UNIVERSITY OF TWENTE.

Ahold Delhaize
EUROPEAN SOURCING B.V. | INBOUND LOGISTICS

Master's Thesis

# Order Optimization: A Comparative Analysis of Heuristics and Machine Learning

submitted by

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# Management summary


Ahold Delhaize Inbound Logistics (ADIL) acts as an internal supplier of the subsidiaries of Ahold Delhaize. ADIL serves its internal customers by group-buying the items of suppliers primarily based in Europe. Ahold Delhaize wants to reduce the overall carbon emissions. The question arises of how ADIL can reduce the environmental impact of their logistics, and improve its logistics decision-making.

The objective of this research is as follows:

> *How can ADIL improve their international freight transportation network considering different kinds of transportation modes within the transportation network?*

**Context analysis** Most orders from suppliers of ADIL are placed in Europe and also have the most potential for emission reduction. According to the GLEC framework, intermodal shipping routes, which include maritime, railway, and inland waterways transportation, have far less pollution per container per kilometer. Currently, about 50% of ADIL's emissions are caused by road transportation, even though road transportation only accounts for approximately 20% of the total distance travelled. About 40% of the emissions are caused by maritime shipping which accounts for 80% of the total distance travelled.

**Literature** The literature proposes synchromodal transportation as a method to optimize transportation objectives, such as cost and emission. Synchromodal transportation is a form of intermodal transport that uses flexible services. The aim is to manage the flow of goods in a transportation network of logistics service providers and reduce total costs and emissions. Most research considers heuristics in a simulation model, while some recent papers focus on implementing learning strategies, such as Approximate Dynamic Programming.

Most studies evaluate stochasticity in transportation, which includes cancelled- and delayed trips. Often transportation demand and capacity play a more significant role at the strategic/tactical level. The literature proposes a few studies on the combination of inventory management and logistics. A few studies evaluate choosing the transportation mode based on the demand during lead time.

**Solution approach** We developed a simulation model based on ADIL data, to investigate the trade-offs in cost and carbon emissions and evaluate easy points of improvement. Furthermore, the simulation model is used to compare a heuristic-based and learning-based approach. The simulation model includes three modules, of which one is the inventory management system, the second is a transportation network, and the third is the transportation decision system. For each supplier, we generate a fixed set of paths to the warehouse in the Netherlands, which is calculated on the least cost, time, and emission (each path has a different cost, time, and emission). Each item has a

stochastic demand. When the inventory falls below the reorder point, the inventory management module triggers an order of full container loads of the items at the supplier. Each container is transported on one path of the fixed set of paths from the supplier to the warehouse in the Netherlands. The transportation decision module, called the order optimizer, determines the best path to choose, based on a weighted objective function that minimizes expected costs and emissions. The expected costs are determined by evaluating different demand observations and transportation delays. In comparison to this heuristic, we develop and test a learning heuristic for the transportation decision module. This method employs a neural network to determine the container path.

**Results and conclusions** The performance of the transportation decision module is compared with a simple heuristic that does not include expected future lost sales and inventory costs, but only the direct transportation costs (myopic policy). We evaluate 12 experiments, of which one is road-only transportation. The other 11 experiments each have a 100%, 90%, 80%, ..., 10%, and 1% cost focus, respectively. The simple heuristic performed close to the performance of the order optimizer, showing slightly worse performance with a 100% cost focus, and a high emission focus. Figure 1 shows the Pareto frontier solutions of the experiments for the simple heuristic and optimization module: the order optimizer. In the used dataset, an approximate emission reduction of 45% is possible with a cost increase of 12%, compared to the 100% cost focus experiment. The Road Only experiment which only uses road transportation, is significantly outperformed in carbon emission, while simultaneously leading to a slight cost reduction, by the Pareto frontier.

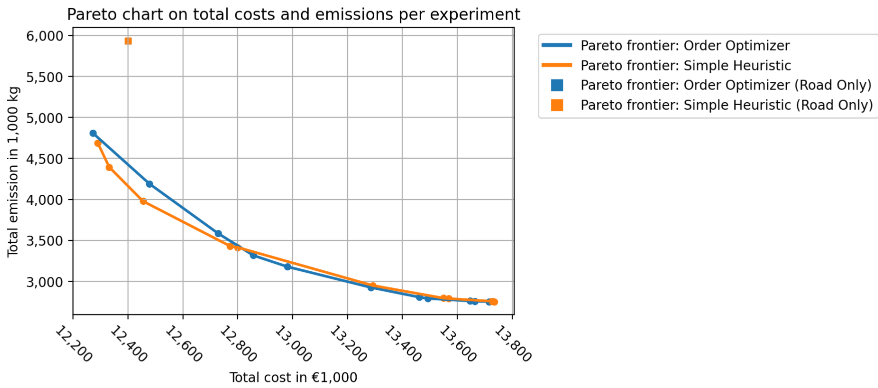


Figure 1.: Pareto frontier solutions for different cost factors

The primary modality of intermodal transport is rail transportation. In a full emission focus experiment, nearly all emissions (close to 90%) are caused by intermodal transportation routes that include rail transportation. Still, about 65% of the emissions are caused by road transportation, but most of the route's emissions are released from the required road sections within the intermodal route.

Within the scope of this research, the learning heuristic tends to show the same performance as simple- or complex heuristics. While the learning heuristic tends to give more consistent results than a simple heuristic, the benefits are not significant.

**Recommendations and future research** We propose the following recommendations to ADIL:

- Evaluate what cost/emission trade-off fits the best to ADIL's objectives. A reduction in emissions goes along with a small increase in costs.
- Due to the standardized procedure of transportation for each supplier of ADIL, implementing a single intermodal transportation path for a supplier is possible. If ADIL desires to include flexible services, such as synchromodal transportation, ADIL should review how this can be implemented into its current systems.
- Within the constraints of this research, a complex heuristic or learning heuristic does not significantly improve the solution for path selection, compared to a simple heuristic. For that reason, if ADIL desires to implement flexible services, we recommend starting with a subset of the transportation routes and simple heuristics before increasing the scope and investigating more complex solutions.

The following key future research topics result from this research:

- In this research, demand is simulated according to a single distribution based on actual demand figures. The actual demand can also be simulated with multiple distributions to accurately cope with promotions, i.e., high peaks in demand. Including two types of demand seasons, such as a standard- and high-demand season may provide relevant results in path selection.
- The problem instance of ADIL has a relatively high lost sales cost, compared to the low holding costs. This results in the optimization model usually preferring more inventory for a reduced risk of lost sales. Researching the problem to optimize the ordering process on lost sales costs and complying with warehouse capacity might be more relevant than the trade-off between holding- and lost sales costs.

# Preface

This thesis is the final product of my graduation assignment for my master's degree Industial Engineering and Management at the University of Twente. I held my graduation assignment about order optimization and transport mode selection with great pleasure at Ahold Delhaize located in Zaandam.

I would like to thank my supervisors Pieter and Rob who gave me the possibility to perform research at such a remarkable company like Ahold Delhaize, and for their guidance during my graduation phase! Further, I would like to thank Martijn and Fabian from the University of Twente for their guidance on my graduation topic to bring this thesis to a successful end! A special thanks to my colleagues, housemates, and family for their contribution to this thesis and for helping me make the right decisions along the way. Also, I would like to thank everybody who directly or indirectly contributed to this research.

Jaap Seinhorst

Enschede, March 2023

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# Acronyms

**ABM** agent-based modeling.

**ACO** ant colony optimization.

**ADIL** Ahold Delhaize Inbound Logistics.

**ADP** approximate dynamic programming.

**AI** artificial intelligence.

**ALNS** adaptive large neighborhood search.

**CIHW** confidence interval half-width.

**ERP** enterpise resource planning.

**FCL** full container load.

**FEU** forty-foot equivalent unit.

**GIS** geographic information system.

**LCL** less than container load.

**LSP** logistics service provider.

**MDP** markov decision process.

**MILP** mixed integer linear programming.

**MIP** mixed integer programming.

**MRP** material requirement planning.

**NFP** network flow planning.

**OPA** ordinal priority approach.

**SKU** stock keeping unit.

**SND** service network design.

**TEU** twenty-foot equivalent unit.

**VFA** value function approximation.

# Glossary

**Banner** Synonym for internal customers of Ahold Delhaize, such as Albert Heijn and Etos.

**Collo** The box in which consumer units are stored. A pallet consists of multiple collo's.

**Directed graph** A graph consisting of nodes and arcs (connecting nodes), where the flow of the arcs goes in one direction.

**Door-to-door connections** A sequence of connections, i.e., transportation services to transport goods from a supplier to a warehouse.

**Flexible services** Flexible services, primarily transportation in this report, can be requested on demand at any moment in time. Non-flexible services have fixed or predefined schedules.

**GLEC framework** A framework that defined an emission per transportation mode per Twenty-foot equivalent per kilometer (Smart Freight Centre, 2022).

**Heuristic** A method to make a decision in an optimization problem, which is often an approximate but not optimal solution.

**Intermodal transportation** Moving goods by more than one mode of transport, with a separate contract for each individual leg of the journey (Containerships, 2020).

**Inventory position** The physical inventory quantity together with all in-transit quantity of an item.

**Lead time** The duration of an activity, e.g., a transportation path.

**Lost sales** The quantity of demand not met, due to a shortage of physical inventory.

**Modal shift** Changing a standardized transportation policy (partially) to another transportation mode.

**Multimodal transportation** Moving goods by more than one mode of transport, under one contract (Containerships, 2020).

**Myopic policy** A policy that chooses the decision that improves the objective function the most.

**Order multiple** A fixed item quantity, which is often, e.g., a full box, pallet, or truck-load.

**Pareto front** An efficient frontier of optimal solutions with two or more objectives.

**Policy (MDP)** In a Markov Decision Process, a policy is the set of decisions to take in all states of the system.

**Post decision state (MDP)** The state the Markov Decision Process ends up in after taking a decision in the current state.

**Reinforcement learning** A form of machine learning that learns optimal decision-making in a sequential decision-making simulation.

**Reorder point** A specific stock level, where if the inventory position drops below this level, a new order is generated.

**State (MDP)** In a Markov Decision Process, a state is defined as the characteristics of a system of a certain moment in time.

**Stochasticity** A term for uncertainty, which is often modelled with a statistical probability distribution.

**Synchromodal transportation** A form of intermodal transport with so-called mode-free booking flexibility (Rivera & Mes, 2022).

**Transportation mode** The method to ship a container. The most common methods are via road, air, rail, maritime, and inland waterways.

**Unimodal transportation** Delivering goods by a single mode of transport, typically by road (Eurosender, 2020).

**Value function approximation (MDP)** A function to approximate the value we assign to a state.

# Contents

# 1. Introduction

This report elaborates on the research at Ahold Delhaize about the optimization of sustainability in freight transportation. This chapter describes the problem identification phase of the research.

First, the context of the research is described in Section 1.1. Section 1.2 elaborates on the motivation of the research. Section 1.3 gives a description of the problem. Section 1.4 shows the objective of the research. Finally, Section 1.5 splits the research into several research questions.

## 1.1. Context description

The research was conducted at Ahold Delhaize located in Zaandam in the Netherlands. Section 1.1.1 gives a brief summary of the company Ahold Delhaize. Then section 1.1.2 introduces the department within Ahold Delhaize where the research has been conducted.

### 1.1.1. Ahold Delhaize

Ahold Delhaize is a large food retail group with its headquarters located in Zaandam, the Netherlands. With famous brands such as Albert Heijn in the Netherlands, and Delhaize in Belgium, and Food Lion in the USA, Ahold Delhaize serves multiple markets in several countries (Ahold Delhaize, 2022a). With a net sales of €75.6 billion in 2021 (€30.1$B$ in Europe and €45.5$B$ in the USA), Ahold Delhaize is continuously trying to grow in its local markets (Ahold Delhaize, 2022b).

Ahold Delhaize was formed by the merger between Ahold and the Delhaize Group in 2016 (Ahold Delhaize, 2022a). With over 150 years of experience, Ahold Delhaize has grown from a small wholesale grocery business to a large multinational group of multiple brands. The Ahold Delhaize group combined with its local brands have over 400,000 people employed in nearly 7,500 stores (Ahold Delhaize, 2022a).

### 1.1.2. Ahold Delhaize Inbound Logistics

Ahold Delhaize Inbound Logistics (ADIL) is a department within the Ahold Delhaize group, also located in Zaandam. ADIL operates as a wholesaler for the internal customers (also called banners) of Ahold Delhaize and is specialized in the international first mile (ADIL, 2021). Where banners such as Albert Heijn arrange contracts with suppliers, ADIL orders, ships, and stores the products in four own warehouses in the Netherlands. Banners can then request products from ADIL's warehouses to their warehouses.

ADIL's suppliers are located around the globe, which causes geographically large transportation networks. Lead times therefore may vary between a single week and multiple months. ADIL has to manage these factors, so its banners can request products with short lead times. Managing these factors is critical to the core business of ADIL.

ADIL makes use of two operational teams. The first team is responsible for demand management, which includes forecasting the demand for products for a maximum of 12 months. The second team is responsible for supply management and orders the products contingent on the forecast.

## 1.2. Motivation

Climate change is the driving force for people and businesses to become aware of the environmental impact of operations. Ahold Delhaize is also trying to reduce its impact on the environment by, e.g., reducing carbon emissions from its operations. By 2050, Ahold Delhaize wants to achieve a net-zero emission. This means that ADIL also has to think about reducing its environmental impact.

Besides environmental factors, ADIL follows recent trends and developments in artificial intelligence (AI). The department is now exploring opportunities for using AI techniques within its business processes. In the past few years, students have already performed some research in the field of artificial intelligence within Ahold Delhaize, but in different types of operations (e.g., warehousing). Now, ADIL wants to explore the potential of AI to optimize its ordering- and logistics processes, and reduce its carbon emissions while maintaining its product availability.

## 1.3. Problem description

As mentioned in the previous section, ADIL needs to reduce carbon emissions within their operations to achieve the net-zero goal of Ahold Delhaize in 2050. Since ADIL's core business is managing the logistics of goods, ADIL's way to reduce carbon emissions is to focus on making transportation more sustainable.

The majority of the suppliers of ADIL are located in Europe. The other suppliers are spread around the world in countries such as China, South Africa, and Chile. Due to the long geographical distance in the supply chains, products can have long- and varying lead times. Some products have specific characteristics and requirements such as a shelf life, which can make the planning of orders quite complex. Currently, the planner is expected to take into account all these factors, which is difficult to optimize in practice.

ADIL desires to optimize their ordering process which can assist the planners to make better decisions in their ordering process. In this problem, multiple objectives are relevant as mentioned in section 1.2. Order optimization includes the control of moving products in the transportation network and the moment of ordering.

### 1.3.1. Problem context

The ordering process of the planners is based on a standardized way of shipping for every supplier, which simplifies the ordering process. For example, the default method of shipping of a supplier in Germany might be road transportation, while a supplier in China uses maritime shipping. However, this can also cause inefficiencies due to not considering other, more efficient and sustainable options. Currently, ADIL does not know to what extent they can improve this logistical process by considering other methods of shipping.

This problem considers multiple constraints and variables. Item characteristics and the supplier location may influence what shipping options are allowed and/or available. Also, warehouses have a finite capacity that limits the amount of storage space. Besides, long- and varying lead times should be considered within the ordering process. Unexpected long lead times may cause inventory shortages.

### 1.3.2. Core problem

The core problem ADIL faces in the problem context is the unawareness of potential efficiency- and sustainability improvements of other transportation options. ADIL currently uses trucks as the major mode of transportation within Europe and wants to explore other methods.

## 1.4. Objective

Concluding from the problem description, the following research objective has been defined.

> *How can ADIL improve their international freight transportation network considering different kinds of transportation modes within the transportation network?*

## 1.5. Research questions

For executing the research, five sub-questions have been defined related to the problem statement.

**RQ1 What does the current ordering process look like at ADIL?**

> First, an understanding of the current ordering process has to be defined. This will be investigated by interviewing the planners and consulting the ERP system on how decisions are made in the ordering process, related to creating- and shipping an order.

**RQ2 What optimization models does the literature propose about multi-objective transportation networks, considering multiple modes of transportation?**

> The literature will be assessed about what modelling techniques are available to optimize the transportation networks based on multiple objectives, e.g., cost and emission.

**RQ3 In what way can the problem be formulated in the case of ADIL?**

> The model needs to be formulated in terms of sets, parameters, decisions, constraints, and an objective. This problem formulation should include all relevant elements for the situation of ADIL. Also, the transportation network of Europe should be modelled.

**RQ4 How should the solution methods, applied to the problem formulation, be designed?**

> The problem formulation should be solved with solution approaches such as heuristics and algorithms. The approach to solving the problem formulation is described.

**RQ5 How do the solutions perform, compared with a simple heuristic?**

> The performance of the developed heuristic solution(s) can be compared with a simple heuristic, using a myopic policy, to validate the performance of the model.

Figure 1.1 shows the structure between the research questions. First, in Chapter 2, the current ordering process is elaborated with relevant key figures such as emissions pollution. Then, Chapter 3 shows what literature has been researched about order optimization, related to transport modelling. Based on the methodology of formulation transportation networks in literature, Chapter 4 formulates the problem instance in terms of sets, parameters, and decisive moments. The solution approach to optimize the problem formulation is described in Chapter 5. Chapter 6 elaborates on the experimental settings in preparation for the results. Finally, Chapter 7 performs the experiments on the problem formulation, using the solution approach.

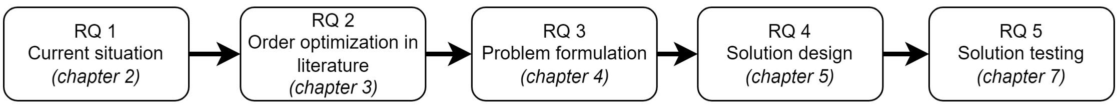



Figure 1.1.: Structure of the research questions.

# 2. Context analysis

In this chapter, context analysis is performed to answer research question 1. First, Section 2.1 has worked out the ordering process of ADIL in more detail. Section 2.2 elaborates further on the method a purchase order is created. Section 2.3 and Section 2.4 show a summary of the product portfolio and the supplier portfolio, respectively. Section 2.5 shows the division of transportation modes used by ADIL, whereas Section 2.6 elaborates on the emissions polluted by transportation. Section 2.7 concludes this chapter with the main conclusions of the context analysis.

## 2.1. Ordering process of ADIL

ADIL is specialised in international first mile logistics as mentioned in Section 1.1.2. Looking at the well-known purchasing process of Weele (2010) in Figure 2.1, ADIL only takes care of the supplying part of the purchasing process.

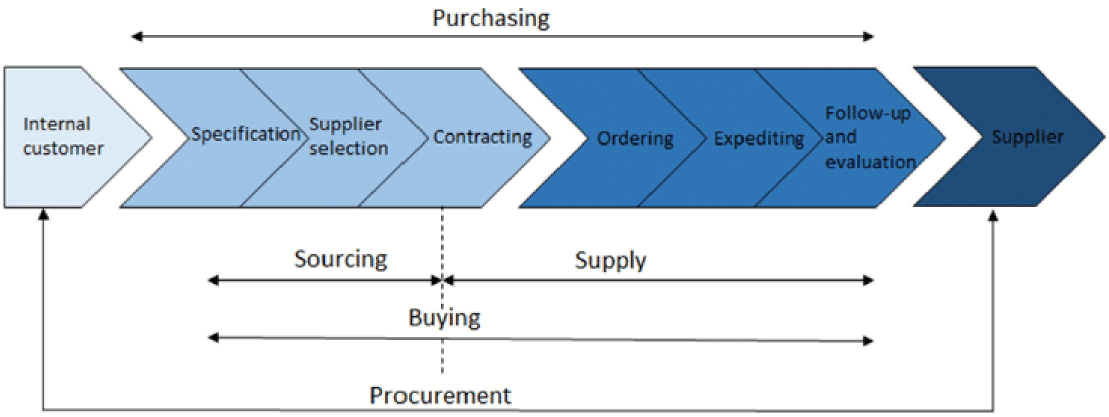



Figure 2.1.: Purchasing process (Weele, 2010).

The ordering process of ADIL consists of several activities. The first part is demand planning, which is done by the demand team. This team of planners is responsible for the forecast of all product demand for the next 52 weeks. This demand has to suffice the standard demand of its internal customer, but also promotions, which cause large demand shocks. This team makes use of a forecasting tool that predicts demand based on historical data.

The second part is supply planning, which is done by the supply team. The supply of products is done according to the demand forecast. This includes purchasing the orders, arranging transportation with third-party suppliers, and monitoring the orders until they are delivered at one of ADIL's warehouses. From this point onwards, banners can order these products from ADIL with their own transportation equipment. Every day, a list of inbound- and outbound products is sent to each warehouse about what products will arrive at the warehouse, and what products will need to be prepared for shipment to the banner.

## 2.2. Purchase order creation

Where the demand team creates the demand forecast, the supply team orders based on the current inventory and the demand forecast. The enterpise resource planning (ERP) system of ADIL assists the planner in purchasing the products at the right time. The system calculates the inventory after lead time based on the current inventory, incoming orders, and demand forecast. If the inventory after the lead time drops below zero, it will notify the planner to make a purchase order.

Every supplier has one or more products they deliver to ADIL. Figure 2.2 shows the number of suppliers that deliver how many unique items. When a planner is ordering a product, the planner will fill one twenty-foot equivalent unit (TEU) container or a forty-foot equivalent unit (FEU) container or equivalent. Based on the inventory of the items of a single supplier, the system proposes the number of pallets to order for each item. This is based on how many weeks forward to order. The planner then is asked to adjust the number of pallets ordered per item to fully pack one or more full container loads.

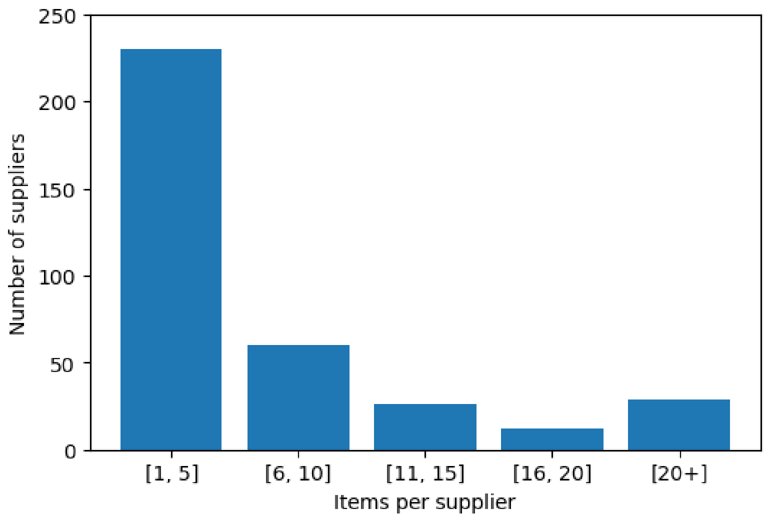



Figure 2.2.: The column represents the number of suppliers that deliver between [x, y] unique items to ADIL.

## 2.3. Product portfolio

ADIL has a product portfolio of a few thousand products. These products range from winery to diapers and shaving needs. The items can be categorised into roughly three categories, which are winery products, food products, and non-food products. Food products can have for example different kinds of characteristics than other categories. For example, certain olives need to be stored in a cooled area below 14 degrees. In Table 2.1 most relevant item characteristics are discussed.

Table 2.1.: Important item characteristics

| **Characteristic** | **Explanation** |
|---|---|
| Cartons on pallets | The number of cartons on a full single pallet. |
| Pallet type | The type of pallet the products are delivered on. |
| Item dimensions | The length, width, and height of a single product. Can also be expressed as the number of items per layer of a pallet. |
| Weight | The weight of a collo[1]. |
| Temperature zone | The temperature zone in which the item should be stored in inventory, and during transport. |
| Shelf-life (PT) | The number of days after production the product can be consumed. |

## 2.4. Supplier portfolio

ADIL has suppliers located all around the globe, which makes their supply chains geographically long. Figure 2.3 shows the expenditure divided per continent of January 2022. The major expenses are made in Europe (about 85%). South America, Asia, and Africa also have some local suppliers that make up about 15% of the total expenses. This concludes that most of ADIL's turnover at suppliers is located in the EU.

[1]A box in which consumer units are stored.

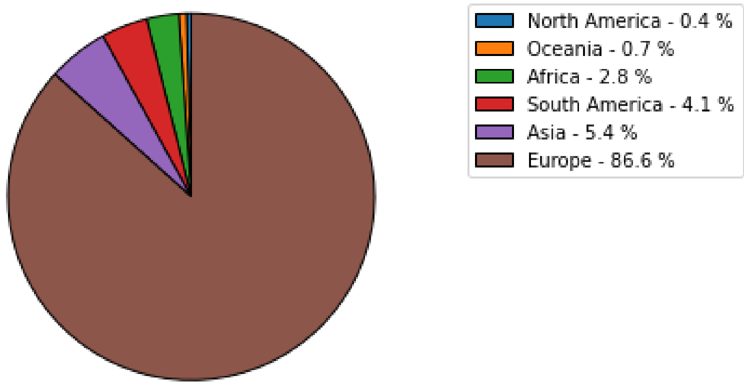



Figure 2.3.: Expenditure of ADIL per continent (January 2022).

ADIL does business with suppliers all across Europe. Countries such as the United Kingdom, Germany, and Italy are the most relevant when it comes to turnover. The majority of the spending is done with western countries, while also eastern countries include some suppliers.

## 2.5. Transportation modes

The transportation industry related to transporting products has 5 common transportation modes: rail, maritime (sea), road, inland waterways, and air (Eurostat, 2019). Some parties also make a distinction between short sea- and deep sea shipping (Eurostat, 2022). ADIL currently makes use of three modes: rail, maritime (short sea & deep sea), and road.

For overseas suppliers that are located outside Europe, deep-sea shipping is the standard transportation mode. Within Europe, the transportation mode can differ from road, rail, and short sea. Currently, only for a limited number of suppliers the rail and short sea transportation modes are used.

ADIL has done about 16,000 shipments in 2021. A distinction between TEUs and FEUs is not possible in the data. Figure 2.4 shows the number of containers shipped from suppliers to the warehouses of ADIL. As the data shows, the majority is shipped by truck. About 25% is shipped by maritime, and about 10% by rail.

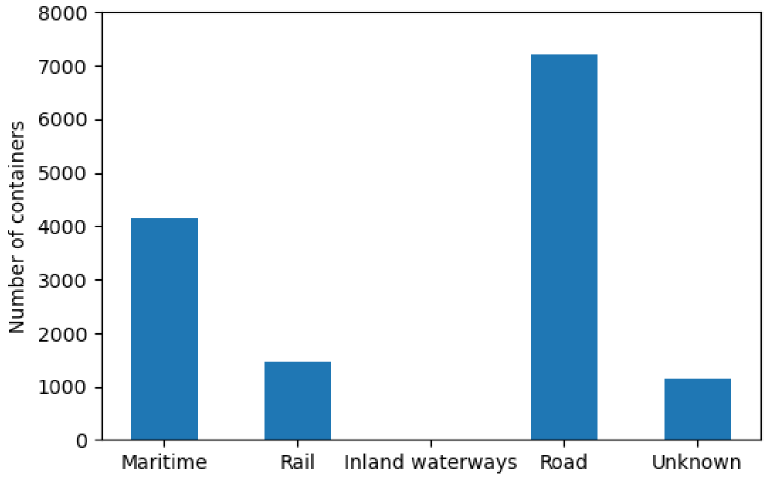



Figure 2.4.: Number of containers ordered in 2021 by transportation mode.

