

UNIVERSITY OF TWENTE

MASTER THESIS

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**Dynamic RTI repositioning  
with IoT technology**

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for the degree of Master of Science in*

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*I hope you enjoy reading my thesis!*

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## Management Summary

Returnable Transport Items (RTIs) are load carriers on which products are loaded for efficient and practical transport between supplier and consumer. RTIs play a role in both the forward and the reverse logistics of a supply chain. Reverse logistics, however, are often overlooked as a trivial part of the supply chain. As such, RTIs are subject to long idle periods where they can not contribute to the value-adding activities of a supply chain. In this study, we investigate how to improve RTI management in the horticultural industry. More specifically, we address how the utilization of RTIs can be increased by strategically repositioning RTIs within the supply chain, answering to the dynamic demand of the supply chain. Our research topic is titled

*In what way and to what extent can dynamic RTI repositioning improve the efficiency of RTI logistics?*

Consider a supply chain network with multiple users and a single depot, the latter serving as a central empty RTI storage location. Each day, some users have products that need to be transported to other users. As part of the forward logistics, these products are loaded on RTIs such that the filled RTIs can flow between users in the supply chain. To fulfill product demand, the origin users require an inventory of empty RTIs, which they can then load products on. Similarly, the destination locations unload products from the received RTIs but are left with an inventory of empty RTIs they might not necessarily require. The reverse logistics are concerned with the recollection of unused empty RTI and the reintroduction of these empty RTI back to where they are needed. In such a supply chain network, the management of RTIs dictates how RTIs are distributed to those who need them and collected from those who do not. Both the forward logistics and the reverse logistics are based on pickup and delivery requests, where routes must be created to efficiently pick up filled or empty RTIs and deliver them to another location. The complexity lies in the fact that both forward and reverse logistics must be executed in the same routes. Coincidentally, the empty RTI inventory of all locations must also be managed.

Under the current RTI management, the concept of RTI trading addresses the PDIRP: when filled RTIs are picked from a user an equal number of empty RTIs are delivered, and when filled RTI are delivered to a user an equal number of empty RTIs is picked. The delivered empty RTIs originate from the depot, whereas the picked empty RTI are destined to the depot. In this study, we introduce a forecast-based RTI management that implements RTI repositioning. RTI repositioning consists of picking empty RTI from a user that does not require them and transporting them to a user that might, thus repositioning an RTI from one user's inventory to another. By directly repositioning RTIs from one user to the next, RTIs do not need to be brought back to the depot, omitting a day of depot storage as well as the handling of RTI within this depot. To analyze the potential of RTI repositioning, we propose four types of reverse RTI strategies:

- Pure depot delivery: a strategy where all reverse logistics are performed by delivering empty RTIs from the depot. This strategy is considered as the current RTI management and used as a baseline to compare the other strategies.
- Pure RTI repositioning: a strategy where all reverse logistics are performed by repositioning empty RTIs between users. In this strategy, no empty RTIs are delivered from the depot except for emergency deliveries.
- Semi-hybrid: this strategy mainly implements RTI repositioning, but also performs depot deliveries for users that require RTIs on a short-term.
- Fully hybrid: this strategy implements both RTI repositioning and depot deliveries, prioritizing RTI repositioning as long as RTIs are available to be repositioned.

Reverse RTI strategy	Pure RTI Repositioning	Semi-hybrid	Fully hybrid
<b>Required RTIs</b>	-21.66%	-13.45%	-19.59%
<b>Kilometers driven</b>	0.40%	0.96%	-0.90%
<b>Depot activity</b>	-91.86%	-82.87%	-59.65%
<b>Emergency deliveries</b>	26.52%	-52.04%	-35.71%

TABLE 1: Relative average performance of each reverse RTI strategy compared to pure depot delivery strategy

The sequential model relies on forecasts of expected empty RTI inventories to identify the supply and demand of empty RTI in the supply chain. A series of hyper-parameters define amongst others the length of the short-term and long-term planning horizon, as well as the picking forecasting horizon. Respectively, these hyper-parameters determine the short-term and long-term empty RTI demand of all users or their empty RTI supply that is available for picking. Through the Hierarchical Knowledge Gradient algorithm, the values for these hyper-parameters are optimized. With the proposed model, we extend the available literature by incorporating multiple pickup and delivery routing structures in a single solution. Forward logistics are based on a 1-1 routing structure. The reverse logistics' routing structure depends on the adopted reverse RTI strategy: the pure depot delivery strategy has a 1-M-1 routing structure, the pure RTI repositioning strategy has an M-M routing structure, and the hybrid methods consist of a combination of both.

In our experimentation, we find that all strategies with RTI repositioning (pure, semi-hybrid, or fully hybrid) result in improved RTI utilization. In Table 1, most performance indicators show a decrease compared to the pure depot delivery strategy. The strategies with RTI repositioning show a significant reduction in the total number of RTIs required whilst barely introducing additional distances driven. These strategies also reduce the total activity within the depot. The pure depot delivery does increase the total number of emergency deliveries due to the limited options with which this strategy can perform reverse logistics. The hybrid strategies, on the other hand, significantly fewer emergency deliveries. Total costs are based on the weighted sum of the total RTI renting costs, the forward and reverse logistics distance costs, the depot activity costs, and the emergency delivery costs. Weights are defined within a specific region in discussion with COMPANY B. Based on the observed KPIs score and least favorable weight values, strategies with RTI repositioning always result in a reduction of costs and thus an increase in efficiency when compared to the pure depot delivery strategy. Specifically, the semi-hybrid strategy shows the most promising results: with a 95% confidence interval, an increase in efficiency between 10.04% and 20.78% is observed. For each instance, the average increase in efficiency is 11.69%, 18.46%, and 16.74% respectively.

Based on this observation, we conclude that RTI repositioning increases the efficiency of RTI logistics. However, RTI repositioning must be considered along with depot deliveries. Costs can significantly be reduced by renting less RTI and requiring fewer handling activities at the dept. Additionally, inventory reliability is increased by minimizing the number of emergency deliveries.

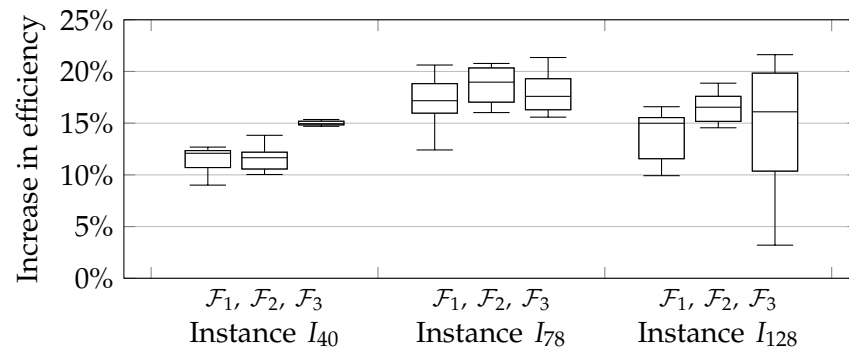


FIGURE 1: Increase in efficiency of the pure RTI repositioning strategy ( $\mathcal{F}_1$ ), the semi-hybrid strategy ( $\mathcal{F}_2$ ) and the fully hybrid strategy ( $\mathcal{F}_3$ ) compared to the depot only strategy.





# List of Definitions

- **Returnable Transport Items (RTI):** Reusable load carriers used for moving or transporting goods. Within the horticultural industry, CC-containers (CC) and Auction Trolleys (AT) are generally used.
- **Forward Logistics:** Forward Logistics are used to manage the forward movement of goods from raw materials to the consumer.
- **Reverse Logistics:** Reverse Logistics are those used to manage the 'reverse' movement of goods, from the end user to the manufacturer.
- **User :** A party in the supply chain that uses RTIs for their forward logistics.
- **Logistical Service Provider (LSP):** The party charged with all logistics in the supply chain.
- **Forward RTI flows:** All transport flows aimed at transporting filled RTI between users.
- **Reverse RTI flows:** All transport flows aimed at transporting empty RTI between users and the depot.
- **Depot deliveries:** Reverse RTI flow charged with delivering empty RTI from the depot to a user.
- **Depot returns:** Reverse RTI flow charged with delivering empty RTI from a user to the depot.
- **RTI Repositioning:** Reverse RTI flow charged with reallocation empty RTIs between users.
- **One-to-One (1-1):** Pickup and delivery routing structure in which each commodity has a single pickup location and a single delivery location.
- **One-to-Many-to-One (1-M-1):** Pickup and delivery routing structure in which commodities are picked at the depot, to be delivered at customer locations or, alternatively, the customers might have commodities that must be picked and delivered at the depot.
- **Many-to-Many (M-M):** Pickup and Delivery routing structure in which commodities are picked at the depot, to be delivered at customer locations or, alternatively, the customers might have commodities that must be picked and delivered at the depot.
- **Reverse RTI strategy:** Set of reverse flow hyper-parameters that define a specific type of RTI management.
- **Reverse flow hyper-parameter:** Hyper-parameter defining which reverse RTI flows may be used in a simulation.
- **Forecasting horizon hyper-parameter:** Hyper-parameter defining the length of a forecasting parameter



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## Chapter 1

# Research Proposal

Over the years, the logistics industry has been transitioning towards sustainable processes. This has led to the appearance of closed-loop supply chains, and the elimination of single-way packaging. As a sustainable alternative, the industry has seen the rise of Returnable Transport Items (RTIs). RTIs allow for better transportation and storage of various products. Well-known examples of RTIs are pallets and crates. Reverse logistics, charged with recuperating used RTIs for a new cycle, present the supply chain with new challenges. In this research, we analyse improvements in the closed-loop supply chain of the Horticultural industry. More specifically, we investigate the potential of RTI repositioning in a Pick-up & Delivery Inventory Routing Problem (PDIRP). In this chapter, we present our research design. In Section 1.1, we introduce the host institution of this research. In Section 1.2, we give a glimpse of the supply chain around RTIs. In Section 1.3, we present the horticultural industry and the involved stakeholders. In Section 1.4, the research design is presented.

### 1.1 Host institution

The research is hosted by COMPANY A, a start-up company located in Venlo, The Netherlands. With “Stay Curious” as their motto, COMPANY A develops new logistics technologies. With their experience in the logistics industry and awareness of what could be improved, they collaborate with various parties around the Netherlands to modernize the industry.

Some examples of COMPANY A’s products include Brightsite and Rail-easy. Brightsite is designed to monitor and predict conditions in controlled atmosphere warehouses. Based on live data from COMPANY A sensors combined with historic and external data, Brightsite alarms when the conditions reach early warning levels and enable the user to take action. Within Rail-easy, smart IoT sensors provide live insight into the traffic on specific railway tracks or rail yards. Additional features increase the safety on site with monitoring of switches and predictive maintenance of railway wagons. A third type of products offered by COMPANY A is encompassed under Smart Packaging solutions, where all types of product packaging are modernized. This research is involved with a specific product within the Smart Packaging solutions: the PRODUCT X system. PRODUCT X is a system that provides autonomous RTI management and end-to-end RTI visibility. The RTI itself tells the system where and in which conditions it is, based on which the system calculates rent, predicts when it will be empty or plan transport in the most cost-efficient and sustainable way.

### 1.2 RTI Logistics

In this section, the general logistics around RTIs are introduced. A more thorough analysis of the RTI supply chain is provided in Chapter 2. We start with an introduction of the origin of RTIs, and their function. Next, we describe the supply chain in which RTIs are used, along with the different actors in this supply chain.

### 1.2.1 Returnable Transport Items

Increased attention to the environmental impact of industrial activities has given birth to the concept of closed-loop supply chain (Iassinovskaia et al., 2017). A closed-loop supply chain refers to all forwards logistics, as well as the reverse logistics (Raj Kumer and Satheesh Kumar, 2013). As defined by Pival (2019), Forward Logistics are used to manage the forward movement of goods from raw materials to the consumer, and Reverse Logistics are those used to manage the 'reverse' movement of goods, from the end-user to the manufacturer. Besides the collection of used products and recyclable waste, packaging is also part of the reverse movement within Reverse Logistics. In operations management, product packaging is organized at a primary, secondary, and tertiary level. The primary package is in direct contact with the contents, whose structural design also serve to differentiate products. The secondary package is used to group primary packages (and their contents) together, and also relates to the issues of visual communication. Finally, the tertiary package is used for warehouse storage, transport and shipping (Regattieri and Santarelli, 2013). Primary packaging is generally used as single-way packaging, whereas secondary and tertiary packaging can be used as both single-way and returnable packaging. Early research has shown that the usage of returnable packaging has more environmental and logistics benefits as opposed to using single-way packaging, such as cardboard boxes (Kroon and Vrijens, 1995). Returnable packaging falls under the more general term Returnable Packaging Items, and are used for moving or transporting goods (GS1, n.d.). Alternative expressions for Returnable Transport Items are any combination based of Returnable/Reusable Transport/Logistical Items/Packaging (Iassinovskaia et al., 2017). For the sake of consistency, the term Returnable Transport Items (RTI) will be used throughout.

### 1.2.2 Transportation Logistics

An RTI closed-loop supply chain is a supply chain where RTIs are used for shipping products along different stages of the chain (Glock, 2017). Ownership of RTIs remains with a single party, whilst being rented out to the logistics service providers in the supply chain. Various authors have provided a general description of the closed-loop supply chain. Using the descriptions of Glock (2017), Ilic et al. (2009) and LogicaCMG (2003), the supply chain can be represented as in Figure 1.1. In this representation, a distinction is made between the Operator Domain and the User Domain. The first domain consists of all parties that are charged with RTI operations such as RTI supply and transport. The User Domain consists of the parties by which RTIs are required for their forward logistics.

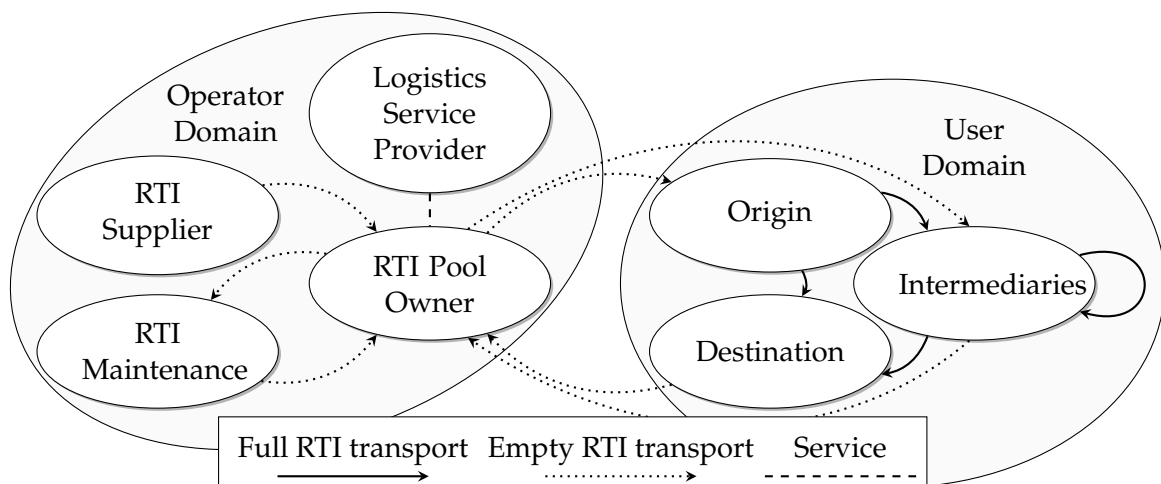


FIGURE 1.1: Representation of the RTI closed-loop supply chain



The Operator Domain consists of suppliers, maintenance, a Pool Owner and Logistics Service Providers (LSPs). These parties will be addressed as ‘Operators’. Suppliers are responsible for the supply of RTIs. They sell them to the Pool Owner, who manages an RTI pool and make them available to the remainder of the supply chain. LSPs rent RTIs from the Pool Owner to perform the logistic processes (e.g., transport, storage, handling). Multiple LSPs can collaborate with a Pool Owner, and each is responsible for a non-exclusive User Domain. Sometimes, an actor is both Pool Owner and LSP. Maintenance is charged with the repair of RTIs. RTI ownership remains at the RTI Pool Owner at all time. They rent the RTIs to the LSP, which is responsible for the flow of RTIs within the user domain.

The User Domain consists of all parties that require RTIs to have their products transported. It includes manufacturers, distribution centres (DCs), retailers and various other types of parties. They will be referred to as ‘Users’. Upon request, empty RTIs are transported to an origin location, which fills the RTI with their produce. Filled RTIs are pick-up and transported to the destination. Occasionally, the RTIs also pass through various intermediate locations, where intermediate operations are performed. Once RTIs are unloaded at their destination, thus ending the produce’s forward logistics, they are collected and returned to the Pool Owner.

How RTI flows between users and the operator domain are managed depends on the RTI control strategy in use. Glock and Kim (2014) differentiates between three types of RTI control strategies: a switch-pool system, a transfer system and a depot system. In the switch-pool system, all users are allocated a portion of all RTIs in circulation. With every pickup and delivery, RTIs are switched: upon delivery of filled RTIs, the receiving locations traded an equal number of RTIs to be returned to the origin location. In the transfer system, each origin location is responsible for tracking, administering, maintaining and storing RTIs. In the depot system, origin locations are provided RTIs from the depot and RTIs are recollected at the end of the forward supply chain. The latter RTI control strategy is most common in larger closer-loop supply chain, such as the one addressed in this study.

As mentioned, the LSP is responsible for the flow of RTIs within the user domain. They ensure all forward and reverse logistics are executed. In this type of supply chain, the LSP uses a central RTI storage for RTIs not used by the user domain: an RTI depot. We differentiate between three types of RTI flow organized by the LSP: the forward RTI flow, the depot delivery flow and the depot return flow. The forward RTI flow consists of all RTI that all transported to fulfill the forward logistics between users. The depot delivery flow consists of all empty RTI being introduced in the user domain from the RTI depot. The depot return flow consists of all RTIs collected at the end of their forward flow, to be returned to the RTI depot.

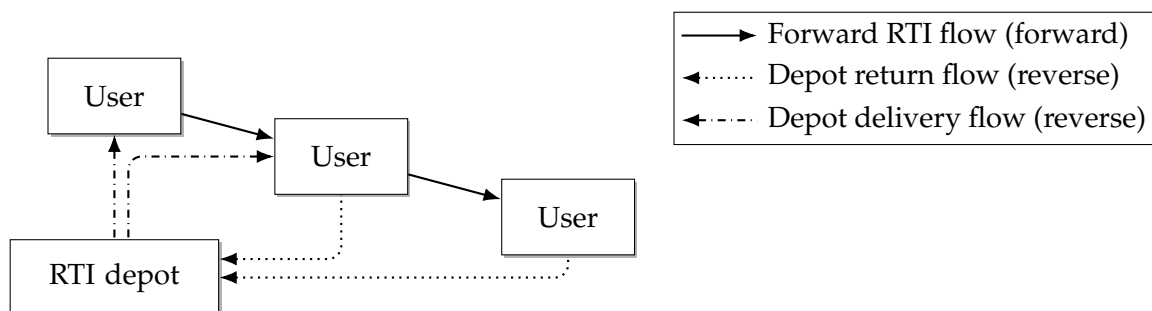


FIGURE 1.2: Types of forward logistics and reverse logistics RTI flows

### 1.3 Context & Stakeholders

In the previous section, we introduced RTI logistics. Different parties in the supply chain were briefly described. In this section, we introduce the research context. Next, we introduce the

various stakeholders, along with their roles within the supply chain. Finally, we dive into the problems currently experienced.

### 1.3.1 Context

In this research, we perform a case study within the horticultural industry. Even after the impact of the global pandemic, this industry remains the largest export industry of the Netherlands, representing 9.5 billion euros in 2020 (1.2% GDP) (CBS, 2021). Multiple parties play a role in the Dutch horticultural industry. A well-known name is that of Royal FloraHolland, the largest flower auction in the world with a turnover of 4.7 billion euros in 2020. This research is limited to the market of COMPANY B (presented in the next section). Generally, two types of RTIs are used: Auction Trolleys and CC-Containers. The horticultural industry is unique due to its strong seasonality. A large majority of all sales are done in high season, between March and May. The remainder of the year is considered low season. Industry-specific RTI characteristics will further be described in Chapter 2.

### 1.3.2 Stakeholders

The Operator Domain consists of COMPANY C and COMPANY B. COMPANY C is the RTI Pool Owner within this Supply Chain and the owner of the so-called ‘COMPANY C Pool System’, the largest RTI pooling system in both the European and Northern-American horticulture industry. Their closed-loop supply chain is organized with various LSPs, amongst which COMPANY B (referred to as COMPANY B). COMPANY B closely collaborates with the Pool Owner. Besides the pick-up and delivery of empty RTIs, they are also responsible for the transport of filled RTIs. Within their fleet, COMPANY B works with numerous trucks and three central depots, respectively located in Venlo, The Netherlands and Kevelaer, Germany. Both these depots serve as a central storage location for RTIs provided by the COMPANY C. RTI supply and maintenance are performed by external parties.

The User Domain consists of various nurseries, plant & flower auction halls and retailers. They are located throughout the Netherlands, Germany and Belgium. Nurseries are flower, plant and tree growers. They require RTIs to transport their produce to retailers or follow-up nurseries. The latter term refers to nurseries that cultivate plants after an initial growth phase in another nursery: some plants have multiple specialized growing stages, performed by various specialized nurseries. While on their way to their destination, some RTIs pass through auction halls. Auction halls serve as a marketplace where potential buyers (e.g., retailers) can bid on various produce. Finally, upon arrival at their final destination, produce are unloaded by the receiving location. After a specific time, RTIs are empty and ready for collection once again, ending the RTI cycle.

### 1.3.3 Current RTI management

COMPANY B functions according to a depot system with switch-pool characteristics. Although depots serve as RTI storage locations, an RTI trading practice is in place in which empty RTIs are traded for filled RTIs at each pickup and delivery. Every user is allocated an RTI balance which is kept at a constant levels as much as possible. This process reduces transport for delivery and pickup of empty RTIs only (trips are combined with forward logistics trips), and simplifies administration as a user’s RTI balance is kept unchanged as much as possible. By minimizing the risk of human administrative errors, missing RTIs are more easily detected in case of an imbalance between administrative and physical RTI inventory. Under this current RTI management, COMPANY B observes high costs which results from a high RTI loss rate and high renting costs.

Although RTI loss is prevented through the current RTI management system, it is still accounts for a lot of costs. Up to 11.7% of all RTIs are lost on a yearly basis within COMPANY C pool. (C, 2020). Loss of RTIs is mainly caused by a lack of RTI visibility, i.e., the awareness of RTI locations. Within the horticultural industry, passive RFID tracking is widely applied. Elaborated on in Section 2.2.2, passive tracking requires manual labour which is subject to human errors. COMPANY B rents their RTIs from COMPANY C, which are then used by users in the pool through a service agreement. COMPANY B remains, however, responsible for all costs of lost RTIs. COMPANY B's service agreement with RTI users excludes renting costs, which are thus paid in full by COMPANY B. Although renting costs are factored in some form within the service agreement, users observe no consequence for large RTI inventories. An argument in defense of such a system is that RTI trading should not result in financial consequences for users: RTI trading is used to improve COMPANY B's RTI management and should not require unfavorable consequences for the users. As a result, however, RTIs remain idle for longer period of time which reduces RTI utilization. Additionally, all RTIs are returned to the depot at the end of a forward logistics cycle. As RTIs remain in the depot at least for a time, idle time is further increase resulting in a decrease of utilization.

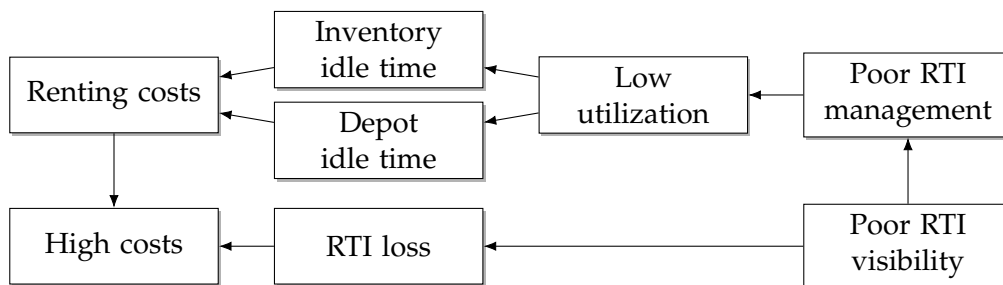


FIGURE 1.3: Problem cluster

Loss of RTIs is direct consequence for a lack of RTI visibility. High renting costs, on the other hand, follow from poor RTI management. Currently, however, improving RTI management is operationally difficult due to this poor RTI visibility: better management requires a better information stream of where RTIs are located. The core problem is thus defined as

*Poor RTI management and poor RTI visibility results in high costs caused by a high RTI loss-rate and low RTI utilization.*

Through COMPANY A' PRODUCT X system, RTI visibility can be improved. Their system relies on active RTI tracking which, in turns, allows for further improvements in RTI management. In this study, we focus on improving RTI management. Specifically, we research how the practice of RTI repositioning can improve RTI utilization and reduce RTI related costs.

## 1.4 Research description

The goal of COMPANY A' PRODUCT X system is to design an autonomous IoT RTI system. Digitally connected RTIs provide live locational information, handled by a central intelligence. The latter autonomously forecasts various logistic events, according to which an optimized planning is designed. Additionally, various logistics improvements can be implemented. Such an implementation can solve the addressed core problem. RTI visibility, RTI repositioning and RTI supply and demand forecast are possibilities to address the core problem; they are currently absent in the supply chain.

### 1.4.1 RTI repositioning

RTI repositioning consists of reallocating empty RTI inventory directly between users. In Figure 1.4, we extend the prior Figure 1.2 to include repositioning flows. Repositioning flows allow RTI to be reused without passing through the depot, reducing idle time by at least a day. Repositioning, in this study, is therefore defined as the pickup and delivery of empty RTI between users. Besides from the efficient allocation of RTIs, RTI repositioning should also consider the operational effects on routing and, more importantly, the trade-off between a better RTI utilization and potential added costs due to transport.

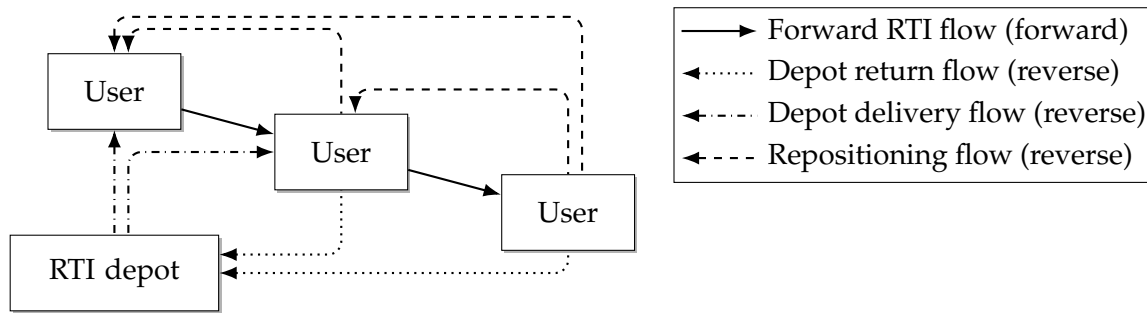


FIGURE 1.4: Types of forward logistics and reverse logistics RTI flows

### 1.4.2 Scope of research

An effective implementation of RTI repositioning requires both accurate RTI visibility and forecast of RTI needs. In this study, COMPANY A's PRODUCT X system is considered implemented, allowing for full RTI visibility. Additionally, we estimate forecasts based on historical data provided by COMPANY B, but do not elaborate on forecasting methods. Rather, the scope of the research is to analyse how RTI visibility and RTI forecasts are used to implement a dynamic RTI repositioning system.

