: 1,012.74, SD: 144.04)
B	12 PM: 25.4 (min: 0.11, max: 618.24, SD: 87.26)	1 PM: 31.42 (min: 0.1, max: 787.51, SD: 108.78)	2 PM: 36.65 (min: 0.1, max: 785.04, SD: 115.68)
C	12 PM: 20.46 (min: 0, max: 278.31, SD: 47.82)	1 PM: 21.3 (min: 0, max: 281.18, SD: 48.33)	2 PM: 22.05 (min: 0, max: 278.41, SD: 48.19)
D	12 PM: 10.91 (min: 0, max: 186.22, SD: 16.59)	1 PM: 13.26 (min: 0, max: 500.44, SD: 34.02)	2 PM: 17.6 (min: 0, max: 610.93, SD: 52.53)
E	12 PM: 8.47 (min: 0, max: 176.53, SD: 14.62)	1 PM: 9.35 (min: 0, max: 238.07, SD: 20.6)	2 PM: 13.45 (min: 0, max: 659.17, SD: 56.25)
F	12 PM: 4.85 (min: 0, max: 22.25, SD: 4.15)	1 PM: 4.88 (min: 0, max: 23.05, SD: 4.2)	2 PM: 4.91 (min: 0, max: 22.23, SD: 4.22)
G	12 PM: 0.4 (min: 0, max: 3.4, SD: 0.61)	1 PM: 0.4 (min: 0, max: 3.15, SD: 0.61)	2 PM: 0.39 (min: 0, max: 2.99, SD: 0.6)