## 2.6. Emission

ADIL is trying to identify sustainability improvements with this research. Different transportation modes also have different emission factors. To compare the different transportation modes, the carbon emissions are used from the GLEC framework (Smart Freight Centre, 2022). The GLEC framework has defined intercontinental average carbon emissions per km per TEU for every transportation mode. Figure 2.5 shows the total distance travelled by all containers, and its corresponding total emissions polluted by the transportation modes. The distance is calculated by taking the great-circle distance in kilometers between the country of origin and destination for all transportation modes. The total emissions are calculated by multiplying the distance with the relevant average emission factor for that route. These values are only for routes defined by a transportation mode.

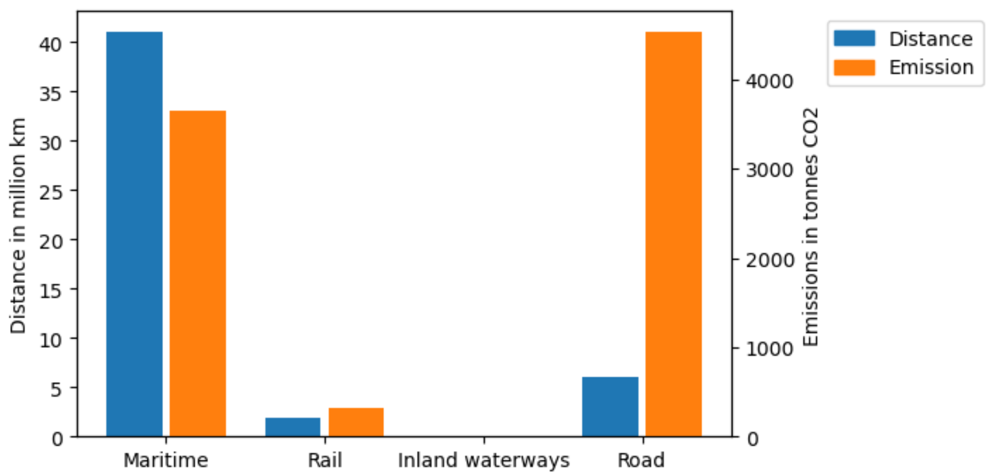



Figure 2.5.: Estimation of total distance travelled and emissions polluted summed over all containers in 2021 by transportation mode.

As Figure 2.5 shows, the majority of the distance travelled is caused by maritime transportation, while the emissions are roughly the same as with the road transportation mode. This is due to the road transportation mode having a way larger emission factor than maritime transportation.

## 2.7. Conclusion

The purchasing process of ADIL is standardized in such a way that the method of transportation is already determined for every supplier. This simplifies the purchasing process but reduces flexibility. The ERP system also assists the planner in determining the quantity of a product to order. The planner can determine at the end what quantity to purchase of what item.

Most of ADIL's spend is done in Europe, where most suppliers are located. The goods from suppliers outside of Europe are transported with maritime shipping. Most shipping inside Europe is still done via road transportation, which causes the most emissions. Currently, only a small amount of containers are transported with rail transportation and no container yet have been transported with inland waterways.

# 3. Literature review

This chapter elaborates on the literature study to answer research question 2. The literature will be reviewed on related work on synchromodal transport and optimization modelling. Table 3.2 shows the division of the subjects. All literature is found in the scientific database Scopus.

Sustainability becomes an increasingly important topic in transportation. Research has been done into, e.g., search for alternative fuels (Kokkinos et al., 2022), and evaluation of electric transportation (Barros et al., 2020). Most studies raise the subject of intermodal- or multimodal transport (Li & Zhang, 2021; Marzano et al., 2022; Tamannaei, Zarei, & Aminzadegan, 2021; Tamannaei, Zarei, & Rasti-Barzoki, 2021; Yin et al., 2021). Table 3.1 gives the definition of four common methods of shipping.

Table 3.1.: Types of modality

| Term | Definition |
|---|---|
| Unimodal | Delivering goods by a single mode of transport, mainly by road (Eurosender, 2020). |
| Multimodal | Moving goods by more than one mode of transport, under one contract (Containerships, 2020). |
| Intermodal | Moving goods by more than one mode of transport, with a separate contract for each individual leg of the journey (Containerships, 2020). |
| Synchromodal | A form of intermodal transport with so-called mode-free booking flexibility (Rivera & Mes, 2022). |

Countries are promoting more sustainable modes of transportation such as railways, sea shipping, and inland waterways (Marzano et al., 2022). Multimodal- and intermodal transport both refer to using a combination of these transportation modes including road transportation. The main difference between these two terms is that multimodal transport is covered by one contract and intermodal transport is covered by multiple contracts within the journey. Transportation by rail, sea, and inland waterways are considered more sustainable than transportation by road (Smart Freight Centre, 2022).

Since ADIL wants to improve their sustainability to contribute to the net-zero scenario (see Section 1.2) related to its transportation, a literature study is performed about intermodal transport and synchromodal transport. Synchromodal transport is an implementation of intermodal transport where for each order the best method of transportation is chosen. The best method of transportation can be defined as, e.g., the most cost-advantageous transportation method for that moment in time.

The study will be divided into four parts. Section 3.1 reviews the literature on synchromodal transport systems and the optimization of synchromodal transport. Section 3.2 summarizes the work done on inventory management in combination with transportation. Section 3.3 shows the modelling of uncertainty in transportation. Section 3.4 searches for learning strategies/learning algorithms to optimize synchromodal transport. Finally, section 3.5 summarizes the most important relevant literature for the optimization model.

Table 3.2.: Literature study subjects

| **Subject** | **Explanation** |
|---|---|
| *Synchromodal transport and optimization* | Synchromodal transport is not a widely researched subject yet, so the relevant available papers have to be examined. |
| *Inventory management with (synchromodal) transport* | Explore what literature provides on the combination of inventory with transportation choices. |
| *Uncertainty/stochasticity in transportation* | Review what uncertainty applies to synchromodal transport and how to overcome this. |
| *Learning strategies in transportation models* | Review what optimization techniques related to AI have been applied. |

## 3.1. Synchromodal transport and optimization

Freight transportation creates remarkable negative effects related to emissions, noise, and congestion (Pamucar et al., 2022). The transportation flow, therefore, requires a model shift, i.e., from road- to rail transportation, to a more efficient system resulting in, e.g., fewer costs and emissions (Pamucar et al., 2022; Zhang, Guo, et al., 2022). Just like multimodal- and synchromodal transport, synchromodal transport makes use of multiple transportation modes for individual orders to maximize the benefits related to emissions, costs, and time (Batarlienė & Šakalys, 2021; Larsen et al., 2021; Zhang, Atasoy, et al., 2022).

synchromodal transport utilizes a transportation network, consisting of different transportation modes between nodes. Xiong and Wang (2014) study such a transportation network with time windows. Based on the speed and cost factor of a transportation mode, the total duration and cost are calculated. Xiong and Wang (2014) used a genetic algorithm in combination with the $k$-shortest path algorithm to find Pareto-optimal solutions on cost and duration. Sawadogo et al. (2012) also optimizes an intermodal transport network to find Pareto-optimal solution on time and costs, but uses multiobjective shortest path algorithm, together with ant colony optimization (ACO). Abdulkadir (2018) uses a more simple approach by using Dijkstra's algorithm for the shortest path for every objective in the model. The paper uses in total four objectives: distance, time, carbon dioxide emission, and cost.

Zhang, Guo, et al. (2022) addresses the case of using flexible services in synchromodal transport, compared to the standard case with only fixed routes. This corresponds with what Pfoser et al. (2022) calls 'mode-free' booking. Zhang, Guo, et al. (2022) has defined the problem as a mixed integer linear programming (MILP). Due to the computational complexity, they also defined an adaptive large neighborhood search (ALNS) as a heuristic to solve the problem. The heuristic is able to achieve an average of 14% cost savings compared to the case with fixed routes in a reasonable time.

Zhang et al. (2021) has developed a route selection model which considers an intermodal transport network in China, which optimizes on five types of cost. These types are (1) transportation cost, (2) transit cost, (3) carbon emission cost, (4) time penalty cost, and (5) damage compensation cost. Three weights have been applied to the cost of these types (weight 1 to the sum of 1-3 and weight 2, 3 to type 4, 5, respectively). A weight sensitivity analysis has been performed to the cost objective. An ant colony optimization algorithm is used as a tool for route selection within the model. The paper uses actual distances, time delay coefficients, and accident damage coefficients specified for each node pair.

Rivera and Mes (2016) consider the problem where a network operator may choose the transportation modes freely based on a synchromodal network with a multi-period horizon. Every day a choice can be made whether to (1) ship a freight to its final destination, (2) ship a freight to an intermediate terminal, or (3) postpone the transport of freight based on a multi-period rolling horizon. Rivera and Mes (2016) formulate this problem as a markov decision process (MDP). Due to the large state space, approximate dynamic programming (ADP) has been used to solve the MDP heuristically. In Rivera and Mes (2017), the authors also used ADP in a similar problem setting with a focus only on cost. They achieved significant cost reductions compared to single-period optimization.

Ambra et al. (2019) makes use of agent-based modeling (ABM) from a decentralized perspective for synchromodal transport. While most papers focus on a logistics service provider (LSP), this paper focuses on the cargo owner's perspective. Besides using ABM, the model also makes use of a geographic information system (GIS) and discrete-event modelling. The optimization model includes disruptions and stochastic events to measure the resilience between different states of the model. Ambra et al. (2019) achieve cost savings up to 5% and a reduced environmental impact of 16% with their optimization model. Tao et al. (2017) focuses, just like Ambra et al. (2019), not on the LSP, but on the cargo owners' perspective, which is a fourth-party LSP. Tao et al. (2017) develop a column-generation approach combined with a graph search heuristic to optimize costs in a transportation network with multiple third-party logistics service providers, considering different cost policies of the LSPs.

**Summary** Synchromodal transport is a form of intermodal transport which uses flexible services. Most papers use the perspective of LSPs that optimizes the movements of goods through a network of nodes and links. A few papers focus on creating paths in a network and moving goods according to the paths. Due to the dynamic environment, most papers' solution approaches have to deal with stochastic events and disruptions. The solution approach often optimizes cost and emissions. The solution approaches, often heuristics, are tested in a simulation model.

## 3.2. Inventory management with transportation

Saldanha (2022) claims the fill rate (percentage of demand fulfilled from available inventory) is an important metric to set the re-order point of stock keeping units (SKUs). Setting the re-order point requires assumptions such as a lead time demand that must follow a certain distribution. Saldanha (2022) has defined a method to set a least-biased estimate of the re-order point with respect to lead-time demand (LTD) distribution and the sample size of the LTD.

Lemmens et al. (2019) introduces a simulation study where a comparison between road- and intermodal transport is presented and evaluated on transport- and inventory costs. The case makes use of a transportation network consisting of one origin, one terminal (transhipment point), and one destination. There are two transportation modes from the origin to the terminal, and from the terminal to the destination. The transportation modes were by road and intermodal, where intermodal was defined by rail in this case. Demand at the destination was independently and identically distributed by a binomial distribution. A base stock policy was chosen as the inventory policy. Lemmens et al. (2019) evaluated six policies. The best policy was parallel usage and real-time switching between the two modes in the transportation network, which resulted in the least total cost, provided that the company has access to intermodal transport infrastructure with fast and efficient transshipments. In this case, inventory costs increased by 7.6% while transport costs decreased by 4% compared to the base case (road transportation only). If no transshipments are available at the terminal, parallel usage of transportation modes without switching is advised.

Some papers focus on optimizing the distribution from a central hub to multiple depots without transshipments. Both Ignaciuk (2019) and Stenius et al. (2018) analyse a similar case with stochastic demand, which is solved with a MILP formulation. Where Ignaciuk (2019) replenishes the depots with batches, Stenius et al. (2018) makes use of an (R, Q) replenishment policy.

**Summary** A few researches have been performed on synchromodal shipping in combination with inventory management. Only basic inventory policies, such as the (R, Q) replenishment policy, have been evaluated in combination with transportation. Studies show that dynamically choosing the transportation mode based on the inventory can reduce total inventory-related costs.

## 3.3. Uncertainty/stochasticity in transportation

Pamucar et al. (2022) has developed a fuzzy multi-criteria decision-making model that uses the ordinal priority approach (OPA) to determine the weight coefficients of criteria. A predefined set of transportation planning strategies is evaluated on the criteria to determine the best strategy. To overcome incomplete-, and uncertain information, Pamucar et al. (2022) uses fuzzy set theory. Where Pamucar et al. (2022) uses fuzzy logic to assess the expert's experience, Koohathongsumrit and Chankham (2022) and Maity et al. (2022) also make use of fuzzy logic but apply it to assess features of certain paths within their problem situations.

Delbart et al. (2021) has performed a literature study on planning models with uncertainty within intermodal- and synchomodal shipping. They have defined a total of six uncertainty types (in order of relevance): transit times, demand, capacity, costs, hub failures, departure times, and cancellations. A total of 42 articles have been categorized by planning level (strategic, tactical, operational) and by uncertainty type.

On the strategic level, Delbart et al. (2021) found that most studies investigated the hub location problem. While some papers proposed exact methods such as linear programming, most papers created (meta)heuristics such as Tabu search, genetic algorithm, and simulated annealing to avoid poor performance of exact methods. These heuristics often perform close to optimal.

On the tactical level, Delbart et al. (2021) mentioned two major models: service network design (SND) and network flow planning (NFP). Both models are for optimally running a given network. SND determines which arcs/services will be planned in a network given a set of orders, and NFP determines the routing of the orders through the network. Demand and transit times are the most commonly researched types of uncertainty for SND models, while for NFP models capacity and transit times are the most common. Most papers use scenario generation as a method to calculate robust solutions/mitigate risks.

On the operational level, Delbart et al. (2021) categorised the papers into two groups: real-time planning and resource management. Real-time planning includes scheduling and routing decisions on real-time information, and resource management includes the allocation or repositioning of resources. Papers dealing with resource management often focus on fleet management with stochastic demand. Most papers focusing on real-time planning use rerouting or replanning as a method to deal with uncertainty/risks. Also, in this case, the majority uses an approximation to solve the problems, varying from a metaheuristic, matheuristic, or genetic algorithm. For example, Burgholzer et al. (2013) uses a microsimulation model to optimize an intermodal network with stochastic arrival times and reduced capacity on links (disruptions). The model can choose to stay on a disrupted link, move to another link on the same transportation mode, or move to another link with a different transportation mode. When minimizing travel time, rail- and road transportation seem to be preferred over inland waterways in case of disruptions.

> **Summary** Uncertainty can be tackled on different levels. On the operational level, rerouting/replanning is often the method to deal with real-time stochastic events. On the tactical- and strategic level, scenario generation is commonly used. Stochastic events are often modelled as delayed, or cancelled trips, with dynamic capacity and demand.

## 3.4. Learning strategies in transportation models

To overcome high-dimensional problems, machine learning might be a better approach to real-life complex problems. As mentioned in Section 3.1, Rivera and Mes (2016) uses Approximate Dynamic Programming as a learning technique to choose the transport mode for a freight.

Ge (2021) makes use of ant colony optimization (ACO) to select the optimal path in a multimodal network. In this problem instance, only the cost and transport time are optimized while considering occasionally delayed shipments. Shipping by waterways was often chosen as the best path due to the low cost. After applying penalty costs for late deliveries, and inventory costs for early deliveries, a combination of highways and waterways was often chosen as optimal.

Farahani et al. (2021) proposes a deep reinforcement learning model of the container allocation problem, where containers are real-time allocated to trucks or trains. The model is compared to and outperforms a heuristic, stochastic program, and method considering re-planning. The model has been formulated as an MDP.

> **Summary** Several papers use learning models to determine good policies. Reinforcement learning is a common method when trying to learn optimal decisions considering the current state. These models often have the ability to perform well in complex environments.

## 3.5. Summary of literature

Synchromodal shipping is the operational activity of choosing the best transport mode given certain circumstances. Where using only road transportation is quite reliable, using multiple modes of transportation can be less reliable with more disruptions. Therefore, the core problem of intermodal-, and thus synchromodal transport, is dealing with uncertainty. The literature considers a variety of optimization models applied to synchromodal transport, such as heuristics, learning models, and agent-based models.

The field of inventory management in combination with transportation is not widely researched in the literature. Often basic replenishment policies are combined with the transportation mode choice. This often leads to little cost reductions.

From an LSP's perspective, the uncertainty of intermodal shipping can be dealt with by generating scenarios including stochasticity to optimally determine the schedules of transportation. Rescheduling is used to overcome uncertainty on the operational level. Uncertainty is often modelled as delayed, or cancelled trips, with dynamic capacity and demand.

# 4. Problem formulation

As mentioned in Chapter 1, ADIL desires to improve their sustainability in its transportation process. The context analysis shows that a high share of shipments is carried out by road transportation. The literature review shows that intermodal transport causes fewer emissions over a certain distance. We conclude that the solution direction should go towards increasing the share of intermodal transport, and subsequently reducing the share of road transportation, to achieve a reduction in total emissions.

This chapter deals with research question 3 by presenting the problem formulation. First, the formulation is introduced in Section 4.1. Section 4.2 summarizes the decisions that can be made in the problem formulation. Section 4.3 shows the MDP formulation of the problem. Section 4.4 lists the requirements and assumptions of the formulation. Finally, Section 4.5 concludes this chapter by stating the conclusions of the problem formulation.

## 4.1. Problem introduction

The problem formulation is elaborated on into three modules, which are the transportation network, inventory management system, and ordering process. Afterwards, we also summarize the stochastic parameters of the formulation.

**Transportation network**

We define a directed graph $G$ as a transportation network, where $G = (\mathcal{V}, \mathcal{E})$. The set $\mathcal{V}$ represent the set of nodes (vertices) in the graph, connected by the set of arcs $\mathcal{E}$ (edges). The set of nodes $\mathcal{V}$ consists of mutually exclusive subsets warehouses $\mathcal{V}^{wh}$, transfer points $\mathcal{V}^{tp}$, and suppliers $\mathcal{V}^{s}$, so $\mathcal{V} = \mathcal{V}^{wh} \cup \mathcal{V}^{tp} \cup \mathcal{V}^{s}$. Each node's location is determined by the latitude and longitude coordinates.

Each arc $e \in \mathcal{E}$ has an origin node and a destination node $v \in \mathcal{V}$. Every arc $e$ is assigned a transportation method $m_e \in \mathcal{M}$. Based on the transportation method $m_e$ and the distance $d_e \in \mathbb{Z}^+$ in kilometers, the duration of an arc $b_e \in \mathbb{Z}^+$ in hours can be calculated with the average velocity in km/h of the transportation method $f_m \in \mathbb{Z}^+, m \in \mathcal{M}$. The emissions $a_e \in \mathbb{Z}^+$ of arc $e$ in kg $CO_2$ can be calculated with the average emission per kilometer per container per transportation method $g_m \in \mathbb{R}^+$. The set of arcs $\mathcal{E}$ consists of the mutually exclusive subsets of road transportation $\mathcal{E}^{road}$, rail transportation $\mathcal{E}^{rail}$, inland waterways transportation $\mathcal{E}^{iww}$, and sea transportation $\mathcal{E}^{sea}$, so $\mathcal{E} = \mathcal{E}^{road} \cup \mathcal{E}^{rail} \cup \mathcal{E}^{iww} \cup \mathcal{E}^{sea}$. All arcs using intermodal transport have fixed scheduled departure times $Z_e, e \in \mathcal{E} \setminus \mathcal{E}^{road}$. Arcs using road transportation are flexible, which means these arcs can be scheduled on request.

In the problem formulation, we may decide to transport goods between nodes via arcs. To reduce the decision problem of which arcs to use, the transportation network $G$ is used to create a fixed set of paths upfront $\mathcal{P}$ for each supplier. Each path $p \in \mathcal{P}$ consist of a set of nodes $\mathcal{V}_p$ and arcs $\mathcal{E}_p$. If we want to transport items from a supplier, we choose a path $p \in \mathcal{P}$ on which the items travel.

**Inventory management system**

We define a set of items $\mathcal{I}$, where each supplier $s \in \mathcal{S}$ has a mutually exclusive set of items $\mathcal{I}_s \subseteq \mathcal{I}$ ($\mathcal{I}_s \cap \mathcal{I}_{s'} = \varnothing; s, s' \in \mathcal{S}; s \neq s'$) which it supplies to ADIL. Each item $i$ has a physical inventory $\alpha_{it}$, inventory position $\beta_{it}$, demand $\lambda_{it}$, ordered volume $\gamma_{it}$, delivered volume $\theta_{it}$, and lost sales $\xi_{it}$ in week $t \in \mathcal{T}$, and are all expressed in number of collo. The actual inventory (4.1) at time $t$ is calculated by the actual inventory minus demand and actually delivered orders of time $t-1$. If lost sales occurred, we add the number of lost sales to the actual inventory to correct for negative inventory. The same applies to the inventory position (4.2) which uses the ordered volume instead of the delivered volume. The ordered quantity (4.3) is calculated by the number of pallets ordered $\omega_{ic}$ of item $i$ in container $c$ in the current time $t$, multiplied by the order multiple $u_i$. The delivered quantity (4.4) is the sum of all pallets ordered, multiplied by the order multiple, of all placed orders until time $t$, where the expected arrival time $t^* + \widehat{b_p}$ of a container $c$ equals $t, t^\star < t$. The expected arrival time is based on the expected path duration $\widehat{b_p}$, which is further elaborated on later in this section. Each item $i$ has a reorder point $w_i$ after which an order is placed. Note that all figures are expressed on collo, while $\omega_{ic}$ is expressed in pallets.

$$\alpha_{it} = \alpha_{it-1} - \lambda_{it-1} + \theta_{it-1} + \xi_{it} \qquad t > 0 \quad \forall i \in \mathcal{I} \tag{4.1}$$

$$\beta_{it} = \beta_{it-1} - \lambda_{it-1} + \gamma_{it-1} + \xi_{it} \qquad t > 0 \quad \forall i \in \mathcal{I} \tag{4.2}$$

$$\gamma_{it} = \sum_{c \in \mathcal{C}_o, o \in \mathcal{O}'_t} \omega_{ic} u_i \qquad t > 0 \quad \forall i \in \mathcal{I} \tag{4.3}$$

$$\theta_{it} = \sum_{o \in \mathcal{O}'_{t^\star}, t^\star \in \mathcal{T}} \quad \sum_{c \in \mathcal{C}_o, t^\star + b_p = t, p \in \mathcal{P}'_o} \omega_{ic} u_i \qquad t^\star < t, t > 0 \quad \forall i \in \mathcal{I} \tag{4.4}$$

**Ordering process**

In this problem instance, we need to comply with the demand of each item $i$. For this reason, we need to order units of item $i$. First of all, items are ordered in multiples of pallets, which contain $u_i \in \mathbb{Z}^+$ collo in one pallet. We transport items by the use of a container, which has a certain capacity of $l$ pallets. We always order a full container load (FCL). Items are placed as pallets in a container $c \in \mathcal{C}$. The amount of pallets placed of item $i$ in container $c$ is $\omega_{ic} \in \mathbb{Z}^{\geq 0}$. Note that different items may be present in a single container $c$. Dependent on the

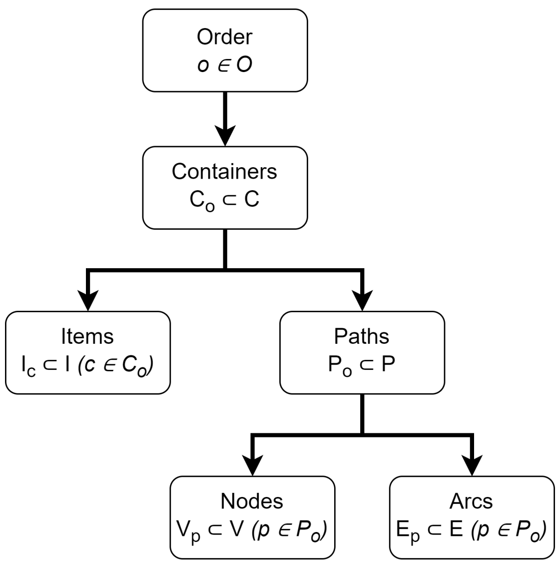



Figure 4.1.: Structure of an order $o \in \mathcal{O}$.

demand of items, we may order multiple containers at a supplier $s$ at time $t$. This set of containers $\mathcal{C}_o \subset \mathcal{C}$ at time $t$ is linked to one order $o \in \mathcal{O}_t$. Note that order $o$ is always linked to a single supplier $s_o \in \mathcal{S}$, which means that individual orders are independent. A container $c \in \mathcal{C}_o, o \in \mathcal{O}_t$ only may be packed with items $\mathcal{I}_s$ of supplier $s_o \in \mathcal{S}$.

The structure of order $o \in \mathcal{O}$ consist of a subset of containers $\mathcal{C}_o \subset \mathcal{C}$ (Figure 4.1). A container $c \in \mathcal{C}_o$ is packed with pallets of a subset of items $\mathcal{I}_{s_o} \subset \mathcal{I}, s_o \in \mathcal{S}$ and can travel via one path of the set of paths $\mathcal{P}_o \subset \mathcal{P}$. A path $p \in \mathcal{P}_o$ is based on a subset of nodes $\mathcal{V}_p \in \mathcal{V}$ and arcs $\mathcal{E}_p \in \mathcal{E}$. For a path $p \in \mathcal{P}$, the parameters distance $d_e$, emission $a_e$, and cost $c_e$ can be also calculated through the sums of the parameter values of all edges $e \in \mathcal{E}_p$, e.g., $d_p = \sum_{e \in \mathcal{E}_p} d_e, \forall p \in \mathcal{P}$. The parameter path duration $b_e$ is calculated slightly differently, according to (4.5). The parameter $2n$ refers to the transfer time to and from an intermodal arc.

$$b_p = \sum_{e \in \mathcal{E}_p} \begin{cases} b_e & m_e = road \\ b_e + 2n & m_e \neq road \end{cases} \quad \forall p \in \mathcal{P} \tag{4.5}$$

We define the subset $\mathcal{O}'_t$ as the subset of executed orders at time $t$, where $\mathcal{O}_t$ represent all orders generated at time $t$, so $\mathcal{O}'_t \subset \mathcal{O}_t$. We also define the set of executed paths $\mathcal{P}'$ which are the executed paths when scheduling an order.

When an order $o \in \mathcal{O}$ is created, the order creation date, ready for transport date, and the required date are determined. The transportation date is determined based on the order creation date, plus the production time $q_s$ of supplier $s \in \mathcal{S}$.

**Stochastic variables**

The demand $\lambda_{it}$ and the path duration delay $\phi_p$ are stochastic variables in this problem formulation. This means that the demand of all items $\mathcal{I}$ at time $t$ is unknown upfront and becomes known at the end of time $t$.