Dynamic RTI repositioning is the process of proactively repositioning RTIs whilst in an RTI cycle: instead of returning an RTI to the depot at the end of the cycle, a new, closer-by, user might require the RTI, preventing excessive transport. Given non-deterministic pick-up and delivery requests, effective proactive repositioning requires accurate RTI requirement forecasts. A repositioning system processes these forecasts into a dynamic RTI planning: not only should it consider what to do with today's RTIs, but it should think days ahead. Live data, obtained through RTI visibility, present clear inventory information, but might also enable a feedback loop to further improve forecasts for future extensions of the PRODUCT X system.

During this research, we analyse the benefits of the operational implementation of dynamic RTI repositioning in the current supply chain. Therefore, the strategic and tactical decisions, such as the number of trucks available in depots, are left out of scope. We will also restrict ourselves to the supply chain organized by COMPANY C & COMPANY B, which is classified as a Pick-up and Delivery Inventory Routing Problem (PDIRP) (Iassinovskaia et al., 2017).

### 1.4.3 Research design

In the research scope, dynamic RTI repositioning is proposed as a solution for the core problem. Accordingly, this research will investigate how to implement such a system, and analyse its potential. Meanwhile, considerations are kept for the desire for eventual real-world implementation in the PRODUCT X system. As such, we define the following research question:

*In what way and to what extent can dynamic RTI repositioning improve the efficiency of RTI logistics?*

To support this research question, we define a few sub-questions that contribute to the answer. First, the current supply chain needs to be analysed further. A better understanding of the supply chain is necessary to chart the decision-making method currently employed. This representation will serve as a baseline to recreate the current situation. Although partially answered in the current chapter, Chapter 2 fully addresses the following question:

1. What operational decision-making methods are currently used by the RTI Operator Domain to organize RTI transport, and what is their effect on the supply chain's performance?

Next, we investigate insights literature has to offer. In Chapter 3, we research existing methods and applications for dynamic RTI repositioning. To do so, we break the literature review down into three sections. First, we investigate PDIRP studies in general. We also research repositioning in routing problems. Extending on our literature, we also investigate parameter tuning methods.

2. What insights can literature offer on PDIRP problems, and which methods have been used to address these problems?
3. How are routing problems with repositioning requirements addressed, according to literature?
4. Which methods have been used to tune parametric algorithms in similar problem settings?

In Chapter 4, we define our solution approach. With insights from the previous sub-questions, a method is proposed that integrated RTI repositioning in the supply chain. In Chapter 5, we define an experimentation strategy and discuss its results and sensitivity. Whilst answering the following sub-questions, we keep in mind the required characteristics for an eventual implementation:

5. How can dynamic RTI repositioning be implemented in the analysed horticultural supply chain?
6. To what extent does an autonomous dynamic RTI repositioning system improve the analysed horticultural supply chain?

The solution design in Chapter 4 and results in Chapter 5 serve as a proof of concept for the PRODUCT X system. In Chapter 6, we provide our conclusion and recommendations. Additionally, we reflect on the potential steps required for full implementation of the system in a near future, given the technologies currently available at COMPANY A:

7. How can an autonomous dynamic RTI repositioning system be implemented in a real-world situation?

#### 1.4.4 Deliverables

Deliverables for this research consist of a Proof of Concept for an autonomous dynamic RTI repositioning system. Along with a proposal for the implementation of such a system in the PRODUCT X system will be delivered.

#### 1.4.5 Research design

This research will be conducted using an analytical model, in which the supply chain is replicated. We use the analytical model to perform an analysis of the baseline scenario and the various proposed solutions. In this analytical model, we can assume full implementation

of the PRODUCT X system, providing the necessary RTI visibility. To obtain the necessary knowledge to replicate the supply chain, a thorough analysis of the RTI supply chain is performed. Information is found in literature, electronic sources and information provided by COMPANY B. The latter has provided a data set of all transportation orders in 2020, which allows for the design of various scenarios. The baseline is created by translating the current pick-up and delivery practices into methods that can be implemented analytically. To design dynamic RTI repositioning solutions, literature research is performed. From the literature, we seek insights to design an algorithm that uses RTI visibility and empty RTI supply and demand forecasts. These forecasts are used for effective proactive RTI repositioning. The whole will be implemented in an algorithm that, trained against the provided data set, will arrange filled RTI transport & empty RTI repositioning. To conclude, various instances and solution methods are run in the analytical model. Numerical outputs will be analysed to make comparisons and analyse the sensitivity of the solutions. Finally, conclusions are drawn based on the data, and final advice regarding the implementation of dynamic RTI repositioning is given.

## Chapter 2

# Current RTI management

In the previous chapter, we introduced what Returnable Transport Items are, how they are used and which parties are generally involved in their management. In this chapter, we elaborate on the characteristics of RTIs within the analysed RTI pool. In Section 2.1, we shortly summarize the information provided in Chapter 1. In Section 2.2, we address the specifics of RTIs within the horticultural industry, as well as the current RTI management by COMPANY B. In Section 2.3, we provide a theoretical numerical example to substantiate the potential of RTI repositioning.

## 2.1 Summary

In the previous chapter, we broadly introduced the logistics around Returnable Transport Items: RTIs serve as load carriers to efficiently transport produce from origin to destination. RTIs are designed to practically carry multiple products and facilitate more efficient loading and unloading from transport vehicles. RTIs are used by parties in the so-called User Domain, but owned and managed by parties in the Operator Domain. The user domain consists of all those who require RTIs for the transport of their products. This includes both the product suppliers as well as the product receivers and users providing intermediate value-adding activities. The Operator Domain consists of multiple parties. The Pool Owner is the owner of the RTI pool. They rent out the RTIs to the user domain. Often, a Logistics Service Provider (LSP) is charged with the logistics within the user domain. They ensure RTIs are made available to the user domain and are charged with transport and (empty) RTI storage.

Within RTI logistics, a distinction is made between forward logistics and reverse logistics. Forward logistics consists of all activities that manage the forward movement of goods, from raw materials to consumers. Reverse logistics consists of all activities that manage the reverse movement of goods, from the consumer back to the manufacturer (Pival, 2019). With the management of RTIs, forward logistics consist of all activities that ensure loaded RTIs flow between an origin location to a final destination. Reverse logistics concern all activities that ensure RTIs are recollected at the end of the forward flow and made available again within the user domain. Sometimes, the reverse logistics process might include temporary storage or cleaning and repair of RTIs. The forward and reverse logistics are materialized by flows of RTI, indicating between which locations RTI may flow, as shown in Figure 1.4.

## 2.2 Horticulture Pool

As introduced in Section 1.3.1, this study is performed in the context of a horticultural supply chain. In Section 1.3.2, the parties in the operator and user domain are briefly introduced. In this section, we further elaborate on their supply chain organization.

### 2.2.1 Used RTI

Let us first elaborate on the types of RTI used in the COMPANY C's RTI pool. Two RTI types are introduced: Auction Trolleys (AT) and CC-Containers (CC). Auction Trolleys and CC-Containers are specialized RTIs used exclusively in the horticultural industry. Auction Trolleys are typically used in auction halls, such as Royal FloraHolland, due to their convenient transport on-site. For remaining transport, CCs are used. They are the preferred RTI as they are very modular, can transport plants of almost any shape and size and are practical to handle during transport and distribution. Both AT and CC are practical due to their modularity. In the appendices, Figure A.1 shows both RTI types, filled and empty and Table A.1 names the modular components.

Both RTI types are often transported together. Their modular nature and standardized sizes ensure that transporting a mix of RTIs is straightforward. In Figure A.2, three trucks load are shown. Although RTIs occupy a two-dimensional surface in a truck, the load can conveniently be approximated in a one-dimensional measure: *RTI meters*. The amount of RTI meters an RTI requires depends on the type and the load: CCs are smaller than ATs and, since both are modular, they can be deconstructed to occupy less volume when empty. A generic truck has a capacity of 13.2 RTI meters. The RTI-meter requirements for RTIs are summarized in Table 2.1. Since empty RTIs can be stacked, they occupy space in batches. As such, a single empty CC requires the same amount of RTI-meters as 10, hence the maximum of 280 empty CC.

	CC filled	empty	AT filled	empty
RTI-meters	0.306	0.0459	0.586	0.293
Batch size	1	10	1	2
Maximum load	13.158	12.852	12.892	12.892
Maximum units	43	280	22	44

TABLE 2.1: AT & CC RTI meter requirements

### 2.2.2 RTI visibility

Although RTIs are used by various parties in the supply chain, COMPANY C remains the owner. As introduced, the loss of RTI results in large costs, and as such COMPANY C requests proper management of RTIs from other parties in the operator domain and user domain. When RTI visibility is coupled with proper managerial actions, RTI investment costs could be reduced by 52% (Johansson and Hellström, 2007).

RTI visibility has improved a lot over the years thanks to new technologies. The first solution consisted of bar-coding every single RTI. More recently, RFID tracking has taken over the industry. RFID tracking consists in equipping every RTI with a Radio-Frequency Identification (RFID) tag, which identifies them upon scanning. Both active and passive RFID tags can be implemented. Active RFID tag signals can autonomously be picked up by readers without much manual activity, but are expensive and require an energy source. Passive RFID tags require manual scanning with electro-magnetic readers but are far less expensive. Passive RFID tracking is widely applied in the horticultural industry. They ensure the authenticity of RTIs, which not only confirms the quality but also ensures the RTI has the correct format to ensure its practical benefits (Section 2.2.1).

Even with these tags, a lot of RTIs are still lost. An unknowing nursery might load their produce in COMPANY C's RTIs when the order will be carried out within another RTI Pool. Alternatively, RTIs might accidentally get swapped for unauthentic RTIs which might only get noticed further down the streams. In their 2020 report, COMPANY C hints towards the



necessity of active RTI tracking in their industry to minimize loss (C, 2020). The PRODUCT X system, proposed by COMPANY A, is such a system. RTIs are autonomously tracked within users' storage locations and upon loading and unloading of RTIs. This project builds on the presence of such a tracking system.

### 2.2.3 User domain

Multiple types of users are involved within the user domain, located throughout the Netherlands, Germany and Belgium. Generally, a horticultural user domain consists of seed breeders, plant nurseries, auction halls and retailers. Seed breeders are specialized in the ennoblement of plant seeds. They form the start of the forward flow: seeds are sold to plant nurseries that cultivate them for the specific ennobled characteristics of the plant. Nurseries consist of all users that grow plants. A nursery often specializes in a specific type of plant in a specific growth stage. Especially for larger plants, such as trees, multiple nurseries with different growth-stage specializations are necessary. When plants are ready for sale, they are sold to retailers in large quantities in auction halls, or sold to said retailers directly. In Figure 2.1, users present in COMPANY B's user domain are plotted. In the long run, we are not specifically interested in the activities of a location (nursery, seed breeder, etc...). Their RTI flow characteristics, on the other hand, show how a location interacts with RTIs. As such, locations are classified by whether they are origin locations, destination locations or both. As their name suggests, origin locations are most commonly the origin of a forward transport flow, such as seed breeders and specific nurseries. Destination locations mostly include retailer stores. As explained, locations can also serve both purposes when they are in the middle of the forward logistics flow. The flow characteristics of a location play a role, as it determines how the reverse logistics should be organised. Reverse logistics are not as black-and-white as one might think: locations might dynamically change from requiring RTIs and providing RTIs.

### 2.2.4 COMPANY B

To organize their transport, COMPANY B uses three central depots, respectively located in Venlo (NL), Herongen (DE) and Lüllingen (DE). The depot in Venlo generally serves as a storage location for empty RTIs, whereas the German two depots also serve as a distribution centre where cross-docking occurs, with the Lüllingen depot being the largest. Transport is handled by a total of 32 trucks, located at one of the three depots.

### 2.2.5 Forward logistics

Each day, users have until midnight to pass their orders for the next day. Although orders consist of products with specific destinations, a transport order will consist of a number of RTIs the products are loaded on. In the industry, full RTIs are generally ordered, which may consist of a variety of plants as long as these originate from the same nursery. Transport orders, consisting of an RTI quantity, are generally sent out by the origin locations, as they are responsible for loading the RTIs. During the night, a team of planners organize the morning's transport activities mostly based on expert judgement: using an interactive map, orders are grouped by origin proximity. While forming groups, orders are removed if the total ordering quantity exceeds the vehicle's capacity, or added if there is still room left. In practice, COMPANY B observes that grouped origins often have close-by destinations. The routing process heavily relies on the expert judgement of drivers: integrated routing solutions are not available in their software. Generally, RTIs are delivered in the reverse order they were picked as. Orders are transported in two shifts during the day: a morning shift and an afternoon shift.

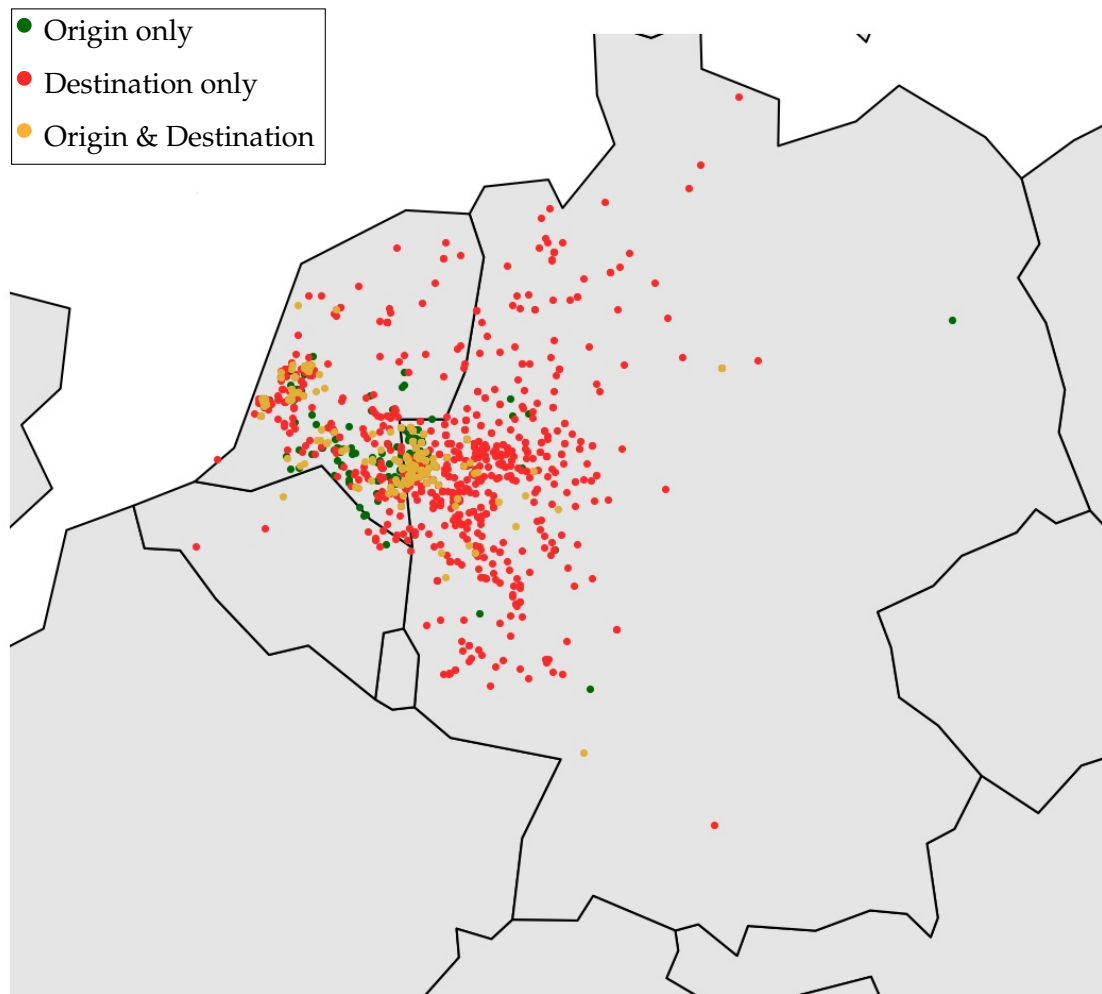


FIGURE 2.1: Plot of all User locations

### 2.2.6 Reverse logistics

Within the user domain, the origin locations of forward logistics transport orders require a stock of empty RTIs to load them. At the end of the forward logistics, filled RTIs are delivered at receiving locations that often have no use for them themselves. The reverse logistics aim at ensuring this asymmetry is corrected. COMPANY B organizes its reverse logistics through the use of an RTI balance. This balance tracks the amount of RTIs a user has at its name. A user can let COMPANY B know what their preferred balance is. To ensure user have their desired amount of RTIs, the concept of *RTI trading* is generally applied.

RTI trading consists of trading empty and full RTIs upon pickup or delivery. When a vehicle departs for their first forward order pickups, they leave the depot with an identical number of empty RTIs. Upon pickup of filled RTI, empty RTIs are directly unloaded. As such, the user's RTI balance is kept stable and his empty RTI inventory is replenished. Upon delivery of forward order, filled RTIs are unloaded and an equal number of empty RTIs are picked. These empty RTIs are then brought back to the depot. During this process, the authenticity of RTIs is checked by scanning the RFID tags.

This trading process is not only meant to ensure users have a desired quantity of empty RTIs. More importantly, this trading procedure ensures that COMPANY B knows where their RTIs are. The reverse logistics process is not coordinated. There are no information streams that track where RTIs are located, except for the RTI balance. By keeping the balance at a constant

level, COMPANY B reduces the chance of (manual) synchronisation mistakes and thus the loss of RTIs, both physically and administratively. Naturally, the dynamics and seasonality of the industry might result in origin locations requiring more (or less) empty RTIs in stock. On their initiative, they can inform COMPANY B of this, after which an empty RTI delivery is scheduled and the user's RTI balance is updated. Similarly, destination locations can request the recollection of empty RTIs.

### 2.2.7 Open-loop and closed-loop

As a point of discussion, we need to indicate the structure of COMPANY C's RTI pool. An RTI pool can be implemented in a *closed loop* supply chain or an *open loop* supply chain. In the context of RTI management, a closed-loop supply chain consists of a pool in which RTIs flow only between the users in this pool. An open-loop supply chain, on the other hand, is also subject to outgoing and incoming flows from external parties. COMPANY C's RTI pool is closed-loop when considering their entire network, spanning all over Western Europe through collaborations with various LSPs. Within this network, COMPANY B only manages a (local) fraction of all users, which we refer to as COMPANY B's local user domain. The horticultural market spans further than a local user domain. Nurseries can produce plants for retailers outside of a local user domain as well. As such, LSPs have overlapping user domains. From COMPANY B's point of view, the RTI pool is therefore considered open-loop. This concept is represented in Figure 2.2a. To remain within the scope of the study, we assume COMPANY B's user domain is closed, as represented in Figure 2.2b. Conceptually, the findings in this study can be extrapolated to COMPANY C's entire RTI pool, as the study regards an operational improvement that can be generally applied throughout their network.

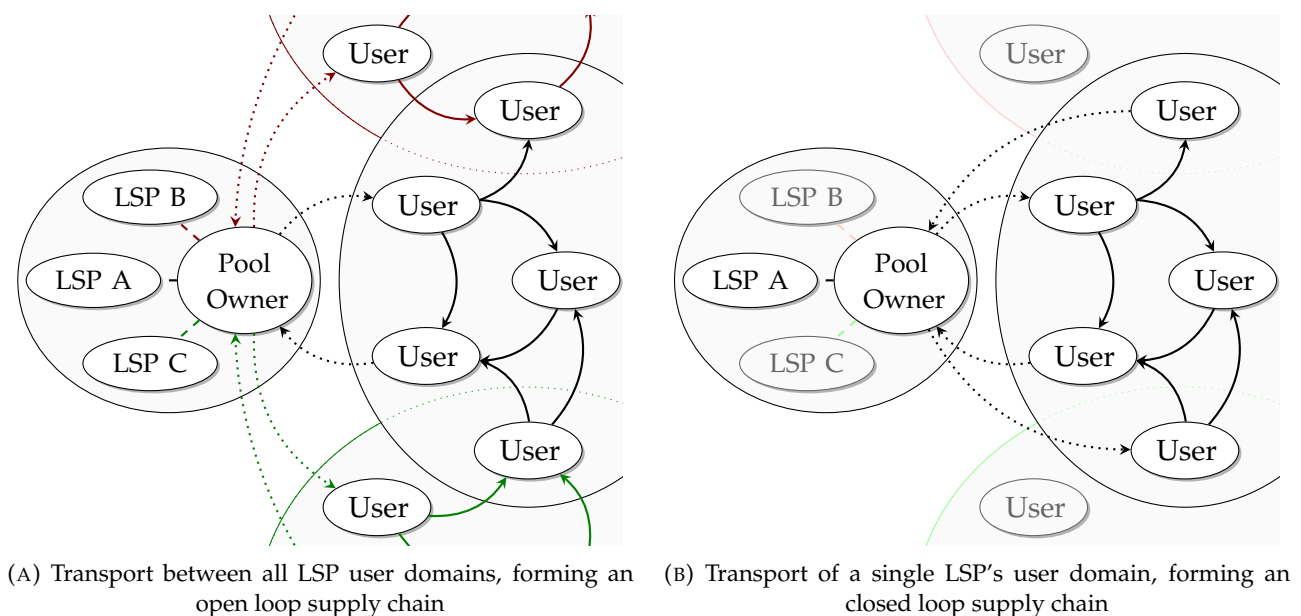


FIGURE 2.2: From an open loop (A) to a closed loop (B) supply chain: all external in- and outbound transport are replaced with empty RTI pickups and deliveries.

### 2.3 Numerical example

Having further introduced the RTI pool, we close the review of the current RTI management by providing a numerical example of its execution, as well as the theorized improvements that follow from RTI repositioning. To this end, considered a small RTI pool with a central depot  $D$ , two nurseries  $A$  &  $B$  and a single retailer  $R$ . In this example, we analyse how the inventory of locations is managed, and how the transport flows are executed.

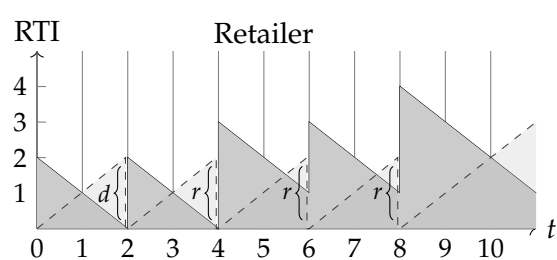
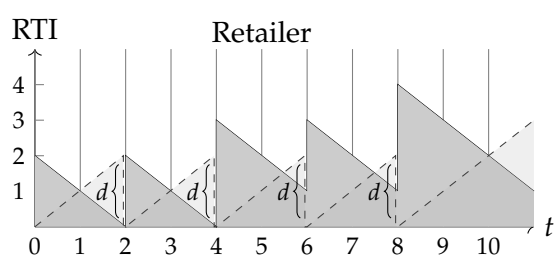
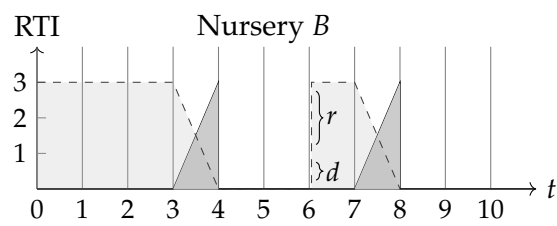
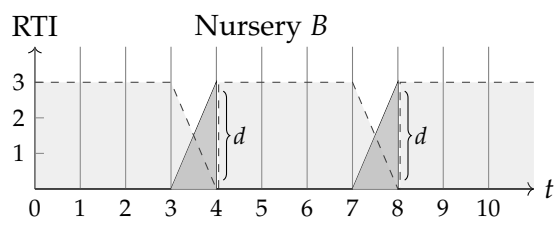
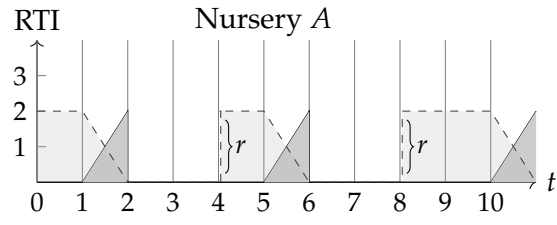
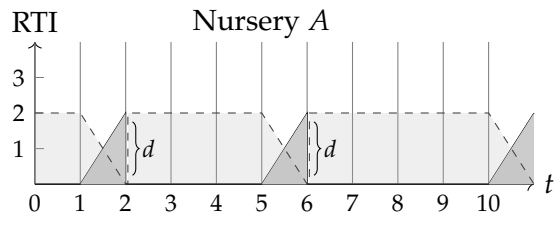
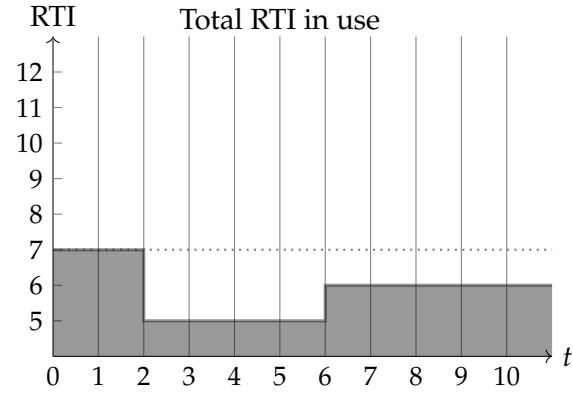
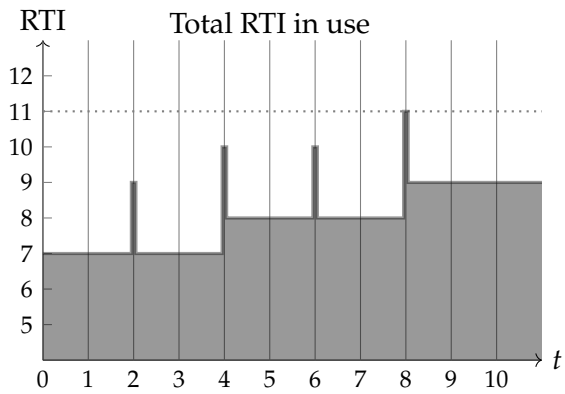
As a short reminder, the supply chain addressed consists of both forward and reverse logistics, with the flow of RTI summarized in Figure 1.4. The forward RTI flows consists of all RTI movement that ensures products loaded on RTI are transported between an origin and a destination. Depot delivery flows ensure that RTI are delivered from the RTI depot to a user, such that the latter can fill the RTI and prepare them for forward transport. Depot return flows consists of the recollection of empty RTI at the end of their forward flows. Finally, repositioning flows consist of the reallocation of RTI between two users. As such, the RTI can be reused directly, omitting a return to the RTI depot and a delivery to a user.

To prepare their orders, the two nurseries fill up empty RTIs they have in storage to prepare them for pickup when an order comes up. This process is assumed to take a single day, regardless of the number of RTIs to prepare. Empty RTIs must be in inventory at the end of the previous day in order for them to be filled. When empty RTIs are filled during a day, they can be picked up the next morning. Filled RTIs are collected and then delivered at the retailer. The retailer slowly unloads the filled RTIs at the rate of one RTI per day. When a filled RTI is unloaded, it is stored as empty and available for reverse logistics flows.