The path delay $\phi_p$ is also stochastic. Every arc $e \in \mathcal{E}_p$ of a path $p$ includes a delay distribution. When we calculate the expected arrival time of a path, we calculate with the expected arc delay $E(\phi_p)$. We define the expected path duration as $\widehat{b_p}$ with (4.5). The actual path duration is a random observation, defined as $b^\star_p$, from the probability distributions $\phi_e \in \mathcal{E}_p$ and is only used for the physical inventory $\alpha_{it}$, which is further elaborated in the model performance evaluation section. The actual path duration $b^\star_p$ becomes known to the model when the container arrives at time $t + b^\star_p$.

$$\widehat{b_p} = \sum_{e \in \mathcal{E}_p} (b_e + \phi_e) \quad \forall p \in \mathcal{P} \tag{4.6}$$

Table 4.1 provides an overview of the sets in the formation. Table 4.2 shows the set of variables that are determined by the solution approach. Table 4.3 shows an overview of all parameters.

Table 4.1.: List of all sets in the problem formulation.

| **Set** | **ID** | **Description** |
|---|---|---|
| Items | $i \in \mathcal{I}$ | Set of items in inventory that need to be replenished by the model. |
| Suppliers | $s \in \mathcal{S}$ | Set of suppliers of the items in inventory. |
| Nodes | $v \in \mathcal{V}$ | Set of all nodes in graph $G$. |
| Arcs | $e \in \mathcal{E}$ | Set of all arcs in graph $G$. |
| Modes | $m \in \mathcal{M}$ | Set of all shipment methods, $\mathcal{M} = \{sea, rail, road, iww, sea\}$. |
| Containers | $c \in \mathcal{C}$ | Set of containers loaded with pallets. |
| Schedules | $z \in \mathcal{Z}$ | Set of schedules (departure times) of an arc. |
| Orders | $o \in \mathcal{O}$ | Set of all possible orders that can be generated by the inventory management system. |
| Paths | $p \in \mathcal{P}$ | Set of all possible paths generated. |
| Time horizon | $t \in \mathcal{T}$ | Set of weeks with length $h$ looking forward, $\mathcal{T} = \{0, 1, \ldots, T\}$. |

Table 4.2.: List of all variables in the problem formulation.

| **Variable** | **ID** | **Description** |
|---|---|---|
| Inventory | $\alpha_{it}$, $\beta_{it}$ | Physical inventory ($\alpha_{it}$) and inventory position ($\beta_{it}$) of item $i \in \mathcal{I}$ at the beginning of week $t \in \mathcal{T}$. |
| Transit inventory | $\gamma_{it}$, $\theta_{it}$ | Ordered volume ($\gamma_{it}$) and delivered volume ($\theta_{it}$) of item $i$ at the beginning of week $t$. |
| Demand | $\lambda_{it}$ | Actual demand of item $i$ in week $t$. |
| Lost sales | $\xi_{it}$ | Lost sales in collo for item $i$ in week $t$. |
| Pallet quantity | $\omega_{ic}$ | Quantity of pallets of item $i$ in container $c$. |
| Arc delay | $\phi_e$ | The delay of arc $e$ in hours. |

Table 4.3.: List of all parameters in the problem.

| Parameter | ID | Description |
|---|---|---|
| Distance | $d_e$ | Distance in kilometers of arc $e \in \mathcal{E}$. |
| Emission | $a_e$ | $CO_2$ emissions caused by arc $e$. |
| Duration | $b_e$ | Duration of arc $e$ in hours. |
| Mode | $m_e$ | Transportation method of arc $e$. |
| Mode velocity | $f_m$ | The average velocity of a transportation method $m \in \mathcal{M}$ in kilometers per hour |
| Mode emissions | $g_m$ | The average amount of kg $CO_2$ emissions caused by transportation method $m$ per kilometer per TEU. |
| Path cost | $c_p$ | Cost of path $p$ in euros (€). |
| Inventory cost | $c^{inv}$, $c^{ls}$ | The holding cost $c_i^{inv}$ **per pallet** per time unit, and the lost sales cost $c_i^{ls}$ **per collo**. |
| Production time | $q_s$ | The number of weeks the supplier $s_s \in \mathcal{S}$ requires to produce an order. |
| Order multiple | $u_i$ | The number of collo of item $i$ that fit on one pallet. |
| Reorder point | $w_i$ | The inventory level after which we place a new order for item $i$. |
| Transfer time | $n$ | The number of hours to transfer a container to and from an intermodal transport mode. |
| Capacity | $l$ | The capacity of a container in number of pallets. |
| Review period | $r$ | The review cycle in days in which articles are checked on their inventory. |
| Planning horizon | $h$ | The number of days looking forward to defining the time horizon $\mathcal{T}$. |

## 4.2. Decision space

This section provides an overview of the decision space in the problem formulation from Section 4.1. The following decisions are relevant to the problem formulation:

1. For every week $t \in \mathcal{T}$, determine if an order $o \in \mathcal{O}_t$ is executed for item $i \in \mathcal{I}$.
2. For every order $o \in \mathcal{O}_t$, determine how many containers are used to transport pallets.
3. For every order $o \in \mathcal{O}_t$, determine how many pallets of items $\mathcal{I}_s$ of supplier $s \in \mathcal{S}$ are ordered.
4. For every order $o \in \mathcal{O}_t$, determine what the allocation is of the pallets into the container(s) $C_o \subset \mathcal{C}$.
5. For every container $c \in \mathcal{C}_o$, determine what path $p \in \mathcal{P}_o$ will be used to transport container $c$.

With a total of five decisions in the problem formulation, the decision space is large. In Chapter 5 we propose the solution approach that will tackle this problem.

## 4.3. MDP formulation

The problem instance can be modelled as a Markov Decision Process. The MDP formulation consists of stages, states, decisions, transitions, and optimality equations. All elements are elaborated on below.

**Stages**

The stages of the MDP model are set to each Monday of the week, which is $t = 0, 7, 14, \ldots \in \mathcal{T}$. Every time $t$ we get to make one or more decisions about shipping orders. At the beginning of stage $t$, we get to make a decision. After making the decision in time $t$, the exogenous information arrives.

**States**

The state of the MDP is determined by the actual inventory $\alpha_{it}$, and the newly defined variable incoming orders $\beta^{\star}_{its}$ for $t \in \mathcal{T}$. We define the new variable $\beta^{\star}_{its}$ as the number of collo of item $i$ in transit at time $t$ which are expected to arrive at time $t + s$, i.e., over $s$ days. This concludes to (4.7). The physical inventory is calculated with the physical inventory of $t - 1$ minus the demand $\lambda_{it}$ (reduced by lost sales $\xi_{it}$) plus the in transit collo with one-time unit left $s = 1$ at time $t - 1$. The in-transit orders are calculated by (4.9) with the in-transit orders at time $t - 1$ with $s + 1$ time units left, added by the executed orders $\mathcal{O}_t$, where the expected path duration $\widehat{b_p} = s$.

$$S_t = [\alpha_{it}, \beta^{\star}_{its}]_{i \in \mathcal{I}} \qquad t \in \mathcal{T} \tag{4.7}$$
$$\alpha_{it} = \alpha_{it-1} - (\lambda_{it-1} - \xi_{it}) + \beta^{\star}_{it-1s} \qquad s = 1, i \in \mathcal{I}, t \in \mathcal{T} \tag{4.8}$$
$$\beta^{\star}_{its} = \beta^{\star}_{it-1s+1} + \sum_{c \in \mathcal{C}_o, \widehat{b_p} = s, p \in \mathcal{P}'_o} \omega_{ic} u_i \quad \forall s, i \in \mathcal{I}, o \in \mathcal{O}'_t, t \in \mathcal{T} \tag{4.9}$$

**Decisions**

During each stage $t$, a set of orders $\mathcal{O}_t$ is generated, which consist of a set of containers $\mathcal{C}_o$ and paths $\mathcal{P}_o, o \in \mathcal{O}_t$. For every order $o \in \mathcal{O}_t$, we decide to ship it on a certain path. The new set $\mathcal{O}'_t$ is defined as the set of orders which is executed at time $t$, so $\mathcal{O}'_t \subseteq \mathcal{O}_t$. All generated orders $\mathcal{O}_t$ are executed when generated, so $\mathcal{O}_t = \mathcal{O}'_t$.

The decision-variable $x_t \in \mathcal{X}_t$ is defined, where $\mathcal{X}_t$ is the set of decisions which can be taken in stage $t$ (4.10). Variable $x_t$ is a binary vector which is 1 if container $c$ is shipped with path $p$ at time $t$, and 0 otherwise. Constraint (4.11) shows that 1 path is chosen for each container.

$$x_t = [x_{cpt}]_{c \in \mathcal{C}_o, p \in \mathcal{P}_o, o \in \mathcal{O}_t} \qquad \forall t \in \mathcal{T} \tag{4.10}$$
$$\sum_{p \in \mathcal{P}_o} x_{cpt} = 1 \qquad \forall c \in \mathcal{C}_o, o \in \mathcal{O}_t, t \in \mathcal{T} \tag{4.11}$$

The decision $x_t$ needs to be translated to the new sets of executed orders $O'$ and executed paths $P'$. The set of executed orders $O'_t$ equal to the generated orders (4.12). The set of executed paths $P_t'$ is determined by (4.13), which adds a path $p \in \mathcal{P}_t$, if path $p$ is chosen for container $c$ at time $t$.

$$\mathcal{O}_t^{\prime,\pi} = \mathcal{O}_t \tag{4.12}$$
$$\mathcal{P}_o^{\prime,\pi} = \left\{p \in \mathcal{P}_o : x_{cpt} = 1, \quad \forall c \in \mathcal{C}_o\right\} \quad \forall o \in \mathcal{O}_t, t \in \mathcal{T} \tag{4.13}$$

**Exogenous information**

As mentioned in the problem introduction (Section 4.1), the problem has two stochastic variables, which are the demand $\lambda_{it}$ and the arc delay $\phi_e$, and thus the actual path duration $b_p^\star$. The actual demand of an item $i$ at time $t$ becomes known at the end of time $t$, i.e. after the decision is chosen. The actual path duration $b_p^\star, p \in \mathcal{P}_\wr, o \in \mathcal{O}_t$ becomes known to the model at time $t + b_p^\star$, but we already know that $b_p^\star \geq b_p$. Therefore, the exogenous information $\Omega_t$ is a vector of the demand figures (4.14) and paths with an actual arrival time $t$.

$$\Omega_t = [\lambda_{it}, b_p^\star]_{\forall i \in \mathcal{I}, p \in \mathcal{P}_o', o \in \mathcal{O}_{t^\star}', t^\star + b_p^\star = t} \quad t \in \mathcal{T} \tag{4.14}$$

**Transition and optimality equations**

The transition function $S^M$ is shown in (4.15). The current state $S_t$ is determined by the transition function $S^M$, based on the previous stage's state $S_{t-1}$, the decision from the previous state $x_{t-1}$, and the exogenous information $\omega_t$. The transition function $S^M$ includes the equations (4.7-4.14) in this section.

$$S_t = S^M(S_{t-1}, x_{t-1}, \Omega_t) \tag{4.15}$$

The total expected costs over the horizon need to be minimized. To achieve this, a policy $\pi$ is defined that takes a decision $x_t^\pi \in \mathcal{X}_t$ in all possible states $S_t \in \mathcal{S}$. We try to find the policy $\pi \in \Pi$ that minimizes the cost function (4.16) over the entire horizon (4.17). Note the extra parameter $c^{CO_2}$ in this equation, which equals the cost for causing one kg of $CO_2$. During each stage $t$, the cost function consists of (1) the action costs, which include path- and emission costs, and (2) the state cost, which consists of holding- and lost sales costs.

$$C_t(x_t^\pi) = \sum_{p \in \mathcal{P}_o^{\prime,\pi}, o \in \mathcal{O}_t^{\prime,\pi}} (c_p + c^{CO_2} a_p) + \sum_{i \in \mathcal{I}} (c_i^{inv} \alpha_{it} + c_i^{ls} \xi_{it}) \tag{4.16}$$
$$\min_{\pi \in \Pi} \mathbb{E} \left[ \sum_{t \in \mathcal{T}} C_t(x_t^\pi) \middle| S_0 \right] \tag{4.17}$$

The decision $x_t$ taken at time $t$, according to policy $\pi$, determines on which path in $\mathcal{P}_t^{\prime,\pi}$ a container is executed in (4.17). The MDP formulation is a stochastic, sequential optimization problem, which is why (4.17) is transformed to (4.18). This formula shows that the value function $V_t(S_t)$ of state $S_t$ minimizes the direct costs with decision $x_t^\pi$ together with the future costs in the next state $S^M(S_t, x_t^\pi, \omega)$.

$$V_t(S_t) = \min_{x_t^\pi \in \mathcal{X}_t} \left( C_t(x_t^\pi) + \sum_{\omega \in \Omega_{t+1}} p_\omega^{\Omega_{t+1}} V_{t+1}(S^*(St, x_t^\pi, \omega)) \right) \quad \forall S_t \in \mathcal{S} \tag{4.18}$$

MDP problems often suffer from three curses of dimensionality, which makes it hard to solve these problems to optimality. These curses are (1) the state space, (2) the decision space, and (3) the transition space. If one or more of these dimensions becomes too large, it is nearly impossible to calculate the optimal solution.

The curses of dimensionality also apply to this case. Consider a single item with a max physical inventory $\alpha_{it}$ of $10^4$ units, and a max of $10^3$ in-transit units with a max of $10^2$ release days. If we consider $10^2$ items, the state space $\mathcal{S}$ already becomes $10^4 10^3 10^2 10^2 = 10^{11}$ states. Looking at the decision space, i.e., the ordering process, if we consider $10^2$ suppliers, each having $10^1$ items, where we order at max $10^2$ pallets in max $10^1$ containers, that may travel with one of $10^1$ different paths. The decision space becomes a total of $10^2 10^1 10^2 10^1 10^1 = 10^7$ decisions at every stage $t$. Finally, looking at the transition space, if we consider $10^2$ items, each having on average $10^2$ possible demand observations every week, and if we execute about $10^2$ containers every week with a time frame of $10^1$ days the containers may actually arrive, the transition space becomes $10^2 10^2 10^2 10^1 = 10^7$ possible transitions. This concludes that the curses of dimensionality also apply to this formulation.

## 4.4. Assumptions

The problem formulation requires a number of assumptions. The assumptions are split into two categories. First, the assumptions related to the preparations for the formulation are stated. Second, the assumptions related to the actual running/optimization of the model are stated.

**Model preparation assumptions**

- The transportation network requires a predefined directed graph, consisting of arcs and nodes.
- The demand distribution statistical parameters per item have to be known.
- A modal change at a transfer node does not result into additional cost or emissions when creating the fixed set of paths per supplier.
- All items are delivered on euro pallets. The order multiple $u_i$ (collo per pallet) of items delivered on block pallets is multiplied by 0.8, as the capacity of a euro pallet is 80% of a block pallet.
- In total one warehouse is considered, for which we use the largest warehouse of ADIL.

**Model optimization assumptions**

- The departure times of intermodal arcs are once a week at a fixed moment in time.
- Production delays at suppliers are not considered, which means an order is always ready at the transportation date at the supplier's location.
- Once an order is executed, the planned transportation path takes place and will not change, regardless of delays.
- Weight of a collo/pallet is not considered a constraint for packing containers.
- All orders are placed on Mondays.

## 4.5. Conclusion

The problem formulation consists of three modules. First, the transportation network creates paths for each supplier in Europe. Second, the inventory management system tracks the inventory of all items and generates orders to create item replenishments to fulfil future demand. The container optimizer determines the best path to follow for a container in an order. The objective of the problem formulation is to reduce costs and emissions.

The problem is modelled as a Markov Decision Process, where the state is defined as the physical and in-transit inventory per item. The state space, decision space, and transition space can become large in this problem (curses of dimensionality), which is why the MDP formulation should be solved approximately with a heuristic approach.

# 5. Solution design

This chapter presents the approach to the solution design which should be able to make the right decision regarding packing- and transporting containers to the warehouse of ADIL. The procedures related to inventory control and transportation path creation are implemented in the solution design.

The problem formulation showed how we formulated our problem in terms of sets, parameters, constraints, and variables. In this chapter, we present the solution approach. We propose the heuristics and algorithms that have been applied in the transportation network module, inventory management module, and order optimizer module. For the order optimizer module, we also propose a machine-learning model.

First, Section 5.1 describes the general structure of the solution. The heuristic to generate paths in the transportation network is discussed in Section 5.2 (module 1). Section 5.3 describes the inventory management and ordering process (module 2). Section 5.4 demonstrates the method to evaluate and choose container-path combinations (module 3). Then, Section 5.5 presents a machine learning approach to solve the container-path evaluation process of module 3, but now with a machine learning strategy. Finally, the conclusions follow in Section 5.6.

## 5.1. Solution approach

As the problem introduction mentions, ADIL desires to reduce their environmental impact by reducing its carbon emissions. In the context of ADIL, the main focus in literature is the modal shift from unimodal transport to intermodal transport (see the introduction of Section 3), since intermodal transport causes on average fewer emissions per unit of distance travelled. Most of ADIL's emissions are caused by road transportation (see Figure 2.5). Therefore, the solution approach aims to decrease total emissions by reducing road transportation and consequently increasing intermodal transport.

Section 4.2 shows an overview of the decision space of the problem formulation. The decisions are categorised into three modules in the solution design. These modules are elaborated in Table 5.1, showing which decision is tackled in which module.

Table 5.1.: Solution modules.

| Module | Decision | Purpose |
|---|---|---|
| Transportation network | - | Create a fixed set of paths for every supplier based on different objectives. |
| Inventory management system | 1, 2, 3, 4 | Create orders for items to increase inventory levels to cope with demand. Orders should include containers packed with pallets containing items. |
| Order optimizer | 5 | Evaluate the characteristics and stochasticity of paths and choose the best path for a container. |

Table 5.1 shows that the transportation network module does not include a decision from the decision space of Section 4.2. That is because the fixed set of paths per supplier can be created upfront and does not change over time. The inventory management system tackles most decisions regarding creating orders. The container scheduler determines the best path choice considering stochastic problem elements. Note that the transportation network- and inventory management system module are considered in both solution approaches, but the container scheduler module differs per approach.

This solution design is presented as a step-by-step approach in Figure 5.1. The three modules from Table 5.1 are linked with one of the eight items in Figure 5.1. The inventory management system corresponds with box (1.), where the set of orders $\mathcal{O}_t$ are generated at time $t$. The transportation network extracts the set of paths $\mathcal{P}_o$ for a supplier $s_o \in \mathcal{S}$ at box (2.). The container scheduler corresponds with box (4.).

The process starts with the inventory management system. This module contains all items $\mathcal{I}$ and suppliers $\mathcal{S}$ with their actual inventory $\alpha_{it}$, inventory position $\beta_{it}$, demand/forecast $\lambda_{it}$, ordered- $\gamma_{it}$ and delivered volume $\theta_{it}$, for all $t \in \mathcal{T}$, where $t$ equals one day in the time horizon. The inventory management system manages the inventory variables of all items and generates orders $\mathcal{O}_t$ at time $t$ to fulfil future demand. The solution approach for the standard problem formulation operates on a weekly basis, which means orders are generated on $t = \{0, 7, 14, \ldots\}$. The orders $\mathcal{O}$ are based on full container loads (FCL) $\mathcal{C}_o$, implying a container $c \in \mathcal{C}_o$ is packed at its max capacity $l_c$.

When the inventory management system generates an order $o \in \mathcal{O}_t$, the transportation network $G$ is consulted to determine the top $k$ paths $\mathcal{P}_o$. The order $o$ needs to be shipped from the supplier's location to the warehouse of ADIL. Based on the transportation network $G$, the top $k$ paths will be generated. Each path $p \in \mathcal{P}_o$ may use different transportation modes $m \in \mathcal{M}$ and arcs $e \in \mathcal{E}$, each having different transportation lead times $b_p$. Also, paths that use intermodal transportation modes ($m \neq road$) have to comply with the set of departure schedules $\mathcal{Z}$ of LSPs.

When an order $o$ is generated, the container scheduler will select a path $p \in \mathcal{P}_o$. Paths using transportation by water or rail may have a longer duration, and often the total emission is lower than paths using transportation by road. The order optimizer determines a path based on a heuristic evaluating different scenarios on the transportation duration of a path.

Box (5.) in Figure 5.1 generates an observation of the path duration $b_p^\star$ which is the actual path duration in the performance evaluation. Box (6.) places the order in the inventory position with the expected path duration, and box (7.) uses the actual path duration which is relevant to the actual inventory. If all orders $\mathcal{O}_t$ and containers $\mathcal{C}_o, o \in \mathcal{O}_t$ are scheduled, the time horizon is increased to $t+1$ in box (8.).

The three interacting modules consist of a number of heuristics to manage the decisions taken. Section 5.2 explains the creation of paths for every supplier, based on the transportation module. Section 5.3 elaborates on the inventory management system module, and Section 5.4 explains the container scheduler module in more detail.

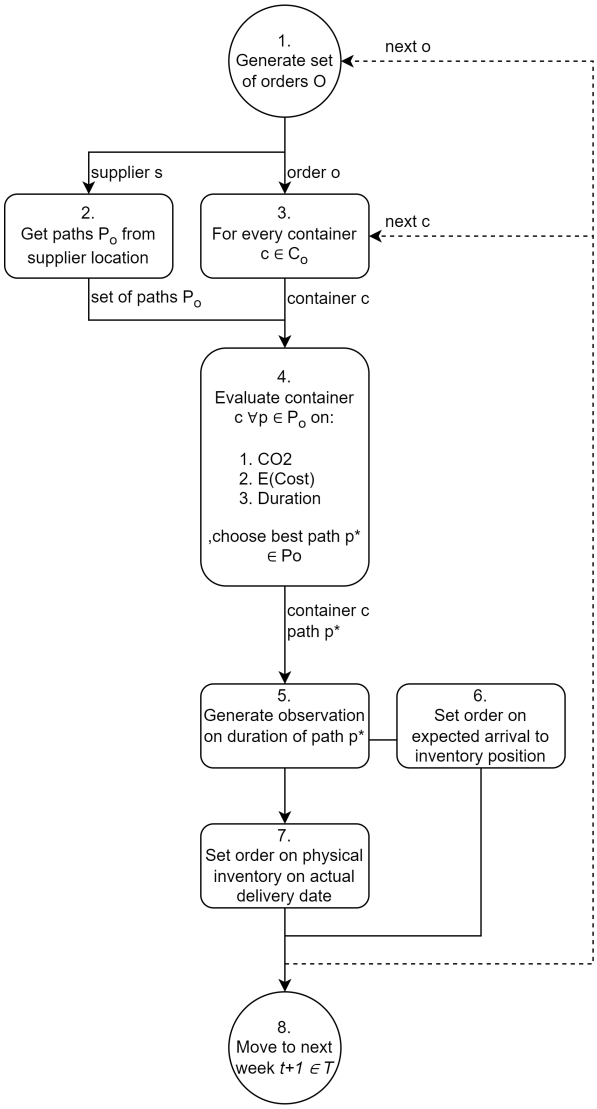



Figure 5.1.: Flowchart of the entire solution approach.

## 5.2. Path generation (module 1)

The transportation network module is consulted to generate a fixed set of paths $P_s$ for each supplier $s \in \mathcal{S}$ which are used for transporting containers. Since these paths do not change over time, the paths can be determined upfront for each supplier. Three objectives are considered in the development of paths, which are (1) cost, (2) emission, and (3) time. While in literature distance is sometimes also used as an objective, it is related to all three objectives and therefore not considered as an objective in determining paths.

This module is split into two subsections. Section 5.2.1 explains the method used to generate a path on a directed graph. Then, Section 5.2.2 shows the method how to generate the top $k$ paths for a supplier.

### 5.2.1. Path generation

The problem formulation mentioned that the transportation network is modelled as a directed graph $G \leftarrow (\mathcal{V}, \mathcal{E})$, where $\mathcal{V}$ represents the nodes (i.e., cities), and $\mathcal{E}$ represents the arcs. A path will be generated with the shortest path algorithm. In this case, 'shortest' means the lowest total cost, emission, or time of a path.

Dijkstra's algorithm (Dijkstra, 1959) will be used as the shortest path algorithm. Dijkstra's algorithm can determine the shortest path in a directed graph and runs in polynomial time. The algorithm determines the shortest path based on a source node and a destination node. The algorithm can run for each objective, which is cost, time, or emission to calculate the path with the least cost, time, or emission, respectively. Algorithm 1 shows the outline of Dijkstra's algorithm.

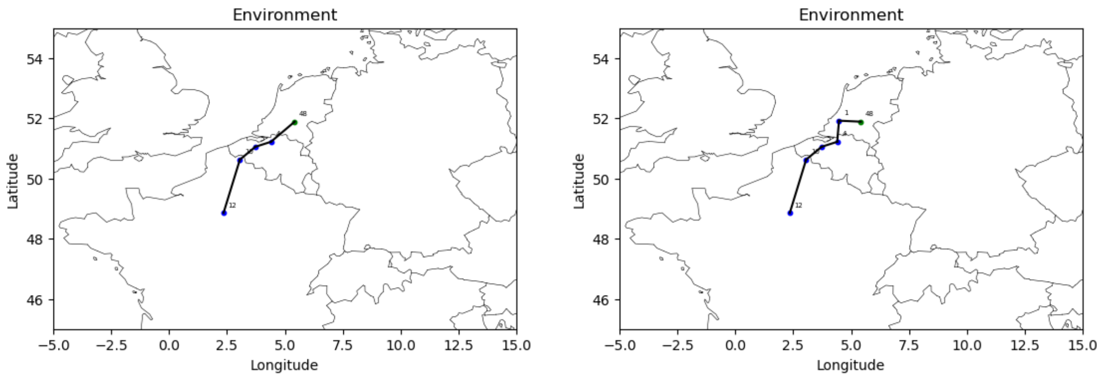
**Algorithm 1** Dijkstra's algorithm (adapted from Mehlhorn and Sanders (2008)).

**Require:** *graph*, *origin*, *destination*,
**for** $\forall v \in$ graph.vertices **do**
  $dist_v \leftarrow \infty$ ▷ Unknown distance from source to v
  $prev_v \leftarrow \varnothing$ ▷ Predecessor of v
  $Q \leftarrow Q \cup \{v\}$
**end for**
**while** $Q \neq \varnothing$ **do**
  $u \leftarrow \min_{v \in Q} dist_v$
  $Q \leftarrow Q \setminus \{u\}$ ▷ Remove u in Q
  **if** $u = target$ **then**
    $S \leftarrow \{\}$
    **while** $u \neq source$ **do** ▷ Construct shortest path
      $S \leftarrow \{u\} \cup S$
      $u \leftarrow prev_u$
    **end while**
    **return** $S$
  **end if**
  **for** neighbor $v$ of $u \in Q$ **do** ▷ Check all neighbors in Q
    $alt \leftarrow dist_u + graph.arcs_{uv}$
    **if** $alt < dist_v$ **then**
      $dist_v \leftarrow alt$
      $prev_v \leftarrow u$
    **end if**
  **end for**
**end while**

### 5.2.2. Generate a set of k-optimal paths

The optimal path, in theory, might not always be the best path in practice. Besides, sometimes a trade-off between costs and emissions is the best option. This requires another method to create paths compared to just calculating the optimal path related to a certain objective. The *k*-shortest path algorithm is used to overcome this problem. The *k*-shortest path algorithm calculates not only the optimal path, but also the second, third, and $k^{\text{th}}$ optimal path. This algorithm returns the set of *k*-optimal paths.

The $k$-shortest path algorithm does have some shortfalls. To provide an example, Figure 5.2a shows a path created with Dijkstra's algorithm from a city in France to a city in the Netherlands. Then the second best path is calculated with the $k$-shortest path algorithm, and is displayed in Figure 5.2b. While the second path is different, it is a very slight adjustment to the first path. If both paths use the same transport modes, path 2 is less relevant for this case to evaluate, due to the little difference in costs and emissions. Preferably, a set of adequately different $k$-optimal paths is returned, focused on using different intermodal paths.




(a) Path 1. (b) Path 2.

Figure 5.2.: Comparison of two nearly-identical paths

A customised version of the $k$-shortest path algorithm is presented to be applicable for this instance. The focus is to create a set of $k$-optimal paths using various arcs with different transportation modes. Algorithm 2 shows the customised version of the $k$-shortest path algorithm. The algorithm uses Dijkstra's algorithm (Algorithm 1) to calculate the paths. After calculating the $\mathbf{k}^{\text{th}}$ shortest path, the algorithm removes arcs using intermodal transportation modes for calculating the $\mathbf{k+1}^{\text{th}}$ shortest path.

To determine the $k$-shortest paths in this case with different transport modes, we introduce a customised $k$-shortest path algorithm. In this instance, a comparison of different paths with different transportation modes has the focus. Therefore, an algorithm is required that generates different paths with different intermodal arcs. Algorithm 2 shows the algorithm applied in this case. The algorithm shows the $k$-optimal paths, where each path has a different set of intermodal arcs.

Algorithm 2 is able to calculate the $k$-shortest paths using different intermodal arcs. The algorithm can be run for all objectives (cost, emission, time). For every supplier in the simulation model, the $k$-shortest path is called for every objective. E.g., when $k = 3$, the top three paths are calculated for each objective. Paths may appear multiple times in the top 3 of different objectives. Therefore the final set of paths for a supplier is determined by the union of all sets.

**Algorithm 2** Customised $k$-shortest path algorithm.

```
Require: origin O, destination D, graph G
P* ← {dijkstra(O, D, G)}                    ▷ List of k-optimal paths, initialize with optimal
for k ← 1, . . . , K − 1 do
    P ← {}                                   ▷ Set of possible k-optimal paths
    arcs ← {e ∈ E_p : e_m ≠ road, ∀e ∈ E_p, p ∈ P*}
    arcs* ← arcs_1 × . . . × arcs_n          ▷ Create Cartesian product of subsets
    for subset in arcs* do
        E ← E \ subset
        P ← P ∪ {dijkstra(O, D)}
        E ← E ∪ subset
    end for
    P.sort
    P* ← P* ∪ {P_0}
end for
return P*
```

## 5.3. Inventory management system (module 2)

The inventory management system needs to create orders every week ($t = 0, 7, 14, \ldots$) to increase inventory to fulfil future demand. This module tracks and predicts the inventory levels of all items based on incoming orders and demand forecasts.

In total, two heuristics are required. Section 5.3.1 explains the first heuristic which determines what items are ordered in what quantity. Section 5.3.2 describes the heuristic that divides the items over the available containers.

### 5.3.1. Heuristic: Item quantity ordering

Inventory problems are often modelled according to a ($r$, $Q$) or ($s$, $S$) policy. In these cases, the points $r$ and $s$ are based on strategies related to safety stock, demand volatility, and lead times. Also in this case, we make use of a reorder point, which is based on the expected demand during lead time. The lead time is based on the supplier production lead time, order horizon, and review period. The $Q$ would be the order multiple, which is one pallet of an item in this case. Due to the case, we order full containers together with other items, we may order the order multiple of item $i$ several times, depending on the demand and inventory of other items. We could therefore describe this case as an ($r$,$nQ$) policy, where we order $n$ times quantity $Q$ if the inventory position falls below the reorder point $r$.

When the inventory position $\beta_{it}$ is expected to go below the reorder point $w_i$, an order $o \in \mathcal{O}_t$ is initialized at time $t$ for item $i$. An order $o$ should at least increase the inventory position up to the reorder point (5.1).

$$\sum_{o \in \mathcal{O}_t} \sum_{c \in \mathcal{C}_o} \omega_{ic} \geq w_i - \beta_{it} \quad \forall i \in \mathcal{I}, t \in \mathcal{T} \tag{5.1}$$

Equation (5.1) determines the demand forecast with $\mu_i$ per time period. Note that all generated orders are also executed, so $\mathcal{O}_t^{'} = \mathcal{O}_t$.

When the required pallets $\omega_i, i \in \mathcal{I}_s$ are calculated, but the containers are not fully loaded yet, items with a higher stock turnover rate are preferred to be added to a container. The inventory management system checks which items are required based on the demand forecast in the near future. Algorithm 3 shows the outline of this heuristic.

**Algorithm 3** Heuristic: Item quantity ordering for a supplier.

**Require:** $s_o \in \mathcal{S}, o \in \mathcal{O}_t, t \in \mathcal{T}, \beta$
  ▷ The variable $\omega_i$ is used without the container $c$ parameter since the division over containers is done separately. Note that $\omega_i$ is different than the reorder point $w_i$.
$\omega \leftarrow \{\}$ ▷ Order quantity for an item in pallets
$LT \leftarrow q_s + h + r$ ▷ Production time + planning horizon + review period
**for** $i \in I_s$ **do** ▷ Calculate minimum $\omega_i$ to fulfill expected $LT$ demand
  $\omega_i \leftarrow \sum_{LT}(\mu_i) - \beta_{it}$
**end for**
**for** $w \leftarrow LT+1, \dots, T$ **do** ▷ Add pallets until container limit
  **for** $i \in \mathcal{I}_s$ **do**
    $\omega_i^* \leftarrow \sum_w(\mu_i) - \beta_{it}$
  **end for**
  **if** $\lceil \frac{\omega_i}{l} \rceil = \lceil \frac{\omega_i^*}{l} \rceil$ **then** ▷ number of containers is the same
    $\omega \leftarrow \omega^*$
  **else** ▷ Required number of containers increased
    **Break**
  **end if**
**end for**
**for** $j \in (\sum_i \omega_i - l)$ **do** ▷ Randomly pack final spaces in container
  $i \leftarrow j \bmod len(\mathcal{I}_s)$
  $\omega_i \leftarrow \omega_i + 1$
**end for**
**return** $O(\omega)$

## 5.3.2. Heuristic: Pallet division over containers

Algorithm 3 explained the procedure of how the required number of pallets $\omega_i$ for item $i$ are calculated. If the pallets fit into one container, the order consists of a single container $c$. If at least two containers are required, an additional decision emerges. With multiple containers, the ordered quantity can be divided in multiple ways to the containers ($\omega_i \rightarrow \omega_{ic}$). A simple heuristic is used to divide the items evenly over the containers. The overall risk of item shortage reduces with this method. If for example one container $c \in \mathcal{C}_o$ experiences significant delay during transportation, another container $c^{'} \in \mathcal{C}_o$ containing approximately the same items moves the stock-out day backwards of all items of a certain supplier $s_o$. Algorithm 4 shows the heuristic.

**Algorithm 4** Heuristic: Pallet division over containers.

**Require:** $s_o \in \mathcal{S},\ o \in \mathcal{O}_t,\ t \in \mathcal{T},\ \omega_i$
$j \leftarrow 0$
**for** $i \in \mathcal{I}_s$ **do**
  **for** $k \in \omega_i$ **do**
    $c \leftarrow j \bmod \sum_i \frac{\omega_i}{l}$ ▷ Result sum equals integer number of containers
    $\omega_{ic} \leftarrow \omega_{ic} + 1$
    $j \leftarrow j + 1$
  **end for**
**end for**
**return** $O(\omega_{ic})$

## 5.4. Optimizing container scheduling (module 3)

Where the inventory management system is able to produce weekly orders $\mathcal{O}_t$ with containers filled with pallets, and the transportation network can generate various paths for a supplier, the actual scheduling of orders/containers can be done in the order optimizer. The purpose of the container scheduling module is to pair containers with paths at a low cost and emission. Paths making use of intermodal transportation arcs have to deal with the departure schedules of LSPs, while road-only transportation paths are more flexible. Therefore, the set of paths generated for a supplier is prepared with departure-, and arrival times. The preparation of the paths is explained in Section 5.4.1. Section 5.4.2 explains the heuristic for the actual pairing of containers and (scheduled) paths.

### 5.4.1. Path scheduling preparation

The available departure- and arrival times need to be determined for every path of a supplier. Each order has an order date, a transportation date, and a required date. The transportation date is the first departure moment for a container $c \in \mathcal{C}_o$ in the order $o$.

To calculate the arrival time, the path duration $b_p$ is added to the departure time of a path $p$. For intermodal arcs, the total duration has to be fitted onto the departure time of an arc $e \in \mathcal{E}_p, m_e \neq \textit{road}$. Figure 5.3 shows a case where an order, using intermodal transport, needs to be scheduled on a path. Between the transport date and the required date, four departure moments $z \in \mathcal{Z}_e, e \in \mathcal{E}_p$ are marked for the intermodal arc. Scenarios 1 and 2 make use of the first two departure times, respectively. Scenario 3 departs too late and therefore arrives after the required date, and should not be chosen as a scheduled path.

The path scheduling process, shown in Figure 5.3, is done for every path $p \in \mathcal{P}_o$ of a supplier $s_o$. All scheduled paths departing after the transportation date and arriving before the required date are considered. Therefore, an initial set of four paths $\mathcal{P}_o$ may result in more *scheduled paths* $\mathcal{P}_o^\star$, since a single path may have multiple departure times. Therefore the set of *scheduled paths* $\mathcal{P}_o^\star$ consist of the paths $p \in \mathcal{P}_o$, but $p$ may occur zero, one, or multiple times. Each path $p \in \mathcal{P}_o^\star$ does have a unique path-departure time combination.

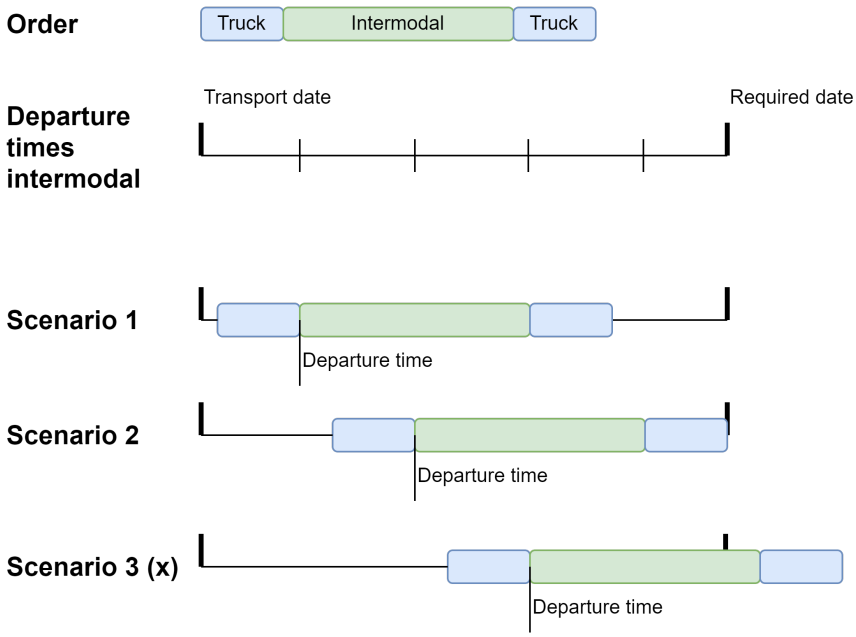



Figure 5.3.: Path preparation scheduling.

### 5.4.2. Pairing containers with paths

After preparing the set of paths $\mathcal{P}_o$ of a supplier into scheduled paths $\mathcal{P}_o^\star$ for every order $o \in \mathcal{O}_t$, the containers $\mathcal{C}_o$ of order $o$ can be paired with the scheduled paths. This module makes this decision, which we want to optimize on the objectives (1) costs, (2) emissions, and (3) time. Each scheduled path $p \in \mathcal{P}_o^\star$ now has a total cost, emission, and departure- and arrival time. We want to evaluate these paths on the stochastic arc delays $\phi_e, e \in \mathcal{E}_p, p \in \mathcal{P}_o^\star$.

To evaluate the stochastic demand and stochastic arc delay in our model, scenarios are generated to calculate the expected arrival time of a path and expected holding and lost sales costs. We generate for each scenario an observation of the path duration $b^\star$ and a total demand observation during the lead time until the order actually arrives. We include lost sales costs $c^{ls}$ for the case the demand is higher than the current inventory position (inventory was not sufficient to fulfil demand), and holding costs $c^{inv}$ for arriving too early. The holding costs are assigned per pallet and lost sales costs are assigned per collo. Currently, ADIL also pays a fixed amount for each pallet in inventory. Each lost sales collo is penalized evenly since every missing collo is treated the same.

With the scenarios, the time dimension is evaluated and expressed in expected costs. This leaves the model with two objectives: expected cost and emission. The expected total cost is the sum of the path cost, expected inventory cost, and expected lost sales costs. A weighted sum model is performed on the expected costs and emissions (Triantaphyllou, 2000). Every path gets a score calculated according to (5.2).

$$\text{score}_p = \text{weight}^c \cdot c'_p + \text{weight}^a \cdot a'_p \qquad \forall p \in \mathcal{P}^\star_o, o \in \mathcal{O}_t \quad \text{, where} \tag{5.2}$$

$$c\prime_p = 1 - \frac{E[c_p] - \min\limits_{p \in \mathcal{P}^\star_o}(E[c_p])}{\max\limits_{p \in \mathcal{P}^\star_o}(E[c]) - \min\limits_{p \in \mathcal{P}^\star_o}(E[c])} \qquad \forall p \in \mathcal{P}^\star_o, o \in \mathcal{O}_t \quad \text{, and} \tag{5.3}$$

$$a'_p = 1 - \frac{a_p - \min\limits_{p \in \mathcal{P}^\star_o}(a_p)}{\max\limits_{p \in \mathcal{P}^\star_o}(a) - \min\limits_{p \in \mathcal{P}^\star_o}(a)} \qquad \forall p \in \mathcal{P}^\star_o, o \in \mathcal{O}_t \quad \text{, so} \tag{5.4}$$

$$p^\star = \underset{p \in \mathcal{P}^\star_o}{\text{argmax}} \left(\text{score}_p\right) \qquad \forall o \in \mathcal{O}_t \quad . \tag{5.5}$$

The path with the highest score $p^\star$ is chosen as the best for the container to travel (5.5). Then the expected delivery date of this container $c \in \mathcal{C}_o$ is scheduled, whereafter the next container $c^{'} \in \mathcal{C}_o$ is scheduled.

## 5.5. Container scheduling: Learning heuristic

The MDP formulation is a model based on sequential decision-making under uncertainty, where the model is in a state $S_t \in \mathcal{S}$, takes a decision $x^\pi_t \in \mathcal{X}^\pi_t$, according to a policy $\pi \in \Pi$, after which the exogenous information $\Omega_t$ arrives. Based on the transition function $S^M$, the model ends in a different state $S_{t+1}$. In this problem case, we use a supervised learning approach to fit a neural network that approximates the future cost. A neural network is able to learn to make the right decisions in a complex environment. We consider this problem instance as a complex environment, due to the two stochastic variables arc delay and demand, and where decisions made now have an impact at a later point in time.

The value function approximation, i.e. neural network, calculates the expected future costs of a post-decision state. The neural network takes the post-decision state $S^x_t$ as the input vector and calculates the value function approximation $\bar{V}^x_t(S^x_t)$ according to the neural network, see Figure 5.4. The post-decision state is the state the model ends up in directly after a decision is taken. As mentioned in Section 4.3, the state $S_t$ consists of the physical inventory $\alpha_{it}$ and the in-transit inventory $\beta^\star_{its}$.

The state space contains all physical- and in-transit inventories for all items $\mathcal{I}$. If we include all items of all suppliers, the entire state space would be too large as input for such a neural network. Besides, each supplier has different characteristics and items have different demand distributions. Since every order $o \in \mathcal{O}$ is independent and connected to one supplier $s \in \mathcal{S}$, we want to train a neural network for one supplier only. This consequently also reduces the state space. For example, the given state space consists of 5 different items with a physical inventory, and an in-transit inventory with max $s = 50$. This lead to the input vector of the state $S_t$ with $5 + 5 \cdot 50 = 255$ nodes, where the first 5 nodes represent the physical inventories, and the other 250 nodes represent the in-transit inventory of item $i$ with release days $s$.

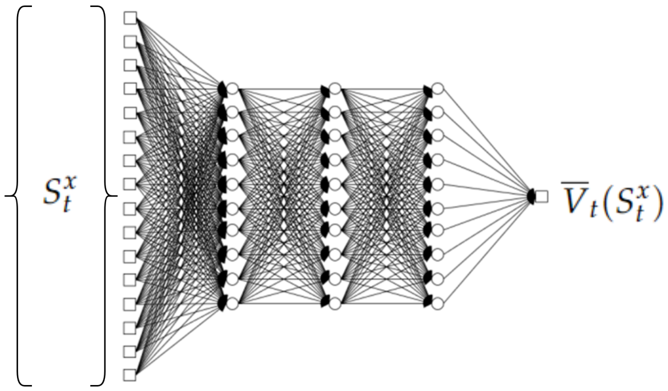



Figure 5.4.: VFA neural network example with the post-decision state as the input.

To further generalize the state space, we sum inventories with release days $s$ to weeks, so we reduce the state space of $\beta^{\star}_{its}$ with a factor 7. Now the parameter $s$ represents the number of weeks until the in-transit inventory is expected to arrive.

**Decision space**

The VFA can evaluate the expected future cost of a post-decision state. We want to evaluate all post-decision state values $\overline{V}_t(S_t^x)$ of each post-decision state $S_t^x$ we may end up in after taking decision $x_t \in \mathcal{X}_t$. The decision set $\mathcal{X}_t$ is the set of scheduled paths $\mathcal{P}'_o$, after which we choose one path for a container. The post-decision state with the minimal decision cost summed with the expected future costs is chosen as the best decision (5.6), where the cost function is given by (4.16).

$$x_t^{\pi} = \arg\min_{x_t \in \mathcal{X}_t} (C_t(x_t^{\pi}) + \overline{V}_t(S_t^x)) \tag{5.6}$$

**Training**

Since we use supervised learning, the network needs to be trained with a large dataset, that consists of the rewards earned in a post-decision state. We use the order optimizer module to make the decision in a given state and save the corresponding reward. Afterwards, we train the neural network on this large dataset. To evaluate the performance of the neural network, we perform a simulation, where the neural network determines the decision.

## 5.6. Conclusion

The problem formulation is solved using multiple heuristics. The transportation network is utilized to create optimal paths using Dijkstra's algorithm, regarding costs, time, or emission. A customised $k$-shortest path algorithm creates a subset of $k$-optimal paths for each supplier $s \in \mathcal{S}$. When executing an order $o$, each container $c \in \mathcal{C}_o$ has to be executed on a path $p \in \mathcal{P}_o$.

The inventory management system creates an order for a supplier $s$ when the inventory position of item $i$ of supplier $s$ falls below the reorder point. The packing of a container is done according to a heuristic where items with a higher stock turnover rate have a higher priority.

The order optimizer schedules paths on departure times $\mathcal{Z}_e$ of arcs $e \in \mathcal{E}$ and evaluates possible scenarios of arc delays and demand observations. The path with the best score, related to a weighted scoring method on expected cost and emission, is chosen as the best path. The performance of the model is measured on the total emissions and costs, related to executing paths, holding inventory, and having lost sales.

For the learning heuristic, we use a supervised learning approach, where the expected future cost of a post-decision state is calculated with a value function approximation that uses a neural network. The optimal decision is chosen as the decision with the lowest direct costs, plus the expected future cost of the post-decision state. The neural network will be fitted for a single supplier since the ordering process for each supplier is independent. We train the neural network on a large dataset, generated by the order optimizer heuristic.

# 6. Experimental design

This chapter elaborates on the experimental setup of the three modules mentioned in the solution design. First, Section 6.1 introduces the general settings of the problem formulation. Then, Section 6.2 shows the construction of the transportation network nodes and arcs. Section 6.3 explains the settings used in the inventory management system. Section 6.4 describes the settings used when combining containers with paths in the order optimizer module. Section 6.5 shows the experimental settings related to the learning heuristic approach. Section 6.6 explains how the performance of the model is evaluated. Section 6.7 shows the setup of experiments for both the order optimizer and learning heuristic. Finally, Section 6.8 concludes this chapter by elaborating on the conclusions of the experimental settings.

## 6.1. General settings

The set of nodes $\mathcal{V}$ and arcs $\mathcal{E}$ can be found in Table A.1 and Table A.2 in appendix A, respectively. The parameters such as distance and duration of arcs can also be found in appendix A. The list of items and suppliers, including attributes of these sets are not presented in this report, due to confidentiality.

Table 6.1 shows the size of the sets used in the optimization model. The establishment of the set of items, for example, is elaborated on in this chapter. The sets of orders $\mathcal{O}$, containers $\mathcal{C}$, paths $\mathcal{P}$, and arc departure times $\mathcal{Z}$ are generated by the model, and therefore not specified in this chapter.

Table 6.1.: Model sets.

| **Set** | **ID** | **Count** | **Description** |
|---|---|---|---|
| Items | $i \in \mathcal{I}$ | 944 | items |
| Suppliers | $s \in \mathcal{S}$ | 177 | suppliers |
| Nodes | $v \in \mathcal{V}$ | 284 | nodes, of which 1 warehouse, 106 transfer nodes, and 177 suppliers |
| Arcs | $e \in \mathcal{E}$ | 181 | arcs (excluding arcs connecting suppliers). |
| Modes | $m \in \mathcal{M}$ | 4 | shipment methods, $\mathcal{M} = \{road, rail, iww, sea\}$. |
| Time horizon | $t \in \mathcal{T}$ | 350 | days (50 weeks) |

Table 6.2 shows the parameter settings of the optimization model. The transportation velocity of road transportation is significantly higher than intermodal transport but has a 3 to 4 times higher rate of $CO_2$ emission. The review period $r$ is set to 7 days, and the

planning horizon $h$ to 14 days. Note that the production time $q_s$ is supplier dependant, and the order multiple is item dependent. For every path generation objective, $k=3$ paths are generated, which results in a maximum of 9 paths per supplier. For a detailed explanation of the choice of $k=3$, see Appendix B. Also, we assumed that the holding cost is significantly lower with €0.19 euro per pallet per day than the lost sales cost of €5.00 for every collo.

Table 6.2.: Model parameter settings.

| **Parameter** | **ID** | **Value** | **Unit of measurement** |
|---|---|---|---|
| Mode velocity[1] | $f_{sea}$ | 20 | km/h |
| | $f_{rail}$ | 25 | km/h |
| | $f_{road}$ | 60 | km/h |
| | $f_{iww}$ | 11 | km/h |
| Mode emissions[2] | $g_{sea}$ | 0.160 | kg $CO_2$ per container per km |
| | $g_{rail}$ | 0.170 | kg $CO_2$ per container per km |
| | $g_{road}$ | 0.750 | kg $CO_2$ per container per km |
| | $g_{iww}$ | 0.260 | kg $CO_2$ per container per km |
| Mode cost[3] | $c^{sea}$ | € 0.95 | euro per container per km |
| | $c^{rail}$ | € 1.27 | euro per container per km |
| | $c^{road}$ | € 1.32 | euro per container per km |
| | $c^{iww}$ | € 0.66 | euro per container per km |
| Transfer time | $n$ | 2 | hours |
| Production time | $q_s$ | [7, 63] | days [min, max] |
| Review period | $r$ | 7 | days |
| Planning horizon | $h$ | 14 | days |
| Order multiple | $u_i$ | [20, 1296] | collo per pallet [min, max] |
| Capacity | $l$ | 33 | (euro)pallets per 45ft container |
| Optimal paths | $k$ | 3 | $k$-optimal paths per objective |
| Scenarios | - | 1,000 | number of scenarios generated per path |
| Holding cost | $c_i^{inv}$ | € 0.19 | euro per pallet per day |
| Lost sales cost | $c_i^{ls}$ | € 5.00 | euro per collo |

## 6.2. Transportation network (module 1)

This section defines the transportation network, which is used to create paths. First, the road transportation network is defined by the TEN-T core network, which is further elaborated in Section 6.2.1. Afterwards, the intermodal network is created by copying a set of intermodal transportation paths from RouteScanner.com. This is further elaborated in Section 6.2.2. Finally, Section 6.2.3 elaborates on the set of warehouses and suppliers used in the transportation network.

[1]Mode velocity determined according to Macharis et al. (2011).
[2]Mode emissions determined according to Smart Freight Centre (2022).
[3]Fictive cost values are assumed.

### 6.2.1. Road transport

Containers are continuously shipped through a large transportation network to transport goods inside and outside Europe. European countries try to optimize their infrastructure to move goods efficiently. The European Commission has started TEN-T projects in the last two decades to identify and improve the main corridors for transporting freight and passengers within EU countries (European Commission, 2020). These corridors include road-, rail-, inland waterways-, and sea shipping. An overview of the main corridors in the EU can be found in Figure 6.1.

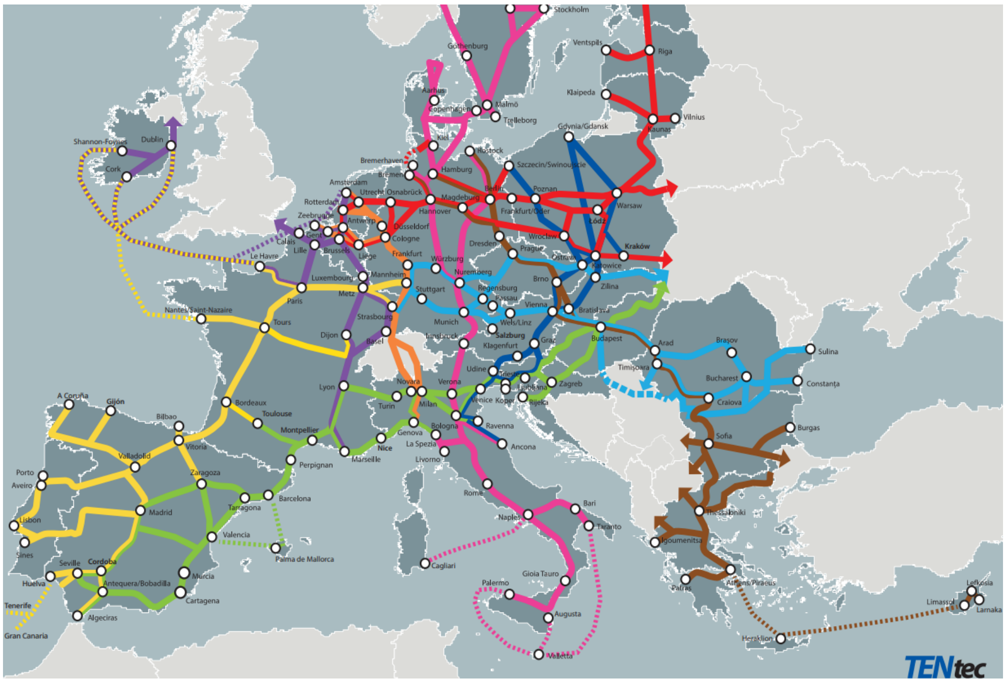



Figure 6.1.: TEN-T Core Network Corridors. Each colour represents one of the nine corridors. While all corridors include road transportation, most corridors also include rail transportation.