We assume that all locations are equally distant from each other. Each location is characterized by two inventory levels: an inventory of filled RTIs, and an inventory of empty RTIs. The inventory levels fluctuate with each transport order of filled or empty RTIs. The nurseries start with an inventory of 2 and 3 empty RTIs respectively. The RTI are loaded when necessary according to the rate discussed above. The retailer starts with 2 filled RTIs in inventory. These RTI are slowly unloaded at the rates discussed above. The depot inventory (not shown in the figures) is assumed to always be sufficient. Finally, we also keep track of the total number of RTIs in use by the three users (nurseries  $A$  &  $B$  and the retailer). The total number of RTI represents the absolute minimum number of RTI that the logistical service provider must rent from the pool owner. We considered a planning horizon of 10 days. During the planning horizon, we assume four transport orders are planned between the nurseries and the retailer:

- $t = 2$  2 RTIs from  $A \rightarrow R$
- $t = 4$  3 RTIs from  $B \rightarrow R$
- $t = 6$  2 RTIs from  $A \rightarrow R$
- $t = 8$  3 RTIs from  $B \rightarrow R$

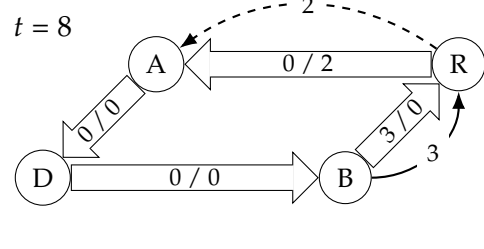
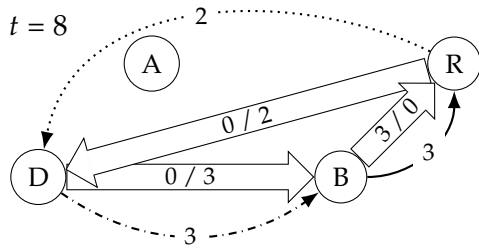
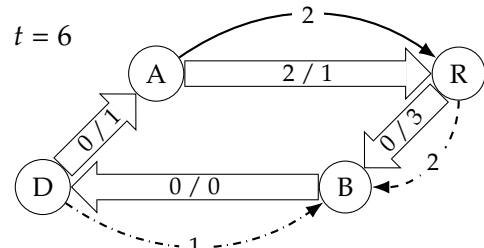
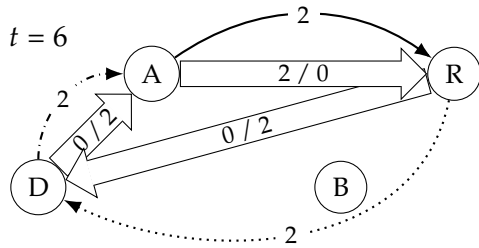
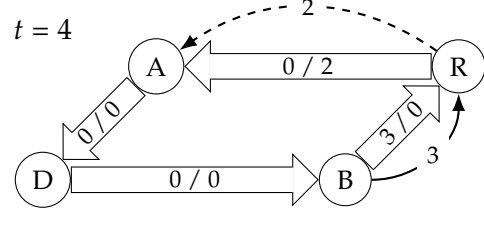
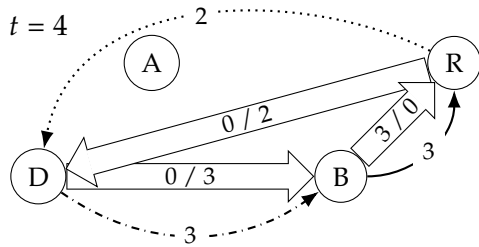
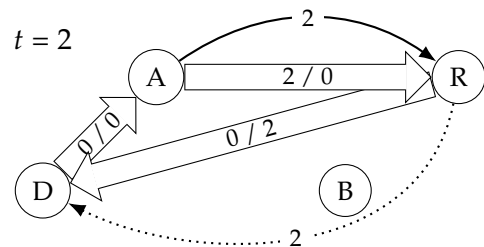
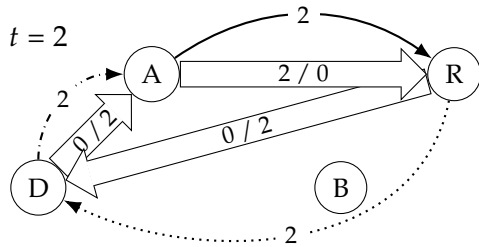
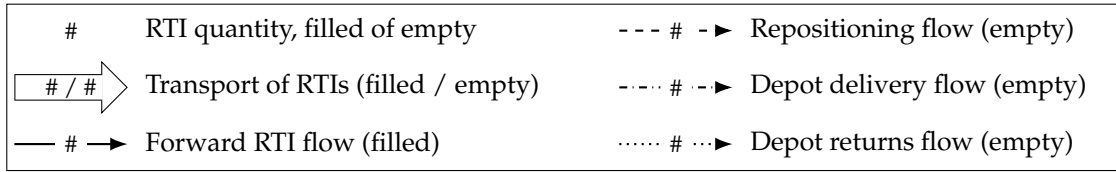
In Figure 2.3a, we indicate how transport is operated under the current RTI management. In this scenario, RTI repositioning is not applied. On days  $t = 2$ ,  $t = 4$ ,  $t = 6$  and  $t = 8$ , a forward transport order is planned. With every order, the concept of RTI trading is applied: if a filled RTI is picked, it is traded for an empty RTI, provided via a depot delivery. Similarly, if a filled RTI is delivered it is traded for an empty RTI, which is returned to the depot. As depot deliveries occur before depot returns, the total RTIs in use see a peak. We can also observe that nurseries almost always have empty RTIs in storage. Figure 2.4a, transport is shown. The transport vehicle departs with a few empty RTIs from the depot, as part of the depot deliveries. It first visits a nursery, delivers the empty RTIs, picks the filled RTIs and continues towards the retailer. Here, filled RTIs are delivered and empty RTI are picked, which are then returned to the depot. Along with the vehicle routes, the flows of RTI according to Figure 1.2 are also indicated.



(A) Without RTI repositioning

(B) With RTI repositioning

FIGURE 2.3: Inventory patterns of the nurseries and the retailer. With each pickup or delivery of empty RTI, the accolade indicates according to which flow it is transported (see Figure 1.2)



(A) Without RTI repositioning

(B) With RTI repositioning

FIGURE 2.4: Transport routes and RTI flows that occur. Only the timestamps with routing are shown (e.g.  $t = 2, 4, 6, 8$ )

In Figure 2.3b and Figure 2.4b, the same forward flows are shown. In this scenario, however, RTIs are repositioned. In this case, Nursery A does not receive a new supply of empty RTIs after its filled RTIs order is picked. Once the order is delivered, the vehicle picks the available empty RTIs and returns them to the depot. In  $t = 4$ , the order from nursery B is picked. Once again, no empty RTIs are delivered from the depot. Upon delivering the order, the available empty RTIs at the retailer are picked. These RTIs, however, are not brought back to the depot but repositioned: they are delivered at nursery A. With one day to spare, nursery A fills the RTIs for the next order. Before picking the order and delivering it, the depot notices that there are only two empty RTIs available for repositioning at the retailer. However, nursery B will (most likely) require three empty RTIs to fulfil their next order. To this end, the vehicle departs from the depot with one empty RTI. Upon picking the order at nursery A and delivering it to the retailer, the vehicle collects the two empty RTIs and repositions them at nursery B along with the additional empty RTIs from the depot. Upon completion of the final order, two RTIs are once again repositioned.

Theoretically, RTI repositioning could reduce the number of RTIs required quite drastically. Without RTI repositioning, a total of 11 RTI would be necessary to execute the planned transport orders, considering also all RTI still in inventory. This can be reduced to 7 by introducing RTI repositioning. The inventory levels at the nurseries are also lowered. As a consequence, however, some additional visits are required at nurseries to deliver repositioned RTI. Without repositioning, the routes have a total length of 12. With repositioning, the total route length is increase to 15.

### 2.3.1 Discussion

As can be observed in this example, a reduction in the number of RTIs can be observed. By reducing the total amount of RTIs necessary, costs can be reduced and the utilization of RTIs increased. RTI repositioning does, however, come at the cost of additional. The example also assumes all future orders are known ahead of time. In practice, orders are known the day before they have to be carried out. As such, RTI repositioning should follow from forecasted information on future orders, which can introduce deviations from reality and could result in additional costs. In the upcoming chapters, we will further research how to design an RTI repositioning method that considers these various aspects.

## 2.4 Conclusion

In this chapter, we further investigate the RTI supply chain. Two types of RTIs are generally used ATs and CCs. These RTIs have a practical nature, especially when it comes to transport: they can efficiently be loaded and unloaded. Additionally, capacity requirements for RTIs can be translated to a one-dimensional measure, RTI-meters, which allows for simple capacity computations. We also present the user and operator domain in further detail. Specifically, we address how COMPANY B manages its forward and reverse logistics. At the end of each day, the forward logistics transport orders are known. Their execution relies on the expertise of both planners and drivers: all routing activities are planned manually. The reverse logistics are largely uncoordinated. An RTI trading system is in place where, upon pickup or delivery of filled RTIs, an equal number of empty RTIs are traded. That is, nurseries receive a new batch of empty RTIs each time filled RTIs are picked, and retailers provide empty RTIs each time an order is delivered. The picked empty RTIs are always returned to the depot. Finally, we indicate the current RTI management's effect on the supply chain through a numerical example. We also extend this example by theorizing how RTI repositioning could result in improved RTI logistics, and which trade-offs to consider.





## Chapter 3

# Literature Review

In this research, we address the efficient usage of RTIs within a supply chain. The management of RTIs should ensure that all users in the supply chain have enough RTIs to organize their activities. At the same time, we must ensure an efficient usage of this resource to minimize costs associated with the management of RTI, such as renting and transportation costs. In this chapter, we investigate how literature addresses operational RTI management problems. In Section 3.1, we introduce pickup and delivery problems along with inventory routing problems, and we explain how this literature relates to RTI management. We also review various studies related to these topics, based on which a parametric solution design is proposed. In Section 3.2, we investigate how to optimize parametric models, and indicate how similar routing problems have addressed this topic.

### 3.1 Pickup & Delivery Inventory Routing Problem

In this section, research relating to the routing characteristics of this study are presented. To provide a clear picture of the problem classification, we first introduce the concepts that have led to the definition of the Pick-up & Delivery Inventory Routing Problem (PDIRP). Next, we analyse specific sub-domains within this classification. Subsequently, we provide a review of existing research related to RTI logistics.

#### 3.1.1 Origins

When inventory is managed by the supplier of goods, as is the case in this research, we speak of Vendor Managed Inventory (VMI). In a VMI partnership, the supplier (e.g., the Pool Operator) makes the main inventory replenishment decisions for the consuming organization (Waller et al., 1999). By taking a holistic view of inventory levels throughout the supply chain, delegating the control of all inventory including shipments between echelons to a single point, transport and inventory holding can be more efficiently managed throughout the supply chain (Disney et al., 2003). The objective of VMI is to ensure receiving parties have enough products to perform their activities, whilst considering limited resource availability and storage costs.

A Vehicle Routing Problem (VRP), on the other hand, is a broad term referencing all combinatorial optimization problems seeking how to most efficiently route a vehicle fleet to deliver to a set of customers. Since its first appearance in 1959, VRP studies have been growing at an exponential rate of 6.09% (Eksioglu et al., 2009). Numerous variations of the VRP have been designed over the years, all applicable to a specific situation. Common VRP variations are the VRP with Time-Windows, the Capacitated VRP and the Multi-depot VRP; referring to VRPs requiring deliveries within a time-window, capacitated delivery vehicles or multiple origin depots respectively.

When a decision-maker is tasked with both the management of inventories (e.g., VMI) and routing decisions of said inventory (e.g., VRP), the problem is referred to as an Inventory Routing Problem (IRP). In an IRP, a commodity often limited in supply must be efficiently

distributed amongst customers to ensure both a high enough service level and an efficient enough transport of commodities. Alternatively, the problem can also address situations in which inventories must be relieved. IRP often deal with inventories reducing over time as well as stochastic demand. As such, the problem is complicated by the considerations to be made between efficient routing and efficient inventory allocation.

Another variation of the VRP is the Pickup and Delivery Problem (PDP), also referred to as the Vehicle Routing Problem with Deliveries and Pickups (VRPDP). The PDP is in itself a broad generalization of various more specific PDPs. Battarra et al. (2014) present an important characteristic, which related to the type of routing structure being considered: One-to-one (1-1), One-to-many-to-one (1-M-1) and many-to-many (M-M). In a 1-1 PDP, each commodity has a single pickup location and a single delivery location. The 1-M-1 considers a problem where commodities are picked at the depot, to be delivered at customer locations or, alternatively, the customers might have commodities that must be picked and delivered at the depot. This problem category can also be limited to a 1-M or M-1 problem. Finally, the M-M PDP considers a problem where each commodity can have multiple origin and destination locations and any location may be the origin or destination of multiple commodities. Van Anholt et al. (2016) even propose a fourth type, the 1-M-M-1, which combines depot-customer, customer-depot and customer-customer streams. This fourth category is essentially a combination of the 1-M-1 and M-M routing structures.

The aforementioned concepts all build-up to the general concept of Pickup and Delivery Inventory Routing Problems (PDIRP). As the name suggests, this describes an IRP where inventory flows must be picked and delivered (Iassinovskaia et al., 2017). Just as in the PDP, the routing structure further specifies the problem type.

### Relation to RTIs

To frame the analysed supply chain in terms of the PDIRP, consider first the forward logistics. Unique supplying locations (e.g., nurseries) require filled RTIs to be transported to unique destination locations, a 1-1 PDP. To prepare the filled RTIs, the supplying locations must have enough empty RTIs in inventory. As such, the inventories of locations must be managed as well. Through reverse logistics, empty RTIs have to be delivered as supplying locations and picked at receiving locations. Based on the applied reverse RTI strategy, the reverse logistics can be classified as a 1-M-1 PDP, an M-M PDP or both. Consider the current practice of trading RTIs: empty RTIs are delivered to the receiving locations from the depot or picked at the receiving locations to be returned to the depot; a 1-M-1 PDIRP. Next, consider RTI repositioning within the supply chain: Any location can hold an inventory from which empty RTIs can be picked, and any location can require an empty RTI delivery (or both); an M-M PDIRP. Just as in the generic IRP, this PDIRP is also subject to stochasticity in that the reverse RTI flows are planned to enable future, unknown, forward orders to be fulfilled.

### 3.1.2 PDIRP in literature

In their review, Coelho et al. (2014) present broad recollection of IRP research, classified amongst others on their routing structure. Most studies address a 1-M-1 structure, the most common type of structure for basic IRP (i.e., without pickup and deliveries). Considering Pickups and deliveries, most IRP studies arise in maritime logistics (e.g., Christiansen (1999) and Ronen (2002)), where a M-M structure is more common. As maritime IRP are, however, structurally different from road-based IRP, they are excluded in the upcoming reviews (Archetti et al., 2018; Archetti et al., 2020). In the following sections, we present a review of IRP, PDP and PDIRP with a road-based structure. First, we address the 1-M-1 structure. Next, the 1-1

structure is addressed and afterwards the M-M structure. Finally, we present how repositioning requirements are addressed in PDIRP.

### one-to-many-to-one

Martinovic et al. (2008) address a deterministic, single period, single-vehicle PDP using a Greedy Random Sequence constructive heuristic and a Simulated Annealing improvement meta-heuristic. The constructive heuristic relies on a cheapest insertion heuristic, with 20% probability of selecting the second cheapest insertion. Huang and Lin (2010) developed a modified Ant Colony meta-heuristic for the 1-M IRP, in which the restocking of vending machines is addressed. These machines have a stochastic demand and as such the multi-vehicle IRP aims to minimize stockout and transportation costs under limited transport capacity. Mes et al. (2014) address a waste collection IRP, where stochastic demand is represented as the picking quantity expected to be available at the various bins. Locations are classified in must-, may- or no-pick locations, after which a routing heuristic computes an efficient route given capacity and route length limitations. The classification heuristic classifies all locations based on their expected number of days until overflow, in which the classification parameters are sought via the HKG Optimal Learning procedure (Mes et al., 2011).

### one-to-one

The 1-1 routing structure is more specific to the PDIRP. Cordeau et al. (2008) review a series of exact and heuristic methods, addressing both the single-vehicle and multi-vehicle variants. Heuristic methods are based on (possibly infeasible) starting solutions improved through common meta-heuristics with swap and move operators. In all cases, a deterministic single-period setting is assumed. Renaud et al. (2002) propose an improvement heuristic based on a deterministic, single period 1-1 PDIRP. First, an initial solution is constructed using a cheapest insertion heuristic, which iteratively inserts an origin-destination pair into the route. An insertion does not require an origin and destination to be visited directly after one another, but it does require the origin to be visited before the destination. Next, a perturbation scheme improves the solution through various (segment) swaps and moves. Şahin et al. (2013) initialize their deterministic problem by constructing a Clarke & Wright solution, which results in a series of successive origin-destination pairs. The solution is then improved in a series of moves and splits. The latter method splits an origin-destination pair into two separate routes and splits the required load. A second phase further optimizes the visitation segments. Soysal et al. (2018) considers a stochastic 1-1 PDIRP with two suppliers, in which an ILP is solved to ensure a 95% service level at all customers.

Besides the routing of products, the structure can also be found in the Dial A Ride Problem (DARP). In car-pooling systems, drivers can provide empty seats in their car to provide a ride to requesting users, called riders. Naturally, both the driver and riders have their unique origins and destination. As such, the DARP assigns riders to drivers while minimizing the additional route length, ideally allowing all users to arrive at their destination at their preferred time. Tafreshian and Masoud (2020) address such a problem as a cluster-first, route-second method. To solve a realistically sized problem in a live setting, the authors propose a  $\epsilon$ -uniform partitioning algorithm that minimizes the dissimilarity between two trips, reducing the total problem size to multiple smaller problems. Algorithmically, cluster-representative trips are selected. All available trips are clustered by minimizing the dissimilarity to the representatives whilst taking care to ensure both drivers and riders are uniformly distributed over the clusters, with an allowed deviation of  $\epsilon$ .

### many-to-many

Benoist et al. (2011) consider a large scale single commodity M-M IRP in a 15 day planning horizon with accurate forecasts. In a first urgency-based construction step, orders are created for all delivery customers, ordered by an increasing expected stock out moment. At each iteration, a customer is added at the end of a shift, possibly including an additional visit to a picking location and allowing for split deliveries. As this solution can result in an infeasible solution (not all stockouts are prevented), a first optimization step is the Stockout Optimization phase. Next, a Logistics Ratio Optimization phase further improves the solution as long as possible. The optimization phases consist of a series of swaps, moves and deletions of picking and/or delivery locations. The logistics ratio is computed as the ratio between a shift's costs and the delivered quantity, altered to include long-term benefits. Van Anholt et al. (2016) study a real-life scenario of an ATM PDIRP, in which all locations, including multiple central depots, can serve as a picking or delivery location based on their inventory. They not only resupply locations but also distribute their inventories more evenly over the network. After geographically clustering all locations around one of multiple depots, a variable fixing procedure classifies all locations into a must-pick, may-pick, must-deliver, may-deliver and not-visit set based on their expected inventory. This *fixes* the ILP variables determining whether a location should serve as a picking location, delivery location or nothing at all, thus reducing the problem's computational complexity. Next, the routing problem is solved through branch-and-cut. In Archetti et al. (2018) and Archetti et al. (2020), the authors address an M-M PDIRP by extending a branch & cut formulation with valid inequalities, amongst others through a strong formulation of lower and upper inventory levels for locations. Ting et al. (2017) address an M-M multi-vehicle single commodity PDIRP. They propose a constructive sweep heuristic, which is then improved by one of three meta-heuristics: TABU, Genetic Algorithms and a Scatter Search. Casazza et al. (2021) propose an elaborate method in which an explicit distinction between a *route* and a *loading plan* is made, combined to define a *routing plan*. A route consists of multiple segments, consisting of one or several picking locations followed by one or several delivery locations. Through column generation and an extensive set of valid inequalities, the route is iteratively created. To ensure picking and delivery requirements are met, a quick algorithm solves the loading plan for each route, providing a routing plan.

### PDIRP & RTI

Research on RTI logistics specifically is mostly focused on the strategic pooling policies a pool owner can implement. These studies generally address a closed-loop supply chain where a single supplier requires RTIs for delivery at multiple retailers. Hellström and Johansson (2010) analyses the impact of RTI control strategies on operational costs in a single-supplier multiple-retailer closed-loop supply chain. They simulate a supply chain and find that a switch pool system would save costs by preventing the loss of RTIs. A switch pool system consists of every user in the RTI pool being allocated a fraction of the total RTIs available. Upon delivery of filled RTIs, they would be traded for an equal amount of empty RTIs. They find the installation of such a system is most efficient in this pool: it reduces the loss of RTIs thanks to a better RTI visibility and prevents the installation of RFID tracking, necessary in the scenario the supply chain sticks with their current RTI management. Glock and Kim (2014) study an IRP where a single vendor transport products in RTIs to multiple retailers. They propose two strategies: an early shipment strategy, in which deliveries are made whilst supply orders are still (partially) in production, and a late shipment strategy in which a delivery can be done only once the order is finished. They analyse how the RTI return lead times have a critical impact on the efficiency of a strategy. In case of long RTI return lead times (in case RTI are used for product storage as well, for instance), an early-shipment strategy is beneficial if the demand rates are low. Tornese

et al. (2018) investigate the environmental impact of two reverse RTI strategies in an M-1 IRP. In a “cross-docking” scenario, RTIs are inspected upon reaching the end of the forward supply chain: if they are in good condition, they are brought back to the Pool Owner’s depot, else they are returned to a repair and cleaning facility. In an alternative “take-back” scenario, all RTIs are returned to a cleaning facility. They found a take-back scenario is more environmentally efficient, whereas a cross-docking scenario would require less RTIs in total given the better utilization rates.

Hardly any research addressed the combination of multiple routing structures, where forward and reverse logistics are addressed simultaneously. Iassinovskaia et al. (2017) analysed a 1-M-1 RTI repositioning model with a single supplier, multiple retailers and an external RTI depot. In their repositioning approach, RTIs are first transported from a central supplier to various customers, after which all emptied RTIs are recollected to be brought back to the supplier. This repositioning would prevent the return of RTIs to the RTI depot. They propose a branch & cut method for smaller instances but also reflect on a cluster-first route-second method for larger, more realistic, situations. SteadieSeifi et al. (2021) address a 1-M-1 PDIRP, with two suppliers instead of one. They propose a formulation in which both forward and reverse logistics are optimized in a 12-hours rolling horizon with dynamic route updating. Their method consists of a comparable repositioning strategy, where empty RTIs are picked at customer locations and brought back to any of the two suppliers, provided that they are required. Although both research topics address repositioning as directly reintroducing the RTIs in the supply chain (and omitting a visit via the pool owner depot), both reverse logistics methods rely on a fixed and restricted set of empty RTI picking and delivery locations.

### 3.1.3 Insights

This section serves two purposes. First, we gained insight on which methods are used to address PDIRP on literature, and we gained insights on the role repositioning plays in these types of problems. We introduced how the forward logistics in the problem at hand are considered a 1-1 PDP, whereas the reverse logistics can be executed as a 1-M-1 PDP or an M-M PDP, depending on the implemented strategy. A single, overarching solution approach for all routing structures was not found. The study of Van Anholt et al. (2016) is closest in this aspect, as it introduces an M-M routing structure in a 1-M-1 PDP. There remains a strong division between 1-1 PDP studies and the other two routing structures. As such, we opt for a sequential solution approach that first addresses the forward logistics as a 1-1 PDP and extends on the solution to include the 1-M-1 or M-M reverse routing heuristics.

The 1-1 PDP is tackled through a basic implementation of Renaud et al. (2002), where orders, consisting of an origin-destination pair, are iteratively inserted into routes through a cheapest insertion heuristic. To extend these routes to include reverse logistics, we derive a concept from the studies of Mes et al. (2014) and Van Anholt et al. (2016). By computing the expected inventories of locations over time, an estimate can be made on whether a location requires empty RTIs, or can provide them. This process (henceforth referred to as *variable fixing*) reduces the complexity of the subsequent routing process. The reverse routing process is defined by the implemented reverse RTI strategy: RTIs are repositioned (M-M), RTIs are delivered from the depot (1-M-1 PDP) or a combination of both. Given a reverse RTI strategy, locations are classified into a repositioning set, a depot-delivery set or a picking set. If empty RTI deliveries are required for locations in the repositioning set, empty RTI pickup locations are retrieved from the picking set. If empty RTI deliveries are required for locations in the depot delivery set, the empty RTIs are picked at the depot. Finally, all locations that remain in the picking set are included in the routes to have their RTIs picked. All insertion must be done in consideration of the routing constraints.

The proposed method is subject to hyperparameters. One such parameter defines the length of the forecasting horizon: how far in time should the expected inventory be computed to efficiently weigh out supply and demand? Another parameter determines which reverse RTI strategies should be implemented, i.e. RTI repositioning or deliveries from the depot. To find the parameters that adequately address the dynamic PDIRP analysed, further insights must be gained on how to find the most efficient set of parameter values, which is reviewed in the next section.

## 3.2 Parameter tuning

In various analytical models, the chosen value for input parameters determines the outcome efficiency. In the context of Simulation Optimization, this consists in applying an optimization strategy to find the most efficient set of input values that govern a simulation model. As represented by Figure 3.1, such a model enables a feedback loop between the simulation model and the learning algorithm. A variety of methods address this topic. In this section, we review relevant parameter tuning literature.

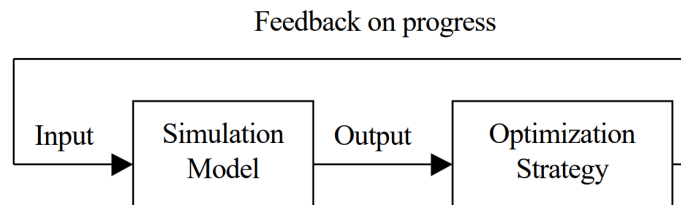


FIGURE 3.1: A Simulation Optimization Model (Carson and Maria, 1997)

### 3.2.1 Heuristic Methods

Common methods to address stochasticity in IRP literature are heuristic methods. This term is broadly used for any algorithmic process optimizing a problem. Here, we specifically relate to the usage of heuristics in the tuning of parameters. These methods include genetic algorithms, simulated annealing and TABU search. Based on the “Survival of the fittest” principle, genetic algorithms encode a set of input values as a genetic code. These genetic codes undergo mutations, resulting in a child node that, when decoded, present a new set of input values. The fitness (i.e., objective value) of a child determines its aptitude for generating new children, whereas unfit solutions are more likely to be discarded. Simulated Annealing, based on the physical annealing process, balances exploration and exploitation throughout iterations by tracking the model temperature: high temperatures allow more solutions to be considered, even without improvements in an iteration, whereas lower temperatures increase the restrictions on accepting only improving solutions. Finally, the TABU search heuristic explores the neighbourhood of a solution, selecting the most efficient neighbour each time, albeit possibly less efficient than the current solution. By forbidding the same neighbour from being selected for a predefined time length (neighbour becomes TABU), the search method avoids getting stuck in local optima. The methods above introduce a form of randomness to accelerate the improvement process. They generally dictate the parameters according to which an analytical model’s heuristics are executed. They are therefore often referred to as meta-heuristics.