The TEN-T core network can be used as the basis of the transportation network $G$ for shipping by road. The transportation network, modelled as a directed graph $G$ is defined with nodes $\mathcal{V}$ and arcs $\mathcal{E}$. Therefore, the set of nodes $\mathcal{V}$ of graph $G$ is set to the nodes/cities of the TEN-T core network. The set of arcs $\mathcal{E}$ now consists of the set of arcs by road $\mathcal{E}^{road}$ of the TEN-T core network. The graph of road transportation arcs is shown in Figure 6.2.

The distances of the arcs are calculated by using the OpenStreetMap API[4] on the latitude and longitude coordinates of the nodes $\mathcal{V}$ to get actual distances $d_e$ of arc $e \in \mathcal{E}$. The duration $b_e$ is based on the model velocity $f_m$ of the transportation mode $m \in \mathcal{M}$.

### 6.2.2. Intermodal transport

Section 6.2.1 defined the TEN-T core network as a directed graph $G$ that consists of the cities $\mathcal{V}$ and arcs $\mathcal{E}$. Currently, only the road transportation arcs $\mathcal{E}^{road}$ have been

[4]See http://project-osrm.org/docs/v5.5.1/api/#nearest-service

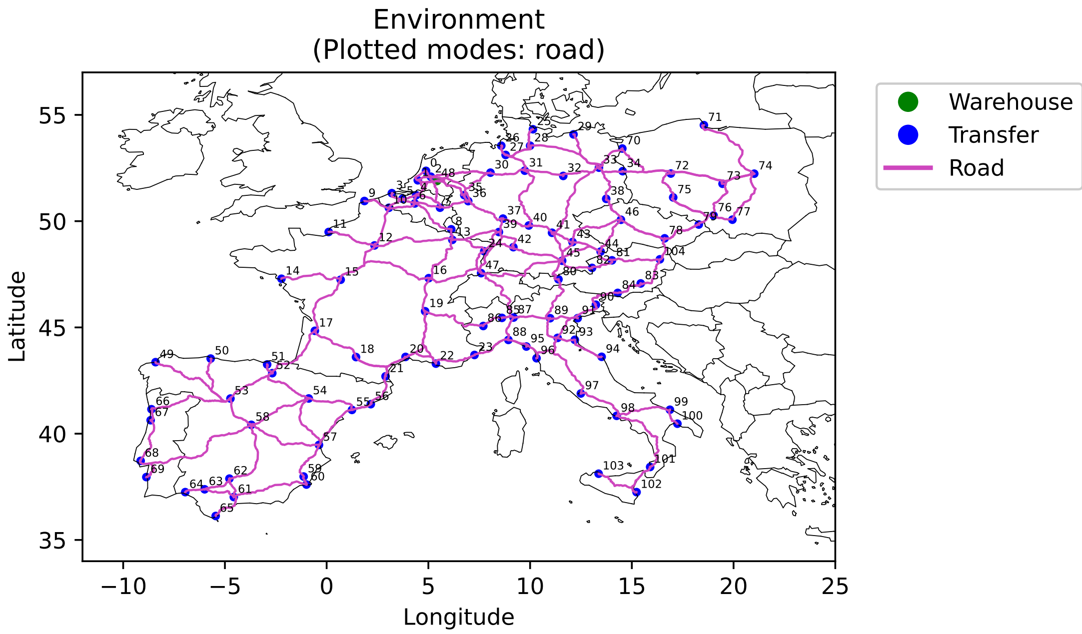



Figure 6.2.: TEN-T core network in the transportation model. This figure shows all road transportation arcs, all transfer points, and the ADIL warehouse located in the Netherlands.

defined. In this section, intermodal arcs are created for graph $G$. For the transportation network, a predefined set of intermodal arcs in Europe are used. These arcs have been chosen based on schedules of RouteScanner[5]. RouteScanner has been founded by the Port of Rotterdam to combine intermodal schedules of LSPs and provide door-to-door connections for containers on request (RouteScanner, 2022). The paths that RouteScanner provides are focused on intermodal shipping and choose the most $CO_2$ neutral option. The emission of the connections of RouteScanner is provided and compared with road-only transportation. The intermodal arcs can be based on rail-, inland waterway-, or sea shipping. Therefore, the set of arcs is extended with the intermodal arcs and becomes $\mathcal{E} = \mathcal{E}^{road} \cup \mathcal{E}^{rail} \cup \mathcal{E}^{iww} \cup \mathcal{E}^{sea}$.

We select for every country about 2-4 routes (from RouteScanner) that depart in this country, to Rotterdam. Preferably, the departure location of different routes should be spread across the country and be close to the locations of ADIL's suppliers. The routes are chosen based on popular routes, i.e., the routes should have multiple providers that offer this route. Besides, all routes include no transfers.

For most European countries in the TEN-T core network, several intermodal paths have been defined for major cities. All of these paths lead to Rotterdam, since Rotterdam is one of the largest ports in Europe, and thus has many intermodal routes that meet here. Besides, it is relatively close to the warehouses of ADIL. Figure 6.3 shows the selection of intermodal routes used from RouteScanner. Most eastern- and central European countries make use of rail transportation, and countries such as Spain, Italy, and France have one or more routes by sea. The intermodal transportation network does not include

[5]See https://www.routescanner.com/

inland waterway arcs. Inland waterway transport is not yet well developed in intermodal transport, and RouteScanner does not provide a wide selection of inland waterway arcs. Figure 6.4 shows the origins of the shipments in a year of ADIL. Note that the departure locations of the intermodal network in Figure 6.3 are partially based on the shipment origin locations.

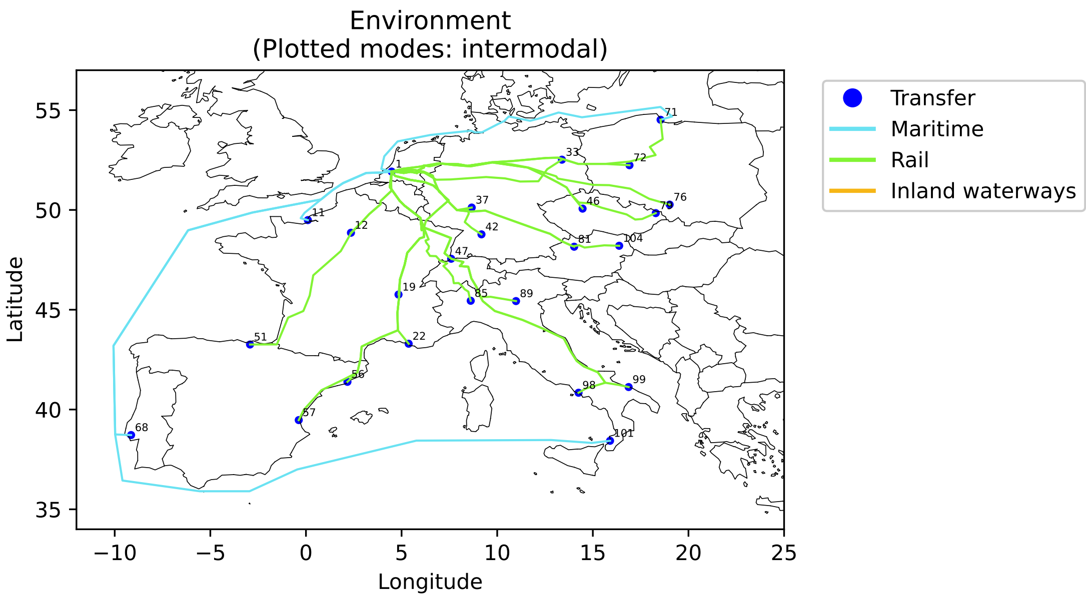



Figure 6.3.: The set of intermodal arcs (maritime, rail, and inland waterways) in the transportation network.

Intermodal arcs are based on scheduled departure times $\mathcal{Z}_e$ of LSPs and cannot be used on request, unlike arcs by road. In the simulation, a random moment of time during a week is generated for every arc. This moment of time is the same for every week and is the departure moment of the arc $e$. The duration $b_e$ and emissions $a_e$ of an intermodal arc are based on the numbers of RouteScanner. RouteScanner makes use of the GLEC framework for calculating $CO_2$ emissions in transportation. The distance $d_e$ of an intermodal arc for rail- and inland waterways shipping is estimated by the rail calculator of the European Commission[6] and by the sea route & distance calculator of Ports.com[7].

### 6.2.3. Warehouses and suppliers

Graph $G$ now contains all road-transportation arcs, together with a subset of intermodal arcs, $\mathcal{E}$ and cities $\mathcal{V}$ of the TEN-T Core Network. The next step is to add the warehouses of ADIL and the suppliers to the network.

ADIL has multiple warehouses in the Netherlands but prioritises a single warehouse. This warehouse stores the largest part of ADIL's goods. For simplicity, only this warehouse is considered in the optimization model and will represent the destination of all paths created. The warehouse is connected to the five closest cities in the network with road transportation arcs.

[6]See Rail calculator
[7]See http://ports.com/sea-route/

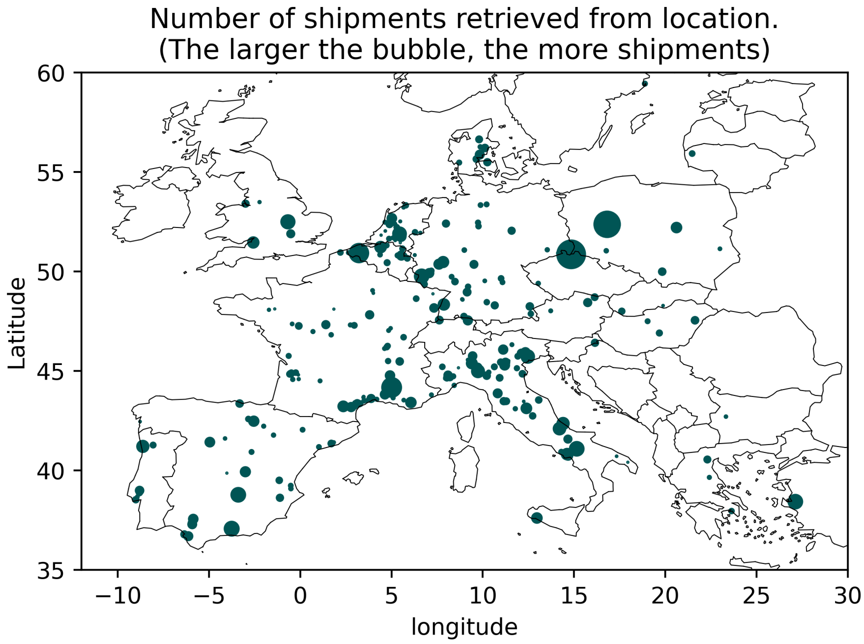



Figure 6.4.: Origins of the European shipments in 2021 of ADIL.

The suppliers of ADIL are also added to the transportation network. Based on the latitude and longitude coordinates, the suppliers $\mathcal{S}$ are located in the network. When a path is generated for a supplier $s$, the supplier is added to the set of nodes $V$ and is connected to the three closest nodes via road transportation with arcs $\mathcal{E}_s^\star$. The distance $d_e, e \in \mathcal{E}^\star$ of an added road transportation arc is approximated with the great circle distance, which calculates the distance between two points on a sphere. This distance $d_e$ is multiplied by a factor 1.3 to get a better approximation of the actual distance via road. When another supplier $s' \neq s$ is considered, the previous supplier $s$ and connecting arcs $\mathcal{E}_s^\star$, are removed from the graph $G$.

## 6.3. Inventory management system (module 2)

The set of suppliers $\mathcal{S}$ is filtered on the supplier's location since we only consider suppliers in Europe. The set of items $\mathcal{I}$ is filtered on demand characteristics, which means the item should have historical demand in 2022. Finally, items without a known supplier and the other way around, are also excluded from the set of items.

Parameters such as the order multiple $u_i$ are set to the number of collo of item $i$ that fit on one euro pallet. The mean demand $\mu_i$ and demand standard deviation $\sigma_i$ of item $i$ is calculated on historical data of the first half of 2022, which is expressed in weekly figures, for each item $i \in \mathcal{I}$.

One of the stochastic parameters of the model is the demand $\lambda_{it}$, which is simulated according to the negative binomial distribution with parameter $r_i$ and $p_i$ (6.1, 6.2, 6.3) (Axsäter, 2015). This requires the mean demand $\mu_i$, and standard deviation $\sigma_i$ of each item $i \in \mathcal{I}$. The demand is simulated on the weekly basis, which means every Monday of the week a demand sample is generated, $t = 0, 7, 14, \ldots$. The demand forecast for horizon $h$ is calculated with the expected demand $\mu_i$, so the expected demand for $h$ weeks is $\sum_h \mu_i$.

$$\lambda_{it} \sim NB(r_i, p_i) \quad \forall i \in \mathcal{I}, t \in \mathcal{T} \tag{6.1}$$

$$p_i = 1 - \frac{\mu_i}{\sigma_i^2} \quad \forall i \in \mathcal{I} \tag{6.2}$$

$$r_i = \mu \frac{(1 - p_i)}{p} \quad \forall i \in \mathcal{I} \tag{6.3}$$

The reorder point $w_i$ is determined such that it should cover 98% of the demand distribution during the production lead time, order horizon, and review period. To calculate the $98_{\text{th}}$ percentile, the demand distribution with a production lead time of, e.g., 3 weeks, equals the sum of 3 times the demand distribution. Since the negative binomial distribution is a sequence of Geometric distributions, (6.5) shows how this can be reduced to $NB(3r_i, p_i)$. Equation (6.6) shows how the reorder point is calculated of the cumulative density function $F(r, p)$. We take the $98\%_{\text{th}}$ percentile of the distribution, which means we are 98% certain that the distribution is less than the reorder point.

$$\text{Let} X_i \sim Geometric(p), X \sim NB(r, p) \quad \text{, then} \tag{6.4}$$

$$\sum_1^3 X = \sum_1^3 (X_1 + \ldots + X_r) = X_1 + \ldots + X_{3r} = NB(3r, p) \tag{6.5}$$

$$w_i = \int_0^{0.98} F(r, p) \tag{6.6}$$

## 6.4. Order optimizer (module 3)

As mentioned in Section 4.3, all three curses of dimensionality apply to our case, which means we cannot solve the MDP exactly. For this reason, we use a heuristic approach with machine learning, since we try to learn to make better decisions.

The container scheduler uses the stochastic parameter arc delay $\phi_e$ to evaluate scenarios of the total path duration. The arc delay will be simulated according to the exponential distribution, so $\phi_e \sim Exp$. We use the assumption that an arc with a high duration also experiences a larger expected average delay, than arcs with a lower duration. For this reason, the arc delay is based on the planned arc duration $b_e$. The arc delay is calculated according to (6.7). Note how the expected duration of an arc $\widehat{b_e}$ can be reduced to $(1 + j_m)b_e$, according to (6.8). We can calculate the expected value of the exponential distribution, which is equal to $1/\lambda$.

$$\phi_e \sim Exp\left(j_m \frac{1}{b_e}\right) \text{, where} \quad m = e_m \quad \forall i \in \mathcal{I} \tag{6.7}$$

$$
\begin{aligned}
\widehat{b_e} &= E\left[b_e + \phi_e\right] = E\left[b_e + Exp\left(j_m \frac{1}{b_e}\right)\right] \\
&= b_e + E\left[Exp\left(j_m \frac{1}{b_e}\right)\right] = b_e + j_m E\left[Exp\left(\frac{1}{b_e}\right)\right] \qquad \forall e \in \mathcal{E} \qquad (6.8)\\
&= b_e + j_m * \frac{1}{\frac{1}{b_e}} = b_e + j_m b_e = (1 + j_m) b_e
\end{aligned}
$$

Equation (6.7) shows an additional factor $j_m$, which is determined per transportation method. For example, intermodal transport might be more vulnerable to delay, so we might decide to set $j_{maritime} > j_{road}$. Table 6.3 shows the values for $j_m$ during the simulation. We chose to make road transportation the most reliable with an average delay of 0.2 times the initial duration, and sea transportation the least reliable with an average delay of 0.4 times the initial duration. The general assumption is $j_{road} < j_{rail}, j_{iww} < j_{sea}$

Table 6.3.: Average delay factor of transportation modes.

| **Transportation mode** | **Average delay factor $j_m$** |
|---|---|
| Sea (maritime) | 0.4 |
| Rail | 0.3 |
| Road | 0.2 |
| Inland waterways | 0.3 |

## 6.5. Container scheduling: Learning heuristic

The learning heuristic of the container scheduler makes use of a supervised learning approach, which heuristically tries to approximate the future costs of the post-decision state. The value function approximation (VFA) uses a neural network to approximate these values. The neural network consists of 5 layers, which are the input layer, three hidden layers, and the output layer. The input layer consists of the post-decision state $S_t^x$, and the output layer consists of a single node that represents the expected future cost $\overline{V}_t(S_t^x)$ of the post-decision node. There are three hidden layers, each consisting of 16 hidden nodes. Each node of the hidden layer is activated with the RELU activation function. The output layer/node uses a sigmoid activation function. The learning rate for the neural network is set to 0.05, which means we update the neural network with 5% of the observed values.

## 6.6. Model performance evaluation

The performance of the problem formulation is evaluated on three types of cost: (1) path execution costs, (2) holding costs, and (3) lost sales costs. The path execution costs are calculated when a path $p \in \mathcal{P}_o$ is chosen for a container $c \in \mathcal{C}_o$. The holding- and lost sales costs are calculated on the actual inventory $\alpha_{it}$ for $\forall i \in \mathcal{I}, t \in \mathcal{T}$. Thus, while the formulation works with the inventory position, the performance of measured on the actual inventory (see Figure 6.5).

The objective is to minimize the total costs (6.9) and emissions (6.10). The total costs can be calculated by (6.9). The total costs exist of path costs $c_p$ for all executed paths $\mathcal{P}'$, and the holding costs per pallet $c_i^{inv}$ and the lost sales cost $c_i^{ls}$ per collo, summed over the whole time horizon $\mathcal{T}$ and items $\mathcal{I}$. Equation 6.9 shows the objective of problem formulation.

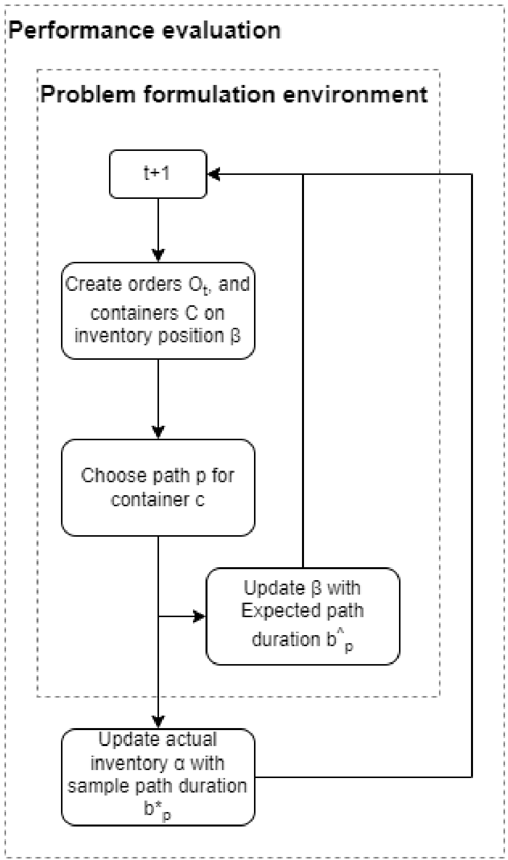



Figure 6.5.: Performance measurement of the model.

$$\min \sum_{p \in \mathcal{P}'} c_p + \sum_{it} (c_i^{inv} \frac{\alpha_{it}}{u_i} + c_i^{ls} \zeta_{it}) \tag{6.9}$$

$$\min \sum_{p \in \mathcal{P}'} a_p \quad \text{, where} \quad a_p = \sum_{e \in \mathcal{E}_p} a_e \tag{6.10}$$

## 6.7. Experiment setup

This section elaborates on the experiment setup for the results in Chapter 7. First, Section 6.7.1 shows the experiments for the order optimizer heuristic. Then, Section 6.7.2 elaborates on the experiments of the learning heuristic.

### 6.7.1. Order optimizer

Table 6.4 shows the parameters that are going to be evaluated with different settings. In this case, we have three parameters which are the cost weight, the emission weight, and the arc delay scenarios. The first experiment has a full focus on costs during normal transport delay. During each following experiment, the focus will shift with 10% towards an emission focus. Eventually, we do the same experiments, but now with a 200% and

300% delay scenario. Table 6.5 shows the set of experiments, including a Road Only experiment to compare costs and emissions. This results in a total of 36 experiments.

Table 6.4.: Set of experimental parameters.

| Parameter | Experiment range | Explanation |
|---|---|---|
| $weight^c$ | $[1.00, 0.90, 0.80, \ldots, .01]$ | Cost weight for evaluating paths. |
| $weight^a$ | $1 - weight^c$ | Emission weight for evaluating paths. |
| $j_m$ | $[100\%, 200\%, 300\%]$ | Arc delay factor. |

Table 6.5.: Set of experiments to evaluate.

| # | Experiment | Parameter | Explanation |
|---|---|---|---|
| 1 | Road Only | - | Use road transportation only, i.e., the fastest path. |
| 2 - 12 | Pareto frontier | $weight^c$, $weight^a$ | Evaluate the total costs and emissions with different focuses. |
| 13 | Road Only, 200% delay | 200% $j_m$ | Use road transportation only, i.e., the fastest path with 200% delay. |
| 14 - 24 | Pareto frontier, 200% delay | $weight^c$, $weight^a$, 200% $j_m$ | Evaluate the total costs and emissions with different focuses with 200% delay. |
| 25 | Road Only, 300% delay | 300% $j_m$ | Use road transportation only, i.e., the fastest path with 300% delay. |
| 26 - 36 | Pareto frontier, 300% delay | $weight^c$, $weight^a$, 300% $j_m$ | Evaluate the total costs and emissions with different focuses with 300% delay. |

All experiments run for a length of 70 weeks, of which 20 weeks is the warm-up period. The demand is equal in each experiment, i.e., generated with common random numbers. Each experiment has four replications, with a 10% significance factor based on the sequential procedure of Law (2015). See Appendix C for a more elaborate explanation of the warm-up period and the number of replications.

### 6.7.2. Learning heuristic

This section elaborates on the results of the learning strategy. We will run the learning strategy for two instances since we run the learning strategy only for a single supplier. Table 6.6 shows the two instances, with their country of origin, number of items, and production days. These two instances were selected to achieve results from two perspectives: (1) Supplier 1 with a few items, and a relatively low production lead time, and (2) Supplier 2 with more items and a relatively high production lead time.

The neural network is trained on a large dataset, generated by the order optimizer heuristic. We train the neural network on the data set and perform simulations. A simulation does use the neural network for calculating the best decision.

Table 6.6.: Supplier instances for the learning strategy.

| Instance | Country | Number of items | Production lead time |
|---|---|---|---|
| Supplier 1 | France | 2 | 21 days |
| Supplier 2 | Spain | 4 | 49 days |

We perform all experiments with a different $CO_2$ cost factor, which are $\{0.0, 0.5, 1.0\}$. This means that a model is trained with a full cost focus, and two models are trained with an increasing cost for emissions. First, we demonstrate the learning process of an experiment with the $CO_2$ cost factor $= 0$, so a full cost focus experiment. Figure 6.6 shows the training process of this experiment. We use 10 replications and a simulation period of 200 weeks (excluding the warm-up period) to increase the accuracy since we only observe a single supplier. After learning about 500,000 decisions, the model shows a decrease in the total cost and seems to give consistent results after. Although the decrease in total costs is only approximately €2,000 (-2.9%), we assume the model is sufficiently trained after about 500,000 iterations. Therefore, all other experiments are trained with 500,000 iterations.

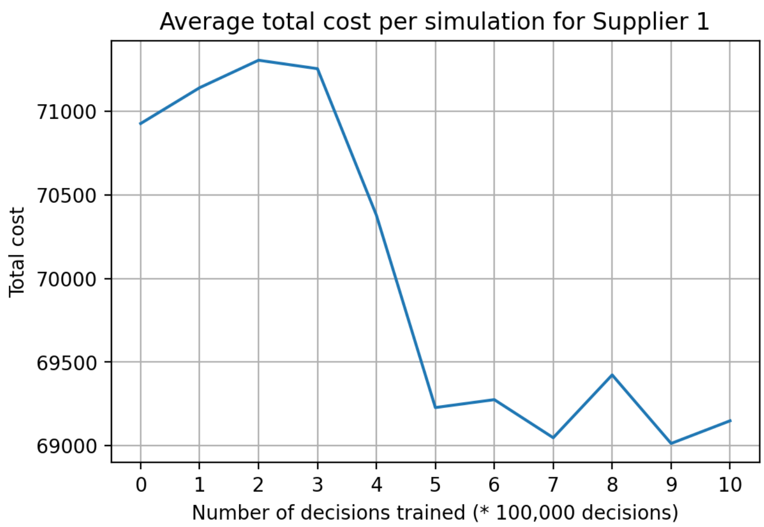



Figure 6.6.: Training process of Supplier 1 with 100% cost focus.

## 6.8. Conclusion

The TEN-T project has been used as the basis for creating the transportation network in Europe. The core network, consisting of cities and corridors, is used to define the road transportation arcs. The intermodal arcs are based on schedules of RouteScanner, which provides door-to-door connections, mainly consisting of intermodal transportation methods. The intermodal transportation arc provide often arcs with low emission with a high duration and road transportation the other way around. While intermodal arcs have to comply with departure times, road transportation arcs are flexible and can be requested on demand.

The stochastic demand of items is simulated according to a negative binomial distribution, and a random observation is generated each Monday of the week. The arc delay variable is simulated according to an exponential distribution. The exponential distribution is based on the initial distribution of the arc.

The VFA of the post-decision state is approximated with a neural network. The input of the neural network equals the physical- and in-transit inventory, grouped by week. The three hidden layers each consist of 16 nodes.

We evaluated three experimental parameters, which are the cost weight, emission weight, and arc delay factor. We calculated Pareto optimal solutions by evaluating a 100%, 90%, 80%, ..., 10%, 1% cost focus, together with a Road Only experiment, which results in 12 experiments. Each set of experiments is performed with a 100%, 200%, and 300% arc delay factor, which results in a total of 36 experiments. For the learning heuristic, we evaluate different $CO_2$ cost values and compare the performance with the simple heuristic and order optimizer.