### 3.2.2 Stochastic Optimization

Stochastic optimization methods address the problem of finding an optimum in a problem subject to stochasticity. Classical stochastic optimization algorithms are iterative schemes based on gradient descent (Carson and Maria, 1997). A simple example consists in defining a set of weights  $w$ , where one aims to optimize some objective function  $Q(w)$ . Iteratively, the gradient of  $Q$  under  $w$  is used to update the updated values for  $w$  given a learning rate  $\eta$ .

$$w \leftarrow w - \eta \nabla Q(w)$$

In their review of Stochastic Optimization methods, Powell (2019) addresses the various fragmented communities that have each addressed stochastic optimization in their fashion. They distinguish between state-independent problems and state-dependent problems. State-independent problems consist of optimization methods where dynamic state-dependent information do not influence the to-be optimized goal function. Examples include the above gradient descent method. State-dependant problems consist of problems where the dynamic state information influences the value functions. With each iteration, a decision is executed which returns a direct reward, depending on the current observed state. The execution of a decision also influences the transition into the next state and thus the values of future decisions. This transition, however, requires the observation of unknown stochastic information. As such, the value of a decision on future states can only be estimated. A state-dependent stochastic optimization method is the Value Function Approximation (VFA). VFA has been applied in IRP where the inventory routing decisions must balance the dynamic demand of users in the system (Kleywegt et al., 2002; Kleywegt et al., 2004). Their approximation consisted in simulating the costs associated with supplying a large number of overlapping customer subsets, where each subset could be delivered a varying quantity of products. The approximation function then estimated the value of a decision by solving a set covering problem which minimizes the expected value whilst representing the full set of customers.

### 3.2.3 Optimal Learning

Another type of simulation optimization method is optimal learning. As opposed to Stochastic Optimization methods where the goal is to find the best decision in a stochastic environment by performing various measurements over the simulation model, Optimal Learning techniques aims at optimizing how these measurements are made (Powell and Frazier, 2008). In an optimal learning setting, each new measurement provides new knowledge on the expected value of decisions. Central to this concept is the choice of measurement policy. Sequential measurement policies make a decision on what to measure next based on past measurements.

Pure exploratory policies choose random measurements, with each measurement having an equal probability of being selected, eventually resulting in a uniform allocation of experimentation resources over all alternatives. A pure exploitation policy, on the other hand, chooses that measurement that maximizes the expected reward. An Epsilon-Greedy measurement policy provides a better balance of both aforementioned policies, where exploration is encouraged in the early measurements. Focus shifts towards exploitation of the most promising measurements as more observations are made. More elaborate methods exist. Before presenting them, let us specify the concept of the Frequentist view and the Bayesian view.

In Optimal Learning, each new measurement increases the knowledge we have on a model. Under the Frequentist View, we assume we have no prior knowledge of the addressed model. All knowledge must be retrieved through measurements. As such, the value of a decision and its stochastic characteristics can only be approximated through measurements. Under the Bayesian view, we assume we have prior knowledge on (for instance) the distribution of

measurement observations, as well as their mean and/or their variance. Within Ranking and Selection Problems, the Knowledge Gradient is such a method assuming a Bayesian view.

Ranking and Selection Problems address an offline learning problem in which a decision between a series of alternatives must be made where limited experimentation resources are available and measurements are subject to (random) noise. The Knowledge Gradient (KG) policy assumes a prior knowledge on the distribution of measurement decisions, as well as their variance (Frazier et al., 2008). Under the KG, one seeks to measure the decision that maximizes the expected increase in value:

$$\max_{x \in \mathcal{X}} \mathbb{E}[V^{n+1}(S^{n+1}(x)) - V^n(S^n) \mid S^n]$$

In this representation,  $S^n$  represents our knowledge after having made  $n - 1$  prior observations. After implementing measurement  $x \in \mathcal{X}$ , our knowledge state transitions to state  $S^{n+1}(x)$ . Function  $V(S)$  returns the value under a state  $S$ . From this function, one can see that we seek to maximize the gradient with respect to the knowledge gained from the measurement (Powell and Frazier, 2008). This expected increase in value is subject to the belief  $S^n$  we currently have on the various measurements, as well as the expected knowledge in the upcoming state  $S^{n+1}$ , which requires the observation of stochastic information after measurement  $n$ .

In Section 3.1.2, an extension of the Knowledge Gradient is abstractly introduced: the Hierarchical Knowledge Gradient (HKG). The HKG extends on the KG by including an aggregation function that groups measurements under aggregated alternatives. As such, a measurement increases not only the knowledge one has on individual measurements but also on the aggregated alternatives they are part of Mes et al. (2011). The application of the HKG in Mes et al. (2014) focuses on determining the optimal parameters according to which locations are classified into must-, may- or no-pick locations. Parameters consist in defining the maximum time until a stockout may occur for a location to be classified in a respective picking set.

### 3.2.4 Insights

This section served the final purpose of our literature review. It provides insights on how to adequately tune parameters under dynamic circumstances. From the above information, we consider an Optimal Learning approach most suited for the model proposed in Section 3.1.3. The proposed hyperparameters selection is not necessarily state-dependent, although it could be extended to accommodate it. As such, the described stochastic optimization techniques seem less relevant. Meta-heuristic methods, on the other hand, seem to inefficiently make use of the available knowledge when compared to the Optimal Learning techniques described. Moreover, the issue of finding the most efficient set of hyperparameters can be described as a ranking and selection problem in which a set of hyper-parameter settings is considered a measurement/decision. The past application of the HKG in a comparable setting has led to the choice of implementing the HKG for the problem at hand.

## 3.3 Conclusion

In this chapter, we conducted a literature search on the Pickup & Delivery Inventory Routing Problem (PDIRP). This problem type addresses both the routing decisions in a pickup and delivery problem (PDP), as well problem of allocating limited resources over locations and managing their inventories. The addressed RTI supply chain can be described as a broad PDIRP: forward and reverse logistics are all consist of pickups and deliveries whilst at the same time the RTI inventory at users must be managed to ensure the forward logistics can be performed.



PDP, as well as the PDIRP, are characterized by their routing structure. The routing structure defines the number of origins and destinations a single commodity flow may have. In a one-to-one (1-1) PDP, every transported commodity has a unique origin and a unique destination. In a one-to-many-to-one (1-M-1), commodities can either flow between a single origin and multiple destinations, flow between multiple origins and a single destination. In a many-to-many (M-M) PDP, commodities can have multiple origins and multiple destinations, in which case each location can be an origin or a destination. The forward logistics in the addressed supply chain can be seen as a 1-1 PDP, whereas the reverse logistics are classified as a 1-M-1 PDP or an M-M PDP based on the reverse logistics strategy implemented.

In Section 3.1.2, we reviewed literature in all three types of routing structures. Additionally, we reflected on the available RTI PDIRP literature available. Our findings have led to the conceptual description of a solution method. First, the forward logistics are addressed through a cheapest insertion heuristic. Forward logistics are the key activities in this supply chain and are prioritized. Then, a variable fixing procedure can be applied to estimate empty RTI demand and supply. By including the variable fixing procedure, we reduce the complexity of the reverse routing heuristic. Next, various reverse RTI strategies can be implemented: RTI repositioning as an M-M PDP, RTI pickup's and deliveries through the depot as a 1-M-1 PDP or a combination of both. In each case, supply and demand of empty RTIs are matched by finding the cheapest insertion of an origin-destination pair in the existing forward logistics routes, extending the latter. This process requires an accurate setting for forecasting horizons and types of reverse RTI strategies to implement. To this end, we propose the use of hyper-heuristics to be optimized in a parameter tuning procedure.

In Section 3.2, we analyse various methods that allow for the optimization of model parameters in an analytical environment. Meta-heuristics explore a search space by managing both exploration and exploitation techniques. Stochastic Optimization techniques learn to estimate the stochastic future value of state-dependent decisions in a dynamic setting. Optimal Learning strategies aim to optimize the increase in knowledge with each measurement, thus reducing the total number of measurements necessary. We have opted for the Hierarchical Knowledge Gradient for the tuning of our routing model parameters. It has shown to be efficient in a comparable setting, and the parameter set can be represented as a Ranking and Selection Problem in which the most efficient set of parameters is sought.



## Chapter 4

# Solution Method

In this chapter, we introduce the solution design we have implemented. In Section 4.1, we describe the addressed problem and summarize the underlying assumptions we have considered while implementing this model. In Section 4.2, the heuristics used to evaluate the routing model are elaborated upon. Their performance depends on the chosen input parameters, which are optimized through the simulation optimization model introduced in Section 4.2.4.

### 4.1 Problem description

In this section, we describe the Pickup and Delivery Inventory Routing Problem in further detail. First, we provide a general introduction to the problem. Next, we summarize the necessary assumptions. Afterwards, a mathematical notation is given and finally the solution approach is presented.

#### 4.1.1 Introduction

Let us start by generally describing the problem we are addressing. In Chapter 2, we introduced the various users in the network. We also introduce the three depot in which COMPANY B stores their idle RTI. Throughout the year, COMPANY B must address both the forward and reverse logistics activities. They also manage the inventories of the users. In our problem, transport orders determine how RTIs flow. A transport order consists of an origin and a destination, as well as a to-be transported RTI quantity. Each day, we differentiate between forward logistics transport orders (forward orders) and reverse logistics transport orders (reverse orders).

The forward orders consist of all transport orders aimed at the transport of filled RTI between their origin and their destination. At the end of each day, the forward orders for the next day are known. A forward order has a unique origin and destination, as is the case in a 1-1 PDP. At any point in time, a user in the supply chain might be the origin or the destination for one or multiple transport orders. They might also be the origin for some transport, and the destination for others. Forward orders are considered the value adding activities of the supply chain. The reverse orders consist of all transport orders for the transport of empty RTI. A reverse order is also characterized by an origin, destination and transport quantity but the origin, destination and quantity are not given. Rather, all locations have a supply or a demand of empty RTI. By matching supply and demand pairs, reverse transport orders are created. Under the current RTI management, all reverse logistics are performed via depot deliveries or depot returns. For depot deliveries, a depot is always the origin, and the destination is a location with an empty RTI demand. For depot returns, a location that has empty RTI supply is the origin and a depot is always the destination. Both these RTI flows are considered a 1-M-1 PDP, where the depots are the central location in the routing problem to which and from which RTI are transported. In this study, we also consider the RTI repositioning flow. Any user can be the origin or the destination of a repositioning flow. By introducing repositioning, the pickup

and delivery routing structures extends to a M-M PDP. Both forward and reverse flows are also shown in Figure 1.4.

Each day, the forward orders and the reverse orders must be processed simultaneously. In the problem, the decision-maker must decide how to route the transport vehicles, and they must also decide how to match supply and demand of empty RTI. The routing problem and the RTI inventory management are interwoven: optimizing routes requires knowing which reverse orders to process, whereas the reverse orders can most efficiently be defined when one knows how the routes are driven. Additionally, the supply and demand of empty RTI depend on uncertain forecasts of future forward orders.

### 4.1.2 Assumptions

We make some assumptions to simplify the problem at hand and to close the gap between real-world characteristics presented in Chapter 2 and the characteristics available in data. First, we assume that only a single depot is used in the supply chain. The three supply chains used by COMPANY B are located close-by one another. Additionally, one of the depots performs most RTI operations. Considering a single depot simplifies the problem at hand without in-so-much obstructing the objectives of the study (Assumption 1). We also simplify the problem by considering only a single RTI type, namely CCs (Assumption 2). Next, we also assume filling and emptying activities are performed during the night. As such, forward orders are prepared the evening before they must be sent out, and all RTI are emptied during the evening after being delivered (Assumption 3). Given all RTI are filled and emptied within a day, we define that empty RTI are filled only during the evening before a forward order occurs and delivered filled RTI are emptied the same day they are delivered. Doing so, we can assume that only the inventory of empty RTI must be tracked, simplifying the inventory management problem (Assumption 4). Due to data limitations, we can not distinguish between transport orders driven in the morning and transport orders driven in the afternoon. As such, we assume that all orders are driven during a single shift (Assumption 5). In line with this assumption, we also assume we always have enough trucks to transport all forward orders: since all forward transport orders are fulfilled during a single shift instead of two, 32 trucks might not be enough. As such, we assume we always have enough trucks to fulfill forward transport orders (Assumption 6). During days when a trucks is not required for forward transport orders, we also assume idle trucks are not used for reverse transport orders, as COMPANY B generally prevent using trucks for transport of empty RTI only as they do not contribute (as much) to the value adding activities (Assumption 7). The assumptions are shortly described below:

- **Assumption 1:** A single depot is used
- **Assumption 2:** We consider only CCs.
- **Assumption 3:** All RTI are filled and emptied within a day.
- **Assumption 4:** Inventory is built up from empty RTI only.
- **Assumption 5:** Days consist of a single driving shift
- **Assumption 6:** Enough trucks to fulfill forward transport orders
- **Assumption 7:** Idle trucks are not used for reverse transport orders

### 4.1.3 Mathematical formulation

Let us now define this problem as a mathematical model. Consider a graph  $G = (V, E)$ , where the vector-set  $V$  represents all locations  $v \in V = \{0, 1, \dots, |V|\}$  and  $v = 0$  is the depot and the edge-set  $E$  represents the symmetric travel distances between all locations  $\{e_{i,j} \mid i, j \in V\}$ . We define  $I_v$  as the empty RTI inventory of location  $v$ . At each new day, we observe the forward order set  $O$ . The forward orders  $o \in O$  have to be planned during this day. They are characterized by an origin and a destination location part of the vector set, indicated by  $o_i, o_j =$

$v \in V$ , and a transport quantity denoted by  $o_q$ . In order to fulfill forward orders, locations must have enough empty RTI in inventory. To fulfill unknown future orders, a location has an empty RTI demand  $d_v$ . Locations that have excess empty RTI in inventory are said to have an RTI supply  $p_v$ . When filled or empty RTI are transported during a day, they can be used to fulfill forward orders starting from the next day. We assume that all forward orders must be satisfied during a day. In case a lack of RTI inventory is observed, resulting in an empty RTI stockout, an emergency delivery of empty RTI is assumed to be scheduled. The emergency deliveries add transportation costs, but they are executed separately from the forward and reverse logistics routing. On each day, a total of  $M$  vehicles are available. All vehicles are constrained by a truck holding capacity  $h$  and maximum driving distance  $g$ . The amount of capacity used by an RTI depends on whether it is filled or empty (see Table 2.1). A filled RTI, transported in forward logistics, occupies a volume of  $\gamma_f$  whereas an empty RTI, transported in reverse logistics, occupies a volume of  $\gamma_e$ . A vehicle  $m$ 's route  $X_m^r$  consists of an ordered set of visited locations. Paired to each route is a set  $X_m^h$  and  $X_m^g$  tracking the capacity used upon leaving a location and the driving distance up until the next location in  $X_m^r$ . We also define functions  $\bar{X}_m^r(k, l) : X_m^r \rightarrow \{k, \dots, l\}$ , which returns the sub-route between  $k$  and  $l$ . Similarly,  $\bar{X}_m^h(k, l)$  and  $\bar{X}_m^g(k, l)$  return the sub-route's used capacity and driving distances. We define functions for the sub-routes due to the nature of 1-1 PDPs: for an order  $o$ , the origin  $o_i$  and destination  $o_j$  are known. The route's used capacity is only increase by  $o_q$  for the sub-route between  $o_i$  and  $o_j$ . Below is an example of a small route visiting 3 locations and the depot, along with the result from the sub-route functions:

$$\begin{array}{ll}
 \text{Route} = \{0 \rightarrow k \rightarrow i \rightarrow j \rightarrow 0\} & \text{Sub-route} = \{k \rightarrow i \rightarrow j\} \\
 X_m^r = \{0, k, i, j, 0\} & \bar{X}_m^r(k, j) = \{k, i, j\} \\
 X_m^h = \{0, 2, 5, 3, 0\} & \bar{X}_m^h(k, j) = \{2, 5, 3\} \\
 X_m^g = \{4, 3, 5, 10, 0\} & \bar{X}_m^g(k, j) = \{3, 5, 10\}
 \end{array}$$

A general requirement is that all current and future forward orders must be satisfied. To ensure each location is provided with enough empty RTI, the empty RTI supply and demand of locations is necessary. Empty RTI supply and demand can, however, only be estimated according to forecasts. On a given day, forecasts  $f_v^t$  indicate the expected inflow of outflow of empty RTIs for a location for each day in a forecasting horizon  $t \in \mathcal{T} = \{0, \dots, T_{max}\}$ . We assume these forecasts are given but subject to uncertainty. Based on these forecasts, an expected future inventory level  $\hat{I}_v^t$  can be computed, according to which empty RTI supply and demand can be determined.

The goal is to ensure this with minimal costs. Costs are built up from three components, as shown in Section 2.3. First, RTI renting costs follow from the total number of RTI required in the system. Considering RTIs must be rented for a full year, the total renting costs follow from the maximum number of RTI required in the system on a given day. Next, transportation costs includes all driven distances: the forward and reverse logistics transportation costs can be minimized through efficient routing and emergency delivery costs can be minimized by preventing stockouts. Finally, the depot activity costs of RTI at the depot is also considered as the total number of RTI that enter and exit the depot.

At the core of this study, we seek to identify how and to what extend repositioning might improve the efficiency of RTI logistics. Theoretically, RTI repositioning introduces additional transportation costs. However, it might improve the utilization of RTI by directly reintroducing RTI in the supply chain without visitation to the depot, reducing the total number of RTI required and prevent depot activity costs.

#### 4.1.4 Solution approach

In this section, we elaborate on the heuristic method employed. In Chapter 3, we concluded our literature review with the observation that the solution to our inventory routing problem should be heuristic-based. In this section, we present our solution approach in more detail. First, we introduce the hyper-parameters that determine how our routing procedure is executed. Next, we explain how the routing procedures works. Finally, we explain how the most efficient hyper-parameter values are sought. The proposed routing model is used for the operational planning of day-to-day routes. Through the incorporation of adjustable parameters, the operational planning also has a direct impact on the long-term cost function. The global framework of our solution approach is shown in Figure 4.1 and the notation used for parameters and variables are summarized in Table 4.1.

The hyper-parameters determine how reverse logistics are organized. Specifically, they determine how empty RTI supply and demand is estimated, and how reverse RTI flows are applied to satisfy empty RTI demand. First, we distinguish between empty RTI demand urgency: short-term, long-term and none. Short-term demand is considered more urgent and is prioritized. Long-term demand is less urgent and is satisfied if possible given routing capacity constraints. Given the urgency, the empty RTI demand  $d_v$  is split in two: a short-term empty RTI demand  $d_v^m$  and a long-term empty RTI demand  $d_v^n$ . The values assigned to of these variables depend on the length of the forecasting horizon, determined through parameters  $T^m$  and  $T^n$ . The short-term forecasting horizon is of length  $T^m$ , and the long-term forecasting horizon is of length  $T^m + T^n$ : the hyper-parameter  $T^n$  extends the short-term forecasting horizon to create the long-term forecasting horizon. The empty RTI demand quantities  $d_v^m$  and  $d_v^n$  are then determined by calculating a location's expected empty RTI requirements according to their current empty RTI inventory and forecasted future orders. Similarly, the empty RTI supply  $p_v$  is determined with a picking forecasting horizon  $T^p$ . Urgency is not considered for pickup of RTI. Based on a location's inventory level and their forecasted future orders, we can determine the total number of excess RTI that can be picked. Hyper-parameters  $T^m$ ,  $T^n$  and  $T^p$  are referred to as the forecasting horizon parameters. Next, we also have a group of reverse flow hyper-parameters:  $F_r^m$ ,  $F_d^m$ ,  $F_r^n$  and  $F_d^n$ . The hyper-parameters take a Boolean value and indicate which type of reverse logistic flows may be employed (see Figure 1.4).  $F_r^m$  determines whether RTI repositioning may be used to satisfy short-term empty RTI demand.  $F_d^m$  determines whether depot delivery flows may be used to satisfy short-term empty RTI demand.  $F_r^n$  determines whether RTI repositioning may be used to satisfy long-term empty RTI demand.  $F_d^n$  determines whether depot delivery flows may be used to satisfy long-term empty RTI demand. Reverse logistics flows are prioritized: first, short-term RTI repositioning flows are planned, then short-term depot-deliveries, then long-term RTI repositioning and finally long-term depot deliveries. Together, the reverse flow hyper-parameters are able to form a specific type of RTI management. Given we have four Boolean hyper-parameters, a total of 16 unique reverse flow hyper-parameters combinations can be created. To simplify notation, we summarize the four Boolean hyper-parameters under a single categorical hyper-parameter  $\mathcal{F} = \{F_r^m, F_d^m, F_r^n, F_d^n\}$ . The set  $\mathcal{F}$  is referred to as a reverse RTI strategy.

Given a value for these parameters, transport orders can be executed. Each day, a sequential routing procedures computes supply and demand of empty RTI, plans forward and reverse transport orders and computes the effect on the supply chain. At the start of each day, stockouts and emergency deliveries are computed. Next, all forward logistics are planned according to the forward routing heuristic. Next, a variable fixing procedure determines the empty RTI demand and supply values according to the hyper-parameter values. Finally, the reverse routing heuristic extends the routes from the forward routing heuristic to include reverse logistics. The forward routing heuristic schedules all forward orders. Each order is characterized by a unique origin and destination. Routes are created through an unpaired insertion heuristic.

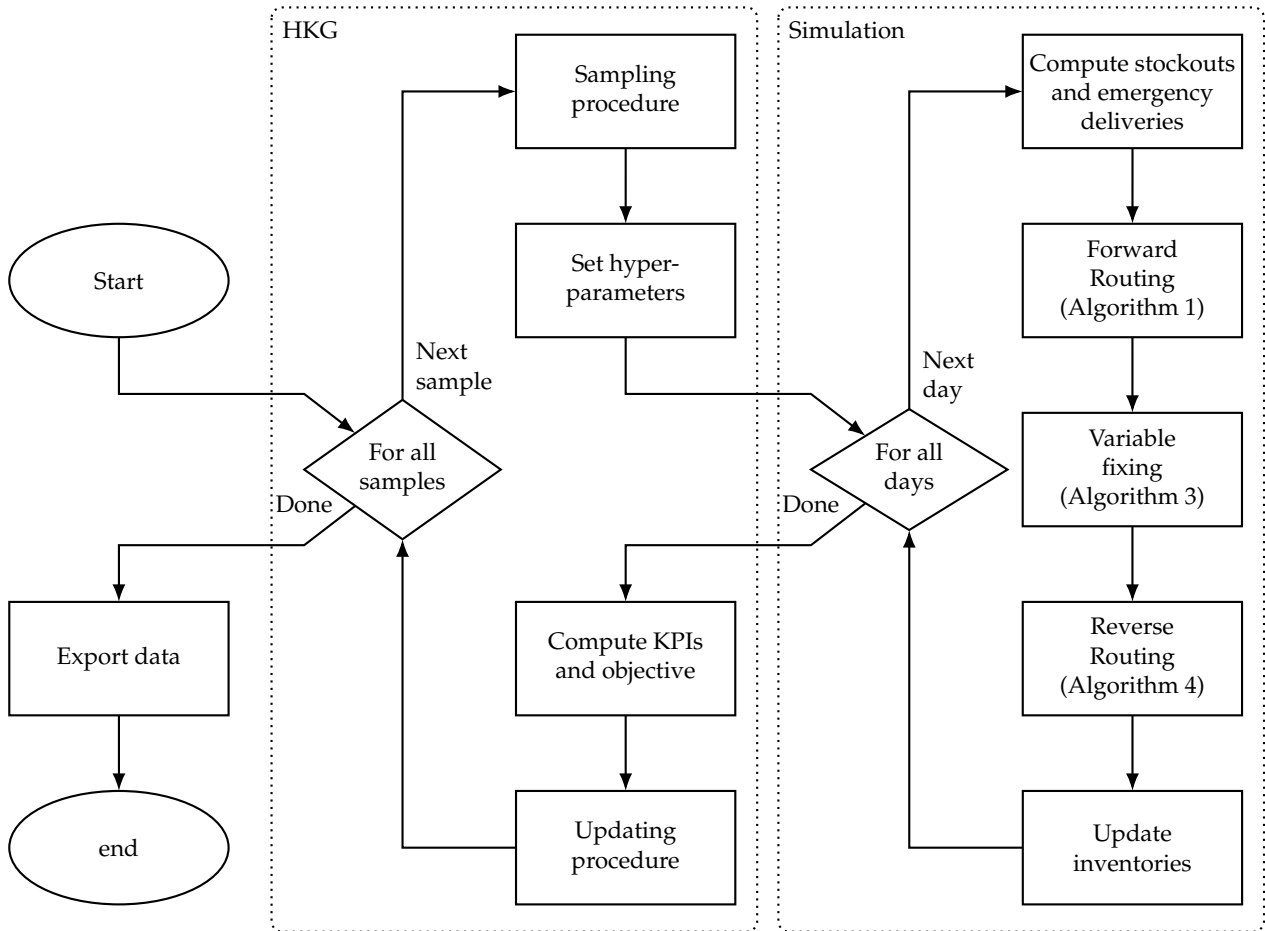


FIGURE 4.1: Solution method framework

First, all orders are sorted based on a prioritization key: large order quantities and long origin-destination distances are prioritized. Next, order are inserted iteratively through a cheapest unpaired insertion. The variable fixing heuristic ensures empty RTI demand and supply is computed according to current inventory and forecasted future orders. It classifies all locations either one of the empty RTI delivery sets, a empty RTI pickup set or a do-nothing set. Empty RTI delivery sets consists of the *short-term repositioning set*  $\mathcal{D}_r^m$ , the *short-term depot delivery set*  $\mathcal{D}_d^m$ , the *long-term repositioning set*  $\mathcal{D}_r^n$  and the *long-term depot delivery set*  $\mathcal{D}_d^n$ . The picking set  $\mathcal{P}$ , consisting of locations from whom empty RTIs may be picked. Locations in  $\mathcal{P}$  serve as the supplying location for repositioning flows, but any unused RTI are also picked for depot returns flows if capacity allows it. Finally, the do-nothing set  $\mathcal{Z}$  consists of all locations that are neither chosen as pick nor delivery locations. The reverse routing heuristic extends the routes created in the forward routing heuristics by inserting cheapest origin-destination pair in the routes. Origins can be locations in the pickup set or the depot, and destinations are locations in one of the four delivery sets. First, delivery locations in the short-term repositioning set  $\mathcal{D}_r^m$  are matched with pickup locations in the pickup set  $\mathcal{P}$ . Next, delivery locations in the depot delivery set  $\mathcal{D}_d^m$  are matched with the depot as pickup location. Next, delivery locations in the long-term sets are planned in a similar order.

The values for the hyperparameters determine how the simulation is executed. In order to find fitting values for these hyperparameters, we apply the Hierarchical Knowledge Gradient (HKG) algorithm. Each hyper-parameter can take a predefined set of values. From this, all possible *decisions* can be considered, where each decision represents a unique combination of hyper-parameter values. Each decision is paired with an expected value, which is unknown.

The HKG addresses the Ranking and Selection Problem, in which the goal is to efficiently find which decision is best. Through an aggregation scheme, the HKG estimates the value of both a single decision and the aggregated decisions they are part of. During a predefined number of observations, the HKG decides which decision to simulate by maximizing both the estimated decision value and estimate precision through added knowledge.