# 7. Results

Chapter 5 presents the heuristics and solution approaches that solve the problem formulation from Chapter 4. Chapter 6 provides the general settings of the solution approach. This chapter presents the experimental results. All experiments are programmed with Python. Note that a single simulation may require about 1 hour to run on a single laptop. For this reason, all simulations have been calculated in parallel on a server with 72 cores.

First, Section 7.1 validates the model performance by comparing it with a simple heuristic. Section 7.2 analyses the experimental results by a Pareto-graph. Section 7.3 elaborates on the total emissions per country for each experiment. Section 7.4 shows the performance of the learning strategy. Section 7.5 shows the sensitivity analysis of the cost parameters in the optimization model. Finally, Section 7.6 concludes this chapter by presenting the conclusions of the results.

## 7.1. Model validation

First, the model is validated by comparing the results with a simple heuristic. This simple heuristic uses the same model, but does not include expected holding-, and lost sales cost when evaluating paths. It only uses the direct path costs and emissions as evaluation parameters, which makes it a myopic policy. Figure 7.1 shows the 12 experiments defined in Table 6.5, where the blue line shows the performance of the order optimizer module and the orange line shows the performance of the simple heuristic.

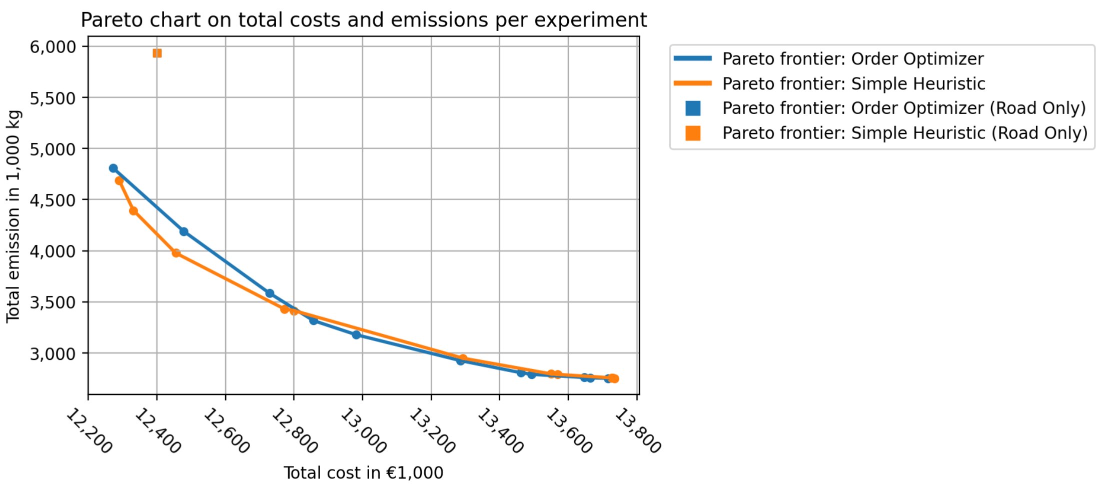



Figure 7.1.: Pareto frontier of the experiments with 100% delay factor is the simple heuristic and order optimizer.

Figure 7.1 shows that both performances are relatively close to each other. Where the simple heuristic performs slightly better with a higher cost weight, the order optimizer performs slightly better with a higher focus on emission. The order optimizer is able to achieve a lower total cost with a 90% or higher cost focus. In both cases, the Road Only experiment performs worse than the Pareto frontier. The Road Only experiments, demonstrated with the squares in Figure 7.1, have the same total costs and emissions and perform worse than 80%, 90%, and 100% cost focus experiments. The Road Only experiment is dominated by all other experiments on total emission.

The little difference between the performance of the simple heuristic and the order optimizer module may be explained due to the expected cost calculation of the order optimizer module. The expected cost calculation is a heuristic that tries to calculate the expected costs for over 10 or more days, depending on the lead time. During these 10+ days, previously placed orders may be late or demand might be high, causing lost sales which change the inventory position. Summarizing, it may be quite difficult to calculate the expected costs, due to the many different events that may happen after taking a decision. For this reason, the order optimizer module may be close to the performance of the simple heuristic, or even slightly worse.

## 7.2. Pareto frontier

This section elaborates on the results of the experiments defined in Table 6.5. In total 36 experiments have been performed, each with 4 replications. First, we elaborate on the total cost and emission in a Pareto graph of all 36 experiments. Figure 7.2 shows the Pareto frontier of the 36 experiments. The dark blue line shows the standard case with the standard delay distribution. This line shows that the order optimizer module with a 100% delay distribution performs better than the other two cases with a 200%- and 300% delay distribution, in total costs and emissions.

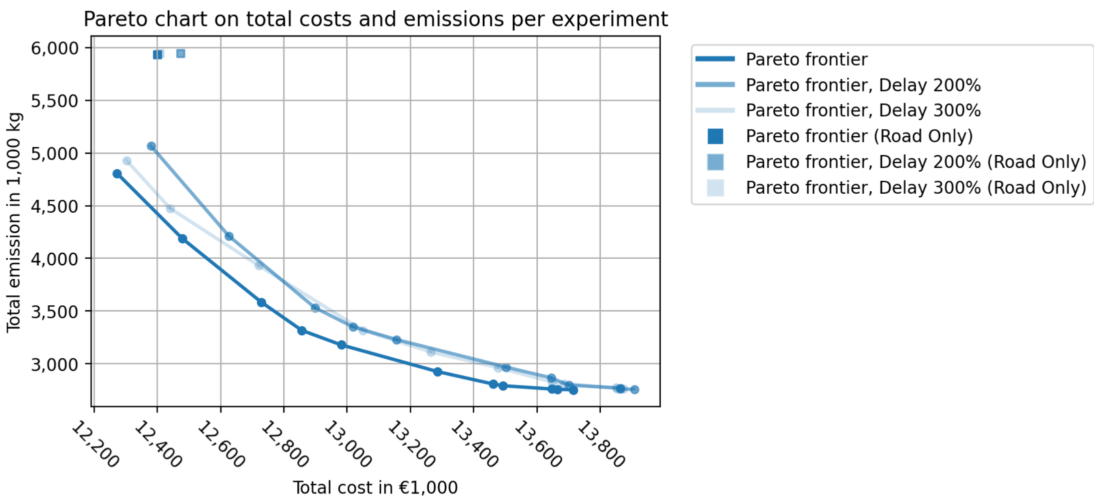



Figure 7.2.: Pareto frontier 36 experiments, based on a cost-emission scale.

With a full emission focus, all three cases end up with approximately 2,750 tons of $CO_2$ emissions and a slightly higher cost for the cases with a higher delay distribution. If we look at the standard case, we have about €4.8 million kg of $CO_2$ and about €12.2 million euro as the total cost. We can reduce the total emission by 43% to a level of 2.75 million kg, by increasing the total costs by approximately 10% to a level of €13.5 million in the case of a 40% cost focus. Table 7.1 shows each experiment the comparison in terms of total costs and emissions, for all three transport delay cases.

Figure 7.3 shows the total costs split per cost category. Most costs (about 80-85%) are path costs, which are for executing containers on paths. The holding costs are the majority of the other costs, with little costs in lost sales. The little cost in lost sales is likely due to the high reorder point that covers 98% of the demand distribution.

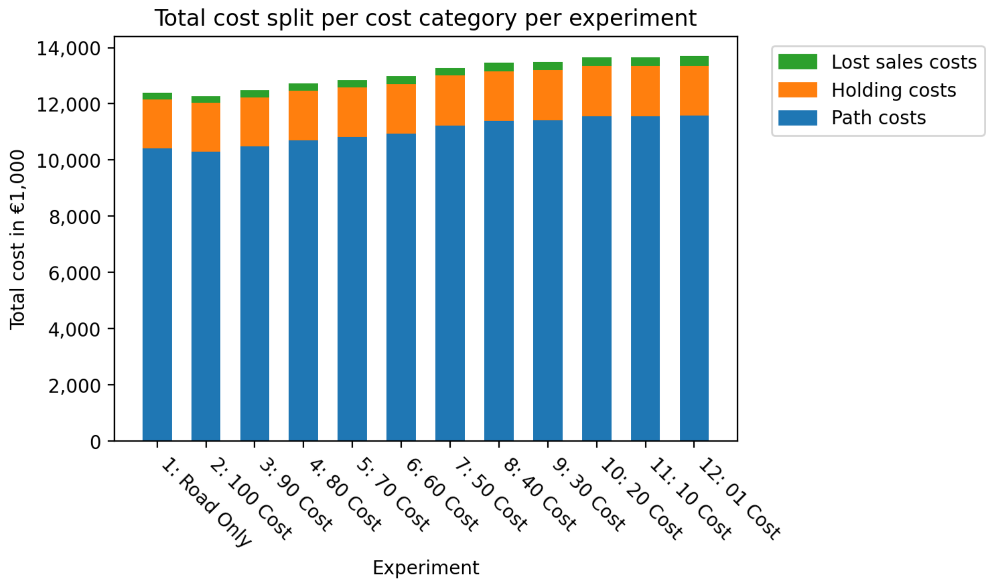



Figure 7.3.: Cost distribution of the experiments in the base case.

As the focus shifts towards a more emission focus, the total costs gradually go up. These costs are primarily present in the path costs that also gradually go up since more sustainable paths sometimes are more expensive and may require some detour. Also, the lost sales costs are slightly increasing, due to taking more risk in transport lead times of intermodal paths. This may be solved for example by increasing the reorder point. The Road Only experiment shows that the total cost is close to the 100% cost focus experiment.

Figure 7.4 shows the number of containers transported per transport method. In total, all experiments ship about 6,600 containers. In the Road Only experiment, all containers are transported via unimodal road. As the emission focus increases up to 50%, more containers are transported via intermodal rail paths. About 1,000 containers remain using unimodal road since the suppliers of these containers are likely to be nearby to the Netherlands. Therefore, these containers are not viable for intermodal transport.

Table 7.1.: Experiment values comparison of costs and emissions. The change percentage is calculated by comparing it with the 100% cost focus experiment.

| Experiment | Total costs (*€1,000) | Chg (%) | Emissions (*1,000 kg) | Chg (%) |
|---|---|---|---|---|
| **Base case (100% of original delay distribution)** | | | | |
| Road only | € 12,401 | + 1.0% | 5,937 | + 23.5% |
| 100% Cost | € 12,273 | | 4,808 | |
| 90% Cost | € 12,478 | + 1.7% | 4,191 | - 12.8% |
| 80% Cost | € 12,728 | + 3.7% | 3,586 | - 25.4% |
| 70% Cost | € 12,857 | + 4.8% | 3,317 | - 31.0% |
| 60% Cost | € 12,981 | + 5.8% | 3,179 | - 33.9% |
| 50% Cost | € 13,285 | + 8.3% | 2,926 | - 39.1% |
| 40% Cost | € 13,461 | + 9.7% | 2,808 | - 41.6% |
| 30% Cost | € 13,492 | + 9.9% | 2,792 | - 41.9% |
| 20% Cost | € 13,648 | + 11.2% | 2,760 | - 42.6% |
| 10% Cost | € 13,665 | + 11.3% | 2,757 | - 42.7% |
| 1% Cost | € 13,715 | + 11.8% | 2,753 | - 42.7% |
| **Case: 200% of original delay distribution** | | | | |
| Road only | € 12,473 | + 0.8% | 5,947 | + 17.3% |
| 100% Cost | € 12,380 | | 5,068 | |
| 90% Cost | € 12,625 | + 2.0% | 4,215 | - 16.8% |
| 80% Cost | € 12,898 | + 4.2% | 3,532 | - 30.3% |
| 70% Cost | € 13,018 | + 5.2% | 3,352 | - 33.9% |
| 60% Cost | € 13,156 | + 6.3% | 3,230 | - 36.3% |
| 50% Cost | € 13,502 | + 9.1% | 2,968 | - 41.4% |
| 40% Cost | € 13,644 | + 10.2% | 2,867 | - 43.4% |
| 30% Cost | € 13,700 | + 10.7% | 2,799 | - 44.8% |
| 20% Cost | € 13,864 | + 12.0% | 2,768 | - 45.4% |
| 10% Cost | € 13,862 | + 12.0% | 2,761 | - 45.5% |
| 1% Cost | € 13,907 | + 12.3% | 2,758 | - 45.6% |
| **Case: 300% of original delay distribution** | | | | |
| Road only | € 12,473 | + 0.8% | 5,950 | + 20.7% |
| 100% Cost | € 12,380 | | 4,930 | |
| 90% Cost | € 12,625 | + 2.0% | 4,475 | - 9.2% |
| 80% Cost | € 12,898 | + 4.2% | 3,930 | - 20.3% |
| 70% Cost | € 13,018 | + 5.2% | 3,318 | - 32.7% |
| 60% Cost | € 13,156 | + 6.3% | 3,112 | - 36.9% |
| 50% Cost | € 13,502 | + 9.1% | 2,963 | - 39.9% |
| 40% Cost | € 13,644 | + 10.2% | 2,829 | - 42.6% |
| 30% Cost | € 13,700 | + 10.7% | 2,811 | - 43.0% |
| 20% Cost | € 13,864 | + 12.0% | 2,772 | - 43.8% |
| 10% Cost | € 13,862 | + 12.0% | 2,765 | - 43.9% |
| 1% Cost | € 13,907 | + 12.3% | 2,761 | - 44.0% |

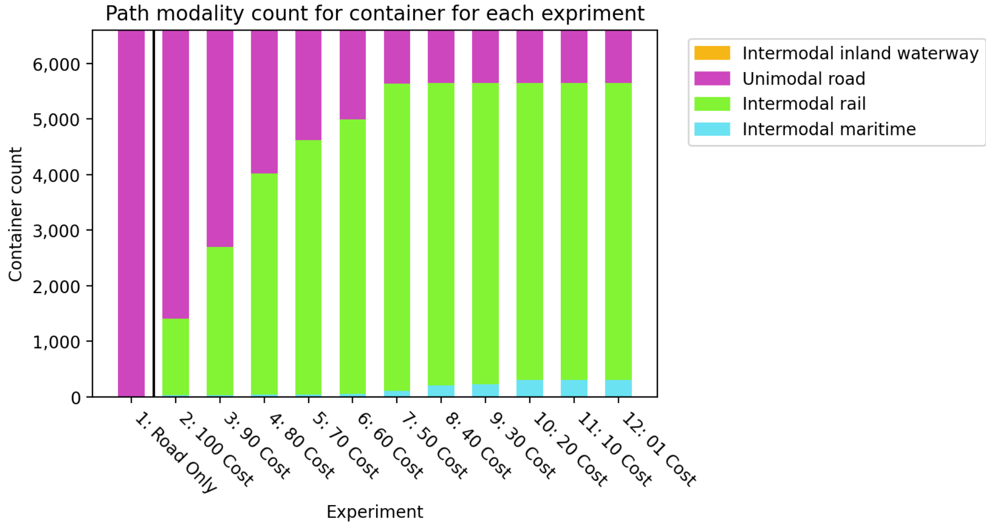



Figure 7.4.: Number of containers transported split per transport method for each experiment of the base case.

As the emission focus gets above 50%, some intermodal rail transportation is replaced by maritime transportation, with 300 containers being shipped via maritime with a 99% emission focus.

Figure 7.5 shows the same transport method categories as Figure 7.4, but now shows the total emission related to the executed paths in the experiments. For example, the Road Only experiment shows a high total emission, since road transportation has a larger emission factor per unit of distance. As the focus shifts towards an emission focus, the total $CO_2$ emissions go down to about 2.75 million kg.

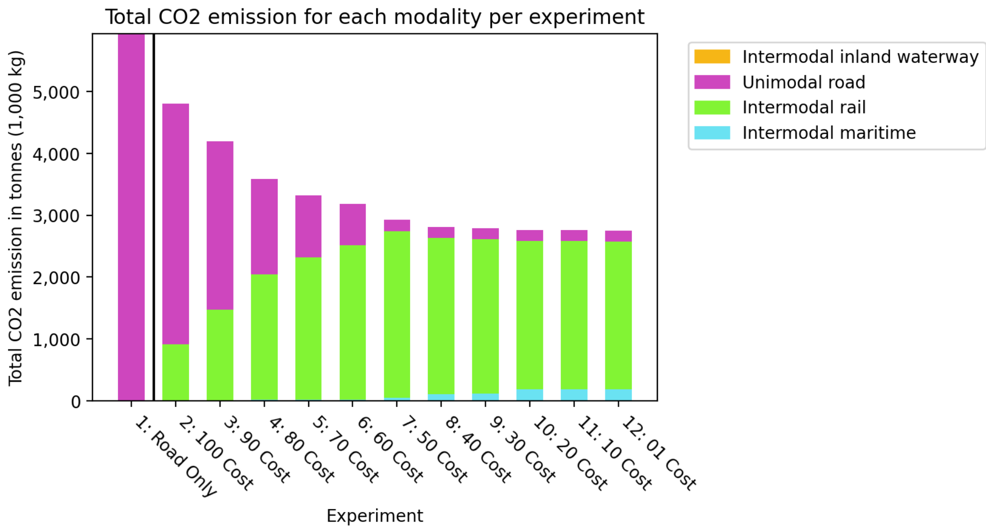



Figure 7.5.: Total emission per experiment split per main transport method.

With an emission focus of 50% or higher, almost all emissions are caused by intermodal rail transportation. Note that intermodal rail transportation includes the emission from road transportation travelling from the supplier to the departure railway station, and from the arrival railway station to the warehouse. The small portion of unimodal road transportation in the 50% emission focus or higher is not relevant to explore for intermodal transport, since these suppliers are likely to be close to the warehouse.

Finally, Figure 7.6 shows the same data as Figure 7.5, but an extra split in intermodal transport. The shaded area in rail transportation and maritime is the emission caused by road transportation for driving towards- and from a railway station. This shows that about 60% of the intermodal rail transportation emission is caused by road transportation, and only about 40% of the emissions is actually from rail transportation. In the 99% emission focus experiment, still, approximately 65% of the total emissions are polluted by road transportation but are not reducible to a lower minimum.

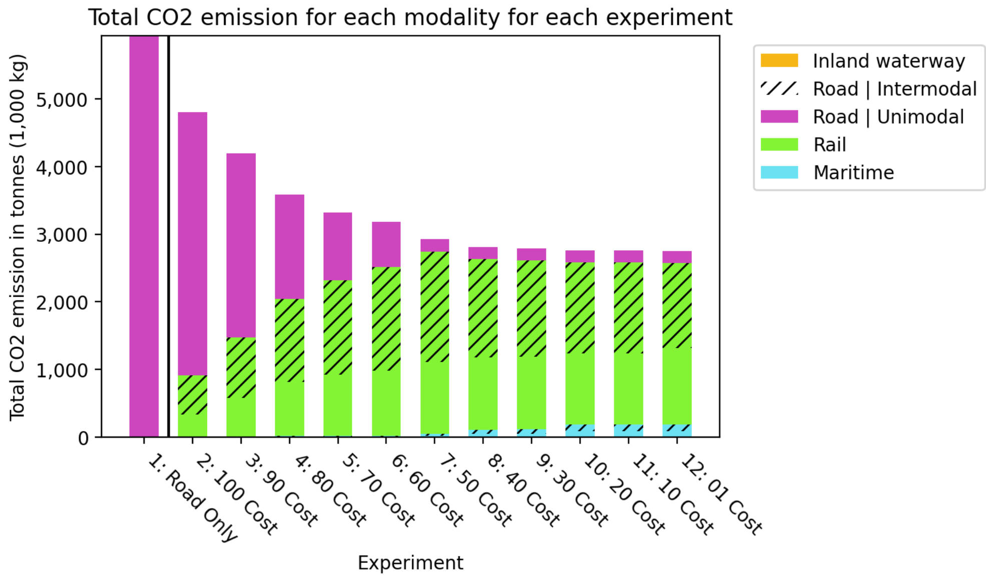



Figure 7.6.: Total emission per experiment split per single transport mode.

## 7.3. Country analysis

In this section, the results related to the total emissions split per country are elaborated. Figure 7.7 shows the total emissions per country for the experiments: Road Only, 100%, 80%, ..., 20%, 1% cost focus. The countries Italy and Spain are the two countries with the most emissions. That is likely due to the high volume done with suppliers in these countries, together with the large distance to the warehouse in the Netherlands. Portugal is the third country with the most emissions, also due to the large distance to the warehouse. Countries such as Belgium, Germany, and the Netherlands do not have a lot of emissions, due to the short distance to the warehouse.

The experiments with a higher emission focus (e.g., lower cost focus) show a lower total emission. Spain is able to reduce the total emissions by close to 60% with the 60% or lower cost focus experiment. The total emissions in Italy also dropped significantly with a higher emission focus, compared to the Road Only or 100% cost focus experiment.

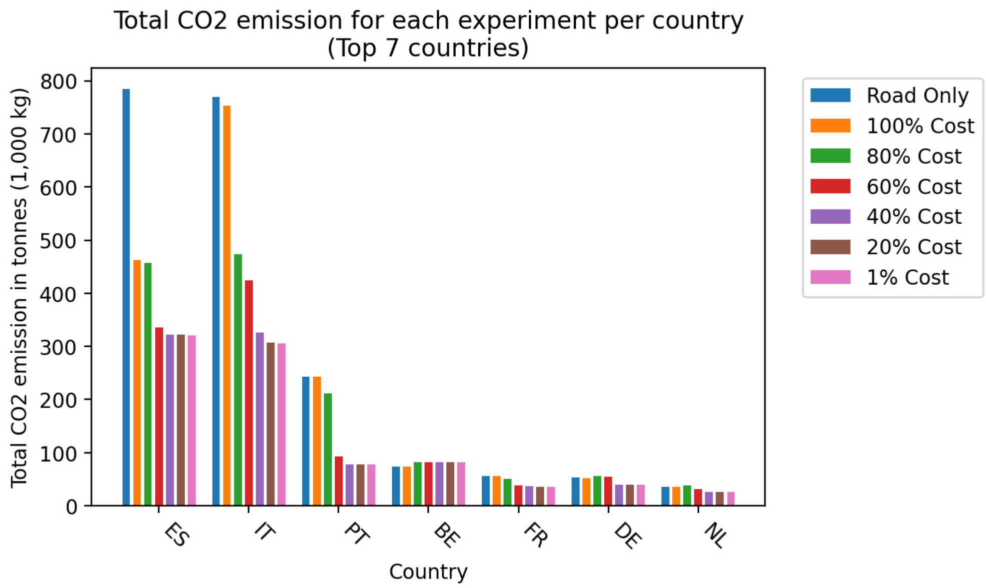



Figure 7.7.: Total emissions per country per experiment.

Figure 7.8 shows the reduction in total emissions for each country, compared to the Road Only experiment. In these cases, Portugal and Italy achieved the most reduced emissions. For the suppliers in Belgium, it did not make a difference what experiment was performed, a single path for each supplier was the most economic, and sustainable option according to the optimization model. Summarizing, for the southern countries in Europe, an emission reduction of 60% to 70% is possible with a large impact on the total emissions, and for the less distant countries in Europe, an average reduction of 30% is achievable with less impact on the total emissions.

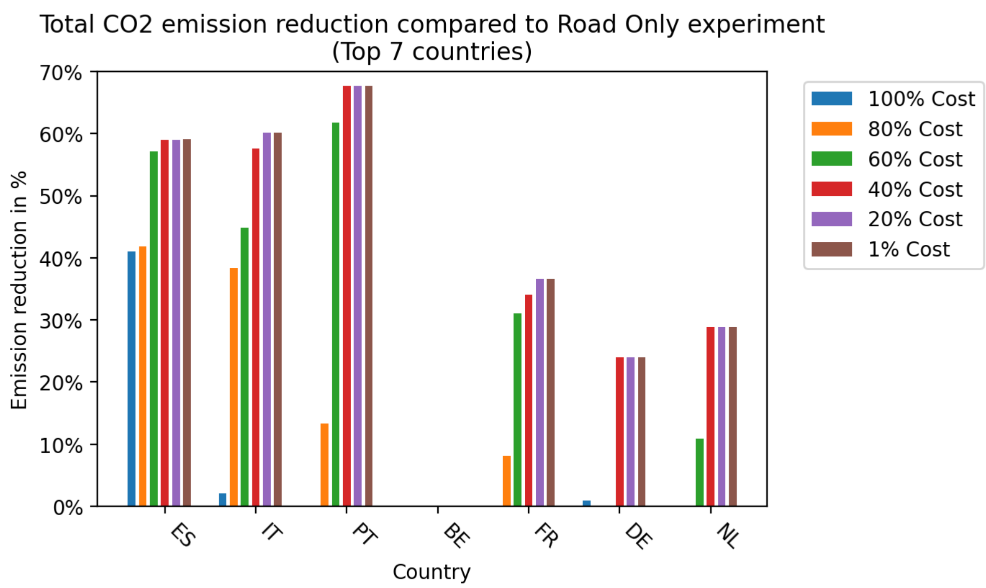



Figure 7.8.: Emission reduction per country, compared to the Road Only experiment.

## 7.4. Order optimizer module: Learning heuristic

Figure 7.9 shows the performance for the Supplier 1 instance of the three strategies, which are the simple heuristic, order optimizer, and the learning strategy. All experiments are performed for the three different $CO_2$ cost values. The blue icons with a full cost focus perform relatively well on the total cost. The simple heuristic outperforms both solutions in terms of costs, whereafter the learning strategy and order optimizer follow, respectively. Note that the cost differences are relatively small with all solutions being in a range between €69,000 and €71,000.

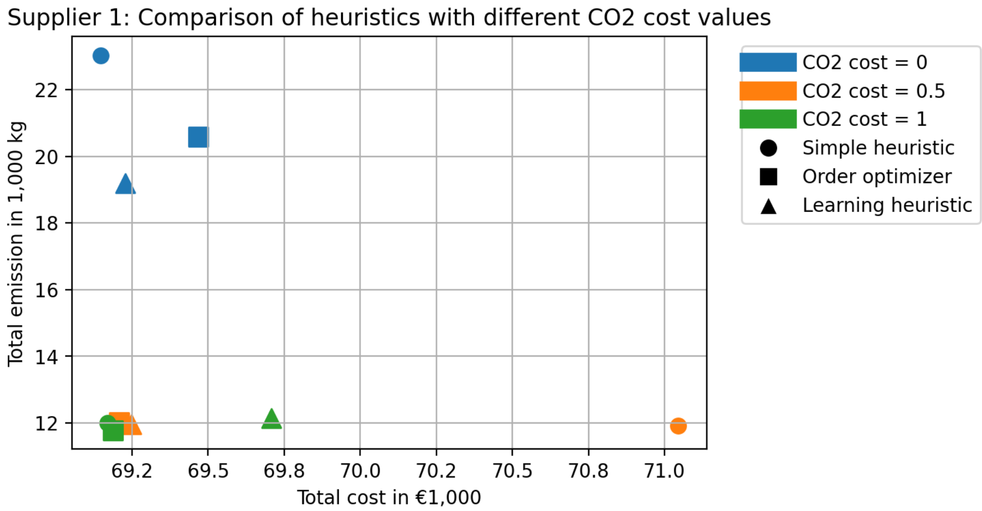



Figure 7.9.: Comparison of different strategies in terms of costs and emissions of the Supplier 1 instance.