Notation	Description
$T^m$	defines the short-term forecasting horizon
$T^n$	defines the long-term forecasting horizon
$T^p$	defines the picking forecasting horizon
$F_r^m$	defines whether short-term RTI repositioning is allowed
$F_d^m$	defines whether short-term depot deliveries are allowed
$F_r^n$	defines whether long-term RTI repositioning is allowed
$F_d^n$	defines whether long-term depot deliveries are enabled
$\mathcal{F}$	A reverse RTI strategy, $\mathcal{F} = \{F_r^m, F_d^m, F_r^n, F_d^n\}$
$V$	Set of all locations $v$ , where $v = 0$ is the depot
$E$	Set of all edges $e_{i,j}$ for $i, j \in V$
$\mathcal{T}$	Forecasting horizon $\{0, 1, \dots, T_{max}\}$
$T_{max}$	The maximum size of the forecasting horizon given, $T_{max} = \max\{T^m + T^n, T^p\}$
$M$	Number of vehicles
$h$	Holding capacity of a vehicle
$g$	Maximum travelling distance of a vehicle
$\gamma_f, \gamma_e$	Used capacity by filled and empty RTIs respectively
$O$	Set of all forward orders $o$ occurring at $t = 0$
$o_i, o_j, o_q$	Origin, destination and quantity of a forward order $o$
$s_o$	Prioritization key for order $o$
$\alpha$	Order prioritization threshold, expressed as a fraction of $h$
$I_v$	Inventory of location $v$
$\hat{I}_v^t$	Expected inventory of location $v$ during $t \in \mathcal{T}$
$f_v^t$	RTI flow forecast for location $v$ during $t \in \mathcal{T}$
$d_v^m$	Desired short-term delivery quantity for location $v$
$d_v^n$	Desired long-term delivery quantity for location $v$
$p_v$	Available picking quantity for location $v$
$\mathcal{D}_r^m$	Set of all locations $v$ that require short-term RTI repositioning
$\mathcal{D}_d^m$	Set of all locations $v$ that require short-term depot deliveries
$\mathcal{D}_r^n$	Set of all locations $v$ that require long-term RTI repositioning
$\mathcal{D}_d^n$	Set of all locations $v$ that require long-term depot deliveries
$\mathcal{P}$	Set of all locations $v$ that have RTIs available for pickup
$\mathcal{Z}$	Set of all unclassified locations
$X_m^r$	An ordered set representing a route
$X_m^h$	An ordered set representing the load carried in the route
$X_m^g$	An ordered set representing the driving distance to the next location in the route
$\bar{X}_m^r(i, j)$	Function which returns the sub-route of $X_m^r$ between locations $i$ and $j$
$\bar{X}_m^h(i, j)$	Function which returns the sub-route's load
$\bar{X}_m^g(i, j)$	Function which returns the sub-route's driving distance

TABLE 4.1: Summary of used notation for parameters and variables



## 4.2 Procedures

In this section, we give a detailed description of the used processes. In Section 4.2.1, the forward routing heuristic is described. The forward routes created form the basis for the reverse logistics. In Section 4.2.2, the variable fixing procedure is described. The variable fixing procedure determines, according to hyper-parameter values, which locations have an empty RTI supply or demand and how empty RTI should flow. In Section 4.2.3, the reverse routing heuristic is described. Given the routes from the forward routing heuristic and empty RTI supply and demand from the variable fixing heuristic, the reverse routing heuristic extends the routes by including origin-destination pair. As such, reverse RTI flows are introduced. This whole process depends on the chosen hyper-parameter values. The most efficient decision is found through the Hierarchical Knowledge Gradient algorithm, presented in Section 4.2.4.

### 4.2.1 Forward routing

The forward routing heuristic is based on the heuristic introduced in Renaud et al. (2002). The routing heuristic aims to iteratively insert the origin and destination of all orders into an existing route. At each iteration, the most cost-effective insertion is found and performed. The heuristic starts by initializing the number of routes  $M$ .

To initialize the  $M$  routes, we first define an auxiliary prioritization key  $s_o$  (Equation 4.2). This key  $s_o$  is used to prioritize orders based on two criteria: order quantity and order distance. The largest values for  $s_o$  will be for orders for which the order quantity is larger than a fraction of the capacity ( $\gamma_f \cdot o_q \geq \alpha \cdot h$ , where  $\alpha$  is user-defined). As these orders have an order quantity larger than some threshold, they are more difficult to insert in routes later on due to their capacity requirements. They are therefore prioritized. Afterwards, the orders are prioritized based on the distance of their origin-destination pair  $e_{i,j}$  where  $i = o_i$  and  $j = o_j$ . They are also less easily inserted in routes later on. The  $M$  routes are then initialized by selecting the  $M$  origin-destination pairs  $(i, j)$  of orders  $o$  with highest values of  $s_o$  and inserting them into a route, where each route starts and ends with the depot:  $X_m^r = \{0, i, j, 0\}$ .

$$s_o = \begin{cases} \max\{e \in E\} + o_q & \text{if } \gamma_f \cdot o_q \geq \alpha \cdot h \\ e_{i,j} & \text{else} \end{cases} \quad (4.2)$$

Next, all remaining orders are inserted into the routes. Renaud et al. (2002)'s heuristic is based on a cheapest insertion technique. For each origin-destination pair  $(i, j)$ , two types of insertion are possible: a paired insertion and an unpaired insertion. The paired insertion consists of inserting the successive pair  $(i, j)$  into an existing pair  $(k, l)$  in any route  $m$ . The unpaired insertion consists of insertion  $(i)$  into an existing pair  $(k, l)$  and  $(j)$  into an existing pair  $(r, s)$  where  $(r, s)$  can only be visited further in the route, after  $(k, l)$ . Upon insertion of an origin-destination pair, the route segments in which they are inserted observe an increase in carried load and driving distance. Assume we wish to make a paired insertion of  $(i, j)$  between  $(k, l)$  in route  $X_m^r$ , where a quantity  $q$  must be transported between  $(i)$  and  $(j)$ : the increased capacity of this route segment is given by Equation 4.3a and increased total driving distance by Equation 4.4a. Similar functions are defined for the unpaired insertion (Equation 4.3b and Equation 4.4b). Note that the input delivery quantity  $\gamma_f \cdot q$  can also be replaced with  $\gamma_e \cdot q$  for empty RTI transport.

$$h_m^p((i, j), (k, l), \gamma_f \cdot q) = \sum \left\{ \bar{X}_m^h(k, l) \right\} + \gamma_f \cdot q \quad (4.3a)$$

$$h_m^u((i, j), (k, l), (r, s), \gamma_f \cdot q) = \sum \left\{ X_m^h(k, s) \right\} + \gamma_f \cdot q \quad (4.3b)$$

$$g_m^p((i, j), (k, l)) = \sum \left\{ X_m^h \right\} + e_{k,i} + e_{i,j} + e_{j,l} - e_{k,l} \quad (4.4a)$$

$$g_m^u((i, j), (k, l), (r, s)) = \sum \left\{ X_m^h \right\} + \begin{matrix} e_{k,i} + e_{i,l} - e_{k,l} \\ + e_{r,j} + e_{j,s} - e_{r,s} \end{matrix} \quad (4.4b)$$

To evaluate an insertion, costs are determined according to the increased route distance and whether or not the capacity and driving constraints are breached. The insertion costs for the paired and unpaired insertion are defined by the cost functions  $C_m^p$  and  $C_m^u$  (Equation 4.5). If, after insertion, a capacity or driving distance constraint is breached, the insertion costs are infinite, making the insertion infeasible. Else, the insertion costs are equal to the increase in driving distance.

$$C_m^p((i, j), (k, l), q) = \begin{cases} \infty & \text{if } h_m^p((i, j), (k, l), \gamma_f \cdot q) > h \quad \text{or} \\ & \text{if } g_m^p((i, j), (k, l)) > g \\ e_{k,i} + e_{i,j} + e_{j,l} - e_{k,l} & \text{else} \end{cases} \quad (4.5a)$$

$$C_m^u((i, j), (k, l), (r, s), q) = \begin{cases} \infty & \text{if } h_m^u((i, j), (k, l), (r, s), \gamma_f \cdot q) > h \quad \text{or} \\ & \text{if } g_m^u((i, j), (k, l), (r, s)) > g \\ e_{k,i} + e_{i,l} - e_{k,l} \\ + e_{r,j} + e_{j,s} - e_{r,s} & \text{else} \end{cases} \quad (4.5b)$$

For orders  $o \in O$ , the order  $o^*$  resulting in the cheapest insertion of  $(o_i^*, o_j^*)$  (paired or unpaired) in any route  $X_m^r$  is selected and its origin and destination locations are inserted in the appropriate sections of the route. The route's loads  $X_m^d$  and driving distances  $X_m^d$  are also updated. Once planned, the order  $o^*$  is removed from  $O$ . This process is repeated until all orders are planned, i.e.  $O = \emptyset$ . The pseudo-code for this heuristic can be found in Algorithm 1.

This process assumes an input value for the number of routes  $M$ . Forward routing orders are not subject to randomness. As such, each new execution results in the exact same forward routes.  $M$  is therefor fixed at the minimum quantity of trucks required for each day, which can be determined by iteratively increasing  $M$  from 0 onward until a feasible route is returned. Thanks to the sorting key  $s_o$ , routes are also initialized more efficiently: about 10% less trucks are required when compared to an initialization without the sorting key.

## 4.2.2 Variable fixing

After the forward routing heuristic is finished, the variable fixing heuristic is called. This heuristic's execution depends on the values for the reverse flow hyper-parameters and the forecasting horizon hyper-parameters. Based on the hyper-parameter values, locations are classified in one of the four delivery sets or the picking set. Each location is also assigned a short-term and/or long-term empty RTI demand or empty RTI supply. In Algorithm 3, the heuristic steps are shown.

The calculation of empty RTI demand and supply is based on the expected future inventory level  $\hat{I}_v^t$ . In a first step, we compute the expected inventory for all locations during the forecasting horizon  $\mathcal{T}$ . The expected inventory  $\hat{I}_v^t$  for  $t = 0$  refers to the expected empty RTI inventory available during the day. This quantity is equal to the starting inventory of the day minus all outbound RTI from forward order origins. The RTI transported during  $t = 0$  may be used again for the forward orders in  $t = 1$ . As such, the expected inventory  $\hat{I}_v^t$  for  $t = 1$  includes all filled RTI transported to their destinations and emptied by them. From  $t = 1$  on, we also include the forecasted RTI flows for a location.

**Algorithm 1** Forward Routing Heuristic

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1: Compute  $s_o \quad \forall o \in O$  ▷ Equation 4.2
2: for all  $m \in M$  do
3:    $o^* \leftarrow \operatorname{argmax}_{o \in O} \{s_o\}$ 
4:    $X_m^r \leftarrow \{0, o_i^*, o_j^*, 0\}$ 
5:   Remove  $o^*$  from  $O$ 
6: end for
7: while  $O \neq \emptyset$  do
8:   for all  $o \in O$  do
9:      $Cost^*, Insertion^* \leftarrow \text{CHEAPEST INSERTION}(o_i, o_j, \gamma_f \cdot o_q)$  ▷ Algorithm 2
10:     $Cost(o) \leftarrow Cost^*$ 
11:     $Insertion(o) \leftarrow Insertion^*$ 
12:    if  $Cost(o) < Cost(o^*)$  then
13:       $o^* \leftarrow o$ 
14:    end if
15:  end for
16:  if  $Cost(o^*) < \infty$  then
17:    Perform insertion  $Insertion(o^*)$ , update  $X_m^h$  and  $X_m^g$ 
18:    Remove  $o^*$  from  $O$ 
19:  end if
20: end while

```

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We initialize this procedure by assigning all locations to the set of unclassified locations  $\mathcal{Z}$ . Based on hyper-parameter values, we classify locations in either delivery sets or pickup, or leave them in the set  $\mathcal{Z}$ . First, we classify locations in the short-term repositioning set  $\mathcal{D}_r^m$ : if short-term repositioning is allowed ( $F_r^m = 1$ ), any location with an negative minimum expected inventory level within the short-term forecasting horizon  $T^m$  is included in the set. We consider minimum expected inventory level during  $t \leq T^m$  as opposed simply the expected inventory level at  $t = T^m$  because we are interested in all expected stockout occurrences. The short-term delivery quantity  $d_v^m$  is defined as this minimum expected inventory level during  $t \leq T^m$ , as this value indicates the most extreme stockout occurrence we wish to prevent. If short-term repositioning is not allowed ( $F_r^m = 0$ ), we check if these locations can be included in the short-term depot delivery set instead, provided it is allowed ( $F_d^m = 1$ ). A location can be planned in only a single short-term delivery set. However, the routing process introduced in the next section is defined such that all unplanned short-term repositioning locations  $v \in \mathcal{D}_r^m$  are transferred to the depot delivery set  $\mathcal{D}_d^m$  if short-term depot deliveries are allowed. This may occur if, for instance, all picking locations  $\mathcal{P}$  are depleted and thus no more repositioning can take place. This process is repeated similarly for the long-term repositioning and long-term depot delivery sets ( $\mathcal{D}_r^n, \mathcal{D}_d^n$ ), considering the adequate long-term hyper-parameters: the long-term repositioning parameter  $F_r^n$ , the long-term depot delivery parameter  $F_d^n$  and the long-term forecasting horizon parameter  $T^n$ . We bring attention to two dissimilarities. The long-term forecasting horizon is built by extending the short-term forecasting horizon with the long-term forecasting horizon parameter, e.g.  $T^m + T^n$ . Also, when considering whether long-term minimum expected inventories are below zero (suggesting a desired long-term delivery quantity) we must take care to exclude any RTI we already plan on delivering through a short-term delivery. Finally, if a location is planned in a delivery set, the location can not be considered for pickup. As such, we remove these location  $v$  from the set  $\mathcal{Z}$ . The remaining locations are checked to see if they can serve as pickup locations. The pickup forecasting horizon parameter  $T^p$  essentially tells us that any inventory expected to be unused after  $T^p$  might as well be used elsewhere. As such, any location with a positive minimum

**Algorithm 2** Cheapest Insertion

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```

1: procedure CHEAPEST INSERTION( $i, j, q$ )  $\triangleright q$  in used volume, as opposed to RTI quantities
2:   for all  $m \in M$  do
3:     for all  $(k, l) \in X_m^r$  do
4:        $Cost \leftarrow C_m^p((i, j), (k, l), q)$   $\triangleright$  Equation 4.5a
5:       if  $Cost < Cost^*$  then
6:          $Cost^* \leftarrow Cost$ 
7:          $Insertion^* \leftarrow (m, (i, j), (k, l))$ 
8:       end if
9:       for all  $(r, s) \in X_m \mid (r, s)$  after  $(k, l)$  do
10:         $Cost \leftarrow C_m^u((i, j), (k, l), (r, s), q)$   $\triangleright$  Equation 4.5b
11:        if  $Cost < C(o)$  then
12:           $Cost^* \leftarrow C$ 
13:           $Insertion^* \leftarrow (m, (i, j), (k, l), (r, s))$ 
14:        end if
15:      end for
16:    end for
17:  end for
18:  return  $Cost^*, Insertion^*$ 
19: end procedure

```

---

expected inventory during the pickup forecasting horizon is considered a pickup location and included in  $\mathcal{P}$ . The minimum expected inventory observed is considered available for pickup and added to the locations empty RTI supply  $p_v$

**Algorithm 3** Variable fixing algorithm

---

**Require:**  $F_r^m, F_d^m, F_r^n, F_d^n, T^m, T^n, T^p$

- 1:  $T_{max} = \max\{T^m + T^n, T^p\}$
- 2:  $\mathcal{T} = \{0, 1, \dots, T_{max}\}$
- 3:  $\mathcal{Z} \leftarrow V$
- 4: **for all**  $v \in \mathcal{Z}$  **do**
- 5:     **for all**  $t \in \mathcal{T}$  **do**
- 6:         **if**  $t = 0$  **then**
- 7:              $\hat{I}_v^t \leftarrow I_v - \sum_{o \in O: o_i=v} \{o_q\}$
- 8:         **else if**  $t = 1$  **then**
- 9:              $\hat{I}_v^t \leftarrow \hat{I}_v^{t-1} + \sum_{o \in O: o_i=v} \{o_q\} + f_v^t$
- 10:         **else**
- 11:              $\hat{I}_v^t \leftarrow \hat{I}_v^{t-1} + f_v^t$
- 12:         **end if**
- 13:     **end for**
- 14: **end for**
- 15: **for all**  $v \in \mathcal{Z}$  **do**
- 16:     **if**  $\min_{t \leq T^m} \{\hat{I}_v^t\} < 0$  **then**
- 17:         **if**  $F_r^m$  **then** ▷ Short-term repositioning
- 18:             Add  $v$  to  $\mathcal{D}_r^m$
- 19:              $d_v^m \leftarrow |\min_{t \leq T^m} \{\hat{I}_v^t\}|$
- 20:         **else if**  $F_d^m$  **then** ▷ Short-term depot deliveries
- 21:             Add  $v$  to  $\mathcal{D}_d^m$
- 22:              $d_v^m \leftarrow |\min_{t \leq T^m} \{\hat{I}_v^t\}|$
- 23:         **end if**
- 24:     **end if**
- 25:     **if**  $\min_{t \leq T^m+T^n} \{\hat{I}_v^t\} - d_v^m < 0$  **then**
- 26:         **if**  $F_r^n$  **then** ▷ Long-term repositioning
- 27:             Add  $v$  to  $\mathcal{D}_r^n$
- 28:              $d_v^n \leftarrow |\min_{t \leq T^m+T^n} \{\hat{I}_v^t\}| - d_v^m$
- 29:         **else if**  $F_d^n$  **then** ▷ Long-term depot deliveries
- 30:             Add  $v$  to  $\mathcal{D}_d^n$
- 31:              $d_v^n \leftarrow |\min_{t \leq T^m+T^n} \{\hat{I}_v^t\}| - d_v^m$
- 32:         **end if**
- 33:     **end if**
- 34:     **if**  $v \in \mathcal{D}_r^m \cup \mathcal{D}_d^m \cup \mathcal{D}_r^n \cup \mathcal{D}_d^n$  **then**
- 35:         Remove  $v$  from  $\mathcal{Z}$  ▷ If  $v$  is part of any delivery set
- 36:     **end if**
- 37: **end for**
- 38: **for all**  $v \in \mathcal{Z}$  **do**
- 39:     **if**  $\min_{t \leq T^p} \{\hat{I}_v^t\} > 0$  **then**
- 40:         Add  $v$  to  $\mathcal{P}$  and remove  $v$  from  $\mathcal{Z}$
- 41:          $p_v \leftarrow \min_{t \leq T^p} \{\hat{I}_v^t\}$
- 42:     **end if**
- 43: **end for**

---

**4.2.3 Reverse routing**

With empty RTI delivery and pickup sets defined, reverse routing is performed. The reverse heuristic consists of three stages. First, the short-term delivery locations are planned. Next,

long-term delivery locations are planned. If any remain at the end, the RTI left at pickup locations are collected if feasible. The routes created in the forward routing heuristic (Section 4.2.1) are extended by performing unpaired insertions of origin-destination pairs (Algorithm 2).

By performing an origin-destination insertion, we create a reverse transport order. The pickup location (say  $i$ ) and the delivery location (say  $j$ ) make the reverse order's origin and destination respectively. However, it has no predetermined ordering quantity. Rather, the ordering quantity is determined as what can at most be transported. Naturally, the ordering quantity can not exceed the delivery location's empty RTI demand ( $d_j^m$  or  $d_j^n$ ) or the pickup location's empty RTI supply ( $p_i$ ). The ordering quantity is also constrained by the maximum remaining transport capacity on the segment between a pickup location and a delivery locations. As such, the maximum reverse order quantity, referred to as  $q^*$ , can be found using the following equation in which  $p_i$  represents the pickup quantity and  $d_j$  the delivery quantity:

$$q^* = \max \left\{ p_i, d_j, \left\lfloor \frac{\max\{\bar{X}_m^h(i, j)\} - h}{\gamma_e} \right\rfloor \right\} \quad (4.6)$$

Creating reverse transport order and inserting them in the routes if done through a recurring procedure, in which a set of delivery locations and pickup locations are given as input. First, we choose a random delivery locations. Next, we seek the pickup location which is closest to the delivery location. If an insertion is feasible, it is performed with reverse order quantity  $q^*$ . After updating the locations' supply and demand, we check whether the empty RTI demand of the delivery location is satisfied: if not, we search a new pickup location for the same delivery location, else the location is removed from the delivery set. Similarly, we also check if the pickup location can still supply RTI, else the location is removed from the pickup set. Whenever the cheapest insertion between a pickup location and a delivery location is infeasible, we assume that no other pickup location might result in a better (feasible) reverse transport order. The location is transferred to a set of remaining delivery locations. Similarly, if the set of pickup locations is empty, the left-over delivery locations are also transferred to the set of remaining delivery locations. The remaining delivery locations are output by the procedure, and can be considered in other executions of the reverse routing procedure.

In a first stage, the reverse routing procedure is executed for the short-term repositioning delivery locations  $\mathcal{D}_r^m$ . The required input sets for delivery and pickup locations are thus  $\mathcal{D}_r^m$  and  $\mathcal{P}$ . Upon completion, we might be returned a set of remaining locations. For these locations, a reverse transport order through RTI repositioning could not be scheduled with our procedure. These remaining locations are added to the set of location that require short-term depot deliveries  $\mathcal{D}_d^m$ . As such, the remaining location that could not obtain their short-term RTI demand through repositioning might obtain them through a depot delivery. In the next stage, we schedule reverse transport orders to the set of short-term depot delivery locations  $\mathcal{D}_d^m$ . In this stage, the set of pickup locations only consists of the depot, i.e.  $\{0\}$ . The depot always has enough RTI ( $p_i = \infty$  with  $i = 0$ ). As such, all short-term depot delivery locations can receive RTI as long as the routing capacity allows it. Any remaining locations are discarded. Next, the first two stages are repeated for the long-term delivery sets  $\mathcal{D}_r^n$  and  $\mathcal{D}_d^n$ . During this whole process, we also consider which types of reverse flows are allowed according to the hyper-parameters  $F_r^m, F_d^m, F_r^n$  and  $F_d^n$ . The last execution stage consists of picking all remaining RTI supply and returning it to the depot. This step is also based on cheapest unpaired insertions where the delivery location is the depot with an unlimited demand ( $d_j = \infty$  with  $j = 0$ ). The complete procedure is represented in Algorithm 4, Algorithm 5 and Algorithm 6.

---

**Algorithm 4** Reverse Routing Heuristic (Part 1)

---

**Require:**  $F_r^m, F_d^m, F_r^n, F_d^n$ 

- 1: **if**  $F_r^m$  **then** REVERSE ROUTING( $\mathcal{D}_r^m, \mathcal{P}$ )  $\rightarrow \mathcal{D}_d^m$  ▷ Short-term RTI repositioning
  - 2: **if**  $F_d^m$  **then** REVERSE ROUTING( $\mathcal{D}_d^m, \{0\}$ ) ▷ Short-term depot delivery
  - 3: **if**  $F_r^n$  **then** REVERSE ROUTING( $\mathcal{D}_r^n, \mathcal{P}$ )  $\rightarrow \mathcal{D}_d^n$  ▷ Long-term RTI repositioning
  - 4: **if**  $F_d^n$  **then** REVERSE ROUTING( $\mathcal{D}_d^n, \{0\}$ ) ▷ Long-term depot delivery
  - 5: DEPOT RETURNS( $\mathcal{P}$ )
- 

---

**Algorithm 5** Reverse Routing Heuristic (Part 2)

---

- 1: **procedure** REVERSE ROUTING(*Delivery*, *Pickup*) ▷ Delivery set and pickup set
  - 2:      $Remaining = \emptyset$  ▷ Set of remaining delivery locations
  - 3:     **while** *Delivery*  $\neq \emptyset$  **do**
  - 4:          $j \leftarrow \text{RANDOM}(\textit{Delivery})$
  - 5:         **while**  $j \in \textit{Delivery}$  **and**  $\textit{Pickup} \neq \emptyset$  **do**
  - 6:              $i \leftarrow \text{argmin}_{i \in \textit{Pickup}} \{e_{i,j}\}$
  - 7:              $Cost^*, Insertion^* \leftarrow \text{CHEAPEST INSERTION}(i, j, \gamma_e)$  ▷ Algorithm 2
  - 8:             **if**  $Cost^* < \infty$  **then**
  - 9:                 Perform insertion  $Insertion^*$  with  $q^*$  ▷ Equation 4.6
  - 10:                 Update  $X_m^h, X_m^g, q_i$  and  $q_j$
  - 11:                 **if**  $q_i = 0$  **then**
  - 12:                     Remove  $i$  from *Pickup*
  - 13:                 **end if**
  - 14:                 **if**  $q_j = 0$  **then**
  - 15:                     Remove  $j$  from *Delivery*
  - 16:                 **end if**
  - 17:             **else**
  - 18:                 Add  $j$  to *Remaining*
  - 19:                 Remove  $j$  from *Delivery*
  - 20:             **end if**
  - 21:         **end while**
  - 22:         **if**  $\textit{Pickup} = \emptyset$  **then**
  - 23:             **for all**  $j \in \textit{Delivery}$  **do**
  - 24:                 Add  $j$  to *Remaining*
  - 25:                 Remove  $j$  from *Delivery*
  - 26:             **end for**
  - 27:         **end if**
  - 28:     **end while**
  - 29:     **return** *Remaining*
  - 30: **end procedure**
-

**Algorithm 6** Reverse Routing Heuristic (Part 3)

---

```

1: procedure DEPOT RETURNS(Pickup)
2:   while Pickup  $\neq \emptyset$  do
3:      $i \leftarrow \text{RANDOM}(\textit{Pickup})$ 
4:      $j \leftarrow 0$  ▷ The depot
5:      $\textit{Cost}^*, \textit{Insertion}^* \leftarrow \text{CHEAPEST INSERTION}(i, j, \gamma_e)$  ▷ Algorithm 2
6:     if  $\textit{Cost}^* < \infty$  then
7:       Perform insertion  $\textit{Insertion}^*$  with  $q^*$  ▷ Equation 4.6
8:       Update  $X_m^h, X_m^g$  and  $q_i$ 
9:       if  $q_i = 0$  then
10:        Remove  $i$  from Pickup
11:       end if
12:     else
13:       Remove  $i$  from Pickup
14:     end if
15:   end while
16: end procedure

```

---

**4.2.4 Hierarchical Knowledge Gradient**

Let us now introduce the Hierarchical Knowledge Gradient (HKG). As described in Section 4.1.4, the HKG addresses the Ranking and Selection Problem in which we seek the best *decision* in an efficient way. A decision essentially represents a unique selection of values for the hyper-parameters. The value of a decision is stochastic and unknown. It can, however, be estimated by simulating the decision a number of times. Through an aggregation structure, the HKG estimates values of all decisions by performing only a single measurements thanks to aggregated alternatives. In this section, we summarize the steps involved in the HKG as per Mes et al. (2011).

Consider a set of all decisions  $x \in \mathcal{X}$ . The decision  $x$  represent a unique set of values for the hyper parameters, i.e.  $x = (F_r^m, F_d^m, F_r^n, F_d^n, T^m, T^n, T^p)$ . Assigned to each alternative is a true mean  $\theta_x$  which is unknown, and a variance  $\lambda_x$  which is known. Through a series of sampling decisions  $n \in \{1, 2, \dots, N\}$ , we seek to estimate all  $\theta_x$ . With each sampling decision, we choose an decision  $x^n$  to simulate in our routing model. Doing so returns a sample observation  $y_x^{n+1}$ . The sample observation increases the knowledge we have over decision  $x^n$ , allowing us to make better estimated for  $\theta_x$ .