The simple heuristic solutions tend to be sensitive to extreme results because all simple heuristic solutions eighter have high costs and low emissions, or have low costs and high emissions. For example, the order optimizer with a $CO_2$ cost value $> 0$ is close to the best solutions found in terms of a cost/emission trade-off. The learning heuristic is less sensitive to extreme results than the simple heuristic. In this case, the learning heuristic performs similarly/better with a $CO_2$ cost value of 0 or 0.5, but performs worse with a cost value of 1, compared to the simple heuristic and order optimizer.

Figure 7.10 shows the same comparison as Figure 7.9, but now for the Supplier 2 instance. The simple heuristic and order optimizer seems to achieve about the same solutions, except for the $CO_2$ cost $= 0.5$. The solutions do seem to follow a clear pattern that shows an increasing cost and decreasing emission when the $CO_2$ cost value increases. The learning heuristic solutions with a $CO_2$ cost value of 0 and 1 tend to be on the Pareto frontier line. However, these solutions do deviate a lot from the order optimizer and simple heuristic solutions. This might conclude that the learning heuristic leads to different results (not particularly better) than the simple heuristic and order optimizer, which often have similar performance.

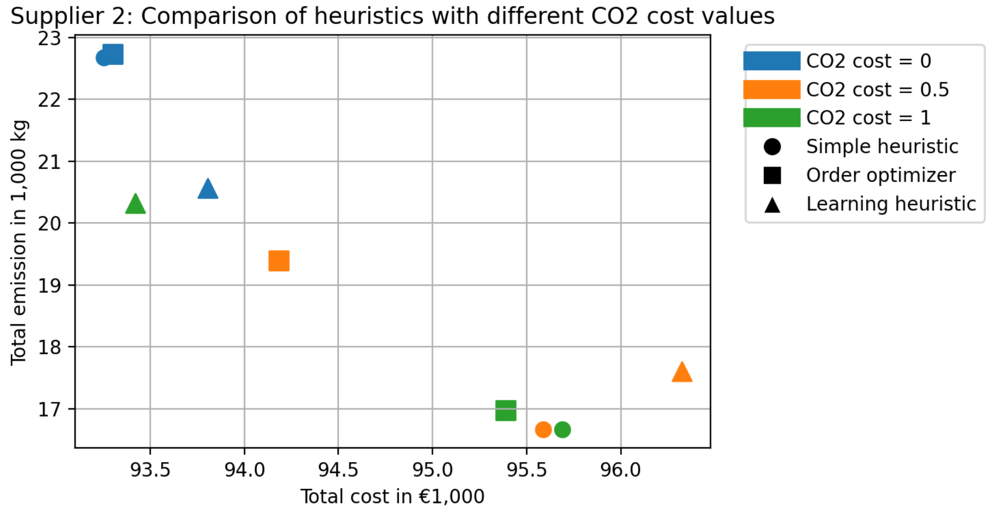



Figure 7.10.: Comparison of different strategies in terms of costs and emissions of the Supplier 2 instance.

## 7.5. Sensitivity analysis

Table 7.2 shows the parameters for the sensitivity analysis. First, an analysis is performed on an increased risk of transportation delay, with 200% and 300% of the original delay. Afterwards, an analysis is performed on holding- and lost sales costs, each with a 50% decrease, and increase.

Table 7.2.: Sensitivity analysis parameters.

| Parameter | Experiment range | Explanation |
|---|---|---|
| $c^{inv}$ | [50%, 100%, 150%] | Unit cost for keeping a pallet in inventory. |
| $c^{ls}$ | [50%, 100%, 150%] | Unit cost for lost sales. |

Figure 7.11 shows the sensitivity performed on the base case of Section 7.2. For this analysis, only the Road Only, 100%, 80%, ..., 20%, and 1% cost-focus experiments have been performed. As expected, increasing the cost factors also increases the total costs. The same applies to reducing the cost factor parameters.

The red- and green lines seem to be deviating more than the orange- and blue lines, which means that the change in holding costs seems to have a larger impact on the total cost than the difference in lost sales cost. This follows from the fact that the total inventory costs are much larger than the total lost sales costs.

## 7.6. Conclusion

We conclude this chapter by summarizing the model validation, Pareto frontier, country analysis, learning heuristic, and sensitivity analysis.

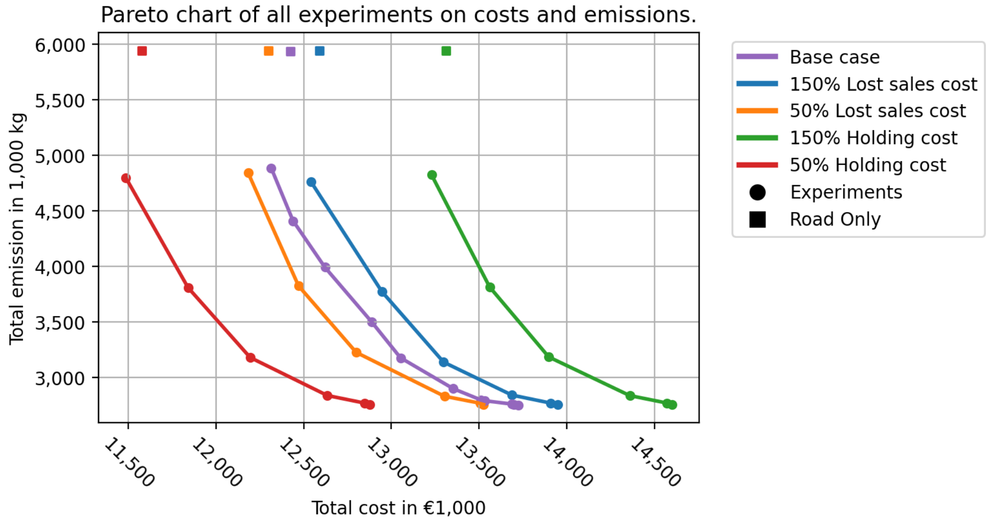



Figure 7.11.: Pareto of Different delay distributions.

**Model validation** We compared the performance of the order optimizer module with a simple heuristic, using a myopic policy. The performance of both heuristics was quite similar, where the order optimizer tends to perform slightly better with a high emission focus, and the simple heuristics performs slightly better with a high cost focus. For this reason, we assume that the expected cost calculation of the order optimizer to not be significantly better than a simple heuristic.

**Pareto frontier** A 100% cost focus during normal delay settings results in a total cost of €12.2 million euro and a total emission of 4.8 million kg of $CO_2$. Shifting the focus to reducing emissions gradually results in higher costs and lower emissions. The 99% emission focus experiment results in €13.7 million euro and 2.7 million kg of $CO_2$, which is an 11.8% cost increase and a 42.7% emission reduction. Increasing the delay distribution to 200% or 300% results in overall more costs and emissions, due to taking less risk in transport, accepting higher emissions, and having more delayed freight.

The path execution costs make up the majority of the total cost, with approximately 80% to 85%. The holding costs are about 10% to 15% of the total cost, and the lost sales costs are $<$ 5% of the total cost. Increasing the focus on emission results in higher path execution costs together with a slight increase in lost sales costs. The holding costs stay approximately the same.

Rail transportation is the primary choice for intermodal transport in the optimization model. When the emission focus is larger than 50%, also maritime shipping is chosen for some shipments but stays a small portion of the total intermodal routes. The majority (approximately 65%) of the emissions with a 50% emission focus or larger is caused by road transportation. A small portion of the 65% is used for unimodal transportation. The majority is polluted for driving from- and to ports and railway stations.

**Country analysis** Spain and Italy have the highest potential for emission reduction, due to the large volume of goods ordered from suppliers in these countries, and the large distance towards the warehouse of ADIL. Portugal is also a relevant country for emission reduction, due to the large distance to the warehouse. Its emissions may reduce by close to 70% compared to the Road Only experiment. Due to the less volume, it has less potential for emission reduction than Spain and Italy. Countries like Belgium, Germany, and the Netherlands have little influence on the total emissions.

**Learning heuristic** The learning heuristic tends to perform relatively similarly to the simple heuristic and order optimizer module. The learning heuristic seems to be less sensitive to extreme results than the simple heuristic, though the difference is relatively small. In general, the learning heuristic performs just as well as the order optimizer and simple heuristic.

**Sensitivity analysis** Changing the holding cost parameter has a larger impact on the cost values, than changing the lost sales cost parameters. This is likely primarily due to the larger total inventory cost compared to the lost sales cost.

# 8. Conclusions and recommendations

In this chapter, we present the conclusions and recommendations based on this research to provide an answer to the research objective. First, the conclusions are presented in Section 8.1. The conclusions start with answering all sub-questions, after which the main conclusions follow. Section 8.2 shows the recommendations, resulting from the conclusions. Section 8.3 elaborates on the limitations of this research. Finally, Section 8.4 mentions a number of possible future research topics, that follow from this research.

## 8.1. Conclusions

The research started by defining the problem statement, objective, and research questions. The core problem is the unawareness of potential efficiency- and sustainability improvements in the transportation process of ADIL. Due to the high share of road transportation, ADIL wants to explore potential efficiency and sustainability improvements within their ordering process. This leads to the following objective:

*How can ADIL improve their international freight transportation network considering different kinds of transportation modes within the transportation network?*

**Context analysis** Inbound transportation is done by multiple logistics service providers for ADIL. For each part of Europe, a standard transportation method is defined in the system for standardization purposes. When a planner creates an order, the logistics service provider directly receives an order for the moment the products need to be shipped from the supplier to the warehouse. Orders include one or multiple transportation units, often trailers for European suppliers, that are loaded with pallets. To maximize efficiency, only full container loads are ordered.

While ADIL has suppliers all around the globe, most of its volume is done in Europe, primarily in Spain and Italy. Most of ADIL's products from European suppliers are ordered in trailers and are shipped by road transportation. The total distance travelled by road is a relatively small portion (<20%) of the total distance travelled, but does account for at least 50% of the total emissions. Other transportation methods, such as maritime, account for the majority of the total distance travelled but have less total emissions. That is because intermodal transportation modes have lower emissions per kilometer than road transportation. For this reason, to reduce the total emission, we want to reduce the distance travelled by road.

**Problem formulation** We formulate our problem by using an inventory model that incorporates all items of ADIL. Every week, orders are generated that consist of one or multiple containers. We may decide what items with what quantity we place in a container. Afterwards, we decide how the containers are transported in a large European transportation network. We generate a fixed set of paths from the supplier to the warehouse, after which we choose one path that the container will travel. Our model includes two stochastic parameters, which are the weekly item demand and transportation delay.

**Solution approach** For each supplier, we generate a fixed set of paths upfront in the transportation network, using a $k$-shortest path algorithm, considering multiple objectives. Each path is calculated according to Dijkstra's algorithm, which finds the shortest path in a graph. We also use an inventory management system that creates replenishment orders for items, grouped in containers. Containers are filled using a heuristic algorithm that adds pallets based on the demand forecast. Eventually, we execute each generated container on one path of the supplier's set of paths.

We determine the expected costs of choosing a path for a container, by calculating the expected lost sales- and holding cost together with the path execution cost. Based on the weight criteria costs and emissions, a score is calculated for each path. The path with the highest score (i.e., lowest emission/cost) is chosen as the best path. We also train a learning heuristic on the path selection model, to evaluate whether the weighted scoring method or learning heuristic performs better.

**Experimental settings** The transportation network is based on the core network of the TEN-T project of the European Commission, which has defined the major transportation network in Europe. Cost figures are based on assumptions and emission figures are based on the GLEC framework. Intermodal routes are extracted from RouteScanner's schedules from the major cities in Europe.

**Results** A simple heuristic is evaluated with both the order optimizer and the learning heuristic to validate the model and evaluate the performance. The simple heuristic tends to perform close to or as well as the order optimizer and learning heuristic. A total emission reduction of about 45% is achievable, also resulting in a cost increase of approximately 12%. Based on a trade-off between costs and emissions, a Pareto optimal solution may be determined. Increased transportation delay results in slightly higher costs. The primary transportation mode for intermodal transport is by rail according to the optimization model. This is likely due to suppliers not being close to ports to ship by maritime and due to the experimental settings of the model.

### 8.1.1. Main conclusions

**Cost/emission tradeoff** ADIL can improve their international freight transportation, by increasing their intermodal transport to reduce overall emissions by up to approximately 45%, and subsequently accepting a cost increase of up to approximately 12%, compared to the 100% cost focus experiment.

**Primary intermodal transportation mode** The primary modality to transport items is rail transportation in Europe. Maritime shipping is the most sustainable transportation method, which occurs in the experimenting with a relatively high emission focus.

**Countries with large emission reduction potential** Suppliers in countries in Southern Europe are relatively attractive for using intermodal transport, due to the high volume of goods and the large distance to the warehouse of ADIL. Countries nearby the warehouse like Belgium and Germany are less attractive for intermodal transport, due to their short distance to the warehouse.

**Heuristics versus learning strategy** The use of the learning heuristic for path selection for ADIL in the constraints of this research is less valuable, due to no- to little better performance compared to the simple heuristic and order optimizer. The simple heuristic sometimes performs nearly as well and sometimes better compared to the order optimizer or a learning heuristic.

**Preference for stockpiling** The holding cost factor for ADIL is relatively low, compared to the relatively high lost sales cost. The algorithm therefore always preferred to order earlier to mitigate risks and increase inventory. Further research should focus on the optimal use of warehouse capacity to reduce lost sales costs, instead of a cost trade-off between holding- and lost sales costs.

**System standardisation** Due to the standardised procedures in the systems of ADIL, intermodal transport is relatively easy to implement. The case of synchromodal transport using flexible services is more difficult, due to having the option to choose between different paths. Currently, ADIL's systems are built in such a way that each item has one transportation route. For this reason, if ADIL desires to use synchromodal transport, it should further investigate in what manner this can be implemented into its systems.

### 8.1.2. Contribution to literature and practice

This research combines different types of solution approaches from the literature. Below, the key topics are explained that contribute to literature and practice:

- **Container packing combined with inventory management** While the topic of inventory management together with transportation management has not been widely researched, this research proposes a solution approach for dealing with inventory management of items, together with transportation path selection, including the container filling procedure. The previous topics together with the container-filling procedure are one of the contributing elements of this research.
- **Pareto optimal solutions** Most transport selection problems in logistics focus on optimizing the movement of goods in a large logistics service provider network. This research focuses on the cargo owner's perspective and provides a cost/emission Pareto frontier with different cost- and emission focuses. Based on this optimization model, the company can determine what trade-off to make between costs and emissions.
- **Path selection learning heuristic** The learning heuristic for path selection of this research also provides a contribution to literature, since most papers focus on arc selection in a service logistics provider's network. This research proposes a learning heuristic for selecting the transportation path from a cargo owner's perspective.

## 8.2. Recommendations

Based on the conclusions, we propose the following recommendations to ADIL:

- **Cost/emission trade-off selection** This research provides an overview of the possible cost increase together with the potential emission decrease, with Pareto frontier solutions. If ADIL desires to reduce their emissions, ADIL can determine to what extent they want to increase costs in order for an emission reduction. We recommend exploring to what extent ADIL wants to reduce their emissions, to evaluate what cost increase might be applicable.

- **Flexible services system implementation** To increase the share of intermodal transport, ADIL needs to evaluate how flexible transportation services can be implemented into their systems, due to their current standardized procedure. Also, an evaluation of to what extent the current logistics service providers can provide intermodal services in Europe is required to be able to increase the share of intermodal transport.

- **Path selection** The order optimizer calculating expected costs in this research was able to slightly outperform a simple heuristic, only in specific cases. Also, the learning heuristic was not able to significantly outperform the simple heuristic and the order optimizer. For this reason, it is not necessary to develop a sophisticated procedure that determines the optimal transportation path for a specific container.

- **Warehouse capacity** This research tries to find the balance between lost sales and holding costs. Due to the large lost sales cost and low holding cost, the model often prioritises transporting the items as early as possible. A relevant topic to research might be to minimize the lost sales cost related to warehouse capacity. Instead of focusing on holding costs, we choose the transportation path based on the available warehouse capacity.

## 8.3. Research limitations

This research is performed on a broad topic and has a large set of parameters. For this reason, it makes the research sensitive for all design choices made. We list a set of limitations related to this research.

- **Inventory management heuristics** The inventory management system module uses two heuristics to determine the order quantity of each item, and how to distribute the items in one or more containers. The choice for the use of a single heuristic for the two subproblems limits the research related to packing the containers with different methods. Evaluating different container packing algorithms might lead to different results.

- **Path creation** This research reduces the problem formulation related to the transportation network by creating a fixed set of paths for each supplier. This resulted in a reduced decision space, which made it easier to make a decision. Consequently, this also limits the potential for the optimization algorithm to make the best decision.

- **Intermodal arcs and departure times** For the experimental settings, a selection of intermodal arcs have been made which the model may use. Increasing the number of intermodal arcs may increase the usage of intermodal transport. Also, the assumption of arcs departing once a week may influence the choice of intermodal transport.

## 8.4. Future research

This research was conducted for ADIL to explore the possibilities for intermodal transport to reduce total emissions, and to explore the use of sophisticated heuristics, such as machine learning, in choosing transportation paths. This research acts as a starting point for further research into transportation path selection, transportation and inventory management control, and the use of machine learning for transportation selection. Below, a summary is shown with possible future research topics that follow from this research.

- **Demand seasons** Retailers such as the subsidiaries of Ahold Delhaize use promotions to attract customers to their stores. These promotions cause high demand shocks. This research considers these promotions as noise and uses a single demand distribution for each item for the entire horizon. Considering, e.g., a standard- and high season with different demand distributions would be interesting to explore what transportation methods would be selected in what conditions.
- **Multiple Transportation unit types** Transportation has different types of transportation units, like containers, and trailers. Each type has different capacities, characteristics, and transportation prices. Training a model into choosing what transportation unit type is the best option for a supplier is also interesting. The same applies to different pallet types, and, e.g., if stackability applies to a certain item. In this research, we assumed a single pallet type and container type for simplicity. For this reason, considering multiple transportation unit types might be future research.
- **Different reorder points** In this research, reorder points were determined on a certain percentage of the demand distribution. A different approach would be to learn what reorder point is relevant for each transportation path.
- **Warehouse capacity constraint** The lost sales costs for Ahold Delhaize are relatively high and holding costs are relatively low. This leads to the model nearly always preferring to order as early as possible. Placing pallets in inventory at low costs is often more rewarding than higher lost sales. For this reason, an optimization model focusing on warehouse capacity constraints might be more relevant. Then the focus becomes to reduce the lost sales by making optimal use of the available warehouse capacity.
- **Order horizon** In this research, a fixed order horizon of three weeks was used to generate different scheduled paths that use intermodal arcs. Having a lower order horizon leads to better predictable demand, but fewer choices in scheduled paths. Experimenting with different order horizon values might lead to relevant results.

- **Intermodal paths** This research used a fixed set of intermodal paths, each having one fixed departure moment per week. More research about what intermodal paths are available for a small set of LSPs, including their departure moments, might lead to more realistic results.
- **Dynamic arc prices** In reality, the price of transport is based on multiple parameters, such as availability, capacity, and demand. This research assumed a fixed price for transport during the entire time horizon. Researching the behaviour of path selection with dynamic pricing might be an interesting future research topic.

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# A. List of all nodes and arcs

This appendix shows the data sets of all nodes and arcs used in the optimization model. Table A.1 shows the list of all nodes, and Table A.2 shows the list of all arcs.

| ID | Type | City | Country | Latitude | Longitude |
|---:|---|---|---:|---:|---:|
| 0 | transfer | Amsterdam | Netherlands | 52.3667 | 4.8833 |
| 1 | transfer | Rotterdam | Netherlands | 51.9225 | 4.4792 |
| 2 | transfer | Utrecht | Netherlands | 52.0908 | 5.1222 |
| 3 | transfer | Zeebrugge | Belgium | 51.3166 | 3.2044 |
| 4 | transfer | Antwerp | Belgium | 51.2206 | 4.4003 |
| 5 | transfer | Gent | Belgium | 51.0536 | 3.7253 |
| 6 | transfer | Brussels | Belgium | 50.8333 | 4.3333 |
| 7 | transfer | Liege | Belgium | 50.6328 | 5.5722 |
| 8 | transfer | Luxembourg | Luxembourg | 49.6168 | 6.1246 |
| 9 | transfer | Calais | France | 50.9481 | 1.8564 |
| 10 | transfer | Lille | France | 50.6278 | 3.0583 |
| 11 | transfer | Le Havre | France | 49.4900 | 0.1000 |
| 12 | transfer | Paris | France | 48.8566 | 2.3522 |
| 13 | transfer | Metz | France | 49.1203 | 6.1778 |
| 14 | transfer | Nantes/Saint-Nazaire | France | 47.2890 | -2.2210 |
| 15 | transfer | Tours | France | 47.2436 | 0.6892 |
| 16 | transfer | Dijon | France | 47.3167 | 5.0167 |
| 17 | transfer | Bordeaux | France | 44.8400 | -0.5800 |
| 18 | transfer | Toulouse | France | 43.6045 | 1.4440 |
| 19 | transfer | Lyon | France | 45.7600 | 4.8400 |
| 20 | transfer | Montpellier | France | 43.6119 | 3.8772 |
| 21 | transfer | Perpignan | France | 42.6986 | 2.8956 |
| 22 | transfer | Marseille | France | 43.2964 | 5.3700 |
| 23 | transfer | Nice | France | 43.7034 | 7.2663 |
| 24 | transfer | Strasbourg | France | 48.5833 | 7.7458 |
| 25 | transfer | Kiel | Germany | 54.3233 | 10.1394 |
| 26 | transfer | Bremerhaven | Germany | 53.5500 | 8.5833 |
| 27 | transfer | Bremen | Germany | 53.1153 | 8.7975 |
| 28 | transfer | Hamburg | Germany | 53.5500 | 10.0000 |
| 29 | transfer | Rostock | Germany | 54.0833 | 12.1333 |
| 30 | transfer | Osnabrück | Germany | 52.2816 | 8.0507 |
| 31 | transfer | Hannover | Germany | 52.3744 | 9.7386 |
| 32 | transfer | Magdeburg | Germany | 52.1278 | 11.6292 |
| 33 | transfer | Berlin | Germany | 52.5167 | 13.3833 |
| 34 | transfer | Frankfurt/Oder | Germany | 52.3504 | 14.5489 |

| ID | Type | City | Country | Latitude | Longitude |
|---|---|---|---|---|---|
| 35 | transfer | Düsseldorf | Germany | 51.2241 | 6.7644 |
| 36 | transfer | Cologne | Germany | 50.9422 | 6.9578 |
| 37 | transfer | Frankfurt | Germany | 50.1194 | 8.6675 |
| 38 | transfer | Dresden | Germany | 51.0500 | 13.7400 |
| 39 | transfer | Mannheim | Germany | 49.4878 | 8.4661 |
| 40 | transfer | Würzburg | Germany | 49.7953 | 9.9389 |
| 41 | transfer | Nuremberg | Germany | 49.4539 | 11.0775 |
| 42 | transfer | Stuttgart | Germany | 48.7761 | 9.1775 |
| 43 | transfer | Regensburg | Germany | 49.0167 | 12.0833 |
| 44 | transfer | Passau | Germany | 48.5667 | 13.4667 |
| 45 | transfer | Munich | Germany | 48.1372 | 11.5755 |
| 46 | transfer | Prague | Czechia | 50.0649 | 14.4637 |
| 47 | transfer | Basel | Zwitserland | 47.5541 | 7.5911 |
| 48 | warehouse | - | Netherlands | - | - |
| 49 | transfer | A Coruna | Spain | 43.3650 | -8.4100 |
| 50 | transfer | Gijón | Spain | 43.5333 | -5.7000 |
| 51 | transfer | Bilbao | Spain | 43.2569 | -2.9236 |
| 52 | transfer | Vitoria | Spain | 42.8469 | -2.6716 |
| 53 | transfer | Valladolid | Spain | 41.6529 | -4.7284 |
| 54 | transfer | Zaragoza | Spain | 41.6568 | -0.8794 |
| 55 | transfer | Tarragona | Spain | 41.1187 | 1.2453 |
| 56 | transfer | Barcelona | Spain | 41.3879 | 2.1699 |
| 57 | transfer | Valencia | Spain | 39.4702 | -0.3768 |
| 58 | transfer | Madrid | Spain | 40.4167 | -3.7003 |
| 59 | transfer | Murcia | Spain | 37.9835 | -1.1299 |
| 60 | transfer | Cartagena | Spain | 37.6057 | -0.9913 |
| 61 | transfer | Antequera/Bobadilla | Spain | 37.0194 | -4.5629 |
| 62 | transfer | Cordoba | Spain | 37.8847 | -4.7791 |
| 63 | transfer | Seville | Spain | 37.3826 | -5.9963 |
| 64 | transfer | Huelva | Spain | 37.2500 | -6.9500 |
| 65 | transfer | Algeciras | Spain | 36.1275 | -5.4539 |
| 66 | transfer | Porto | Portugal | 41.1502 | -8.6103 |
| 67 | transfer | Aveiro | Portugal | 40.6333 | -8.6500 |
| 68 | transfer | Lisbon | Portugal | 38.7206 | -9.1423 |
| 69 | transfer | Sines | Portugal | 37.9574 | -8.8613 |
| 70 | transfer | Szczecin/Swinoujscie | Poland | 53.4169 | 14.5323 |
| 71 | transfer | Gdynia/Gdansk | Poland | 54.5168 | 18.5419 |
| 72 | transfer | Poznan | Poland | 52.2400 | 16.9167 |
| 73 | transfer | Lódz | Poland | 51.7591 | 19.4586 |
| 74 | transfer | Warsaw | Poland | 52.2333 | 21.0167 |
| 75 | transfer | Wroclaw | Poland | 51.1167 | 17.0333 |
| 76 | transfer | Ostrava | Poland | 49.8408 | 18.2909 |
| 77 | transfer | Katowice | Poland | 50.2667 | 19.0167 |
| 78 | transfer | Kraków | Poland | 50.0689 | 19.9425 |

| ID | Type | City | Country | Latitude | Longitude |
|---:|---|---|---:|---:|---:|
| 79 | transfer | Brno | Czechia | 49.1921 | 16.6132 |
| 80 | transfer | Ostrava | Czechia | 49.8408 | 18.2909 |
| 81 | transfer | Innsbruck | Austria | 47.2627 | 11.3947 |
| 82 | transfer | Wels/Linz | Austria | 48.1566 | 14.0244 |
| 83 | transfer | Salzburg | Austria | 47.8005 | 13.0444 |
| 84 | transfer | Graz | Austria | 47.0696 | 15.4382 |
| 85 | transfer | Klagenfurt | Austria | 46.6237 | 14.3076 |
| 86 | transfer | Novara | Italy | 45.4480 | 8.6152 |
| 87 | transfer | Turin | Italy | 45.0667 | 7.7000 |
| 88 | transfer | Milan | Italy | 45.4636 | 9.1881 |
| 89 | transfer | Genova | Italy | 44.4111 | 8.9328 |
| 90 | transfer | Verona | Italy | 45.4333 | 10.9833 |
| 91 | transfer | Udine | Italy | 46.0667 | 13.2333 |
| 92 | transfer | Venice | Italy | 45.4346 | 12.3389 |
| 93 | transfer | Bologna | Italy | 44.5075 | 11.3514 |
| 94 | transfer | Ravenna | Italy | 44.4157 | 12.1966 |
| 95 | transfer | Ancona | Italy | 43.6171 | 13.5160 |
| 96 | transfer | La Spezia | Italy | 44.1000 | 9.8167 |
| 97 | transfer | Livorno | Italy | 43.5500 | 10.3167 |
| 98 | transfer | Rome | Italy | 41.8906 | 12.4943 |
| 99 | transfer | Naples | Italy | 40.8400 | 14.2525 |
| 100 | transfer | Bari | Italy | 41.1259 | 16.8721 |
| 101 | transfer | Taranto | Italy | 40.4692 | 17.2401 |
| 102 | transfer | Gioia Tauro | Italy | 38.4333 | 15.9000 |
| 103 | transfer | Augusta | Italy | 37.2492 | 15.2326 |
| 104 | transfer | Palermo | Italy | 38.1167 | 13.3667 |
| 105 | transfer | Vienna | Austria | 48.2041 | 16.3781 |