Say, we have performed  $n - 1$  samples so far and have to decide which decision  $x^n \in \mathcal{X}$  to sample next. By  $\mu_x^n$ , we indicate the estimated value of decision  $x$  so far. The estimate  $\mu_x^n$  is subject to an estimated deviation  $\sigma_x^n$ . More so, this deviation is better represented as a *precision*  $\beta_x^n = 1/(\sigma_x^n)^2$ , which indicates how exact the current estimate of decision  $x$  is.

All decisions  $x \in \mathcal{X}$  are also part of an aggregation scheme. Consider a number of aggregation levels  $G$  and a set of these aggregation levels  $g \in \mathcal{G} = \{0, 1, \dots, G\}$ . On each level, a decision  $x$  is part of a so-called aggregated alternative. Just as the individual decisions, each aggregated alternative has an estimated (aggregated) value  $\mu_x^{g,n}$  and precision  $\beta_x^{g,n}$ . The lowest aggregation level  $g = 0$  consists of aggregated alternatives of which only a single decision is part. On the highest aggregation level  $g = G$ , all decisions are part of the aggregated alternative. When a decision  $x^n$  is sampled, the sample observation  $y_x^{n+1}$  provides information regarding the individual decision estimates as well as the aggregated estimates. Consider the example in Figure 4.2. We have decisions  $x \in \mathcal{X} = \{1, 2, \dots, 9\}$  and three aggregation levels  $\mathcal{G} = \{0, 1, 2\}$ . In this example, decisions  $x = 1, 2, 3$  are part of the same aggregated alternative on level  $g = 1$  (indicated by 10). In this case, the estimated value for the aggregated alternative



is equal for all of them:  $\mu_1^{1,n} = \mu_2^{1,n} = \mu_3^{1,n}$ . The same goes for the aggregated precision for this aggregated alternative and all others. If, for instance, we choose to sample  $x^n = 2$  then the sample observation  $y_x^{n+1}$  can be used to update the decision's estimates as well as the estimates of all aggregated alternatives they are part of.

$g = 2$	13								
$g = 1$	10			11			12		
$g = 0$	1	2	3	4	5	6	7	8	9

FIGURE 4.2: Example aggregation structure

The HKG is built from two central procedures: the updating procedure and the sampling procedure. The updating procedure ensures that, with each new sampling decision, all (aggregated) decision estimates are correctly updated. Based on the known estimates at sampling moment  $n$ , the sampling procedure decides which decision  $x \in \mathcal{X}$  to sample next. Broadly speaking, for each decision the knowledge gradient,  $v_x^{KG}(S^n)$ , is computed according to:

$$v_x^{KG}(S^n) = \mathbb{E} \left[ \max_{x' \in \mathcal{X}} \mu_{x'}^{n+1} \mid S^n, x^n = x \right] - \max_{x' \in \mathcal{X}} \mathbb{E} \left[ \mu_{x'}^{n+1} \mid S^n, x^n = x \right] \quad (4.7)$$

where  $S^n$  represents the knowledge obtained through the first  $n$  sampling decision, i.e.  $S^n = \{\mu_x^{g,n}, \beta_x^{g,n} \forall x \in \mathcal{X}, g \in \mathcal{G}\}$ . Essentially, the knowledge gradient of each decision is computed as the expected increase in valuable knowledge. By sampling decision  $x^n$ , the estimated mean and precision of decision  $x^n$  and the aggregated decisions he is part of are updated according to the sampling observation  $y_x^{n+1}$ . Although we do not know the value of  $y_x^{n+1}$  before sampling  $x^n$ , we can estimate it's distribution according to  $\mu_x^n$  and  $\beta_x^n$ . As such, given the probability of a specific value for  $y_x^{n+1}$  occurring, we can anticipate on the updating procedure. As such, the left-hand term of Equation 4.7 represents the average value of the largest decision estimates after sampling decision  $x^n$  and observing  $y_x^{n+1}$ . The right-hand side represents the value of the decision  $x'$  with the highest expected updated estimate  $\mu_{x'}^{n+1}$  after sampling decision  $x^n$  and observing  $y_x^{n+1}$ . By subtracting the right-hand side from the left-hand side, the outcome represents the expected increase in valuable knowledge of the model. For every possible decision  $x \in \mathcal{X}$ , a knowledge gradient is computed and the decision with the highest  $v_x^{KG}(S^n)$  is sampled next.

In order to estimate the values in Equation 4.7, one requires an estimate on the mean and precision of a decision. Through the aggregation scheme, the HKG can quickly approximate a mean and precision of a decision without measuring it. As such, a good estimate for all decisions in  $\mathcal{X}$  can found in minimal measurements. In the computation of the knowledge gradient, a trade-off is made between often sampled decision  $x_1$  with good mean estimates and less sampled decision  $x_2$  with a lower estimate. As the latter is sampled less often, the decision's precision is low. As such, the range of values  $y_{x_2}^{n+1}$  might take is broader, thus resulting in potentially valuable observations. This trade-off is considered in Equation 4.7 in the maximization of expected updated estimates  $\mu_{x'}^{n+1}$ .

So far, we broadly described how the HKG works. For a more detailed description of the sampling and updating procedures, we refer to Mes et al. (2011). We use the HKG to quickly estimate the value of a decision  $x$ , which consists of a value for each for the hyper-parameters  $x = (F_r^m, F_d^m, F_r^n, F_d^n, T^m, T^n, T^p)$ . The HKG requires a prior knowledge on the aggregation structure of decisions as well as knowledge on the variance of the decisions' value  $\lambda_x$ . In order to define the aggregation structure, the structure of decisions must be well known. Given our decision structure, an aggregation structure can be defined in which each new aggregation level incorporate an additional hyper-parameter. Finding an exact value for  $\lambda_x$  also requires extensive knowledge on the decision, which we currently do not have. Mes et al. (2011)

note that an estimate for  $\lambda_x$  also works in the HKG. In our model, we adopt a generalized variance  $\lambda$  for all decisions ( $\lambda_x = \lambda \forall x \in \mathcal{X}$ ). The variance  $\lambda$  can then be estimated through experimentation.

### 4.3 Conclusions

In this chapter, we introduced the method through which the potential of RTI repositioning will be analysed. In Section 4.1, the Pickup and Delivery Inventory Routing Problem is further described along with assumptions and a mathematical notation. Based on this formulation, a solution approach is provided.

The solution approach consists of a parametric and sequential routing procedure which create a planning for daily routing activities. In order to incorporate benefits on a long-term cost-functions, adjustable parameters determine how the reverse logistics are executed. In the reverse logistics, we distinguish between short-term and long-term empty RTI demand. Two forecasting horizon hyper-parameters influence the value for each of these. A third forecasting horizon hyper-parameter influences the available empty RTI supply available at users. Given a demand and supply for users, empty RTI demand can be satisfied via depot delivery flows or RTI repositioning flows. Four Boolean reverse flow hyper-parameters determine whether short-term and long-term demand may be satisfied via any of these flows. Together, reverse flow hyper-parameters represent a reverse RTI strategy.

Given a set of hyper-parameter values, the forward routing heuristic first initializes forward routes in a cheapest insertion heuristic. The routes created serve as the basis for reverse logistics to be planned on. Next, A variable fixing heuristic determine short-term and long-term empty RTI demand as well as empty RTI supply and classifies delivery locations in delivery sets. Based on demand, supply and the delivery set classification, the reverse routing procedure matches supply and demand pair and inserts them through a cheapest insertion heuristic.

Efficient execution of the routing heuristics on an instance relies on the efficient selection of reverse flow and forecasting horizon parameters. To find the set of values that best solve the simulation, we make use of the Hierarchical Knowledge Gradient (HKG) algorithm is applied. The HKG algorithm is a learning strategy that utilizes an aggregation structure to efficiently accumulate information on hyperparameters decisions with limited observations.

## Chapter 5

# Experimentation & Results

In this chapter, we introduce the experiments performed and discuss their results. During the experimentation phase, we seek insights into the efficiency of RTI repositioning when compared to the situation without RTI repositioning. We also analyze the sensitivity of our results. In Section 5.1, we provide a description of the used instances and the relevant key performance indicators. In Section 5.2, we perform our experiments. In Section 5.3, we provide a recommendation with managerial insights. In Section 5.4, we elaborate on some points of discussion.

## 5.1 Experimental Setting

In this setting, we describe the setting in which the experiments are performed. First, we introduce three instances in Section 5.1.1. These instances consist of representative fractions of the available data set. Next, we repeat the simulation hyper-parameters that govern the model in Section 5.1.2. For the latter, an aggregation structure for the HGK is also defined. Finally, we introduce key performance indicators (KPI) in Section 5.1.3. These KPIs summarize an experiment's logistic efficiency in various aspects. We also introduce an objective function based on the weighted sum of these KPIs.

### 5.1.1 Instance description

The data used in this research has been provided by COMPANY B. The full set consists of 1657 locations and 45155 forward orders between 01/01/2020 and 31/12/2020. Each forward order consists of an origin ID, a destination ID, a transported RTI type, and a transport quantity (which never exceeds 43 RTI). In their daily businesses, COMPANY B uses three depots, one of which is most common. For our experiments, we assume only one depot, the largest, is used for empty RTI storage in line with Assumption 1. We reduced this data-set to three smaller instance sizes, including location 0 to serve as the depot. As can be seen in Table 5.1, this drastically reduces the number of unique locations in the set whilst still containing a large fraction of the supply chain's demand. This reduction was also necessary due to computational limitations. Given the set of locations  $V = \{0, 1, \dots\}$  where  $v = 0$  is the depot, an edge set  $E$  is generated according to the straight-line distance between all coordinate points in  $V$ . For each of these instances, a full year of transport orders is simulated.

Instance	Size	Forward orders	Forward RTIs	Starting inventory
Original set	1657	45155	234572	
$I_{128}$	128	30022 (66%)	180776 (77%)	10000
$I_{78}$	78	23399 (52%)	152753 (65%)	8000
$I_{40}$	40	16094 (36%)	105289 (45%)	6000

TABLE 5.1: Instances

In Section 4.1.3, we introduced the mathematical notation used in this problem. The values for some of the variables are fixed through the experimentation phase. The vehicle capacity is set at  $h = 13.2$  meters (Section 2.2.1) and the maximum driving distance at  $g = 700$  kilometres. In line with Assumption 2, we have chosen the CC RTI-type as the leading RTI type in the model. As such, filled RTIs occupy a volume of  $\gamma_f = 0.306$  and empty RTIs occupy a volume of  $\gamma_e = 0.00459$ . Prior experiments provided quick feasible forward routing solutions with  $\alpha = 0.9$ . The depot's inventory is initialized at 10000, 8000 and 6000 for the instances  $I_{128}$ ,  $I_{78}$  and  $I_{40}$  respectively. All remaining locations have a starting inventory of 0.

### 5.1.2 Hyper-parameters

In Section 4.1.4, we introduce the reverse flow hyper-parameters and the forecasting horizon hyper-parameters. The reverse flow hyper-parameters consist of four Boolean values indicating which types of short-term and long-term reverse RTI flows are allowed. The forecasting horizon hyper-parameters define the lengths of the short-term and long-term forecasting horizon as well as the picking forecasting horizon.

Together, the reverse flow hyper-parameters form a reverse RTI strategy. They define how RTI may flow in the network.  $F_r^m$  determines whether RTI repositioning may be used to satisfy short-term empty RTI demand.  $F_d^m$  determines whether depot delivery flows may be used to satisfy short-term empty RTI demand.  $F_r^n$  determines whether RTI repositioning may be used to satisfy long-term empty RTI demand.  $F_d^n$  determines whether depot delivery flows may be used to satisfy long-term empty RTI demand. A total of 16 unique reverse RTI strategies  $\mathcal{F} = \{F_r^m, F_d^m, F_r^n, F_d^n\}$  can be derived for the Boolean hyper-parameters. Each unique strategy can be represented as  $\mathcal{F}_n$  for  $n = \{1, \dots, 16\}$ . However, we argue that some of these strategies are unrealistic. Consider, for instance, a strategy where no reverse RTI method is implemented, i.e.  $\mathcal{F} = \{0, 0, 0, 0\}$ . This strategy will result in only emergency deliveries and is therefore unrealistic. We also define that a long-term reverse RTI method is only possible if its short-term counterpart is also enabled. As such, a strategy  $\mathcal{F} = \{0, 0, 1, 1\}$  would also be prevented. As such, we limit our study to four reverse RTI strategies, defined in Table 5.2.  $\mathcal{F}_1$  consists of a strategy where reverse logistics is exclusively performed through RTI repositioning, both short- and long-term. It is referred to as the pure RTI repositioning strategy.  $\mathcal{F}_2$ , referred to as a semi-hybrid strategy, implements short-term and long-term RTI repositioning, as well as short-term depot deliveries.  $\mathcal{F}_3$  is considered fully hybrid as both RTI repositioning and depot deliveries are implemented for both short-term and long-term deliveries. Finally,  $\mathcal{F}_4$  relies on depot deliveries only and is therefore referred to as the pure depot delivery strategy. During the experimentation phase, we no longer refer to individual reverse flow hyper-parameters. Instead, we will refer to the reverse RTI strategies  $\mathcal{F}_n$ .

The forecasting horizon hyperparameters  $T^m$ ,  $T^n$ , and  $T^p$  are bound in a discrete domain. The short-term and long-term forecasting horizon are chosen in a range of 5 days, i.e.  $T^m \in \{0, 5\}$  and  $T^n \in \{0, 5\}$ . Keep in mind that the long-term forecasting horizon is determined by  $T^m + T^n$ . The picking forecasting horizon is chosen as  $T^p \in \{0, 10\}$ . As such, both the empty RTI demand forecasting horizon ( $T^m + T^n$ ) and the empty RTI supply forecasting horizon ( $T^p$ ) have

Option	Description	$F_r^m$	$F_d^m$	$F_r^n$	$F_d^n$
$\mathcal{F}_1$	Pure RTI repositioning	1	0	1	0
$\mathcal{F}_2$	Semi-hybrid	1	1	1	0
$\mathcal{F}_3$	Fully-hybrid	1	1	0	1
$\mathcal{F}_4$	Pure depot delivery	0	1	0	1

TABLE 5.2: Four considered options for the hyperparameters values of  $\mathcal{F}$ 

the same upper bound of 10. This upper bound is in line with the fast-moving horticultural industry. Note that if a forecasting horizon equals 0, no forecasting is done for this specific delivery or picking set. As such, this process is disabled. This aspect has also led to a point of discussion, presented in Section 5.4.4

Having further specified the four types of reverse RTI strategies and the bounds of the forecasting horizon hyper-parameters, we now present the aggregation structure. The top-most level of the aggregation structure is the overarching aggregation consisting of all decisions. Next, the decision space is aggregate on the  $\mathcal{F}$  provided in Table 5.2. Next, the forecasting horizon parameters are sequentially added. The resulting aggregation structure is defined in Table 5.3

Level	$\mathcal{F}_n$	$T^m$	$T^n$	$T^p$	Aggregation space
0	*	*	*	*	$4 \times 6 \times 6 \times 11 = 1584$
1	*	*	*	-	$4 \times 6 \times 6 \times 1 = 144$
2	*	*	-	-	$4 \times 6 \times 1 \times 1 = 24$
3	*	-	-	-	$4 \times 1 \times 1 \times 1 = 4$
4	-	-	-	-	$1 \times 1 \times 1 \times 1 = 1$

TABLE 5.3: Aggregation structure

### 5.1.3 Key Performance Indicators & objective

During the experimentation phase, we make use of various KPIs that summarize the results of a full simulation. In this section, we introduce the following key performance indicators (KPI) as well as a cost function. These KPIs and cost function are presented as absolute values. Due to the difference in instance sizes, they are interchangeably presented relative to the instance's total order count (e.g., KPI per order).

By tracking inventory levels of locations and especially the depot, the minimum amount of RTI required to keep the system running can also be obtained. This indicates how many RTI could have been used as opposed to the predefined inventory levels per instance.

- *KPI 1* (Required RTIs): Tracks the minimum amount of RTIs required over the year.

Next, our routing model keeps track of the distances driven in the forward and reverse logistics. First, the amount of kilometers required for the completion of forward logistics is tracked. This value is constant over the various simulations, based on the addressed instance. The reverse logistics kilometers are also tracked. This consists of the required distance for depot deliveries, depot returns, and repositioning. This results in the following KPI tracking the total amount of kilometers.

- *KPI 2* (Kilometres): Tracks the total amount of distance travelled for forward and reverse logistics.

Finally, we also keep track of the total activity within the depot, consisting of the number of RTI loaded and unloaded. By loading and unloading RTI at the depot, no contribution to the value-adding forward logistics is made.

- *KPI 3 (Depot activity)*: Tracks the amount of loading and unloading activities at the depot.

Finally, each time a stockout occurs an emergency delivery is scheduled. The emergency delivery consists of a direct return trip to a user delivering exactly the number of missing RTIs. Emergency deliveries should always be prevented. The following KPI tracks the total distance driven for emergency deliveries.

- *KPI 4 (Emergency deliveries)*: Tracks the distance driven for emergency deliveries

Using these KPIs, we can present two objective functions. A first objective function consists of the total costs of a simulation. The required RTIs must be rented for a full year which induces costs. Stockouts lead to emergency deliveries which, along with the forward and reverse logistics distances, induce transportation costs. The act of handling RTI in the depot also induces costs for each RTI handled, be it loading or unloading. In discussion with COMPANY B, costs for transport kilometers and depot activity are approximated as fractions or multiplication of the daily RTI renting costs. A similar calculation is done for emergency deliveries. These so-called cost factors, referred to as  $\omega_1$ ,  $\omega_2$  and  $\omega_3$ , allow for the definition of the cost-function shown in Equation 5.1.

$$\text{costs} = 365 \cdot \text{Req. RTIs} + \omega_1 \cdot \text{Kilometers} + \omega_2 \cdot \text{Depot Act.} + \omega_3 \cdot \text{Emergency deliveries} \quad (5.1)$$

The cost-factors  $\omega_1$ ,  $\omega_2$  and  $\omega_3$  depend a lot based on the circumstances. The kilometer cost-factor  $\omega_1$  depends on the region one drives in. In the Netherlands, shorter driving distances and higher fuel costs result in kilometers costing twice as much as daily RTI renting costs. In Germany, driving distances are longer and fuel less expensive resulting in each driven kilometer being equally expensive as renting a single RTI for a day. The kilometer cost-factor thus varies between 1 and 2 ( $\omega_1 \in [1, 2]$ ). The cost of depot activities ( $\omega_2$ ) depends largely on the batch size: larger batch sizes result in more efficient work and thus fewer costs. The depot activity cost-factor also varies between 1 and 2 based on an approximation by COMPANY B ( $\omega_2 \in [1, 2]$ ). Finally, the emergency delivery cost-factor is chosen experimentally. Emergency deliveries are uncommon in the current supply chain due to the manual planning activities. To prevent emergency deliveries as much as possible, we fix a high value for  $\omega_3$ . In Section 2.3, the numerical example indicates RTI will increase distances driven but reduce both RTIs and activity at the depot. For the experimentation phase, we consider a 'worst-case' scenario where the cost-factors are set to the least-favorable setting. As such, the kilometer cost-factor is set at  $\omega_1 = 2$  and the depot activity cost-factor is set at  $\omega_2 = 1$ . The emergency delivery cost factor is fixed at  $\omega_3 = 10$ , chosen through prior experimentation in agreement with stakeholders. Both the yearly RTI renting costs and the fact that cost-factors are fixed are discussed in Section 5.4.3 and Section 5.4.2.

## 5.2 Experiments & Results

In this section, the various experiments and their results are presented. In Section 5.2.1, values for the decision variance required for the HKG are experimented with. In Section 5.2.2, we experiment with fixed values for the various hyper-parameters to analyze their sensitivity. In Section 5.2.3, we extensively study the efficiency of the different reverse RTI strategies.

### 5.2.1 Tuning of $\lambda$

The chosen value for the observation variance  $\lambda$  influences the convergence of the HKG algorithm towards the optimal strategy. As denoted in Section 4.2.4, the HKG algorithm aims to maximize the expected increase in information with each new iteration, as well as to find the highest expected reward. The variance of a decision (e.g., set of hyper-parameter values) does not need to be exact. Considering this, we choose to consider a common variance for all decisions in an instance. Some prior experimentation shows that a rough approximation  $\sqrt{\lambda} = 5 \cdot 10^4$  can be taken for all instances. In this subsection, we experiment with different magnitudes for  $\sqrt{\lambda}$

In Figure 5.1, the convergence results are plotted. For all three instances, convergence is slow when  $\sqrt{\lambda}$  is too low. On the other hand, the HKG is less likely to consider new decisions when  $\sqrt{\lambda}$  is too high. For instance  $I_{40}$ , a slow convergence and high costs are observed when  $\sqrt{\lambda} = 5 \cdot 10^5$  or  $\sqrt{\lambda} = 5 \cdot 10^6$ . The remaining values for  $\sqrt{\lambda}$  seem to provide similar convergence speeds as well as low costs. For instance  $I_{78}$ ,  $\sqrt{\lambda} = 5 \cdot 10^5$  and  $\sqrt{\lambda} = 5 \cdot 10^6$  result in a slow convergence as well.  $\sqrt{\lambda} = 5 \cdot 10^4$  also shows signs of slow convergence.  $\sqrt{\lambda} = 5 \cdot 10^2$  provides good initial results but does not progress towards better decisions.  $\sqrt{\lambda} = 5 \cdot 10^3$  seems to provide both low costs and good convergence. For instance  $I_{128}$ , convergence is best for  $\sqrt{\lambda} = 5 \cdot 10^5$ . Lower values for  $\sqrt{\lambda}$  do not converge as much, and  $\sqrt{\lambda} = 5 \cdot 10^6$  results in such high costs and slow convergence it is only barely visible on the chart. Based on these observations, instance  $I_{40}$  is assigned  $\sqrt{\lambda} = 5 \cdot 10^2$ , instance  $I_{78}$  is assigned  $\sqrt{\lambda} = 5 \cdot 10^3$  and instance  $I_{128}$  is assigned  $\sqrt{\lambda} = 5 \cdot 10^5$ .

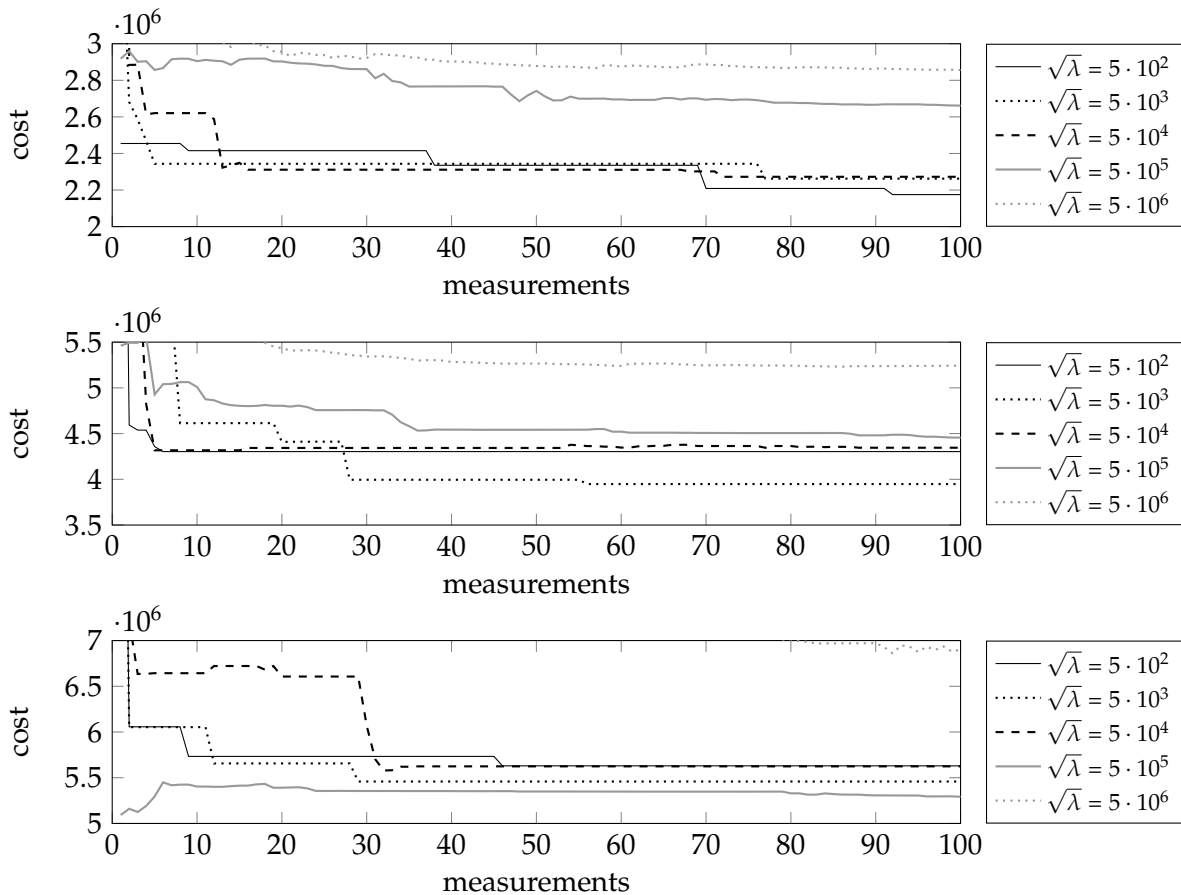
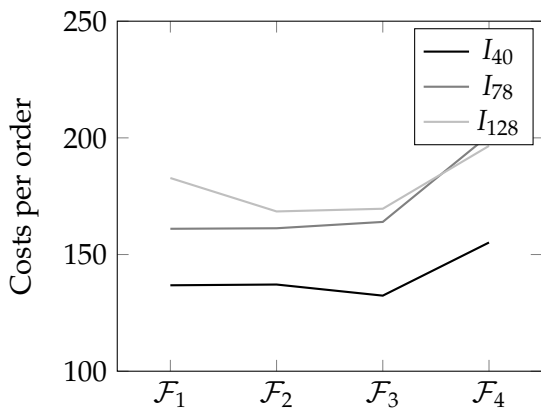


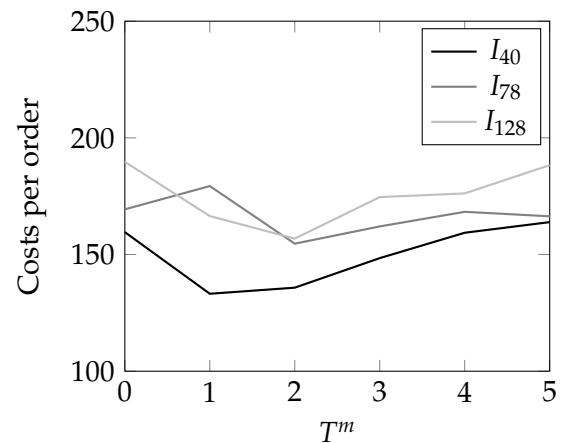
FIGURE 5.1: Convergence with various levels for  $\sqrt{\lambda}$   
top:  $I_{40}$ , middle:  $I_{78}$ , bottom:  $I_{128}$

## 5.2.2 Hyper-parameter sensitivity

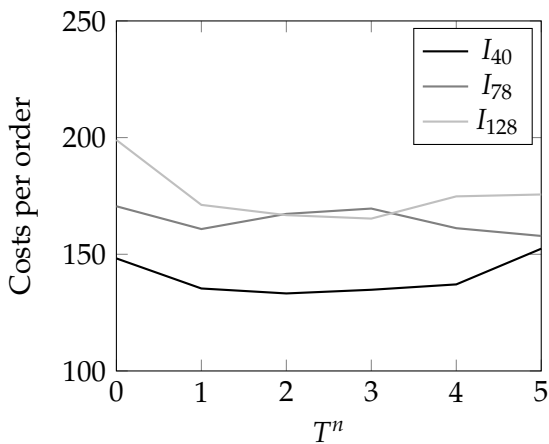
To understand the impact of hyper-parameter settings on the model, we experiment with fixed values for each of the four hyper-parameter types. For each of the values a hyper-parameter is set to take, 50 measurements were simulated for each network instance. In Figure 5.2a, the four reverse RTI strategies are fixed. Results are slightly consistent over the instances. The hybrid strategies ( $\mathcal{F}_2$  and  $\mathcal{F}_3$ ) seem to result in lower costs, whereas the pure depot delivery strategy results in higher costs in all instances. In Figure 5.2b, the short-term forecasting horizon length ( $T^m$ ) is fixed. Generally, lower values around 1 or 2 days seem to be preferred. In Figure 5.2c, the long-term forecasting horizon length ( $T^n$ ) is fixed. In this figure, we observe that a wider range between 1 and 4 days is preferred. Results vary over the various instances, however. In Figure 5.2d, the picking forecasting horizon length ( $T^p$ ) is fixed. Results seem consistent over the instance. Oddly enough, the forecasting horizon gives the best results when it is either low or high, whereas an intermediate forecasting horizon leads to additional costs in all instances. For all three forecasting horizon hyper-parameters, we also find that a value of 0, which disables forecasting, generally results in higher costs. We can also deduce that both the forecasting horizon and the reverse RTI strategy have an observable impact on the model's efficiency, indicating there is a significant trade-off to be made between the renting costs, driving costs, and depot activity.



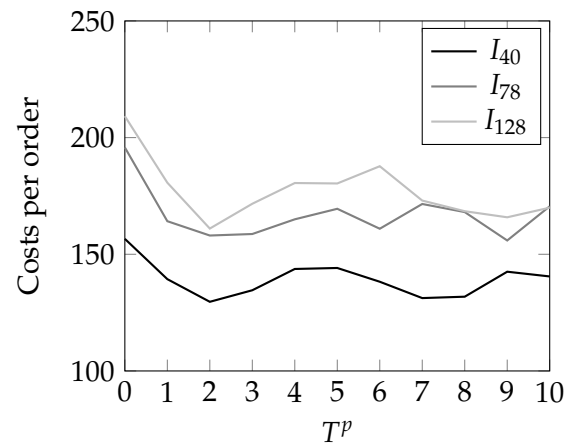
(A) Effect of fixed values for reverse RTI strategies  $\mathcal{F}_n$  on all instances



(B) Effect of fixed values for the short-term forecasting horizon  $T^m$  on all instances



(C) Effect of fixed values for the long-term forecasting horizon  $T^n$  on all instances



(D) Effect of fixed values for the picking forecasting horizon  $T^p$  on all instances



### 5.2.3 Reverse RTI strategies

In this study, we seek to identify the potential of RTI repositioning. As mentioned in Section 5.1.2, the reverse RTI strategies are structured such that they can represent specific types of reverse RTI management. The pure depot delivery strategy ( $\mathcal{F}_4$ ) most resembles the current RTI management: although the concept of “RTI trading” (see Section 2.2.6) is not actively carried out, all RTIs must flow through the depot (Discussed in Section 5.4.1). In this experiment, we propose a more thorough analysis of the operational differences between this method and the proposed strategies with some form of RTI repositioning. In this experiment, we fix each of the reverse RTI method hyperparameters according to the various reverse RTI strategies (see Table 5.2) while keeping the forecasting horizon hyperparameters variable. Each setting is trained in 5 runs with 200 HKG measurements. Finally, the resulting hyper-parameter settings were each simulated another 10 times to obtain additional insights into the stochastic influences in the solution. The absolute average KPI scores of this experiment can be found in Table 5.4. To analyze these KPIs on a comparable scale, each KPI value is divided by the instance’s total number of forward orders.

#### Required RTIs

In Figure 5.3, the number of used RTI per order are depicted. Results show small but noticeable differences per reverse RTI strategy. For this KPI, we observe that the pure RTI repositioning strategy ( $\mathcal{F}_1$ ) requires the amount of RTI and the pure depot delivery strategy requires ( $\mathcal{F}_4$ ) most. The hybrid strategy ( $\mathcal{F}_2$  and  $\mathcal{F}_3$ ) score comparably well and can be considered average. There is some variance involved in this measure. However, we can safely state that a strategy with RTI repositioning ( $\mathcal{F}_1$ ,  $\mathcal{F}_2$  or  $\mathcal{F}_3$ ) generally scores better than the strategy without RTI repositioning ( $\mathcal{F}_4$ ).

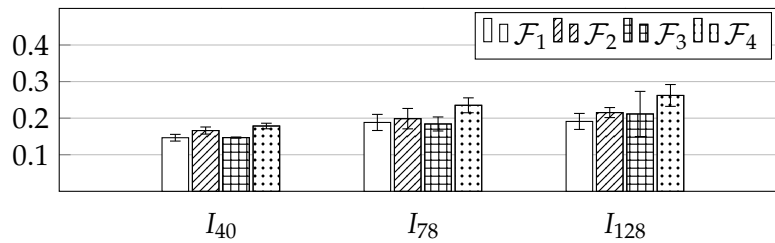


FIGURE 5.3: Average required RTIs (KPI 1) per order, with a 95% confidence interval.

#### Kilometers

In Figure 5.4, the kilometres per order are depicted. Over the instances, the differences in kilometers driven for forward and reverse logistics are relatively comparable. The pure RTI repositioning strategy ( $\mathcal{F}_1$ ) results in a few more kilometers, and the other strategies each have comparable results. This indicates that the distance driven does not seem to correlate with the employed reverse RTI strategy.

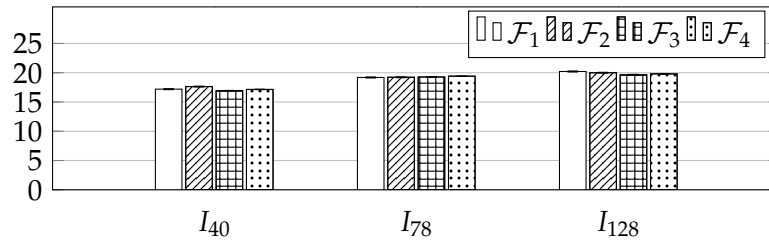


FIGURE 5.4: Average kilometers driven per order (KPI 2), with a 95% confidence interval.

### Depot activity

In Figure 5.5, the depot activity per order is depicted. This figure represents the observed amount of additional RTI handling within the depot. We see a large reduction of depot activity for all strategies using RTI repositioning ( $\mathcal{F}_1$ ,  $\mathcal{F}_2$  and  $\mathcal{F}_3$ ). This indicates a clear trend in which RTI repositioning reduces total depot activity. This is a logical consequence of the fact that RTIs do not need to be processed in the depot with RTI repositioning.

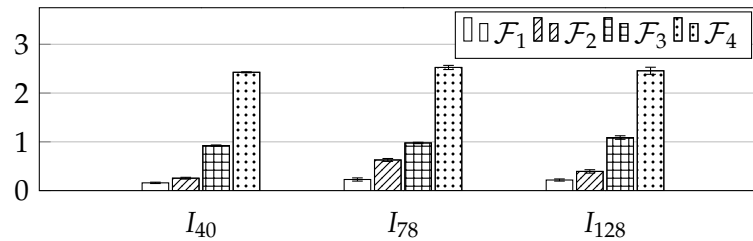


FIGURE 5.5: Average depot activity per order (KPI 3), with a 95% confidence interval.

### Emergency deliveries

In Figure 5.6, the depot activity per order is depicted. The pure RTI repositioning strategy ( $\mathcal{F}_1$ ) stands out: it generally results in the highest required emergency delivery distance. The pure depot delivery strategy ( $\mathcal{F}_4$ ) is slightly better, but still quite high relative to the hybrid strategies ( $\mathcal{F}_2$  or  $\mathcal{F}_3$ ). This measure seems quite high in general, but especially in instance  $I_{128}$ . In Figure 5.4, the average forward and reverse kilometer driven per order is 20 kilometers for instance  $I_{128}$ , with an average of 2.5 kilometers for emergency deliveries. This can be explained by the fact that a minimal number of trucks is initialized in the forward routing heuristic (Section 4.2.1). As such, a lack of capacity for reverse activities increases emergency deliveries. This can explain why the pure strategies ( $\mathcal{F}_1$  and  $\mathcal{F}_4$ ) have higher emergency deliveries: the pure RTI repositioning strategy is limited by the additional distance required. The pure depot delivery strategy, on the other hand, requires less distance but all empty RTI have to be loaded at the start of the day and is thus limited by the capacity available in vehicles.

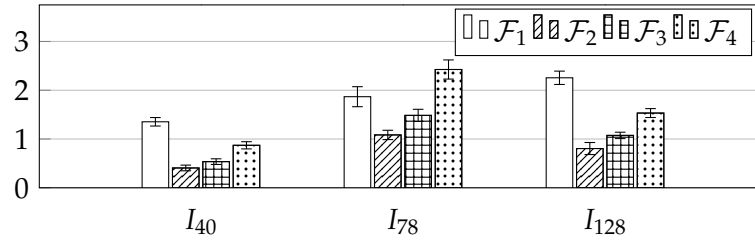


FIGURE 5.6: Average depot activity per order (KPI 3), with a 95% confidence interval.

### Costs

In Figure 5.7, the costs per order are plotted. The costs are calculated as the weighted sum of all prior KPIs, as per Equation 5.1. The individual contribution of each KPI to the total costs is also shown. First and foremost, we observe that the pure depot delivery strategy ( $\mathcal{F}_4$ ) leads to the most costs in all three instances. On average, the three strategies with some form of RTI repositioning ( $\mathcal{F}_1$ ,  $\mathcal{F}_2$  and  $\mathcal{F}_3$ ) result in a significant cost reduction. Based on the applied strategy, there are some deviations involved, however, they do not result in significantly different conclusions. We also observe that the rent of RTIs and the distances driven for forward and reverse logistics make up the largest cost components. Depot activity costs are relatively small but are far higher for the pure depot delivery strategy ( $\mathcal{F}_4$ ). The costs of emergency deliveries have a moderate impact on the total costs, mainly due to the high value for the cost-factor.

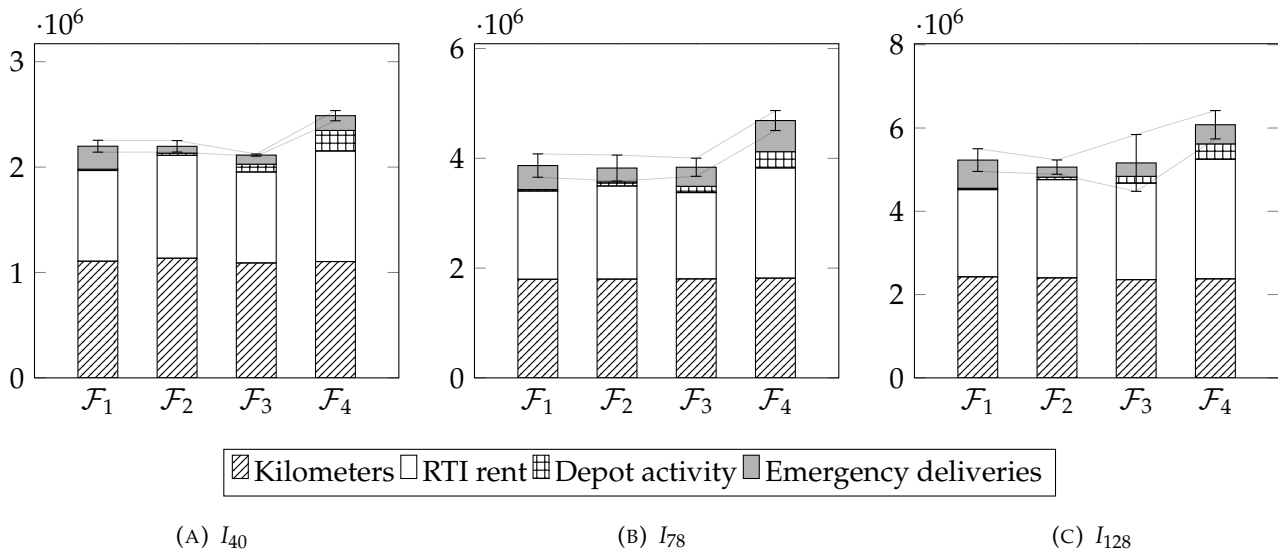


FIGURE 5.7: Cost buildup for each instance and reverse RTI strategy with  $\omega_1 = 2$ ,  $\omega_2 = 1$  and  $\omega_3 = 10$

		Required RTIs	Kilometers	Depot activity	Emergency km.	Cost
$I_{40}$	$\mathcal{F}_1$	2358	553448	12794	21778	2198065
	$\mathcal{F}_2$	2674	567642	20462	6539	2196996
	$\mathcal{F}_3$	2364	545285	74274	8626	2113855
	$\mathcal{F}_4$	2874	551863	195197	14017	2487916
$I_{78}$	$\mathcal{F}_1$	4406	898149	26654	43700	3867958
	$\mathcal{F}_2$	4648	899707	73504	25357	3822861
	$\mathcal{F}_3$	4308	901706	114328	34734	3837392
	$\mathcal{F}_4$	5503	908335	295402	56748	4688039
$I_{128}$	$\mathcal{F}_1$	5736	1213486	32600	67704	5230110
	$\mathcal{F}_2$	6463	1200825	59040	24157	5061255
	$\mathcal{F}_3$	6348	1179489	163328	32244	5161878
	$\mathcal{F}_4$	7868	1189066	368796	45997	6078831

TABLE 5.4: Absolute average KPI and objective values.

### Forecasting horizon settings

Finally, let us discuss the forecasting horizon settings for each of the reverse RTI strategies, shown in Table 5.5. The large variety in forecasting horizon settings amongst instances suggests a high dependency on the instance dynamics as well as the reverse RTI strategy. Generally speaking, when a forecasting horizon is low, its associated demand or supply is also lower.

Instance	$\mathcal{F}$	$T^m$	$T^n$	$T^p$
$I_{40}$	$\mathcal{F}_1$	2	4	3
$I_{78}$	$\mathcal{F}_1$	2	5	4
$I_{128}$	$\mathcal{F}_1$	5	5	2
$I_{40}$	$\mathcal{F}_2$	2	5	2
$I_{78}$	$\mathcal{F}_2$	2	1	6
$I_{128}$	$\mathcal{F}_2$	2	5	3
$I_{40}$	$\mathcal{F}_3$	0	2	8
$I_{78}$	$\mathcal{F}_3$	0	2	6
$I_{128}$	$\mathcal{F}_3$	2	0	8
$I_{40}$	$\mathcal{F}_4$	0	2	7
$I_{78}$	$\mathcal{F}_4$	0	2	10
$I_{128}$	$\mathcal{F}_4$	1	2	10

TABLE 5.5: Forecasting horizon settings for fixed reverse RTI strategies.

The pure RTI repositioning strategy ( $\mathcal{F}_1$ ) generally has a smaller short-term and larger long-term forecasting horizon and lower picking forecasting horizon. This suggests a distinction between short-term and long-term demand is important when all empty RTI deliveries are performed via RTI repositioning. A smaller picking forecasting horizon suggests empty RTI inventories are quickly considered for repositioning. In two instances ( $I_{40}$ ,  $I_{128}$ ), the semi-hybrid strategy ( $\mathcal{F}_2$ ) implements a small short-term forecasting horizon and a large long-term forecasting horizon. combined with a small picking forecasting horizon. This strategy suggests a higher urgency demand should be delivered via RTI repositioning or depot deliveries in case there is no empty RTI supply at users. Once high urgency short-term deliveries have

Forecasting horizon	Short-term	Long-term	Picking
Instance users	0.46	-0.05	0.09
Instance forward orders	0.43	-0.06	0.11
Instance forward RTI	0.40	-0.08	0.14
Relative RTI repositioning	0.75	0.68	-0.86

TABLE 5.6: Correlation between instance characteristics and forecasting horizon lengths, and correlation between relative RTI repositioning and forecasting horizon lengths.

been planned, the less urgent long-term demand can be planned in via repositioning as long as logistic capacity and empty RTI supply are sufficient. In instance  $I_{78}$ , the small long-term forecasting horizon and large picking forecasting horizon suggest that most empty RTI demand should be handled via short-term RTI repositioning: a longer picking forecasting horizon results in a higher empty RTI supply, but since the long-term forecasting horizon is small, most repositioned RTI will be picked for short-term demand. The fully hybrid strategy ( $\mathcal{F}_3$ ) has set either the short-term forecasting horizon or the long-term forecasting horizon at 0. By doing so, the short-term or long-term demand is disabled. For the first two instances, the short-term forecasting horizon is set to 0. Under this setting, empty RTI demand is provided by long-term repositioning flows first, with remaining RTI demand being delivered via long-term depot deliveries. In the third instance, the long-term forecasting horizon is set at zero, but the result is identical. For the pure depot delivery strategy ( $\mathcal{F}_4$ ), a similar effect is observed. By setting either the short-term or the long-term forecasting horizon at zero, no prioritization is made for the delivery of RTI: as long as vehicle capacity permits, RTIs are delivered with equal priority. The exception is instance  $I_{128}$ , where a small short-term forecasting horizon is prioritized.

In Table 5.6, we show how the instance characteristics (Table 5.1) correlate with the forecasting horizon lengths. At a glance, we find that only the short-term forecasting horizon correlates with the instance characteristics. Large instances generally lead to higher short-term forecasting horizons. The long-term forecasting horizon and the picking forecasting horizon, however, have little to no correlation with the instance characteristics. All forecasting horizons have a significant correlation with the amount of RTI repositioning. Say, we consider the relative fraction of RTI repositioning for each reverse RTI strategy as:

- 100% RTI repositioning: pure RTI repositioning.
- 66% RTI repositioning: Semi-hybrid
- 33% RTI repositioning: Fully hybrid
- 0% RTI repositioning: pure depot delivery

Then the correlations are computed as shown in Table 5.6. The short-term and long-term forecasting horizon tends to decrease as we progress from the pure RTI repositioning strategy ( $\mathcal{F}_1$ ) to the pure depot delivery strategy ( $\mathcal{F}_4$ ), whereas the picking forecasting horizon increase. All in all, this suggests the forecasting horizon settings are correlated with the chosen strategy, more so than the addressed instance. Alternatively, this indicates that each reverse RTI strategy has a generally preferred forecasting horizon setting, regardless of the instance address.

### 5.3 Managerial Implications

In the previous section, we reviewed the results of the experiments. In this section, we reflect on the implications for a managerial decision-maker. To analyze an experiment, we designed four key performance indicators and a single cost objective function. The KPIs summarize the

cost components of the supply chain. They consist of the total number of RTIs required in the supply chain, the total distance driven in forward and reverse logistics, the total amount of RTI handling in the depot, and the total amount of emergency deliveries. The cost function is a weighted summation of these four KPIs. The cost-factors (e.g., weights) of each component are situational. Based on input from COMPANY B, they were set on the least-favorable setting to reduce any bias the cost-factors might introduce.

The simulation model designed in Chapter 4 was tested on three instances. Each instance represents a portion of the historical transport orders provided by COMPANY B. During the experimentation phase, an initial focus was put on the comparison between the reverse RTI strategies proposed in Section 5.1.2. A first strategy, the pure RTI repositioning strategy, consisted in performing all reverse logistics through RTI repositioning. As such, both short-term and long-term RTI requests are delivered by repositioning the RTIs available at supplying users. A second strategy, referred to as semi-hybrid, performs short-term and long-term RTI repositioning as well as short-term depot deliveries. The third strategy, a fully hybrid strategy, applies short-term and long-term RTI repositioning as well as short-term and long-term depot deliveries. Finally, the pure depot delivery strategy only applies short-term and long-term depot deliveries.

In Section 5.2.3, we analyzed the performance of each reverse RTI strategy on three instances. We observe that each strategy returns consistent KPI results over the experiments. Strategies that incorporate some form of RTI repositioning (pure or hybrid) considerably reduce the total number of RTI required, as well as the total activity in the depot. The total distance driven for forward and reverse logistics is similar for all strategies. Although initial theories suggested an increase in distance driven for RTI repositioning, this turned out not to be the case. In regards to stockouts, we observe that the pure strategies result in large emergency deliveries being driven. These strategies are limited by loading capacity and driving limits. The hybrid strategies incorporate more flexibility and are more prone to dynamically managing user inventories.

Regarding total costs, we find that a strategy focused purely on depot deliveries always results in higher costs. These costs mainly follow from an increased total number of RTIs required and are augmented by the high depot activity costs. Since all strategies with some form of RTI repositioning lead to fewer costs, we can already conclude that RTI repositioning does improve RTI logistics efficiency. Quantifying this statement, we propose Figure 5.8, in which the relative reduction in costs compared to the pure depot delivery strategy is shown (in other words: the relative increase in efficiency). From a general point of view, RTI repositioning can increase efficiency between 3.20% and 21.62%. The average scores per instance and reverse RTI strategy are shown in Table 5.7

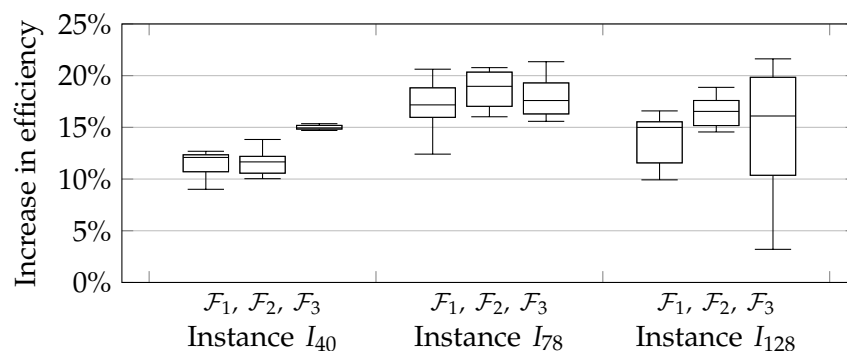


FIGURE 5.8: Increase in efficiency of the pure RTI repositioning strategy ( $\mathcal{F}_1$ ), the semi-hybrid strategy ( $\mathcal{F}_2$ ) and the fully hybrid strategy ( $\mathcal{F}_3$ ) compared to the depot only strategy ( $\mathcal{F}_4$ ).

However, not every such strategy should blindly be adopted. We find that the pure RTI repositioning results in a relatively high number of emergency deliveries. Reverse logistics under this strategy are relatively quickly obstructed due to logistical limitations. As such, the pure strategy is not recommended. We also observe a high variance in the efficiency of the fully hybrid strategy. Although the average performance of the fully hybrid strategy is still respectable, we recommend adopting a semi-hybrid strategy as it is more consistent. Under a semi-hybrid strategy, the model is most flexible in the trade-off between RTI repositioning and depot deliveries. Under the semi-hybrid strategy, the emergency deliveries are minimized and the total increase in efficiency is highest on average. With this strategy, an increase in efficiency between 10.04% and 20.78% is observed with a 95% confidence interval. For each instance, the average increase in efficiency is 11.69%, 18.46% and 16.74% respectively.

		Average increase in efficiency
$I_{40}$	$\mathcal{F}_1$	11.65%
	$\mathcal{F}_2$	11.69%
	$\mathcal{F}_3$	15.04%
$I_{78}$	$\mathcal{F}_1$	17.49%
	$\mathcal{F}_2$	18.46%
	$\mathcal{F}_3$	18.15%
$I_{128}$	$\mathcal{F}_1$	13.96%
	$\mathcal{F}_2$	16.74%
	$\mathcal{F}_3$	15.08%

TABLE 5.7: Average increase in efficiency of the strategy with RTI repositioning ( $\mathcal{F}_1, \mathcal{F}_2, \mathcal{F}_3$ ) compared to the pure depot delivery strategy.

## 5.4 Discussion

On a final note, we address some points of discussion. First, we address some distinctions between COMPANY B's supply chain and the simulated supply chain. Next, we address some sensitivity discussion in regards to the cost factors. Next, we discuss the effect if RTI were rented for a shorter period. Finally, we discuss an inefficiency of our HKG aggregation structure.

### 5.4.1 Current supply chain

One of the goals of this study was to identify if RTI repositioning would improve the current supply chain. This task proved difficult because the current supply chain is difficult to replicate. The current supply chain largely depends on the expert intuition of planners. The forward logistics routing method consists of grouping close-by origin locations that, at the same time, have close-by destination locations. During the modeling phase, this process resulted in largely inefficient routes. By implementing the currently used forward routing heuristic whilst considering some assumptions, route efficiencies were more realistic. The next challenging aspect is the process of RTI trading: planners decide when nurseries might require new RTIs. Their decisions are based on expert intuition and are difficult to replicate. To do so, we observed two major inefficiencies: very high inventories and very high stockouts. The high inventories were due to the strict implementation of the trading principle: each time an order was sent out, the exact amount of empty RTIs was traded back, and vice-versa for retailers. As a consequence, a

nursery that would only sporadically send out RTIs was left with a high inventory for most of the year, and retailers that would only be visited sporadically would have to store empty RTIs between the (long) inter-visit periods. Similarly, when trading RTIs, only an amount of empty RTIs equal to the transported order quantity was delivered. As a consequence, an emergency delivery was necessary every time an order was increased by a single RTI. The replication of the trading procedure thus resulted in high inefficiencies that are not observed in the actual supply chain thanks to the expert judgment of planners as well as the fact that any locations can update COMPANY B in case they require delivery or pickup of empty RTIs. The inefficiencies due to RTI trading are especially high when reverse logistics are only performed via depot deliveries. As such, a simulation model based on this process would wrongfully conclude RTI repositioning leads to large savings.

### 5.4.2 Cost factors

In Section 5.1.3, the cost function is introduced as the weighted sum of all KPIs. These weights are introduced as being situational: the kilometer cost factor varies based on the region one drives in, the depot activity cost-factor depends on the total number of RTIs to unload and the emergency delivery cost factor is set to a high value to minimize emergency deliveries in general. Two points are worth discussing regarding this topic: the effect of cost-factors on the current conclusion and the effect of cost-factors on model training.

The effect of cost-factors refers to how sensitive the current objective values are with changing cost factors. One might ask: given the same KPI results, could a different set of cost-factor values result in a different conclusion? Consider two arguments. First, we note that the semi-hybrid strategy ( $\mathcal{F}_2$ ) results in the least emergency deliveries in each instance (Figure 5.6), regardless of the assigned cost-factor ( $\omega_3$ ). The fully hybrid strategy ( $\mathcal{F}_3$ ) also is a close second on all instances, whilst the pure RTI repositioning consistently results in high emergency deliveries ( $\mathcal{F}_1$ ). Second, we consider the possible changes in the cost function. Since the costs associated with emergency deliveries will always support our current conclusion, let us set the emergency delivery cost-factor at zero ( $\omega_3 = 0$ ). The kilometer cost-factor ( $\omega_1$ ) and the depot activity cost-factor ( $\omega_2$ ) are varied within the range given estimated by COMPANY B:  $\omega_1, \omega_2 \in [1, 2]$ . As the cost function is linear, the highest and lowest efficiency increases are observed at the extremities of each cost-factor. In Table 5.8, the increase in efficiency of each strategy with RTI repositioning compared to the pure depot delivery strategy is shown. In all cases, a positive increase in efficiency is observed, indicating all strategies are more efficient than the pure depot delivery strategy. Summarizing, we state that, given the current simulation results, the semi-hybrid strategy objectively scores best regarding emergency deliveries. Even when emergency deliveries are left out of consideration, the semi-hybrid strategy still consistently results in an increase in efficiency for any kilometer and depot activity cost-factor.