Table A.1.: Set of all nodes.

| Arc ID | From ID | To ID | Transport method ID | Distance (km) | Duration (h) | Emission (kg $CO_2$) | Transfers |
|---|---|---|---|---|---|---|---|
| 0 | 0 | 1 | 3 | 73 | 2 | 55 | 0 |
| 1 | 0 | 2 | 3 | 43 | 1 | 32 | 0 |
| 2 | 1 | 2 | 3 | 59 | 1 | 44 | 0 |
| 3 | 1 | 4 | 3 | 98 | 2 | 74 | 0 |
| 4 | 2 | 30 | 3 | 220 | 4 | 165 | 0 |
| 5 | 3 | 5 | 3 | 71 | 2 | 53 | 0 |
| 6 | 4 | 5 | 3 | 60 | 1 | 45 | 0 |
| 7 | 4 | 6 | 3 | 48 | 1 | 36 | 0 |
| 8 | 4 | 7 | 3 | 121 | 3 | 91 | 0 |
| 9 | 5 | 6 | 3 | 62 | 2 | 47 | 0 |
| 10 | 6 | 7 | 3 | 98 | 2 | 74 | 0 |
| 11 | 7 | 36 | 3 | 123 | 3 | 92 | 0 |
| 12 | 8 | 6 | 3 | 213 | 4 | 160 | 0 |
| 13 | 9 | 10 | 3 | 110 | 2 | 83 | 0 |
| 14 | 10 | 5 | 3 | 75 | 2 | 56 | 0 |
| 15 | 10 | 6 | 3 | 109 | 2 | 82 | 0 |
| 16 | 10 | 12 | 3 | 220 | 4 | 165 | 0 |
| 17 | 11 | 12 | 3 | 197 | 4 | 148 | 0 |
| 18 | 12 | 13 | 3 | 332 | 6 | 249 | 0 |
| 19 | 12 | 15 | 3 | 258 | 5 | 194 | 0 |
| 20 | 13 | 8 | 3 | 65 | 2 | 49 | 0 |
| 21 | 13 | 39 | 3 | 197 | 4 | 148 | 0 |
| 22 | 15 | 14 | 3 | 272 | 5 | 204 | 0 |
| 23 | 15 | 16 | 3 | 438 | 8 | 329 | 0 |
| 24 | 15 | 17 | 3 | 334 | 6 | 251 | 0 |
| 25 | 16 | 13 | 3 | 271 | 5 | 203 | 0 |
| 26 | 17 | 18 | 3 | 245 | 5 | 184 | 0 |
| 27 | 18 | 20 | 3 | 243 | 5 | 182 | 0 |
| 28 | 18 | 21 | 3 | 205 | 4 | 154 | 0 |
| 29 | 19 | 16 | 3 | 193 | 4 | 145 | 0 |
| 30 | 20 | 19 | 3 | 304 | 6 | 228 | 0 |
| 31 | 20 | 21 | 3 | 157 | 3 | 118 | 0 |
| 32 | 20 | 22 | 3 | 169 | 3 | 127 | 0 |
| 33 | 22 | 19 | 3 | 315 | 6 | 236 | 0 |
| 34 | 22 | 23 | 3 | 200 | 4 | 150 | 0 |
| 35 | 24 | 13 | 3 | 163 | 3 | 122 | 0 |
| 36 | 24 | 39 | 3 | 135 | 3 | 101 | 0 |
| 37 | 25 | 26 | 3 | 266 | 5 | 200 | 0 |
| 38 | 25 | 28 | 3 | 99 | 2 | 74 | 0 |
| 39 | 26 | 27 | 3 | 62 | 2 | 47 | 0 |
| 40 | 27 | 31 | 3 | 126 | 3 | 95 | 0 |
| 41 | 28 | 27 | 3 | 123 | 3 | 92 | 0 |
| 42 | 29 | 33 | 3 | 222 | 4 | 167 | 0 |
| 43 | 30 | 36 | 3 | 215 | 4 | 161 | 0 |

| Arc ID | From ID | To ID | Transport method ID | Distance (km) | Duration (h) | Emission (kg $CO_2$) | Transfers |
|---|---|---|---|---|---|---|---|
| 44 | 31 | 30 | 3 | 142 | 3 | 107 | 0 |
| 45 | 32 | 31 | 3 | 147 | 3 | 110 | 0 |
| 46 | 33 | 28 | 3 | 283 | 5 | 212 | 0 |
| 47 | 33 | 32 | 3 | 153 | 3 | 115 | 0 |
| 48 | 33 | 34 | 3 | 104 | 2 | 78 | 0 |
| 49 | 33 | 38 | 3 | 193 | 4 | 145 | 0 |
| 50 | 35 | 1 | 3 | 223 | 4 | 167 | 0 |
| 51 | 35 | 2 | 3 | 196 | 4 | 147 | 0 |
| 52 | 35 | 36 | 3 | 40 | 1 | 30 | 0 |
| 53 | 36 | 37 | 3 | 190 | 4 | 143 | 0 |
| 54 | 37 | 39 | 3 | 80 | 2 | 60 | 0 |
| 55 | 37 | 40 | 3 | 122 | 3 | 92 | 0 |
| 56 | 39 | 42 | 3 | 134 | 3 | 101 | 0 |
| 57 | 40 | 31 | 3 | 366 | 7 | 275 | 0 |
| 58 | 41 | 33 | 3 | 435 | 8 | 326 | 0 |
| 59 | 41 | 40 | 3 | 108 | 2 | 81 | 0 |
| 60 | 41 | 43 | 3 | 107 | 2 | 80 | 0 |
| 61 | 42 | 45 | 3 | 220 | 4 | 165 | 0 |
| 62 | 43 | 44 | 3 | 123 | 3 | 92 | 0 |
| 63 | 45 | 41 | 3 | 172 | 3 | 129 | 0 |
| 64 | 45 | 43 | 3 | 124 | 3 | 93 | 0 |
| 65 | 19 | 1 | 2 | 855 | 66 | 150 | 0 |
| 66 | 47 | 39 | 3 | 260 | 5 | 195 | 0 |
| 67 | 47 | 42 | 3 | 266 | 5 | 200 | 0 |
| 68 | 47 | 44 | 3 | 581 | 10 | 436 | 0 |
| 69 | 46 | 1 | 2 | 911 | 22 | 165 | 0 |
| 70 | 33 | 1 | 2 | 695 | 43 | 155 | 2 |
| 71 | 37 | 1 | 2 | 455 | 24 | 85 | 0 |
| 72 | 37 | 1 | 8 | 455 | 56 | 135 | 0 |
| 73 | 42 | 1 | 2 | 631 | 36 | 115 | 0 |
| 74 | 22 | 1 | 2 | 1165 | 120 | 205 | 0 |
| 75 | 11 | 1 | 1 | 621 | 43 | 70 | 0 |
| 76 | 12 | 1 | 2 | 443 | 120 | 80 | 0 |
| 77 | 47 | 1 | 2 | 679 | 18 | 130 | 0 |
| 78 | 16 | 47 | 3 | 258 | 5 | 194 | 0 |
| 79 | 24 | 47 | 3 | 140 | 3 | 105 | 0 |
| 80 | 2 | 48 | 3 | 51 | 1 | 38 | 0 |
| 81 | 4 | 48 | 3 | 128 | 3 | 96 | 0 |
| 82 | 7 | 48 | 3 | 177 | 3 | 133 | 0 |
| 83 | 35 | 48 | 3 | 151 | 3 | 113 | 0 |
| 84 | 30 | 48 | 3 | 221 | 4 | 166 | 0 |
| 85 | 17 | 52 | 3 | 335 | 6 | 251 | 0 |
| 86 | 51 | 52 | 3 | 65 | 2 | 49 | 0 |
| 87 | 52 | 53 | 3 | 238 | 4 | 179 | 0 |

| Arc ID | From ID | To ID | Transport method ID | Distance (km) | Duration (h) | Emission (kg $CO_2$) | Transfers |
|---|---|---|---|---|---|---|---|
| 88 | 52 | 54 | 3 | 261 | 5 | 196 | 0 |
| 89 | 21 | 56 | 3 | 194 | 4 | 146 | 0 |
| 90 | 55 | 56 | 3 | 96 | 2 | 72 | 0 |
| 91 | 54 | 55 | 3 | 233 | 4 | 175 | 0 |
| 92 | 55 | 57 | 3 | 256 | 5 | 192 | 0 |
| 93 | 54 | 58 | 3 | 316 | 6 | 237 | 0 |
| 94 | 53 | 58 | 3 | 191 | 4 | 143 | 0 |
| 95 | 53 | 50 | 3 | 316 | 6 | 237 | 0 |
| 96 | 53 | 49 | 3 | 440 | 8 | 330 | 0 |
| 97 | 58 | 62 | 3 | 394 | 7 | 296 | 0 |
| 98 | 62 | 61 | 3 | 115 | 2 | 86 | 0 |
| 99 | 62 | 63 | 3 | 143 | 3 | 107 | 0 |
| 100 | 63 | 64 | 3 | 95 | 2 | 71 | 0 |
| 101 | 61 | 65 | 3 | 184 | 4 | 138 | 0 |
| 102 | 60 | 61 | 3 | 383 | 7 | 287 | 0 |
| 103 | 60 | 59 | 3 | 51 | 1 | 38 | 0 |
| 104 | 58 | 69 | 3 | 664 | 12 | 498 | 0 |
| 105 | 68 | 69 | 3 | 160 | 3 | 120 | 0 |
| 106 | 68 | 67 | 3 | 253 | 5 | 190 | 0 |
| 107 | 66 | 67 | 3 | 75 | 2 | 56 | 0 |
| 108 | 33 | 70 | 3 | 143 | 3 | 107 | 0 |
| 109 | 70 | 72 | 3 | 276 | 5 | 207 | 0 |
| 110 | 34 | 72 | 3 | 181 | 4 | 136 | 0 |
| 111 | 72 | 75 | 3 | 166 | 3 | 125 | 0 |
| 112 | 71 | 74 | 3 | 443 | 8 | 332 | 0 |
| 113 | 72 | 74 | 3 | 327 | 6 | 245 | 0 |
| 114 | 72 | 73 | 3 | 220 | 4 | 165 | 0 |
| 115 | 73 | 74 | 3 | 138 | 3 | 104 | 0 |
| 116 | 75 | 80 | 3 | 237 | 4 | 178 | 0 |
| 117 | 75 | 77 | 3 | 196 | 4 | 147 | 0 |
| 118 | 77 | 80 | 3 | 89 | 2 | 67 | 0 |
| 119 | 77 | 78 | 3 | 80 | 2 | 60 | 0 |
| 120 | 78 | 74 | 3 | 291 | 5 | 218 | 0 |
| 121 | 38 | 46 | 3 | 150 | 3 | 113 | 0 |
| 122 | 46 | 79 | 3 | 204 | 4 | 153 | 0 |
| 123 | 46 | 80 | 3 | 371 | 7 | 278 | 0 |
| 124 | 79 | 80 | 3 | 172 | 3 | 129 | 0 |
| 125 | 43 | 46 | 3 | 269 | 5 | 202 | 0 |
| 126 | 44 | 46 | 3 | 224 | 4 | 168 | 0 |
| 127 | 44 | 82 | 3 | 95 | 2 | 71 | 0 |
| 128 | 82 | 83 | 3 | 113 | 2 | 85 | 0 |
| 129 | 45 | 81 | 3 | 144 | 3 | 108 | 0 |
| 130 | 84 | 85 | 3 | 137 | 3 | 103 | 0 |
| 131 | 85 | 91 | 3 | 161 | 3 | 121 | 0 |

| Arc ID | From ID | To ID | Transport method ID | Distance (km) | Duration (h) | Emission (kg $CO_2$) | Transfers |
|---|---|---|---|---|---|---|---|
| 132 | 105 | 84 | 3 | 194 | 4 | 146 | 0 |
| 133 | 105 | 82 | 3 | 198 | 4 | 149 | 0 |
| 134 | 105 | 79 | 3 | 137 | 3 | 103 | 0 |
| 135 | 87 | 19 | 3 | 306 | 6 | 230 | 0 |
| 136 | 87 | 86 | 3 | 97 | 2 | 73 | 0 |
| 137 | 86 | 88 | 3 | 52 | 1 | 39 | 0 |
| 138 | 47 | 86 | 3 | 366 | 7 | 275 | 0 |
| 139 | 23 | 89 | 3 | 194 | 4 | 146 | 0 |
| 140 | 88 | 89 | 3 | 144 | 3 | 108 | 0 |
| 141 | 89 | 96 | 3 | 105 | 2 | 79 | 0 |
| 142 | 96 | 97 | 3 | 99 | 2 | 74 | 0 |
| 143 | 93 | 97 | 3 | 200 | 4 | 150 | 0 |
| 144 | 90 | 92 | 3 | 121 | 3 | 91 | 0 |
| 145 | 90 | 93 | 3 | 146 | 3 | 110 | 0 |
| 146 | 92 | 93 | 3 | 154 | 3 | 116 | 0 |
| 147 | 90 | 88 | 3 | 157 | 3 | 118 | 0 |
| 148 | 93 | 94 | 3 | 78 | 2 | 59 | 0 |
| 149 | 94 | 95 | 3 | 166 | 3 | 125 | 0 |
| 150 | 98 | 93 | 3 | 380 | 7 | 285 | 0 |
| 151 | 99 | 98 | 3 | 228 | 4 | 171 | 0 |
| 152 | 99 | 100 | 3 | 263 | 5 | 197 | 0 |
| 153 | 100 | 101 | 3 | 96 | 2 | 72 | 0 |
| 154 | 99 | 102 | 3 | 443 | 8 | 332 | 0 |
| 155 | 103 | 102 | 3 | 194 | 4 | 146 | 0 |
| 156 | 57 | 59 | 3 | 220 | 4 | 165 | 0 |
| 157 | 57 | 58 | 3 | 355 | 6 | 266 | 0 |
| 158 | 66 | 53 | 3 | 401 | 7 | 301 | 0 |
| 159 | 61 | 63 | 3 | 162 | 3 | 122 | 0 |
| 160 | 54 | 57 | 3 | 312 | 6 | 234 | 0 |
| 161 | 81 | 90 | 3 | 270 | 5 | 203 | 0 |
| 162 | 91 | 92 | 3 | 130 | 3 | 98 | 0 |
| 163 | 83 | 45 | 3 | 145 | 3 | 109 | 0 |
| 164 | 73 | 77 | 3 | 217 | 4 | 163 | 0 |
| 165 | 103 | 104 | 3 | 240 | 4 | 180 | 0 |
| 166 | 51 | 1 | 1 | 1747 | 58 | 170 | 0 |
| 167 | 57 | 1 | 1 | 3782 | 144 | 385 | 0 |
| 168 | 68 | 1 | 1 | 2403 | 95 | 240 | 0 |
| 169 | 56 | 1 | 2 | 1397 | 87 | 300 | 1 |
| 170 | 90 | 1 | 2 | 1216 | 19 | 210 | 0 |
| 171 | 86 | 1 | 2 | 1042 | 24 | 190 | 0 |
| 172 | 99 | 1 | 1 | 5142 | 192 | 525 | 0 |
| 173 | 102 | 1 | 1 | 5101 | 264 | 515 | 0 |
| 174 | 100 | 1 | 2 | 1896 | 67 | 335 | 0 |
| 175 | 72 | 1 | 2 | 956 | 65 | 160 | 0 |

| Arc ID | From ID | To ID | Transport method ID | Distance (km) | Duration (h) | Emission (kg $CO_2$) | Transfers |
|---|---|---|---|---|---|---|---|
| 176 | 71 | 1 | 1 | 1964 | 120 | 260 | 1 |
| 177 | 71 | 1 | 2 | 1277 | 71 | 250 | 1 |
| 178 | 77 | 1 | 2 | 1203 | 31 | 225 | 0 |
| 179 | 80 | 1 | 2 | 1250 | 64 | 200 | 0 |
| 180 | 105 | 1 | 2 | 1162 | 64 | 205 | 0 |
| 181 | 82 | 1 | 2 | 999 | 44 | 175 | 0 |

Table A.2.: Set of all arcs.

# B. K-optimal path specification

In the problem formulation, we create a fixed set of paths for every supplier. Based on the transportation network, the fixed set of paths is determined for each supplier. In the experiments, we choose a $k = 3$, which means that for every objective: time, cost, emission, top 3 paths are generated, and the union is taken of this set. This means that for $k = 3, 3^2 = 9$ paths are generated at maximum.

In the experiments, we have 177 suppliers, which results in 177 sets of paths. Figure B.1 shows the count of the number of paths per supplier. E.g., about 100 suppliers have a set of 4 fixed paths to choose from. This means that of the maximum 9 generated paths, the union equals 4 paths, which are the most important paths.

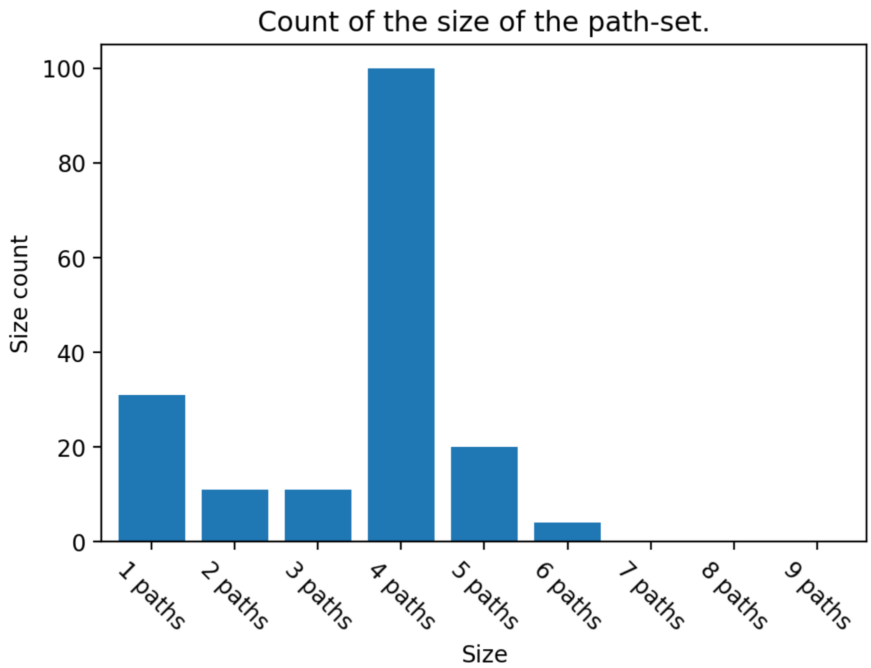


Figure B.1.: Count of the set of paths size.

If we investigate a single supplier with different experiments in Figure B.2, we see that a supplier in most experiments often prefers a single path, except during the full cost focus. For this reason, we conclude that $k = 3$ is sufficient for all suppliers to create a sufficiently diverse set of paths.

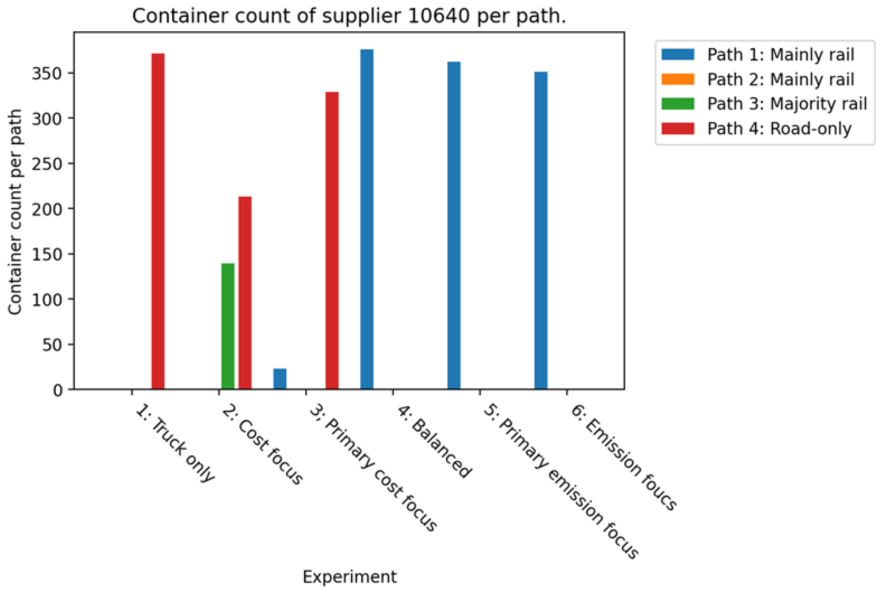


Figure B.2.: Count of different paths for a specific supplier during several experiments.

# C. Warm-up period and replications analysis

**Warm-up period**

The inventory management system starts as an empty system with no inventory. Therefore, the system requires at least a warm-up period of 12 weeks, which is the sum of the maximum production lead time, 9 weeks, and the planning horizon, 3 weeks. This means that the demand starts in week 13. This way, the system has sufficient time to determine the first set of orders to fill the system.

Figure C.1 shows the number of orders placed each week. In the first week, all orders are placed such that the safety stock is satisfied for each supplier. the demand start is week 13, after which the number of orders starts to stabilize. Also, Figure C.2 shows that the costs stabilize after 12 weeks. We include an extra margin of 8 weeks to be sure the system is stable, which results in a total warm-up period of 20 weeks.

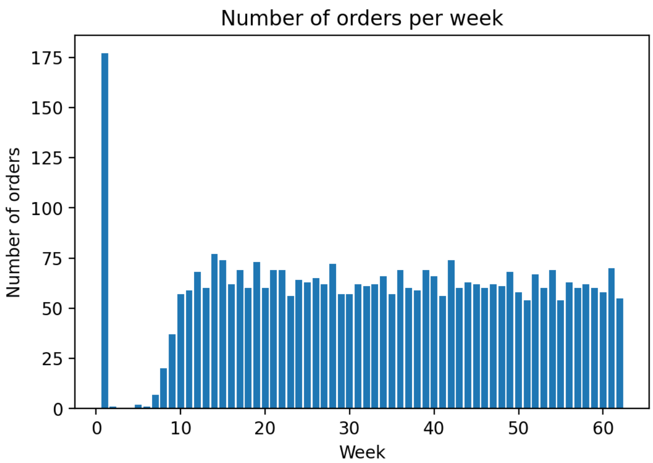


Figure C.1.: Number of orders placed in a specific week, where the demand starts in week 13.

**Replications**

To gain an estimate of the number of replications, the sequential procedure of Law (2015) is used. We apply a maximum error of $\gamma = 0.1$, which leads to a corrected target value $\gamma' = \frac{\gamma}{1+\gamma} = 0.0909$. When the relative error becomes lower than the corrected target value $\gamma'$, we have sufficient replications.

We use two KPIs to evaluate the number of replications, which are the total cost and total emission per experiment. We perform six 100% cost focus experiments and assume the

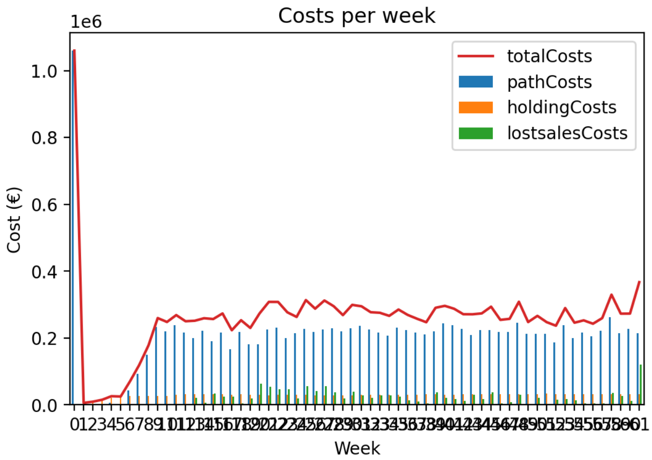


Figure C.2.: Total cost, also split per cost category, per week during a simulation run.

relative error of the results is approximately the same across other experiments. Table C.1 shows the results for the number of replications.

Table C.1.: KPI evaluation for the number of replications.

| Exp | KPI | Running avg | Running var | Tvalue | CIHW[1] | delta |
|---|---|---|---|---|---|---|
| **Cost KPI** | | | | | | |
| 1 | 13,258,963 | - | - | - | - | - |
| 2 | 12,344,799 | 12,801,881 | 417,847,991,723 | 6.31 | 2,885,902 | 0.2254 |
| 3 | 12,087,558 | 12,563,773 | 379,010,061,986 | 2.92 | 1,037,876 | **0.0826** |
| 4 | 13,886,487 | 12,894,452 | 690,066,337,062 | 2.35 | 977,472 | 0.0758 |
| 5 | 12,059,787 | 12,727,519 | 656,882,920,297 | 2.13 | 772,707 | 0.0607 |
| 6 | 12,275,412 | 12,652,168 | 559,573,159,903 | 2.02 | 615,373 | 0.0486 |
| **Emission KPI** | | | | | | |
| 1 | 5,312,563 | - | - | - | - | - |
| 2 | 5,148,344 | 5,230,454 | 13,483,939,981 | 6.31 | 518,419 | 0.0991 |
| 3 | 4,738,302 | 5,066,403 | 87,479,669,641 | 2.92 | 498,625 | 0.0984 |
| 4 | 5,218,754 | 5,104,491 | 64,122,486,561 | 2.35 | 297,964 | **0.0584** |
| 5 | 4,550,937 | 4,993,780 | 109,376,215,749 | 2.13 | 315,306 | 0.0631 |
| 6 | 4,557,146 | 4,921,008 | 119,275,847,591 | 2.02 | 284,110 | 0.0577 |

Table C.1 shows that for the cost KPI, at least 3 replications are required, and for the emission KPI, 4 replications are required. For that reason, all experiments will be run with 4 replications.

[1]Confidence Interval Half Width.