		$\omega_1 = 1$	$\omega_1 = 1$	$\omega_1 = 2$	$\omega_1 = 2$
		$\omega_2 = 1$	$\omega_2 = 2$	$\omega_2 = 1$	$\omega_2 = 2$
$I_{40}$	$\mathcal{F}_1$	20.54%	27.69%	15.65%	21.62%
	$\mathcal{F}_2$	12.91%	20.42%	09.20%	15.37%
	$\mathcal{F}_3$	17.46%	21.82%	13.63%	17.34%
$I_{78}$	$\mathcal{F}_1$	21.15%	27.03%	16.73%	21.70%
	$\mathcal{F}_2$	16.89%	21.79%	13.37%	17.50%
	$\mathcal{F}_3$	19.42%	22.94%	15.30%	18.37%
$I_{128}$	$\mathcal{F}_1$	24.61%	29.72%	18.96%	23.41%
	$\mathcal{F}_2$	18.30%	23.35%	14.22%	18.52%
	$\mathcal{F}_3$	17.37%	20.32%	13.87%	16.44%

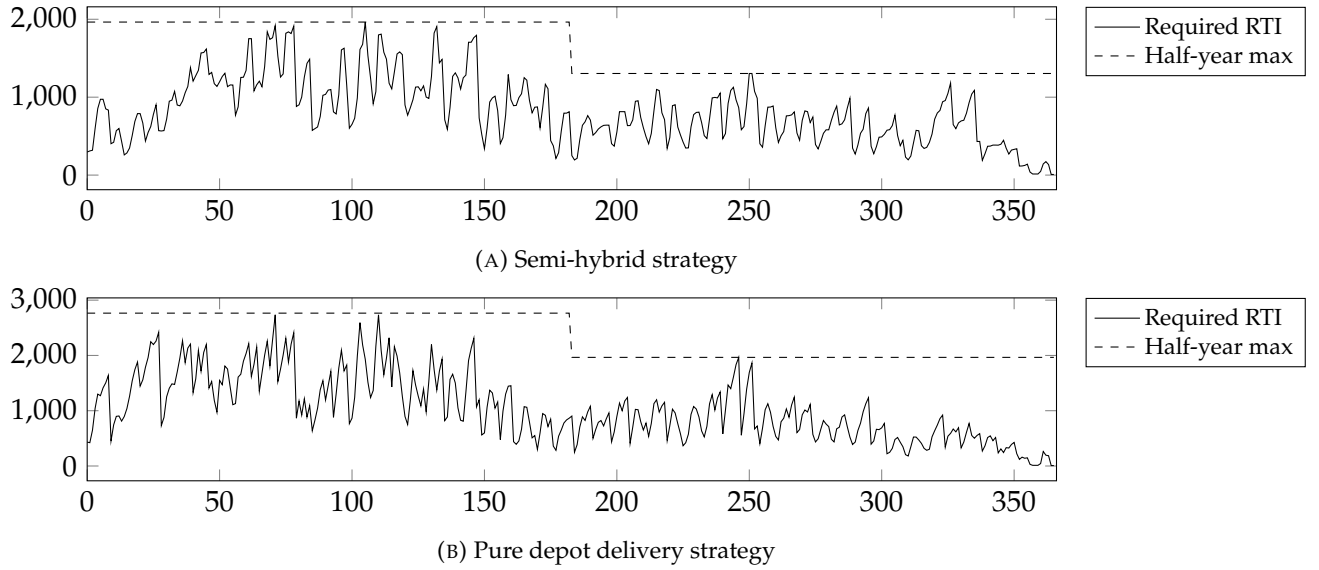
TABLE 5.8: Average increase in efficiency of the strategy with RTI repositioning ( $\mathcal{F}_1, \mathcal{F}_2, \mathcal{F}_3$ ) with variable kilometer cost factors  $\omega_1$  and variable depot activity cost-factor  $\omega_2$ , and emergency deliveries costs omitted (i.e.,  $\omega_3 = 0$ )

One might also wonder how the simulation will turn out if different cost-factors are considered. This has not been studied and might be interesting to look into. We have opted to base our simulation on the least-favorable cost functions: we speculated RTI repositioning would increase the number of kilometers driven and decrease the total depot activity. As such, the kilometer cost-factor was set at its highest value ( $\omega_1 = 2$ ) and the depot activity cost-factor was set at its lowest value ( $\omega_2 = 1$ ) to consider a worst-case scenario. Some small prior experiments have been done to fix the emergency delivery cost factor ( $\omega_3 = 10$ ) although this cost-factor mainly serves to minimize emergency deliveries by introducing a significant impact on costs.

### 5.4.3 Minimum RTI required

In our analysis, the minimum number of RTIs required has a large impact on the costs of a reverse RTI strategy. For the computation of the related costs, we assume that the minimum number of RTI required is fixed for a whole year. However, the seasonality of the supply chain results in a distinction between the minimum number of RTI required during high season and low season. Realistically, COMPANY B will dynamically adapt the number of RTI required throughout the year to fit the demand of that period.

Consider the graph in Figure 5.9, where the daily minimum RTI requirements are plotted. This daily minimum RTI requirement includes all RTIs in inventory as well as those needed for emergency deliveries for instance  $I_{40}$  under the semi-hybrid strategy and the pure depot delivery strategy (similar patterns are found for the other strategies and instances). In the second half of the year, merely 66% and 70% of the RTI used in the first half are required. As fewer RTIs are rented in the second half of the year, the amplitude of the increased efficiency of the reverse RTI strategies with RTI repositioning might be less. As such, let us consider a reduction of 75% of the observed minimum RTIs required: 100% in the first half of the year and 50% in the second half of the year. The effect on the efficiency of the various reverse RTI strategies and instances are shown in Table 5.9. With less RTI rented, a positive increase in efficiency is still observed for all instances and reverse RTI strategies, with minimal differences when compared to the initial average improvements.

FIGURE 5.9: Daily number of required RTIs for two examples in instance  $I_{40}$ 

		100% RTI	75% RTI	Difference
$I_{40}$	$\mathcal{F}_1$	11.65 %	10.90%	-0.74%
	$\mathcal{F}_2$	11.69 %	12.25%	0.55%
	$\mathcal{F}_3$	15.03 %	14.71%	-0.31%
$I_{78}$	$\mathcal{F}_1$	17.49 %	17.19%	-0.29%
	$\mathcal{F}_2$	18.45 %	18.80%	0.34%
	$\mathcal{F}_3$	18.14 %	17.71%	-0.42%
$I_{128}$	$\mathcal{F}_1$	13.96 %	12.20%	-1.76%
	$\mathcal{F}_2$	16.73 %	16.58%	-0.15%
	$\mathcal{F}_3$	15.08 %	14.51%	-0.56%

TABLE 5.9: Average increase in efficiency of the strategy with RTI repositioning ( $\mathcal{F}_1, \mathcal{F}_2, \mathcal{F}_3$ ) with either 100% required RTI or 75% required RTI

#### 5.4.4 HKG aggregation

The HKG algorithm is based on the structure defined in Section 5.1.2. As a point of discussion, we note that there some strategies give similar model executions under different hyperparameter settings. Consider all decisions where the reverse RTI strategy is some strategy  $f$ , short-term forecasting horizon is 0, the long-term forecasting horizon some value  $x$ , and the picking forecasting horizon some value  $y$ . These decisions are identical to all decisions where the reverse RTI strategy is set as the same strategy  $f$ , short-term forecasting horizon is  $x$ , the long-term forecasting horizon 0, and the picking forecasting horizon the value  $y$ .

$$\begin{bmatrix} \mathcal{F}_n = f \\ T^m = \mathbf{0} \\ T^n = \mathbf{x} \\ T^p = y \end{bmatrix} = \begin{bmatrix} \mathcal{F}_n = f \\ T^m = \mathbf{x} \\ T^n = \mathbf{0} \\ T^p = y \end{bmatrix}$$

As the range of values for both the short-term and long-term forecasting horizon is between 0 and 5 ( $T^m, T^n \in [0, 5]$ ), this could have been prevented by setting the minimum value of one of the ranges to 1 ( $T^m \in [1, 5]$  or  $T^n \in [1, 5]$ ). By doing so, the total number of decisions is decreased from 1584 to 1320.

## 5.5 Conclusion

In this chapter, we performed experiments to address the research question: “To what extent does an autonomous dynamic RTI repositioning system improve the analyzed horticultural supply chain?”.

In Section 5.1, we summarized the experimental settings we have defined. Stakeholder COMPANY B has provided a large set of data, from which we derived three representative instances of different sizes. We also introduce the aggregation structure we used for the hierarchical knowledge gradient and explain how specific combinations of the reverse flow parameters represent specific reverse RTI strategies. From this, we derived four strategies that we extensively study: a pure RTI repositioning strategy, a semi-hybrid strategy, a fully hybrid strategy, and a pure depot delivery strategy. These strategies are evaluated based on a set of KPIs representing a simulation’s efficiency and an objective: a cost function based on the weighted sum of these KPIs

In Section 5.2, we performed our experiments. As the simulation study is based around the hierarchical knowledge gradient, we first address how different values for the generalized variances affect the convergence speed. Next, we evaluate how each hyper-parameter affects the simulation objective. We find that the effects of each hyper-parameter are consistent throughout the instances. Next, we extensively investigate the efficiencies of the different reverse RTI strategies. In line with expectations, we find that strategies that involve some form of RTI repositioning tend to require fewer RTIs when compared to the pure depot delivery strategy. Against expectations, the additional distance required to satisfy reverse logistics is only marginally higher when RTI repositioning is included. These strategies also result in a considerable reduction in depot activity, which is a direct result of repositioned RTI not being handled at the depot. Another observation is that the pure RTI repositioning strategy and the pure depot delivery strategy both result in high emergency deliveries, as vehicle capacities are not fully utilized. Cost-wise, we find that strategies with RTI repositioning always result in the least costs.

We also analyse the relation between the forecasting horizon length’s against the instance characteristics. We find that the short-term forecasting horizon length has a moderate negative correlation with the size of the instances, suggesting larger instances require smaller short-term forecasting horizons. The the long-term forecasting horizon and the picking forecasting horizon do no have a significant correlation with the instances. All forecasting horizon’s do have a large correlation with the chosen reverse RTI strategy. Generally, we find that the more RTI are repositioned, the longer the short-term and long-term forecasting horizon should be, whereas the picking forecasting horizon should be lower as more RTIs are repositioned.

On a concluding note, we provide a managerial insight on the results in Section 5.3. We address the main research question by reviewing the increase of efficiency resulting from the effective incorporation of RTI repositioning. We find that all reverse RTI strategies increase RTI logistics efficiency. The semi-hybrid strategy is considered most efficient thanks to its low emergency deliveries and high increase in efficiency between 10.04% and 20.78%, generalized over all instances. For each instance, the average increase in efficiency is 11.69%, 18.46% and 16.74% respectively.



## Chapter 6

# Conclusions, Recommendations & Implementation

### 6.1 Conclusions

In this study, we address the supply chain around returnable transport items (RTIs) in the horticultural industry. RTIs play a central role in both forward and reverse logistics. As forward logistics embody the value-adding activities, reverse logistics are less prioritized. This results in a potential efficiency increase. In this study, we focus on the potential of RTI repositioning. Currently, RTIs arriving at the end of the forward logistics flow are collected and returned to the depot. Next, they can be reintroduced in the supply chain. By making use of accurate RTI visibility and empty RTI supply and demand forecasts, RTIs can dynamically be repositioned between users in the supply chain, omitting a visit to the depot and allowing for a more dynamic inventory allocation. As such, the research topic addressed in this study is:

*In what way and to what extent can dynamic RTI repositioning improve the efficiency of RTI logistics?*

To answer this research question, we first obtain a better understanding of the organization of the current supply chain. This analysis, performed in Chapter 1 and Chapter 2, provides insights into the particulars of the supply chain. The planning of forward logistics and reverse logistics fully relies on the expert opinion of COMPANY B's planners. Thanks to their understanding of the users in the RTI pool, they intuitively combine forward transport orders and roughly estimate empty RTI needs. We also introduce a numerical example that generalizes COMPANY B's current RTI management and theorizes the potential costs and benefits of RTI repositioning.

In Chapter 3, we review literature to further understand the intricacies of the routing problem at hand. RTI management in the horticultural industry is considered a Pickup and Delivery Inventory Routing Problem (PDIRP). The PDIRP is characterized by its routing structure. Based on the type of RTI management used, RTI management can consist of all three types of routing structures, but studies concerned with multiple coinciding routing structures are rare.

From our findings, we define a sequential heuristic in Chapter 4. The heuristic addresses the forward logistics first and extends these routes to introduce reverse logistics. As reverse logistics is charged with both matching supply and demand of empty RTI as well as routing the matched pickup and delivery pairs, we also introduce a variable fixing procedure. Based on uncertain forecasted demand, the procedure finds for each location a short-term and long-term demand. Additionally, each type of demand can be assigned to be delivered via RTI repositioning or depot deliveries. Another forecast determines the available empty RTI supply for all locations. When all locations are classified as either demand or supply locations (or none) the reverse routing heuristic matches pickup and delivery pairs accordingly, realizing the reverse logistics. The sequential heuristic is based on a set of hyper-parameters that define

which types of reverse RTI flows are allowed as well as the length of the short-term, long-term, and picking forecasting horizon. The Hierarchical Knowledge Gradient is applied to optimize the selection of hyper-parameter values.

In Chapter 5, a extensive experimentation phase is performed. The experiments were performed for three instances of different sizes. The HKG algorithm optimizes the hyper-parameter settings according to the total logistics costs, consisting of the number of required RTI, the total forward and reverse logistics distance, the total activity at the depot, and the distance of emergency deliveries. Also, we define four reverse RTI strategies representing a unique type of RTI management: a pure RTI repositioning strategy, a pure depot delivery strategy, a semi-hybrid strategy including short-term depot deliveries, and a fully hybrid strategy. During the experimentation phase, we consider the pure depot delivery strategy as the current supply chain and use for to determine if and by how much RTI repositioning improves the supply chain.

- Strategies with RTI repositioning result in a reduction in the total RTI required in the supply chain. By directly repositioning RTIs in the supply chain, depot visits are prevented. This ensures RTI can directly be reintroduced in the supply chain.
- Strategies with RTI repositioning do not result in a significant increase in kilometers driven for the execution of reverse logistics.
- Strategies with RTI repositioning result in a decrease of depot activity. Once again, by skipping a trip to the depot, operational activities are not required at the depot.
- The pure RTI repositioning and pure depot delivery strategies result in high emergency deliveries. These strategies are limited by the amount of empty RTI they can supply as all empty RTI demand has to flow via a single reverse RTI flow. The semi-hybrid strategy results in a large improvement in emergency deliveries, with a similar but less considerable improvement for the fully-hybrid strategy.
- Strategies with RTI repositioning always result in fewer costs than the pure depot delivery strategy. Cost savings mainly follow from the reduced number of rented RTI and the prevention of emergency deliveries (for the hybrid strategies).
- There is little correlation between forecasting horizon settings and instance characteristics.
- There is a high correlation between forecasting horizon settings and employed reverse RTI strategy. The more RTI repositioning is prevalent in a strategy, the longer the short-term and long-term forecasting horizons are and the shorter the picking forecasting horizon.

Based on this analysis, a final comparison between reverse RTI strategies indicates that the semi-hybrid strategy is most efficient. This strategy results in the least emergency deliveries and has relatively consistent results over the instances. It also shows low costs. With a 95% confidence, we observe an increase between 10.04% and 20.78% when compared to the pure depot delivery strategy, with an average of 11.69%, 18.46% and 16.74% for each of the three instances respectively. We conclude this study by stating that RTI repositioning does increase the efficiency of the RTI supply chain. Through better utilization of RTIs and transport, costs can be reduced.

## 6.2 Recommendations & Implementation advice

We recommend COMPANY A and COMPANY B to further analyze how RTI repositioning can be implemented in a hybrid fashion: both depot delivery flows and RTI repositioning flows contribute to efficient RTI management. This recommendation strongly relies on the presence of good RTI visibility as well as some form empty RTI supply and demand forecast.

To implement RTI repositioning, careful steps must be undertaken: there is not a single best RTI repositioning method. Naturally, evidence for the right type of RTI repositioning must be found in practice. Considering the final objective of a fully autonomous transport system, we present a few steps that can lead to eventual implementation. On this basis, an increased RTI visibility is necessary.

### 6.2.1 Interactive RTI management system

First and foremost, the current RTI management system must be updated. In combination with COMPANY A' SMA.RTI system, RTI visibility is automatically ensured: all RTI locations are known. As tracking information is automatically updated with the loading and unloading of RTIs, no trading practices are necessary anymore.

To ensure each user still receives their RTIs, they can indicate so through this interactive system. They can indicate when they require RTIs and how much. Alternatively, they can indicate how many RTIs they have available for picking. Additionally, to prevent these users from being burdened with too much additional labor, they can engage forms of collaboration with COMPANY B to ensure they have their required RTIs. For instance, a nursery can indicate they expect to send out 15 RTIs every week, and to do so, they require these 15 RTIs at the latest on Friday. COMPANY B can then ensure that they have their required RTIs delivered.

The goal of this system is to create a user/specific forecast of both supply and demand. With this information, the system can make reverse RTI management proposals to the planning team: based on the current forward orders (which the planners receive every night), empty RTI origin and demand pairs can be proposed. The supply and demand pairs should extend on the forward routes created by the planners. As such, this system can be implemented as an extension of the current transport management system.

### 6.2.2 Forecasting system

The next step is to further research autonomous forecasting techniques that can estimate the RTI necessities based on various external factors. Several insightful features are readily available: weather forecasts and market trends. Additionally, one can go further in detail by developing user-specific forecasts. If information is obtained on the type of plants cultivated, better estimates can be made. At this point, reverse RTI strategies are still provided as advice to the planner. As such, the planner remains in control and can anticipate unexpected changes.

### 6.2.3 Autonomous routing

Finally, during the two prior phases, COMPANY B can get an understanding of the effects of RTI repositioning on their supply chain. Based on the observed effects, an autonomous system can be designed to manage both routing activities and empty RTI inventory allocation. This system automatically plans the forward logistics and correctly interprets reverse logistics needs.

### 6.2.4 Further improvements

Finally, such an autonomous system can continuously be improved and extended. A desire within COMPANY B is to have routing software that can react to disruptions during routing. Disruptions can consist of a forward logistic transport order that turns out to consist of additional RTIs, of missing empty RTIs that are to be repositioned. Through a live disruption manager, ongoing routes of all (or some) vehicles can be updated to minimize the consequences as much as possible.

## 6.3 Further research

Further research can provide additional insights into the concept of RTI trading, but also in the routing challenges for Pickup and Delivery Problems (PDP) with multiple structures. As such, we propose a few topics that have a theoretical or a practical value.

- PDPs are characterized by their routing structures: 1-1, 1-M-1, M-M. The routing structures have individually been addressed in linear forms and solved to optimality for (very) small instances. A large distinction between routing structures are their linear formulation (see Cordeau et al. (2008) for a 1-1 PDP and Dongyang et al. (2020) for an M-M PDP formulation). Further research can be done on exact approaches for PDPs that combine multiple routing structures. This, in turn, can lead to the development of new methods that address both types of routing structures through nested methods. One particularly interesting algorithm is the decomposition approach by Casazza et al. (2021).
- Extending on the previous proposal, further research can also consider the consideration for time windows. Our current research was limited by the available data, but time windows play a role in the horticultural supply chain as well as in other applications.
- Within this study, an assumption of present forecasts was made. A study on forecasting methods within the horticultural industry is necessary. Forecasting can be done on a product-specific or RTI level. Within the industry, the weather has a large influence on the growth speed as well as the consumer plant desire.
- An final topic worth investigating is disruption routing: how can ongoing routes be improved to minimize the impact of disruptions in the supply chain?



## Appendix A

# Auction Trolleys & CC-containers

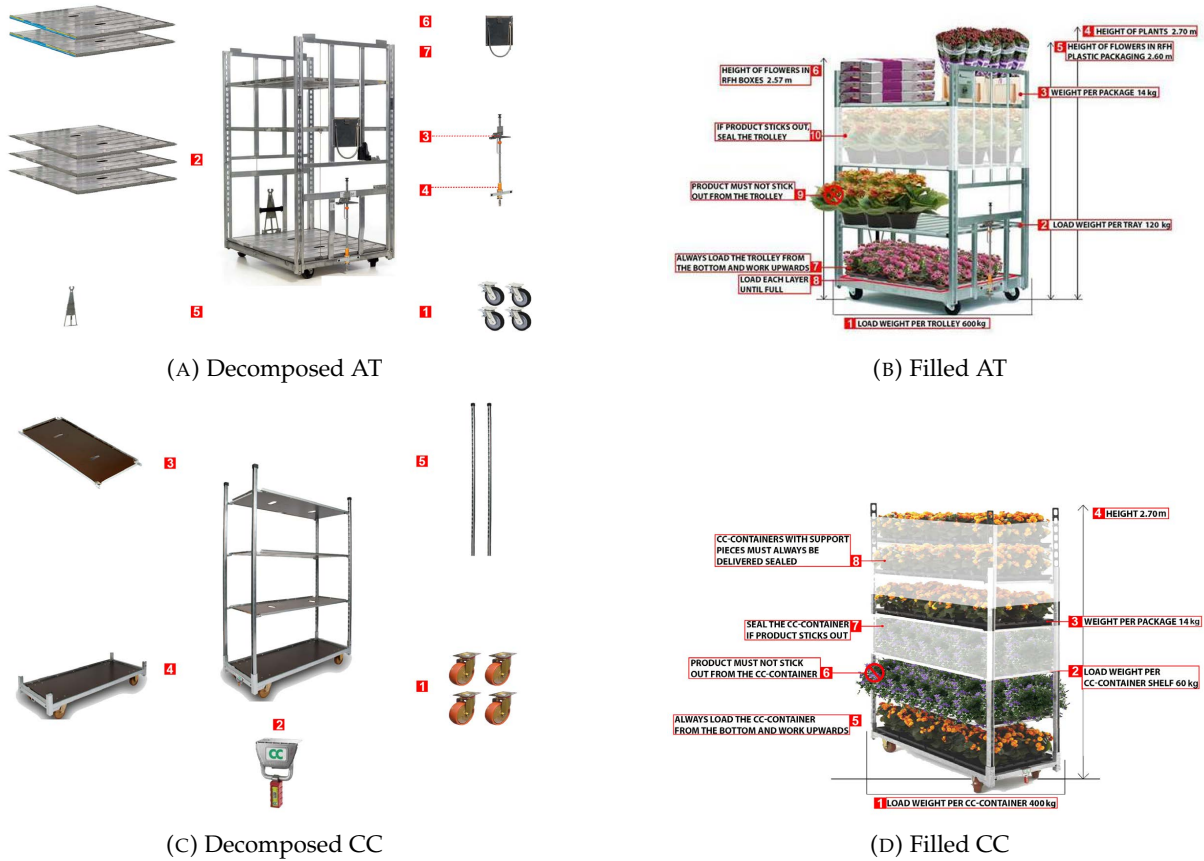


FIGURE A.1: Auction Trolleys and CC-Containers (FloraHolland, 2018)

AT (A.1a)	Description	CC (A.1c)	Description
1	Four wheels	1	Four wheels
2	Three fixed trays	2	CC tag
3	A straight tow pin	3	Full-size shelves
4	A plastic tube on the tow pin	4	A base
5	Coupling hook	5	Four posts
6	Form clamp		
7	Pulling handle		

TABLE A.1: AT & CC Components (FloraHolland, 2018)

## Belading / Beladung Trailer

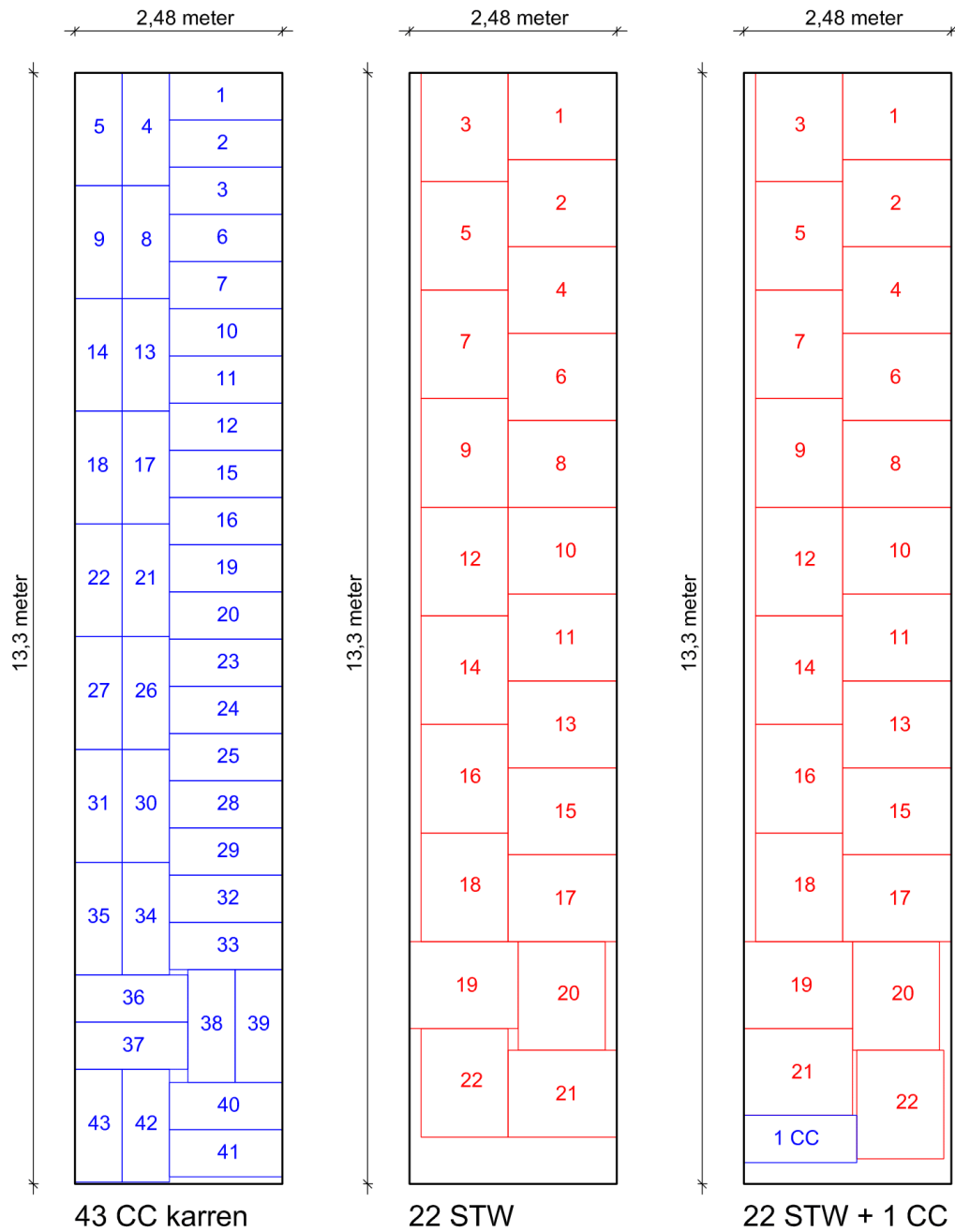


FIGURE A.2: Truck layout when loaded with both CCs & ATs ("STW")

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